Thomas O. Binford
Artificial Intelligence Laboratory
Computer Science Department
Stanford University

Survey of Model-Based Image Analysis Systems

Reprinted from *International Journal of Robotics Research*, Volume 1, Number 1, 1982, pages 18-64, "Survey of Model-Based Image Analysis Systems" by T.O. Binford by permission of The MIT Press, Cambridge, Massachusetts.

Abstract

A survey and critique of the state of the art in model-based image analysis systems is presented. The paper includes summaries of a selection of systems and evaluates them from the viewpoint of progress toward general vision systems. The paper also describes principles of design of general vision systems.

1. Introduction

Human beings pursue many goals in an unconstrained, constantly changing world with many objects; they work within a *general vision system*. Robots work in manufacturing performing a single, repeated task with few objects, all known, in constrained environments engineered to simplify those tasks. In vision systems for manufacturing, many special-case tricks are used that do not generally apply to worlds with many objects and many goals. However, those systems must eventually come to resemble general vision systems more than is generally acknowledged.

Consider what is required to make improvements in current industrial vision systems to make them saleable in a large market. A single system must (1) be easily programmed to accomplish many tasks of visual control or inspection, (2) not need extensive special-case engineering, and (3) be insensitive to variations in lighting. A single system must be instructed effectively to determine many classes of defects, including rare defects and those not encountered in training, and to distinguish cosmetic from real defects. While a single industrial task is very constrained, the range of tasks and objects in a major company, industry, or industries is not. It is not cost-effective to build a separate system for each task; thus, an adequate system must have modules specialized for a particular task. Other applications now being pursued impose even more severe requirements for high-speed object classification in complex environments.

We work to make machines see as people do, to understand how people see, to implement performance systems for visual applications, and to incorporate current capabilities in an experimental system to support further research. Those activities all depend on common visual operations and common representations.

In this paper, *prediction* refers to mappings from object models to their predicted appearances in images (i.e., top-down mappings in the direction from symbol to signal). *Description* and *observation* refer to mappings from sensed images to perceived surfaces and objects (i.e., bottom-up mappings from signal to symbol). *Interpretation* refers to mappings between predictions and descriptions. *Generic* means defined over a class (e.g., generic with respect to viewpoint meaning defined over a range of viewpoints). One example of interpretation is *template matching*, that is, finding the best embedding of a template subimage to an observed image, over all translations and rotations. One example of prediction is the mapping of a specific object model to a specific image from a particular viewpoint by techniques of computer graphics. Neither example is interesting for general vision systems.

In the "bad old days," work on vision systems was commonly justified by statements that general segmentation and description were impossible, a dead end. Description modules might be improved a bit, but not much. It was not necessary to improve them. With that doctrine, powerful vision systems could be made by combining existing modules into systems that used extensive world knowledge. Not only was this the way to successful applications pro-

The International Journal of Robotics Research
Vol. 1, No. 1, Spring 1982.
0278-3649/82/010018-47 $05.00/0

grams, but it was a basis for human visual performance.

A minority held the contrary view that low-level vision modules were weak, fulfilling less than 1% of their potential. This minority felt that although the problems are fundamental, segmentation and description are powerful in humans and will eventually be powerful in machines. Combining ineffective procedures, they thought, would produce little of interest. (Three pieces of junk are usually worth less than one; there are more to get rid of.) Vision systems would be inherently limited by performance of segmentation modules. Further, ad hoc building of systems would be frustrated because without effective representation and description, knowledge cannot be used effectively. There are deep problems in encoding and using world knowledge in a general way in a wide range of situations, that is, in relating world knowledge to image structures where world knowledge is typically about object classes in *three space*. This view held that combination of existing modules to build vision systems would not lead to powerful vision systems. Useful systems might be made for limited applications, however, and building systems is a useful exercise for looking at the full problem. Yet this group believed that careful theoretical analysis and implementation of individual vision operations was an essential basis for building vision systems and especially for effective applications.

The minority opinion is now held by the majority, and studies of fundamental vision science are under way. System building is no longer an end in itself, but is used for applications and demonstrations. It is now time to look at both applications and the total problem.

2. Observations About Systems Surveyed

Except for the first four, the systems surveyed will be discussed in alphabetical order. One vision system has succeeded in labeling large regions in aerial photographs (Nagao, Matsuyama, and Ikeda 1978); another has labeled large regions in a few outdoor scenes from ground-level views (Ohta 1980). ACRONYM has identified aircraft in aerial photographs (Brooks 1981). Another system has labeled objects in typical scenes of a desk (Shirai 1978). The results of these and other efforts are encouraging as first demonstrations. As general vision systems, they have a long way to go.

With several of the summaries of systems are comments about their limitations as general-purpose vision systems. The lists of limitations are only reminders with examples, not complete descriptions of the ways in which these systems would not have general applications. Complete descriptions of problems follow summaries of systems.

What works in the best of these systems? What makes them go? They succeed with quasi–two-dimensional scenes; for example, aerial photographs, industrial scenes from a fixed viewpoint, x-ray images, and ground-level photos from a fixed viewpoint. Even ACRONYM, which incorporates viewpoint-insensitive mechanisms, has been demonstrated only on aerial images, although there is reason to believe that ACRONYM will succeed with ground-level photographs also. Ohta (1980) demonstrated some success with a set of similar scenes from several viewpoints. Still, the system uses relations that are manifestly viewpoint-dependent.

The systems "use" image models. In Ohta's system (1980), the model includes the following relations: the sky touches the upper edge of the picture; the road touches the lower edge of the picture; trees are in the middle of the picture; and buildings have a linear upper boundary with the sky. One type of image model includes maps and symbolic sketches. Several systems use maps in registration of images with symbolic databases. An exception, ACRONYM (Brooks 1981), generates viewpoint-insensitive image models from object models in three space.

The systems "know" few objects. Ohta's (1980) has four objects with subobjects. Nagao (1978) mentions about nine classes of areas, but the system described apparently distinguishes only four: fields (with vegetation or bare); buildings; wooded areas; and linear features (roads, rivers, rail). ACRONYM has models of generic wide-bodied passenger aircraft, Lockheed's L-1011, and Boeing's 747-B and 747-SP. Shirai's (1978) includes a few objects found on desks: a lamp, a book stand, a cup, a telephone, and some small objects such as a pen. These four systems take advantage of the limited set of objects by using predominantly top-down interpretation of images, and relying heavily on prediction. The systems use models of specific objects. For example, Ohta's (1980) uses a model in which a car is darker than the road against which it appears.

Depth information is powerful. With depth data, input and models are at the same level. Depth data directly describes surfaces, which are natural for object interpretation. Images are two-dimensional, while objects are three-dimensional. Image-level invariants are weak, while three-dimensional invariants are strong and valuable for object-level interpretations. The projection process destroys information. The remark is often made that vision is the inverse of graphics, as if to imply that vision is thus somehow simpler than we find it to be. The inverse of projection is indeed simple, but it is useless. There is no unique inverse, only very high orders of continuous infinities of projectively equivalent surfaces. Depth can be inferred from sequences of images (stereo, observer motion, object motion, photometric stereo). A primary problem is determining corresponding elements in the sequence. Direct depth measurement avoids the correspondence problems of reconstructing depth data from image sequences. There are much greater problems in inferring surface structure and depth relations from single images.

One key to performance of systems is in their use of measurements that are simply related to characteristic properties of surfaces and to three-space relations of surfaces. Surface reflectivity and surface material are often characteristic (e.g., concrete and asphalt roads, or vegetation). Surface material can be partially inferred from color and texture. Intrinsic properties such as color, texture, and shape thus provide powerful and simple clues to interpretation. In Rubin's system (1978), 44% identification of pixels was achieved with the intensity of the blue channel alone. Remote sensing has depended on pixel classification based on spectral properties. Nagao, Matsuyama, and Ikeda (1978) use spectral properties of vegetation; shape descriptors, including elongation and straight boundary; and a simple texture descriptor. Ohta (1980) uses color, simple texture, straight boundary, and hole, in addition to nonintrinsic relations that are viewpoint-dependent. ACRONYM (Brooks 1981) utilizes shape descriptors that are ribbons and ellipses and describes a larger class of quasi-invariant observables of shape. The use of simple intrinsic properties can be pushed much further than has been done thus far.

2.1. Limitations

What are the limitations of these systems in the restricted domains for which they were designed? How do they limit attempts to extend them to general vision systems?

In my opinion, most systems have not attempted to be general vision systems. The performance they achieve is based on a severely limited context and reveals low ambitions for the quality of scene description they generate. ACRONYM does demonstrate some progress toward the goal of a general vision system, a goal that is still distant. The fundamentalist view of systems appears to have been accurate: first, performance of vision systems is strongly limited by performance of segmentation modules; second, systems make weak use of world knowledge. Existing systems have weak description, with little use of shape. Systems, like description operations, have achieved less than 1% of their potential, even allowing for weak description. They use little information in weak ways. Systems primarily relate image relations to image observables; they lack most the ability to relate three-space models to images. Systems are being built, but there is relatively little emphasis on basic vision problems in system building. Until recently, systems efforts have been small and short-lived—a few years' effort. Focused and continuous efforts are necessary but not sufficient for system building. Just the system programming task in building a vision system is enormous.

With the exception of ACRONYM, the systems surveyed do not appear to have the capability of viewpoint-insensitive interpretation. Since the systems depend on image models and relations, they are strongly viewpoint-dependent. To generalize would require three-dimensional modeling and interpretation, as in ACRONYM.

The systems do not appear to be effective in environments with many objects. They jump to conclusions based on flimsy evidence and would probably not distinguish many objects in a complex visual environment. Humans may occasionally hallucinate in the same way, but usually they have strong evidence for interpretation.

The primary limitation in seeking stronger evidence for interpretation is weak segmentation capability and weak implementation of observation primitives. For example, in Ohta's system (1980), shadows are identified as having low intensity; black objects would be confused with shadows in typical scenes. In indoor scenes, contrast across shadow boundaries can be low. Most systems surveyed segmented images based on *pointwise properties*, that is, connected components of points that independently fall in some spectral band. Few systems used shape in segmentation of regions, that is, used continuity of edges that form ribbons. In other words, most systems segment regions then describe their shape, while a few segment well-formed regions. Simple texture measures are used; however, segmentation of extended edges is a major void, especially segmentation of textured regions. Correspondingly, shape description is primitive. Interpretation systems do not appear yet to make full use of even these limited capabilities. No system surveyed has effective texture segmentation and description such that surface texture is an intrinsic property in identification. Where range measurements are available, surfaces can be segmented directly at occlusions, that is position discontinuities. This is not the same as segmenting objects as humans do, because an object resting on a plane will not be segmented from the plane; the object and the plane are coincident. Even with range data, systems make poor symbolic, segmented descriptions of surfaces because of the fundamental weakness in segmentation.

None of the systems duplicates the human capability of color constancy, that is, the systems are incapable of sensitivity to source spectrum. Brightness constancy is related, inferring which surfaces are white and black in black-and-white images. Color constancy and brightness constancy are obtained by estimating surface reflectivity by a global partial ordering of local relations (Land and McCann 1971). It is no accident that multispectral data are useful, since surface reflectivity is characteristic in many cases (but not unique). It is also no accident that color constancy and brightness constancy have not been integrated in the systems surveyed, since constancy requires a global computation that is much more complex than pointwise, multispectral calculation and that requires effective segmentation. Horn (1973) has demonstrated partial success with color constancy; however, that capability is not integrated in any system. To my knowledge, no use has been made of surface reflectivity in black-and-white images for those same reasons. In the case of an active ranging sensor, reflectivity can be computed directly at points from reflected intensity and range.

Systems typically use the hypothesis-verification paradigm. Hypothesis generation is the crucial part. Hypothesis generation is trivialized in the top-down case. For example, ACRONYM now searches only for aircraft. Another approach to hypothesis generation is evident in the systems surveyed. If an object class has a stable property, they assign the object class as an interpretation for any image region that has that property. For example, they assign vegetation as an interpretation for any image region that has the right color: green. That assignment has utility in restricted scene domains. But in typical cases, assignment must be generalized. For example, a house has straight lines, but to assign a house interpretation to image regions with straight lines would have little usefulness. The appropriate interpretation is not necessarily the union of all objects with straight edges, since that class is very large and the simple prescription does not tell how to break down the class. Rather, systems should relate straight lines to structural elements with straight edges. That requires powerful capabilities for inference of shape such as those being developed in ACRONYM (Binford 1981). Thus, that method of hypothesis generation is successful in restricted scene domains with a few object classes that are easily separated by local operations.

2.2. NAGAO, MATSUYAMA, AND IKEDA

In the systems described by Nagao, Matsuyama, and Ikeda (1978; 1980), an aerial photograph is first segmented into regions by several processes. Judging from the dominant features of each extracted region, specialized feature extraction and recognition programs are applied to that region only. Properties of objects are summarized and are fed back in order to reanalyze ambiguous regions.

To extract major regions, the following operations are used: (1) edge-preserving smoothing; (2) segmentation into regions that are continuous in spectral properties; (3) extraction of five kinds of regions, called *cue regions;* (4) analysis of each cue region by an object-detection program specific to region type; and (5) summary of properties of regions fed back to subsystems.

Cue regions include large homogeneous regions, elongated regions, shadow and shadow-making regions, vegetation regions, water regions, and high-contrast-texture regions. Each kind of cue region is extracted independently of the others. Some regions may appear in several types of cue regions.

Nagao and Matsuyama's book shows data from several pictures with four spectral bands taken at low altitude from an airplane. The pictures are 256×256 with 8 bits per pixel, corresponding to 50×50 cm on the ground. Spectral bands are red, green, blue, and infrared.

Pictures are first processed by an edge-preserving smoothing operator. It is intended to remove "noise" and to remove the blurring at edges of regions for pixels that overlap two regions. It is somewhat successful; however, it erodes thin lines and small regions (smaller than 3×3). It presumably rounds corners.

After smoothing, each picture in the four bands is divided into small patches with constant gray level. Patches with similar spectral properties are grouped together: if the differences in four bands are less than a threshold between a labeled pixel and its neighbor, the neighbor is merged. This is a gradient operation that allows shading. The threshold value in each spectral band is adaptively determined as follows. The differentiated picture is divided into 16 64×64 blocks and a histogram made of nearest-neighbor differences for each block. A valley is found for each histogram where the valley has a value lower than the succeeding nine values. The minimum value is chosen for valleys among the 16 blocks. This follows the reasoning that noise will have a large peak, and edges will have a smaller peak.

Small regions with less than 4 pixels are merged with neighboring large regions with the most similar spectral properties. This is done because boundaries of homogeneous regions sometimes are ragged as a result of separate smoothing in each spectral band.

One shape descriptor is the best *minimum bounding rectangle* (MBR), defined as the MBR with maximum ratio of region area/area of MBR over angles 10° apart. Elongation and direction are taken from the best MBR.

Large homogeneous regions are defined by making a histogram of homogeneous region size and applying a valley-detection algorithm. Small regions are assumed to result from noise. Regions larger than the threshold are processed further. They may be fields, grasslands, lakes, and sea.

Some regions are flat (e.g., fields and the sea); however, houses, buildings, and trees have height. Shadows give information about height. Shadows are usually available because aerial pictures are usually taken in good weather. Shadows are obtained in the following way. A histogram is made of brightness of smoothed pictures. The average brightness in the whole picture is calculated. The brightness is calculated that makes the interclass scatter minimum when divided into two classes. If the gradient at this value is small, it is chosen as the threshold brightness, I1. Otherwise a search is made for a valley near that value (I1). Homogeneous regions whose average brightness is less than the value I1 are chosen as shadows. Shadow-making regions are chosen to be those adjacent to shadows with a long common boundary in the direction away from the sun. Shadows are used to discriminate between flat objects and those with height.

Elongated objects include roads, rivers, and railroad lines. No analysis is made of railroad lines. Elongated regions may be broken by cars, trains, or shadows, and they may be curved. For curved regions, the MBR does not give a good estimate of elongation; the system determines an elongation effective for curved regions by taking the longest path on the skeleton of a region. If length/width >3, regions are considered to be elongated.

Vegetation areas have a small ratio of red to infrared intensity, a property that is quite stable. However, blue roofs have the same property. Thus, the system was made to exclude regions with large intensity in the blue band. Adjacent vegetation regions are merged into a large vegetation region. Water regions are identified by spectral properties, with the additional condition that water regions are darker than adjacent regions. Problems were found for water in shadow and where there were weeds. Extraction of vegetation and water are two examples of segmentation according to intrinsic properties of materials.

High-contrast texture regions are treated as follows. After smoothing, only coarse texture remains from objects 1.5 m on a side. Woods and residential areas contain small objects such as trees, houses, roads, and shadows. The authors found it almost impossible to recognize these small objects using only individual properties such as shape. Thus, the system extracts a set of small regions as a whole and recognizes each constituent region based on properties of the group of small regions. The system extracts homogeneous regions, then moves a $N \times N$ window over the image; if the window contains more than 2 N boundary points, the system considers the central point of the window as part of a high-contrast texture region. The system removes small holes and peninsulas by growing regions two steps, shrinking four steps, then growing two steps. The system merges any homogeneous region that has more than half its area in high contrast but that is not a large homogeneous region. The common area between the high-contrast regions and the large vegetation regions is registered as a high-contrast vegetation region.

A large homogeneous region may be a crop field, bare soil, or a grassy area. Boundaries of large homogeneous regions composed of straight lines are designated *crop field* unless they are elongated regions. Boundaries are called *straight* if more than 60% of pairs of forward and backward boundary chords have angles of less than 22.5° (for point i, the forward chord is the pair of points indexed by i, i + 5, the backward chord is the pair indexed by i, i − 5). Crop fields so designated are put into two classes, one with vegetation, the other without. A region adjacent to a crop field or bare crop field is a *candidate* for either if its area is greater than half the threshold for large homogeneous regions.

Elongated regions include rivers and roads, which are used to register images. Elongated regions may be broken by bridges, cars, and shadows. They are not vegetation regions, shadows, or shadow-making regions. Road candidates are elongated, not vegetation, and not water regions. The system examines all pairs of candidate regions and connects those that have nearly the same intensity and color, adjacent ends, the same width, and the same direction. The conditions are difference of average gray scale in the four spectral bands less than a threshold (separate for each band); ratio of widths near 1 (between $^2/_3$ and $^3/_2$); smallest separation between ends less than 3 W, where W is the smaller of the two widths; and direction difference less than 45°. Roads are candidates with elongation >8 from length/width along the *skeleton* and for which the variance of widths along the skeleton is small. Intervening gaps may not be vegetation or water regions. The system traces any such road and picks up nearby side roads connected to it, with small difference in hue, with ratio of widths between $^1/_2$ and $^2/_1$, and with one end point within 3 W of the first road found. The system recurses on side roads to find their side roads. Cars are recognized as rectangular regions on roads.

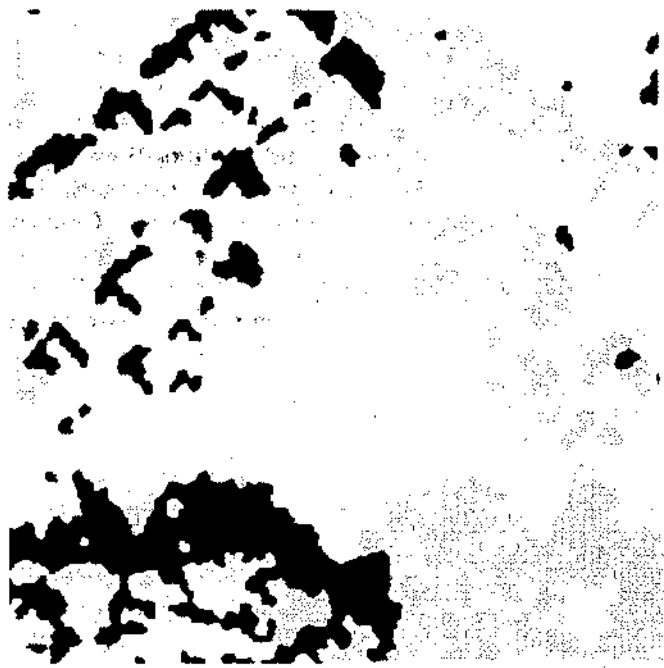
River candidate regions are water regions, not necessarily elongated. Analysis of rivers is similar to that of roads. Multispectral properties of water in shadow are greatly affected. Thus, shadow regions are merged with water if they are adjacent to a water region, if they are not a vegetation region, and if merged regions have increased elongation.

Each high-contrast vegetation area is assumed to be a wooded area. Small elements should have irregular shape (from the straightness condition above). A high-contrast vegetation region contains shadows and shadow-making regions; this distinguishes woods from grass.

The approach for finding houses is to identify candidates for residential areas first and then find houses. High-contrast regions that are not large homogeneous regions and not large vegetation areas are candidates for residential areas. Residential areas are identified as areas in which gradients are strong

Fig. 1. An aerial photograph, basis for system identifications shown in Figs. 2–17. (From Nagao and Matsuyama 1980.)

Fig. 2. Shadow regions. (From Nagao and Matsuyama 1980.)



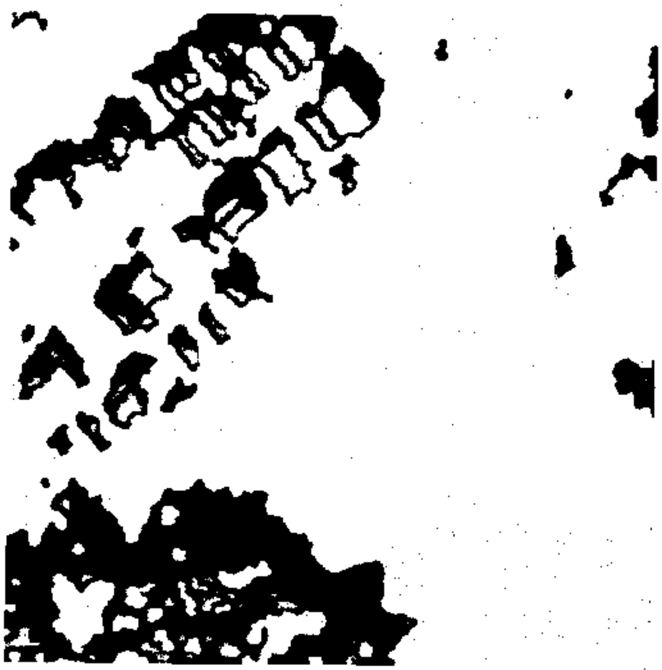
in two orthogonal directions. Houses typically have walls at right angles. The method would be valid where houses are laid out on an orthogonal grid. HOUSE1, a recognition routine for houses, uses these properties: in a residential area; not a vegetation region, not a shadow region, not a water region, but a shadow-making region; rectangular shape. HOUSE2 extracts regions whose average gray levels in the four spectral bands are similar to those of any houses recognized by HOUSE1. HOUSE2 requires a weaker condition on rectangularity, and waives the condition that the region be a shadow-making region if it is in a residential area. Houses also appear as two rectangular elements, where two inclined surfaces are segmented as separate, adjacent regions. HOUSE3 tries to recognize parts of a roof that are not recognized and that are adjacent to roofs already recognized. HOUSE4 looks for missing houses in regular arrays. It looks for regions that fall on sites determined by "regularity vectors" of the pattern of houses. Candidates must not be vegetation region, water region, shadow region, or elongated region and must satisfy rectangular fit. Buildings are designated as regions that are not vegetation or water regions, that are shadow-making regions, that have area greater than an ad hoc value, and a predominantly straight boundary.

System control tries to resolve conflict labels and to deal with unlabeled regions. If a region has more than one label, the most reliable label is chosen and other interpretations are rejected. Interpretations that are dependent on rejected interpretations (e.g., car identified from road) are also rejected. If regions are unlabeled because their shapes do not satisfy conditions of object classes, the system activates a split-and-merge process to attempt to split the region into two regions or to merge the region with adjacent regions. This sometimes corrects faulty segmentations. Splitting takes place at bottlenecks in width along the longest path on the skeleton of the region.

Results are shown for several images in the book (Nagao and Matsuyama 1980). The system does well for roads, fields, and forest. Figures 1–17 show steps in an example of analysis. Some areas are falsely labeled as houses by HOUSE2 (seven in one picture). About 3% of the scene is shadow that is unlabeled. Small shadows on roads and rivers can be correctly labeled; shadowed vegetation areas can

Fig. 3. Shadow-making regions. Regions enclosed by black lines show the shadow-making regions; gray shading denotes shadow regions. (From Nagao and Matsuyama 1980.)

Fig. 4. Vegetation regions. (From Nagao and Matsuyama 1980.)



also be labeled. Otherwise, there is difficulty with large shadowed areas. A large area around houses is left unlabeled. The system has difficulties with urban scenes. For five scenes, unlabeled shadow and unrecognized areas are 3%, 19%; 1.6%, 16%; 10%, 31%; 22%, 30%; and 4%, 16% respectively. Thus, 20–52% of the area is unlabeled. This is a pessimistic evaluation, since significance of many details is not related to size. The interpretation process requires about 200 s per multispectral picture on a machine with 90 ns average instruction time, plus about 240 s of smoothing.

This is a fine and well-crafted system. It performs interesting interpretations on these examples. Its approach is to use special subsystems to recognize specific objects. Thus, it is not intended as a general vision system. The following limitations appear when it is considered as a general vision system.

Description and segmentation are limited. The system makes weak use of texture, a problem throughout the computer vision community. Its only texture descriptor is textured versus nontextured, based on boundary density. The system's shadow identification is not general and not reliable. It is unlikely that in general scenes a valley will show up in the histogram, and unlikely that any intensity threshold will separate shadow from nonshadow. Reflectivities vary by about 0.05 to 0.90, a factor of 16, while shadow to full illumination typically has a ratio of 0.1/1.0. Their ranges overlap. Segmentation appears highly dependent on color input. The smoothing operation degrades the picture considerably.

Interpretation depends on assumptions that are not broadly useful. Shadows provide the only three-dimensional interpretation. No use is made of shadows to determine shape of objects other than as non-flat. Shadows are assumed to be adjacent to shadow-casting regions. This is not generally true and, even when true, makes assumptions about surface marking and performance of edge operators. Interpretation is appropriate for large areas, not for human-scale objects for which shape is important. There are models for only a few objects. Weak use is made of shape. Even for the domain of aerial photos, interpretations are made on weak assumptions. Grass pastures can have straight boundaries. Water can appear brighter or darker than surrounding land; the condition that water appears dark

Fig. 5. Large vegetation areas. Each area consists of many elementary regions. (From Nagao and Matsuyama 1980.)

relative to adjacent land is not general. Interpretation is image-oriented. In a view from ground level, fields would not be as prominent and models for fields would not be adequate. Houses would not appear as rectangular or L-shaped roofs.

2.3. Ohta

Ohta (1980) describes a system that assigns semantic labels to regions in color images of outdoor scenes. Ohta presents a new set of color parameters used in an Ohlander-like region analysis system (Ohlander 1975) that forms regions by splitting, using thresholds selected from histograms of the new color parameters. A plan is generated by an initial bottom-up coarse region segmentation. A symbolic description of the scene is made by top-down analysis using a production system, with knowledge of the world represented as a set of rules.

Region analysis tends to "oversegment"; that is, to split semantic regions (images of surfaces or objects) into several regions. In part, this is because the author's choice of color parameters is intensity-dependent. Matching searches for a many-to-one correspondence between regions and images of surfaces. Each region is evaluated for each surface interpretation rule.

Ohta determines the best set of parameters for segmentation of color regions. Ohta proposes as color parameters the three eigenvectors of the covariance matrix (Karhunen-Loeve transformation). He starts out to find eigenvectors dynamically, but finds it about as satisfactory to determine eigenvectors once and for all. The eigenvectors turn out to be: $x1 = (r + g + b)/3$; $x2 = (r - b)/2$ or $(-r + b)/2$; $x3 = (-r + 2b - b)/4$. Eight scenes were used in an experimental analysis. Ohta used 109 selected regions, large regions that split into "not-small" regions. In the *wr*, *wb* plane, eigenvector $x1$ is in the first quadrant (83 regions), $x2$ is in second and fourth quadrants (22 regions), and $x3$ is in the third quadrant (4 regions). Thus, $x1$ is by far the most important, $x2$ next, and $x3$ almost negligible. If images are synthesized based on only $x1$, $x2$, with a constant value for $x3$, the results are reasonably good except for several small regions. That is, color is roughly two-dimensional. $x1$, $x2$, and $x3$ are intensity-dependent, which may not be acceptable to everyone. Regions tend not to have constant intensity; thus, regions are broken into bands using this set of color parameters.

The system processes images 256×256, with 5 bits or 6 bits. Region segmentation fails with texture, so the author segments off textured regions, obtained as follows. In a 9×9 window, if the Laplacian of 8 out of 9 subwindows (3×3) exceeds threshold, it is considered a texture window. In a building scene, this process obtained the outer portions of a tree. The remainder (not strongly textured) is segmented by recursively applying thresholds determined from peaks of histograms of color parameters. A score is calculated for each peak, including the relative depth of the valleys and the sharpness of the peak. Regions thus obtained are evaluated by a *looseness criterion* related to the fraction of border cells to total cells. The segmentation with minimum looseness is chosen. Regions with size greater than a threshold are scanned with a 32×32 window. The data structure includes regions, boundaries, and ver-

Fig. 6. ***A****. Boundaries of elementary regions.* ***B****. Areas with high density of boundary points.* ***C****. Result of removing small holes and thin peninsulas.* ***D****. High-contrast texture area consisting of elementary regions. (From Nagao and Matsuyama 1980.)*

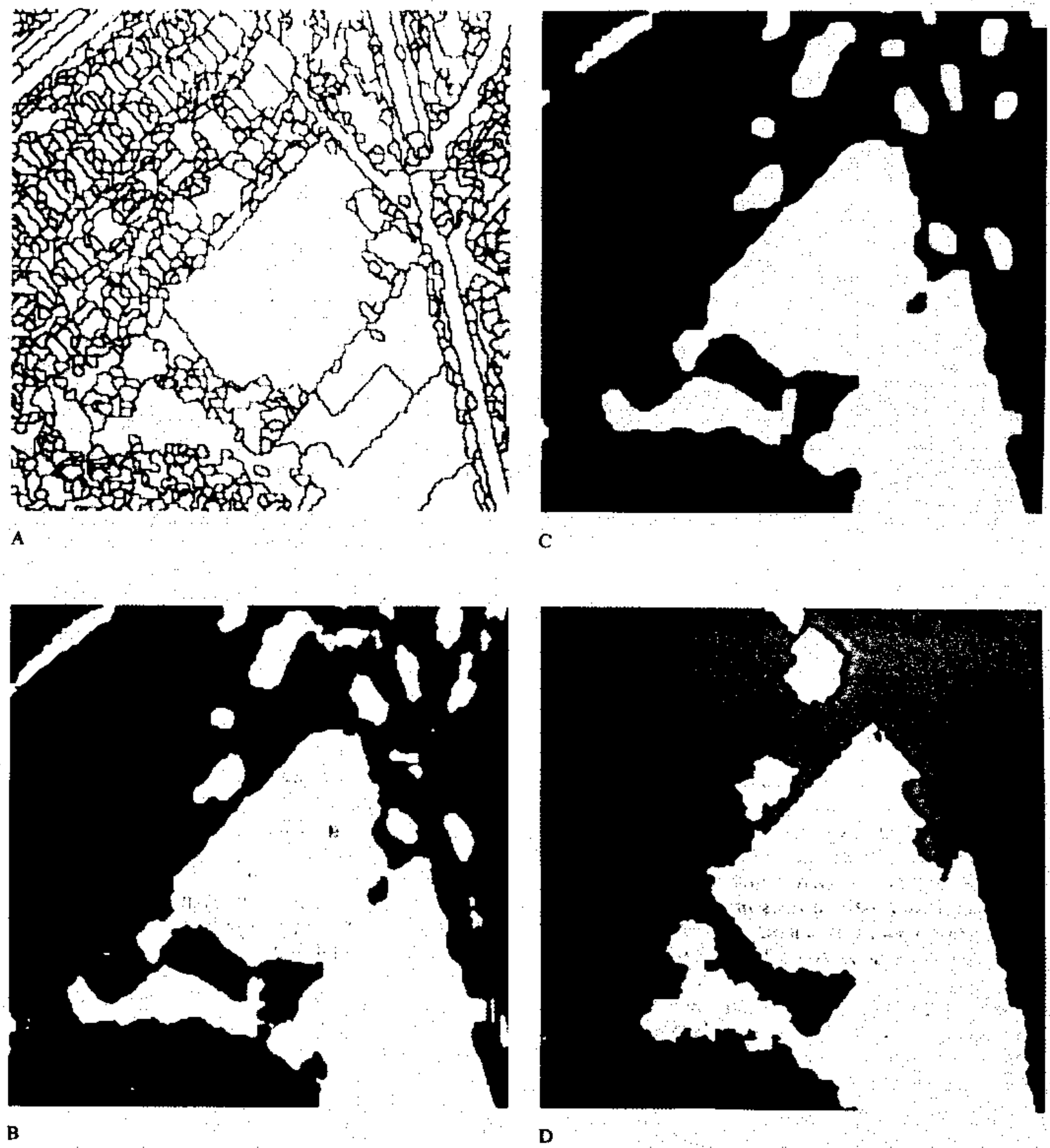


Fig. 7. A. Recognized crop fields. B. Recognized bare soil fields. (From Nagao and Matsuyama 1980.)

A B

tices. Boundaries are four-neighbor connected and segmented into straight lines with iterative end-point fits.

Only primary features are in the data structure. Regions are represented by area; mean intensity of red, green, blue; degree of texture; contour length; center of mass; number of holes; scatter matrix of pixel positions; and MBR. The degree of texture is the mean value of the Laplacian for texture, described above. The scattering matrix is the covariance matrix of pixel positions, equivalent to an ellipse fit. Boundary segments include chain code, length, and contrast. Vertices include position and number of boundary segments. Holes have contour length. Line segments have distance from origin (rho), orientation, length, and positions of end points. Topological relations have pointers among regions and boundary curves and vertices, together with subset/superset relations for holes. In order to retrieve regions with similar color, a history of the tree of segmentations is maintained.

Calculation of properties of merged regions is described. Various secondary features can be computed easily from primary features. Only primary features are in the database. There are three functions for retrieving regions: ALL-FETCH, THERE-IS, and T-FETCH, corresponding to all regions from a set with specified properties, the first region of a set with specified properties, and all regions adjacent to a region respectively. In two results of segmentation, there are 339 and 391 regions, occupying about 90 KB for data structures.

There are four object classes: sky, trees, buildings with subobjects (windows), and roads with subobjects (cars). A plan image is generated by taking regions with large areas, called *keypatches*. The system tentatively merges all small patches to adjacent keypatches by choosing the highest score based on similarity of color and compactness of merged region. No semantic information is used in the merge.

The plan formulated by the bottom-up process is a set of object labels for keypatches and estimates of their correctness. The top-down process examines these interpretations and analyzes small, detailed structures in the context of large patches that have already been interpreted. When the top-down process makes a significant decision, the bottom-up process is activated to reevaluate the plan.

Fig. 8. A. Candidate areas for forests. B. Result of extracting large connected areas. Each area consists of a set of elementary regions. C. Result of extending shadow-making regions in candidate areas. D. Recognized forest areas. (From Nagao and Matsuyama 1980.)

Fig. 9. Recognized grasslands. Some regions are recognized as crop field and forest area as well as grassland. These conflicts are resolved by the system. (From Nagao and Matsuyama 1980.)

Fig. 10. Major roads isolated by program. (From Nagao and Matsuyama 1980.)

Rules for the plan are unary properties of objects and binary relations between objects. The plan manager computes a correctness value for every applicable rule applied to applicable regions in the plan image. Evaluation of relations takes place only after labels of regions are assigned.

In the top-down phase, each rule applied to each applicable region produces a score and an action to be registered on the agenda. At each step of analysis, the action with the highest score is executed and the database is changed. The agenda controls activation of production rules according to changes in the database. The agenda is updated whenever the database is changed. Each time, the number of tests is (the number of regions) times (the number of surfaces), that is, several hundreds times several tens, a total of thousands. In order to decrease computation, a coarse-to-fine analysis is made in a scene phase and an object phase. When a keypatch is labeled, the agenda activates the scene phase to reexamine keypatches that have not been interpreted. When a patch of an object is labeled, the agenda activates the object phase for that object to examine patches touching the patch just labeled. As a result, the number of tests at each stage is several tens.

Each rule has a condition and an action. The condition is a fuzzy predicate. There are TO-DO and IF-DONE rules, corresponding to antecedent and consequent theorems of PLANNER (Hewitt 1968). Since only one region at a time is examined, there is a problem with global shape involving multiple regions. The system uses three mechanisms: the plan image; sets of patches retrieved from the database; and special rules (e.g., extracting the shape of a building).

The world model is a network of knowledge blocks that define objects, materials, and concepts. Production rules are divided into subsets stored in particular knowledge blocks; the subset for scene-level analysis is stored in the block SCENE, the subset to analyze objects is stored with the object.

Results are shown for several scenes. Patches with area greater than 300 pixels are keypatches. There were 57 rules in total. Figures 18–23 show examples of three scenes processed. A region of the building is initially assigned a high correctness value for SKY

Fig. 11. Recognized cars. (From Nagao and Matsuyama 1980.)

Fig. 12. Candidates for residential areas. (From Nagao and Matsuyama 1980.)

Fig. 13. Residential areas. (From Nagao and Matsuyama 1980.)

Fig. 14. Houses recognized by the HOUSE1 subsystem. Since the conditions are very strict, only about half the houses are recognized. (From Nagao and Matsuyama 1980.)

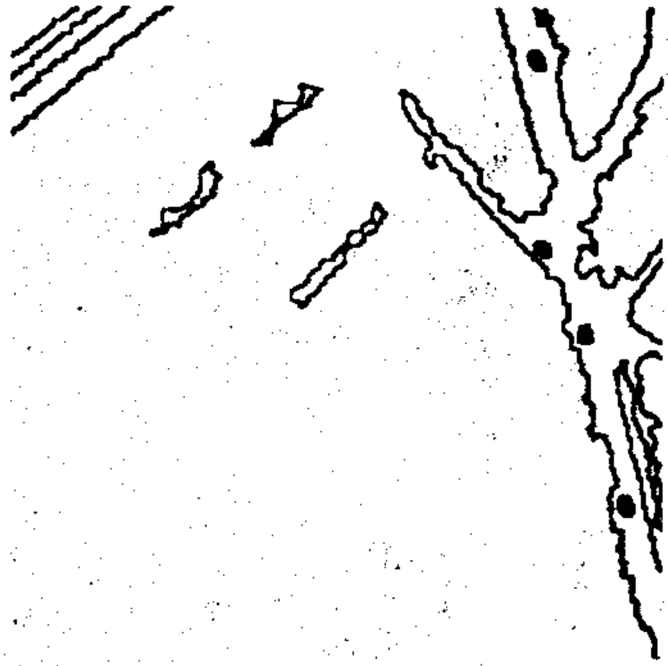


Figure 11

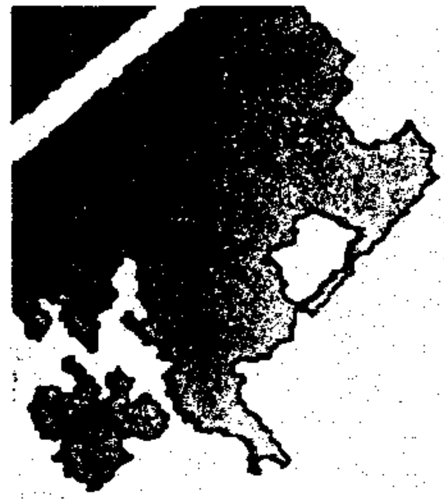


Figure 13

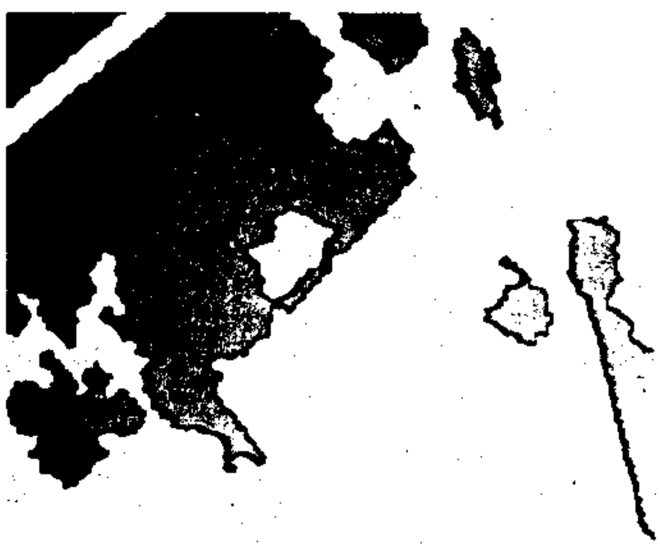


Figure 12

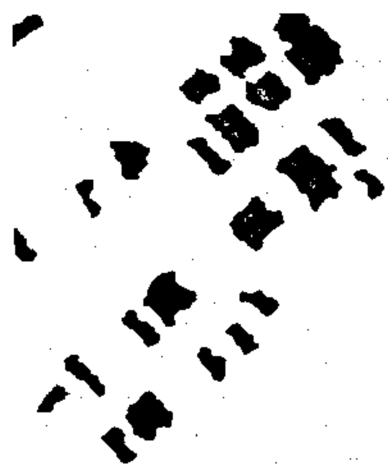


Figure 14

Fig. 15. Houses newly recognized by the HOUSE2 subsystem, using the multispectral properties of the already recognized houses (see Fig. 14). (From Nagao and Matsuyama 1980.)

Fig. 16. Houses newly recognized by the HOUSE3 subsystem. Two adjacent roofs of a house are merged into one region. (From Nagao and Matsuyama 1980.)

Fig. 17. Houses newly recognized by the HOUSE4 subsystem. "Missing houses" in the large residential area are recognized. (From Nagao and Matsuyama 1980.)

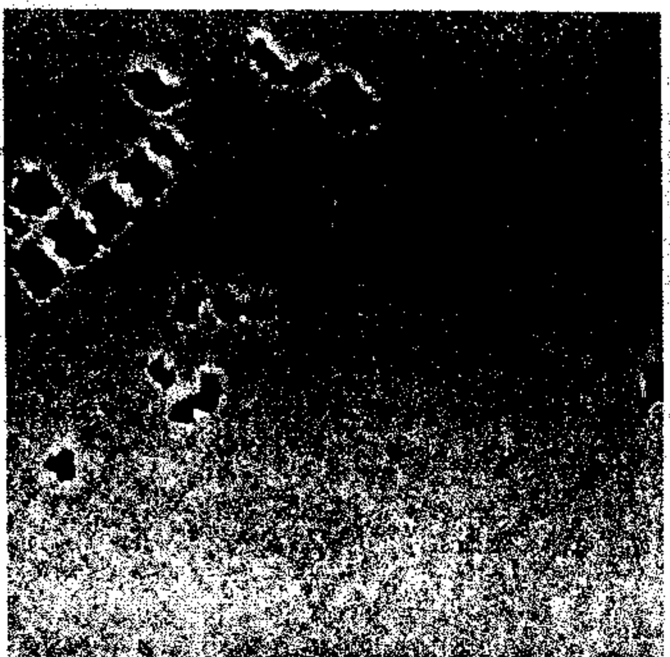


Figure 15

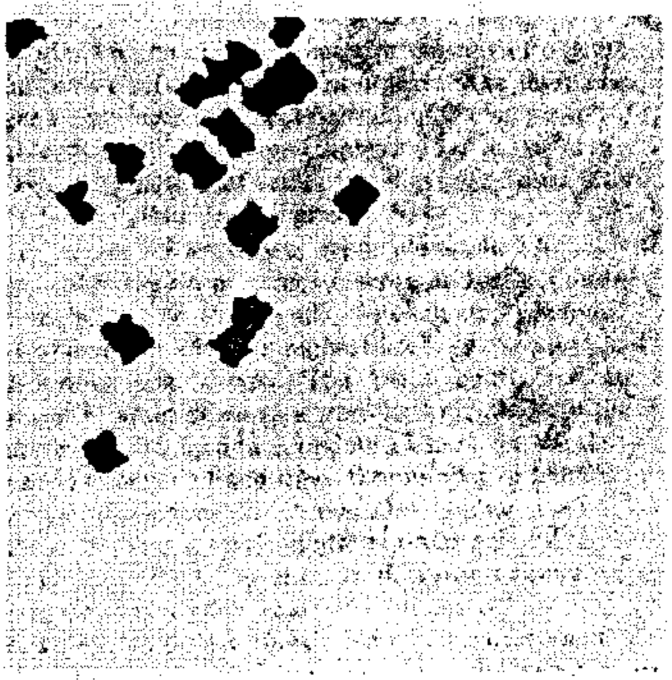


Figure 16

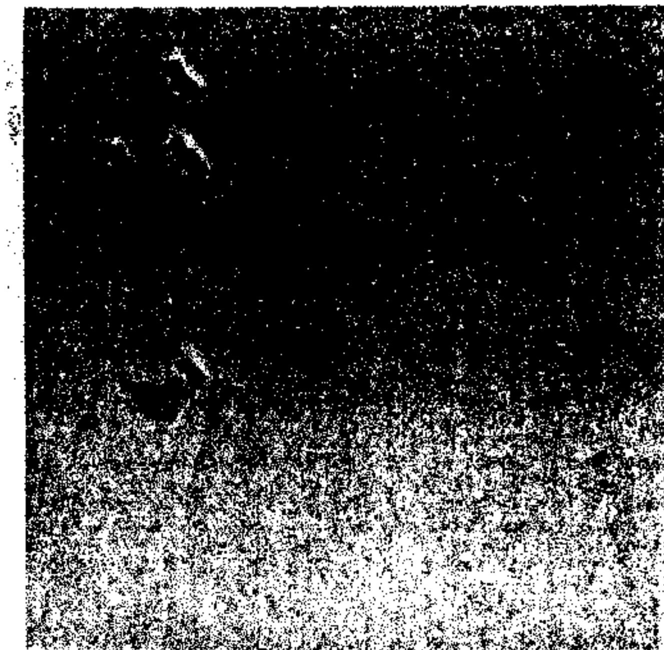


Figure 17

because it is bright and gray. In the revised plan, it has a high correctness value for BUILDING because of the relation between building and sky. Horizon is detected by a production rule. The horizon appears to be found as the lower bound of the sky by distinguishing SKY from ROAD.

The system does well overall. It demonstrates one of a few examples of reasonable performance on scenes of moderate complexity for a handful of rather different images. Ohta's thesis does not describe the rules themselves, except by a listing, or help very much in analyzing the system's performance and expected limitations. There are only a few objects in the model.

Models for analysis follow. The ROAD model has subobjects: car, shadow. It is made of asphalt, concrete. It has properties: horizontally long, touching lower edge of picture. It has relations: below horizon. The CAR in the ROAD model is horizontally long, dark, and above the ROAD. The SKY model has properties: not touching lower edge, shining, blue or gray, not texture, and touching upper edge. It has relations: linear boundary on the lower side. TREE is made of leaves. It has properties: in the

Fig. 18. Result of the rule-based analysis: example 1. A. Digitized input scene, basis for identifications shown in Fig. 19. B. Result of preliminary segmentation. C. Plan image. D. Result of meaningful segmentation. S = sky; T = tree; R = road; B = building; U = unknown. (From Ohta 1980.)

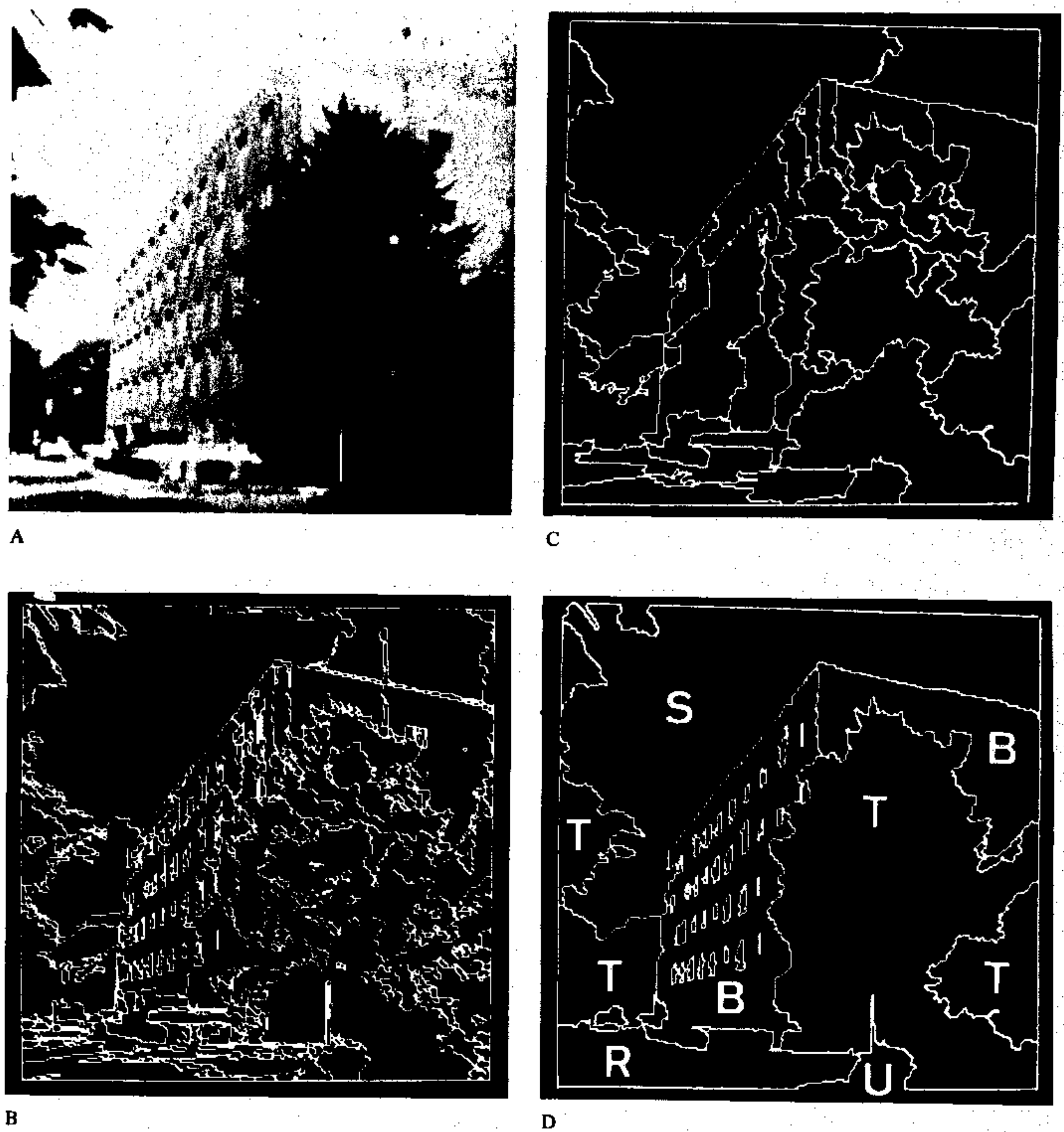
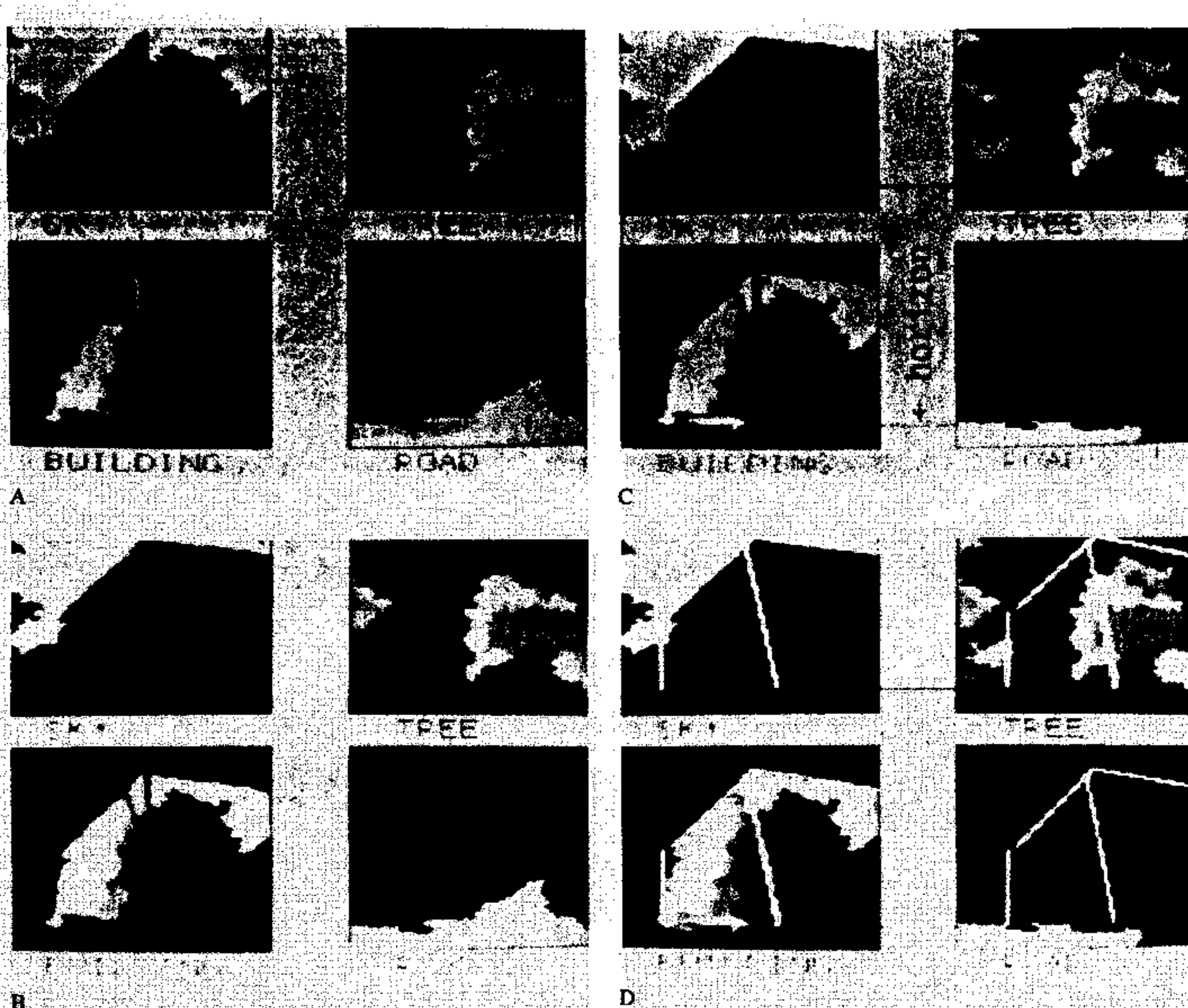


Fig. 19. Plans generated for the scene in Fig. 18. A. First plan, obtained by using only the property rules. B. Plan obtained after using the relation rules. C. Plan obtained after extracting the horizon by the top-down analysis. D. Outlines of the building extracted by the top-down analysis. (From Ohta 1980.)



middle of the picture, heavy texture. The BUILDING is made of concrete, tile, or brick. It has subobjects: WINDOW. Its properties are in the middle of the picture, many holes, many straight lines, hole straight lines. It has a relation of linear upper boundary with the sky.

Some limitations of Ohta's system follow. The quality of segmentation is weak. Thin linear features that do not show up in histograms are important (e.g., in identification of cars). The description of texture is weak. The organization of relations among patches is weak. For example, colinearity of window boundaries is not determined. Interpretation is image-dependent. Models are image-dependent. The model for road (touching the bottom edge of the picture) is too specific to be useful. Models are weak. The model for car depends on a car being on the road. It has the relation that the car appears dark relative to the road, which is not adequate even for this domain. It makes weak use of shape. A human would identify the car's make in many cases; the system's performance is inferior. There are models for few objects. The assumption that a single region contains only one object is not realistic. The ap-

Fig. 20. Result of the rule-based analysis: example 2. A. Digitized input scene. B. Result of preliminary segmentation. C. Plan image. D. Result of meaningful segmentation. S = sky; T = tree; B = building; R = road; C = car; CS = car shadow. (From Ohta 1980.)

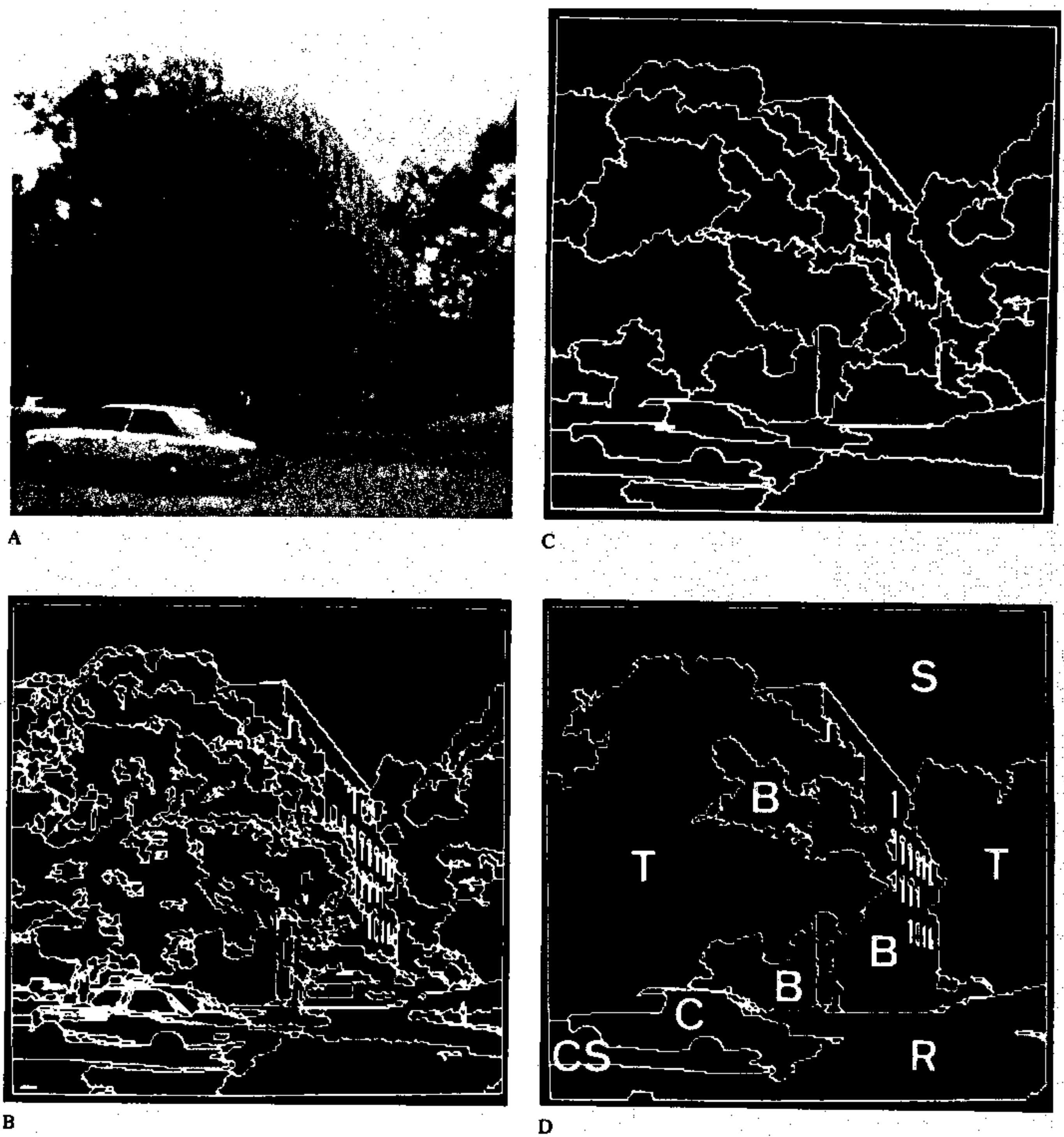
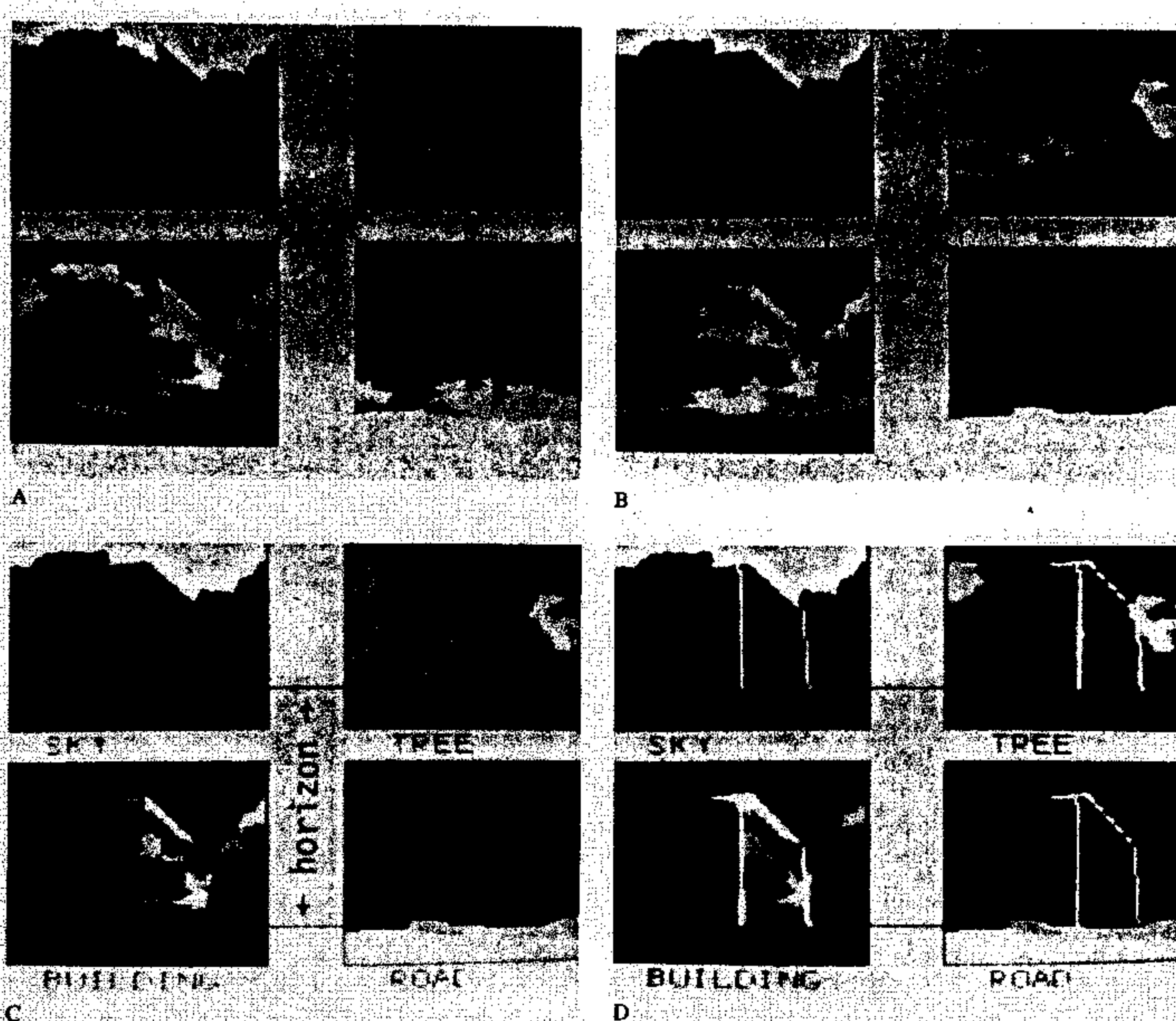


Fig. 21. Plans generated for the scene in Fig. 20. A. First plan, obtained using only the property rules. B. plan obtained using the relation rules. C. Plan obtained after extracting the horizon from the top-down analysis. D. Outlines of the building extracted by the top-down analysis. (From Ohta 1980.)



proach is ineffective in many situations in which fine details determine object labels.

2.4. ACRONYM–Brooks

ACRONYM (Brooks 1981) is an implemented interpretation system containing a substantial core of fundamental mechanisms that are powerful and general. Its performance demonstrated thus far depends on domain-independent capabilities, not on special domain-dependent tricks. ACRONYM as it stands is a large system that is part of a larger scheme for a general vision system. I am biased by my enthusiasm for ACRONYM, which is meant to be a general vision system. This objective requires an enormous effort involving all levels of a vision system—an effort beyond the state of the art. Substantial progress

Fig. 22. Result of the rule-based analysis: example 3. A. Digitized input scene. B. result of preliminary segmentation. C. Plan image. D. Result of meaningful segmentation. S = sky; T = tree; B = building; R = road; C = car; U = unknown; CS = car shadow. (From Ohta 1980.)

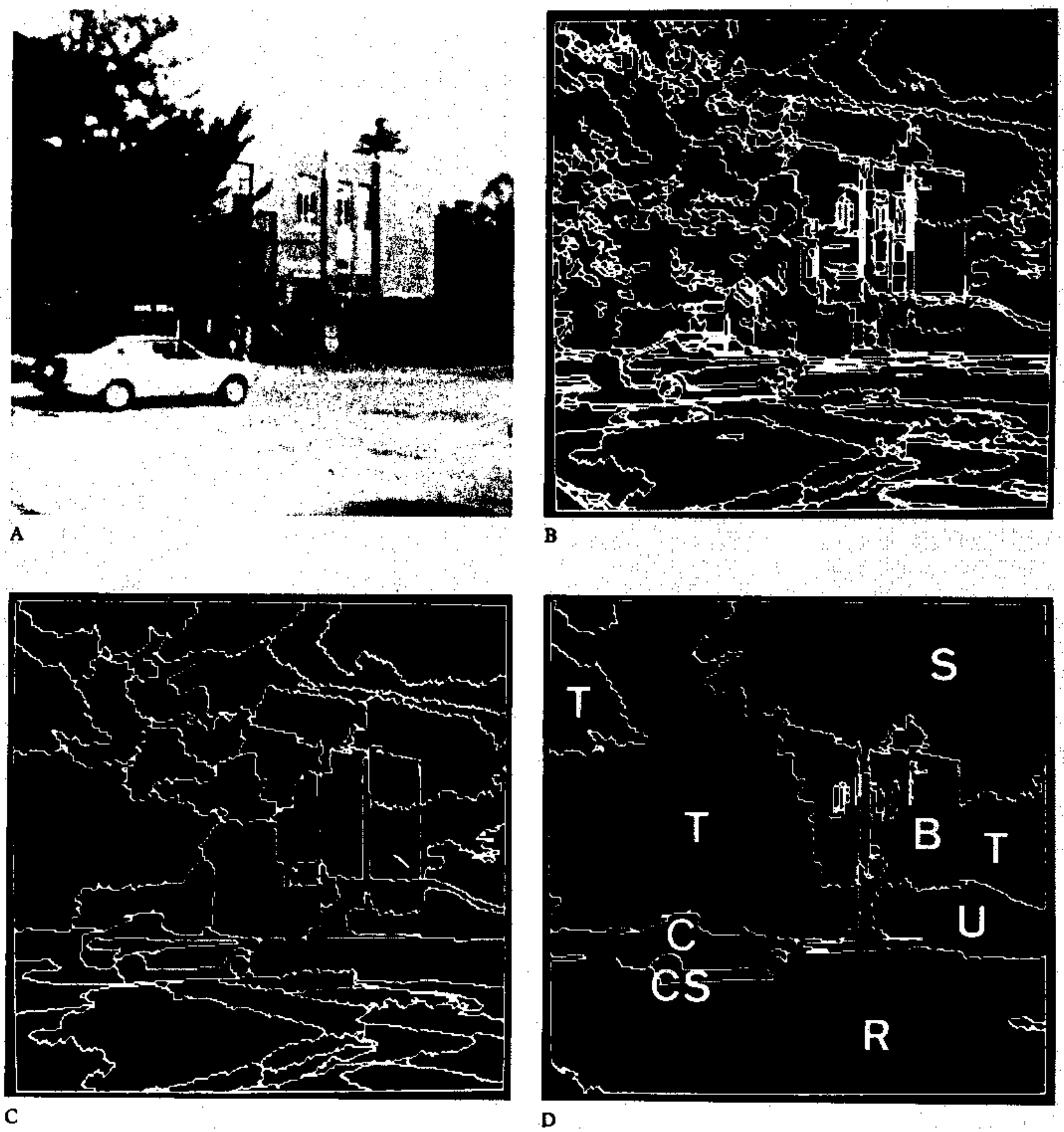
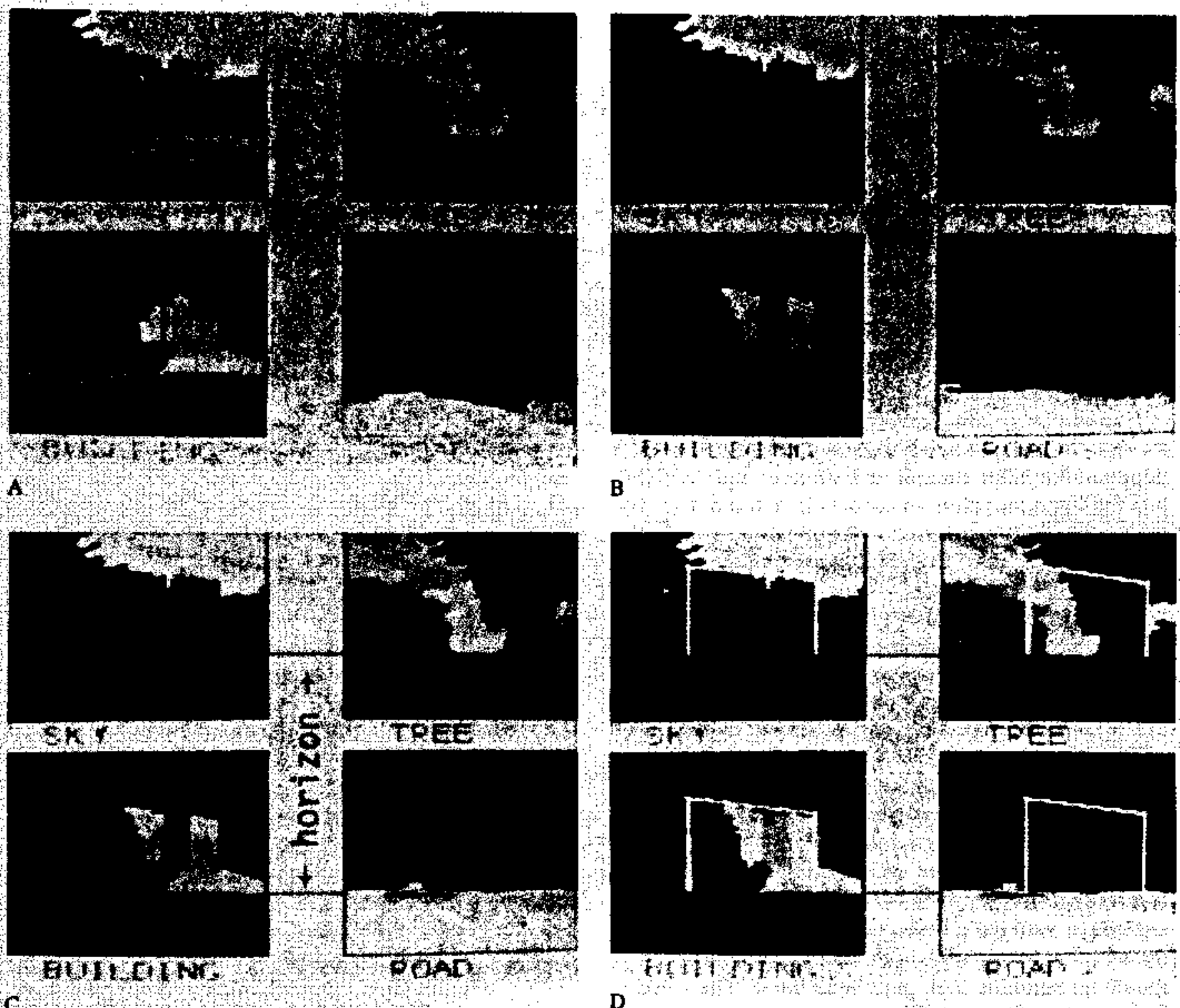


Fig. 23. Plans generated for the scene in Fig. 22. A. First plan, obtained using only the property rules. B. Plan obtained after using the relation rules. C. Plan obtained after extracting the horizon by the top-down analysis. D. Outlines of the building extracted by the top-down analysis. (From Ohta 1980.)



has been achieved. Immediate plans call for mechanisms that will greatly increase ACRONYM's power and breadth.

Objectives for ACRONYM include the attainment of three-dimensional interpretation, a rigorous scientific basis, and high performance. Important applications are typically difficult. Carefully built high-performance modules enable generality. It is intended to provide an option for a standard system, with a user base providing technology transfer. It has a large general core of powerful capabilities on which to base applications. Interpretation is generic with respect to object class, providing commonality of programs for similar applications and providing a means for inspection to distinguish essential from cosmetic flaws. Interpretation is generic with respect to observation, that is, ACRONYM is insensitive to viewpoint and flexible with varied sensor inputs.

Mechanisms use special-case information and data. ACRONYM is complete. In the sense that interpretation makes use of total information, data, and knowledge, including multisensor data, knowledge of experts, geometric models of objects, and prediction of expectations. It incorporates powerful use of shape in modules for edges, texture and image organization, depth, shape from shading, and shape from shape. It incorporates mathematics and physics. The system is a critical mass effort over a continuing period, during which collaboration and applications are sought. It is engineered for easy use, facilitating input in the form of geometric models and rule bases, automatic programming, and user aids.

A user should program ACRONYM using geometric models and geometric task specifications, a common language natural to both user and ACRONYM. The user refers to models in a geometric database and shows examples of typical members of the object class. ACRONYM should infer specific and generic properties of the object class and contexts, especially causal relations. ACRONYM constructs perceptual programs to carry out the assigned task. ACRONYM should be general and generalizable in the sense that problem-specific information can be embedded in general, problem-independent mechanisms that provide for a natural decomposition of problems into physically meaningful elements. A core built up from a few problem domains should cover most capabilities required for other domains.

ACRONYM has been shown to be successful on a few images of aircraft in aerial images but not enough to warrant a claim of generality. Figure 24 shows an example with high resolution. Figure 25 shows an example with poor resolution. The ribbon finder has problems with the poor-resolution image, but ACRONYM recognizes the three aircraft for which ribbons are reasonable. In another image like Fig. 25, the ribbon finder did not turn up any adequate ribbon descriptions.

In a real sense, ACRONYM reasons from first principles. ACRONYM has a general core in that its rules implement algebra and projective geometry. There are no special rules for aerial images or aircraft. There is no profound reason why ACRONYM could not recognize aircraft in images taken at ground level, although it will probably break when tested on such images because of bugs or missing capabilities that were not exercised previously. For example, at ground level the fuselage appears more or less the same as from above. Wings are less observable, but engine pods and tail are more prominent. The rule base will need to be extended considerably in dealing with varied object classes, (e.g., manufactured parts, vehicles, and buildings).

ACRONYM has viewpoint-independent, three-dimensional object models in the form of part/whole graphs, in terms of generalized cylinder primitives. ACRONYM represents object classes, for which subclasses and specific objects are represented as restrictions, by constraints in the form of symbolic expressions with numeric type.

ACRONYM searches for instances of models in images. It employs geometric reasoning in the form of a rule-based, problem-solving system. Geometry is the key, while the rule-based system is simply a way of implementing geometry. A formal representation of geometry is probably necessary to make a compact and coherent set of rules in order to get additivity and consistency in a rule base. Despite claims to the contrary, it seems clear that a rule-based system in itself does not aid in making additivity and consistency of reasoning. Building a vision system is 1% a system effort of the sort familiar in computer science and 99% basic science.

ACRONYM predicts appearances of models in terms of ribbons and ellipses. It uses an edge finder to make observations of ribbons and ellipses in images. ACRONYM finds observed ribbons consistent with predicted ribbons and restricts interpretations to those which are parts of clusters consistent with predicted structures of ribbons. It interprets in three dimensions by enforcing constraints of the three-dimensional model. Thus, to identify aircraft it matches observed ribbons to predicted ribbons for wings and fuselage, then finds clusters of ribbons that are consistent with the combined wings and fuselage of a three-dimensional aircraft model.

ACRONYM makes predictions that are viewpoint-insensitive in the form of symbolic constraint expressions with variables. One mechanism of viewpoint-insensitive prediction is the use of observables that are invariant and quasi-invariant over large ranges of viewing angle. ACRONYM does not generate all

Fig. 24. Illustration of ACRONYM's performance on a high-resolution image. (From Brooks 1981.)

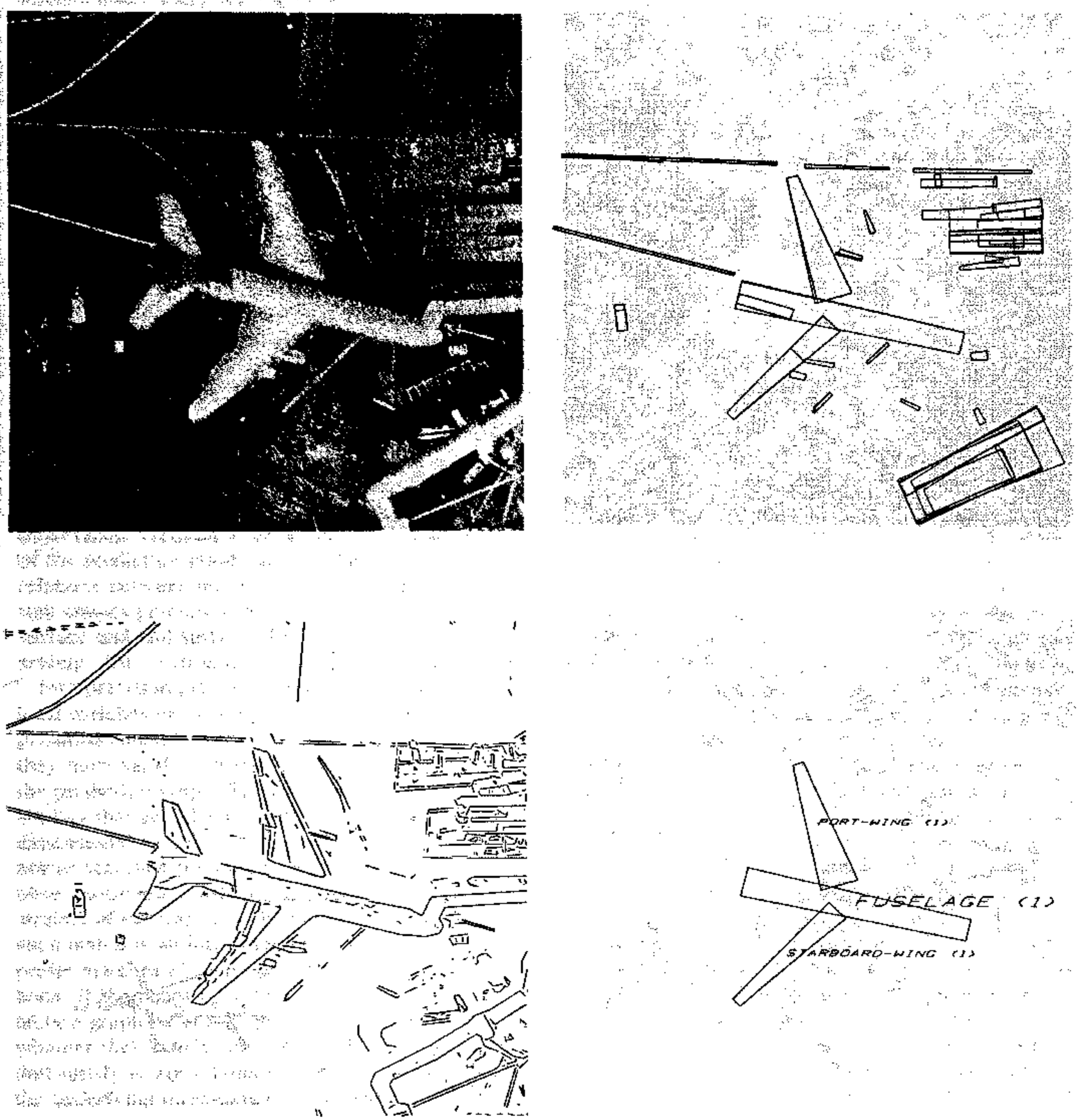
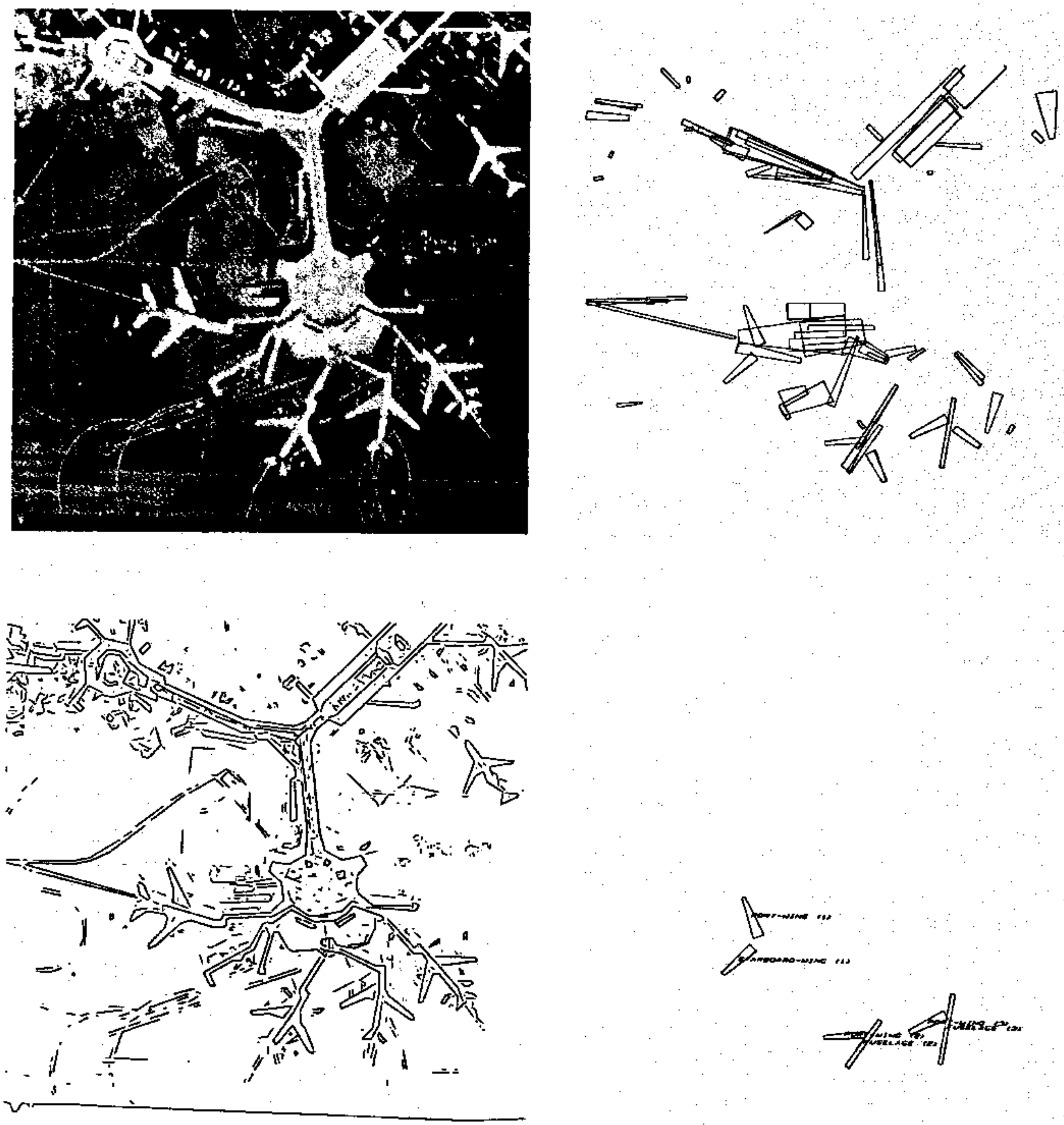


Fig. 25. ACRONYM's performance on a low-resolution image. (From Brooks 1981.)



possible views of an object. Total prediction has combinatorial complexity. For a polyhedron with n distinct faces, there are 2 n views. Instead, ACRONYM predicts partial views for individual faces of which there are of order n. Coherence of several features comes from merging constraints. The image-shape descriptors are invariant under image rotation. To generate predictions, ACRONYM starts with models in their coordinate frames. All contours of faces that might be visible are identified. They are transformed into the camera's coordinate frame, with symbolic translations and rotations represented by variables. The system simplifies the corresponding expressions and makes a projective transformation. Visible contours are identified. Relations between these contours are predicted, and the shape of the contour is predicted. Back constraints that relate image observables to model parameters are generated. Relations between ribbons are generated. Each ribbon provides a number of back constraints that combine to constrain model parameters. ACRONYM automatically determines ribbons and ellipses for parts of the object that it determines are most observable. Predictions of feature shapes are nodes of the prediction graph; arcs of the graph are image relations between features. Arcs relate multiple feature shapes predicted for a single cone. The swept surface and end surface of a cone are predicted separately. A prediction is made that they are coincident.

Interpretation proceeds by the combination of local matches of ribbons into clusters. Global interpretations must be consistent in two ways. First, they must satisfy constraints specified by the arcs of the prediction graph. Second, accumulated constraints that each local match imposes on the three-dimensional model must be satisfiable. The interpreter searches for maximum subgraphs of the observation graph that are consistent with constraints of subgraphs of the prediction graph. Each such match is an interpretation graph. The interpreter matches ribbons against predictions of ribbons. It then tries to instantiate arcs of the prediction graph by checking pairs of regions to see whether they satisfy relations predicted. For pairs that satisfy image relations, it merges constraints on the underlying three-dimensional model.

ACRONYM has been used as the basis for a simulator for robot systems and for automated grasping of objects, with a rule base for determining which surfaces are accessible in the initial position, which surfaces are accessible in the final position, and ways to grasp with maximum stability.

The top-down paradigm is only one part of the ACRONYM design. A top-down system is far from general. It is believed that this paradigm can provide only a small part of human performance, even though prediction has been made relatively powerful in ACRONYM by use of predictions that are generic with respect to object class and that are viewpoint-insensitive. The way to a general vision system lies in spatial understanding, as opposed to image understanding. That is, prediction of images and matching at the level of images is inherently limited (a convenient expedient reflecting the weakness of our descriptive mechanisms) but it is not a fundamental approach. Instead, the major part of interpretation is not at the image level but at the level of volumes. Descriptive mechanisms that generate volume descriptions are essential combined with prediction and interpretation at the level of volumes. Certainly stereo, motion parallax, and object motion are important observation capabilities, together with shading. Recent theoretical work on monocular interpretation of surfaces from images (Binford 1981; Lowe and Binford 1981) appear to promise that general mechanisms for generating spatial observations from images will be developed soon to support general vision systems.

Limitations of ACRONYM as a general system follow. ACRONYM has weak segmentation. The ribbon finder determines spurious ribbons. It misses small ribbons. Grouping of ribbons is not done in segmentation, only in interpretation. The line finder and ribbon finder perform badly with texture.

Interpretation is limited. Image prediction and matching are not sufficiently general for scenes with many objects. Interpretation has been tried with only a few objects, and the system models for very few. It tests all pairs of ribbons in establishing relations, ignoring proximity. It has been tried on only a single viewpoint. The top-down paradigm is inadequate for complex scenes.

2.5. Shirai

In Shirai's system (1978), obvious edges are found in the entire scene. They are described by straight lines or ellipses. Edge points are found, using one-dimensional profiles; edge points are classified into three types. Averaging is done over small areas, typically 3×3. The direction of the edge is determined from the gradient. An *edge kernel* is determined by a set of edge points of the same type with similar gradient directions. Continuations of edge kernels must have the same edge type. The tracking phase predicts an edge element and verifies it. Tracking may insert a fictitious edge point at the predicted position. Tracking proceeds in both directions until both ends terminate by connecting to another end. Some edges are extended to fill small gaps.

Curve description has two phases, segmentation and curve fitting. *Segmentation* uses curvature versus arc length along the curve, while *curvature* is defined as the angle difference at a center point between chords a fixed distance on either side (approximately the difference of tangents). The routine finds sequences of high curvature to place knots. It tries to classify curves: if sagitta is large, it is a curve; if angle change is small, it is a line. It tries to merge adjacent undefined or curved segments. A method symmetric in x and y is used to fit curves. Curves are fit with ellipses. If the search does not converge, the number of parameters is decreased, successively fitting a circle and straight line.

Analysis of the scene starts from the most obvious object and proceeds to the next most obvious. For object recognition, it finds the most obvious feature, then finds a secondary feature to verify identity and determine object range. It then finds other lines on the object. For recognition of a lamp, the program locates the lamp shade, then looks for the trunk of the lamp, which supports the shade, then the lamp base.

The objects in Fig. 26 include a lamp, a book stand, a cup, a telephone, and small objects. For the lamp, the primary feature is a bright elongated strip for the shade. Secondary features are a pair of vertical edges corresponding to the trunk and the contour of the lamp base. The primary feature for the book stand is a cluster of long vertical lines in a rectangular region. Secondary features are lines connected to the verticals. The cup has a pair of vertical edges; secondary features include the ends of the cup connected to the verticals. The telephone has an ellipse for the dial and one outside the numerals; secondary features include features surrounding the ellipses. Small objects have shape and size of contour as primary features; secondary features are shape details and light intensity of the surface.

Small objects such as pens or erasers are tried after large objects are found or many edges are obtained. Otherwise, a small object might be confused with part of a large object. The system finds more edges by decreasing the reliability level and looking in delimited areas. The system may take a close-up image where necessary.

Experiments have been conducted successfully with a range of positions and orientations of objects and varied lighting conditions.

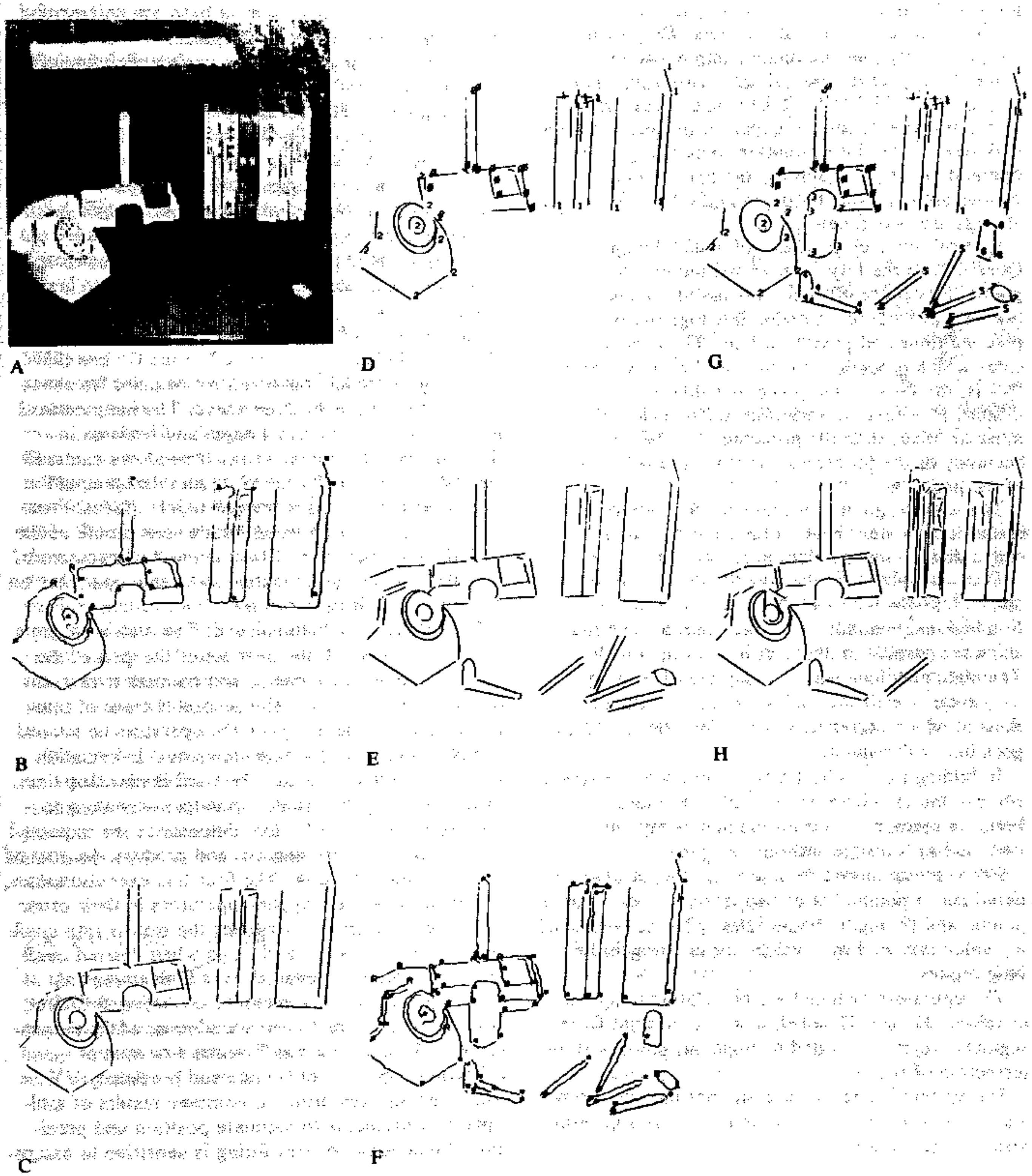
As with previous systems, this system has substantial limitations as a general vision system. The edge finder is adequate for this task, but it would not perform well in complex scenes; the system cannot deal effectively with texture; and the system has no organization of related edges. Interpretation is likewise limited. There are only image models, not object models; there are only few objects; and the analysis is top-down, which is reasonable for few objects.

2.6. Ballard, Brown, and Feldman

Ballard, Brown, and Feldman (1978) use image models in locating ships at docks and in locating ribs in chest x-rays. Geometric constraints are used. The system is oriented to answering queries; the level of detail is determined by the query. Only a portion of the image is interpreted. The system is structured in three levels: (1) the model; (2) the sketchmap synthesized during image analysis (it relates the model and the image); and (3) image data structures, including images at different resolutions and spectral components, texture images, and edge images.

The structure is similar to that of VISIONS (see below). Perhaps the main difference is that in VISIONS, segmentation is made to a level determined by the model so that the image will be understood as

Fig. 26. An example of the recognition process. A. Original scene. B. Edges found in cycle 1. C. Description. D. Recognition. E. Description in cycle 2. F. Edges found in cycle 4. G. Recognition. 0 = lamp; 1 = book stand; 2 = telephone; 3 = cup; 4 = pipe; 5 = pen, pencil, ballpoint pen, felt-tip pen. H. Description of edges found without feedback from the recognition process. (From Shirai 1978.)



fully as possible. Here, the query determines the level of detail.

Links encode constraint relations. They include the probability that the relationship holds and include the expected value of the relationship. For example, SHIP ADJACENT DOCK is a constraint with a probability and an expected distance. A node may have a cost for evaluation, depending on its operand nodes. This allows cost-benefit analysis. Locations are delimited by union and intersection. Constraints are two-dimensional.

Control involves synthesis of a sketchmap. Queries take the form of user-written executive programs. Procedure invocation is based on a description of a procedure's capabilities, together with preconditions and postconditions. The executive decides which procedure to run based on cost-benefit, that is, the lowest cost procedure that meets preconditions. Procedure descriptions include slots that must be filled, slots the procedure can fill, cost and accuracy of the procedure, and the a priori reliability of the procedure.

The user program is responsible for "strategic" resource allocation beyond the executive level. No single domain-independent problem solving is used.

One example is discovering the location of docked ships. A photo with matching map is used; registration is done manually. The constraint is used that ships are parallel to docks at half a ship's width. Template matching was the only visual technique; the center is estimated midway between the locations at which correlation goes above threshold and goes below threshold.

In finding ribs in chest x-rays, only lower edges of ribs are found. There are procedures to locate parabolic rib segments, to translate and verify adjacent ribs, and to translate without verifying.

The representations used are (1) straight lines: ordered list of points, list of segments, circular lists of points, and (2) region boundaries: *y* list consisting of a *y* value followed by *x* values for entering and exiting region.

The operators included are correlation template matching, Hough, Hueckel, distance of point from segment, segment parallel to segment, union and intersection of regions.

The system is special-case and not intended to be a general vision system. Its limitations as a general vision system are many.

2.7. The Verification Vision System · Bolles

The verification vision (VV) system (Bolles 1976) uses object models and image models. It is intended for inspection and visual control in repetitive manufacturing tasks. The VV system makes use of three-dimensional models, but it requires that sensed images be very similar to image models. Thus, for a camera that is 1 m from an object, the position of the object may vary by about ± 1 cm, and its orientation may vary by $\pm 15°$, but there may not be major shifts in appearance or major changes in occlusion. The major reason for that restriction is that VV's primary visual operator is area correlation of small windows of an image with reference windows (Moravec 1980).

An object model contains a set of point features and their locations in three space. The image model includes a set of training images and features in those images. Features are small windows centered around elements determined by an interest operator (Moravec 1980). This is a weak object model. From the training set, the system builds an estimate of the variations of locations of features and an estimate of the effectiveness of its feature detection operators on the designated image features.

Four stages are distinguished. The first is programming time, in which the user states the goal of the task, calibrates the camera, and chooses potential operator/feature pairs. The second is training time, in which the system applies the operators to several sample pictures and gathers statistical information about their effectiveness. The third is planning time, in which the system ranks operators according to their expected contribution, determines the expected number of operators needed, and predicts the cost of accomplishing the task. The fourth is execution time, in which the system applies operators in their order of cost-effectiveness, combines the results into confidences and precision, and stops when desired confidence has been achieved or cost limit exceeded.

The goal of the task includes achieving sufficient confidence of correct correspondence, adequate precision of location, and sufficiently low cost of achieving required confidence and precision. VV uses least-squares fitting to combine results of multiple measurements to estimate position and precision. Since least-squares fitting is sensitive to assignment errors, a Bayesian estimation scheme is used to choose assignments with few errors. Two sorts of information are used in making correct matches of image features to reference features: (1) confidences obtained from values returned by operators, and (2) relative image position of subsets of features. Because of combinatorics, the second method must be used with small subsets of features. Later, a search for maximal cliques consistent in three-space separations was used. The latter approach is much more satisfying conceptually, since relative image distances are not invariant, and their errors are not predictable without use of a three-dimensional model. Two types of features were studied: (1) cornerlike features obtained by an interest operator and matched by a binary-search correlator (Moravec 1980) and (2) curve features predicted by a geometric model of the object (Miyamoto and Binford 1975) and determined by a curve-verification procedure based on the Hueckel edge operator (Hueckel 1973). The latter were not integrated into the VV system.

The programming of VV problems was automated considerably. The program produces a set of features. The programmer filters out suggested features that are judged unreliable. In gathering statistics, VV displays a reference picture side by side with a training picture, with matching features marked. The system makes its best assignments according to consistent subsets. It asks the user for confirmation. It ranks operators according to an ad hoc quality measure. In execution, it applies operators in order of the measure.

The system is limited in that it primarily depends on small correlation windows as features. Thus, it is restricted in viewpoint. It was intended for a few objects. It uses three-dimensional models of objects, but they are point models and without shape relations.

2.8. Faugeras and Price

In the system described by Faugeras and Price (1980), the input is a network of segments from procedures for region-based image segmentation and linear feature extraction. There are about 100–200 total segments of both types. Properties of segments include average color, simple texture measures, position, orientation, and simple shape measures. Relations between image segments include adjacency, proximity, and relative position. The model description is identical to the network of image segments. If a relation occurs in the model, it is expected to occur in the image description. The model is not a complete description of the scene, but apparently an image model.

Matching is a graph endomorphism. It is solved by stochastic matching (relaxation). Initial compatibilities are computed without relations because labels are not known; they combine weighted differences, taking up to 30 possible labels, or those with compatibility greater than $^1/_{10}$ of the best, whichever is fewer. The compatibility measure with relations is computed only with the most likely assignments for the second object (usually only one assignment). Compatibilities are computed as needed. The compatibility measure is the dot product $\mathbf{p} \cdot \mathbf{q}$, where $\mathbf{p}$ is the probability vector $(\mathbf{p}(11), \mathbf{p}(12), \ldots)$ and $\mathbf{q}$ is the prediction vector $(\mathbf{q}(11), \mathbf{q}(12), \ldots)$ for labels li.

It becomes a constrained optimization approached by steepest descent. Macro-iterations of steps are composed in order to make decisions to assign names to units with high probability (above 80%).

It is hard to tell what its performance is for the two images shown by the authors. The system has image-dependent models and is strongly restricted in viewpoint. Segmentation is relatively weak.

2.9. Garvey

The function of the system described by Garvey (1976) is to locate objects in an office environment in which it is assumed that all objects are known. The system has as input measurements of range, reflectivity at one wavelength, and three color images. The system's strategy is to acquire image samples that might belong to the object, to validate the hypothesis, and to bound the image of the object. The system uses simple, local features rather than structured shape descriptions. It uses contextual relations, for example, a telephone is on a desk, to decrease search and to minimize the set of possibly ambiguous objects. The approach follows a belief that in a sufficiently restricted environment, a set of local distinguishing features can be found that are effective in initial screening for candidate matches. This depends on having models for all objects and not having many objects.

The system searches for cost-effective strategies of sequences of operators. In acquisition, it chooses an appropriate limited-search window of the image, sampling the image at a density determined by the object's size, maximum range, and least favorable orientation. Estimates are made of the cost of search with various operators and of the likelihood that the operator will be successful and correct. Which operators are effective depends on all objects in the image.

The system is programmed interactively. Objects are shown to the system by outlining them in an image. Objects are automatically characterized by conjunctions of histograms of local surface attributes such as hue, orientation, range and height, and relationships between surfaces. These characterizations provide ingredients for strategies for object finding.

In experiments, this system's performance rests strongly on having depth data and surface orientation derived from depth. To be found, a desk must have a desktop 2.5 ft high and horizontal orientation. For a door, height, orientation, and hue are not enough. Its size and location, together with a vertical rectangle characterization, are essential.

Regions are represented as lists of samples, as a list of vertices of a closed polygon boundary, by a bounding rectangle, and by vertical and horizontal bounding rectangles in space. Objects are represented by distributions of attributes of surfaces, with shape of surfaces and relations between surfaces.

Some limitations of the system follow from the approach of distinguishing features. In choosing simple features that distinguish regions corresponding to objects of interest, it is assumed that there are few objects and that all are known. The interpretation is strongly dependent on depth data and probably would not achieve similar performance without depth data. Shape, other than that obtained from depth, is used in a weak way. Also, the top-down approach does not go far in a world of many objects.

2.10. Levine

Levine (1978) describes a three-level system, of which the first two levels have been implemented. The first level segments pictures into regions without scene context. The second level has a local phase and a global phase. The local phase matches image templates with observed image regions, using A* graph search. It performs global optimization using dynamic programming to merge regions and assign labels to them. The highest-level design includes a standard relational database and a system similar to production rules.

The system is implemented using MIPS, an interactive image processing system. Two data types are used uniformly throughout: image arrays and feature vectors. Low-level region analysis obtains about 200 regions from a 256×256 image, a reduction of about 300 to 1 in items, not necessarily in storage.

The intermediate level deals with standard views. The output of the intermediate level is an ordered list of interpretations for each region. The local intermediate-level process is a form of template matching of object descriptions. It is model-driven and uses heuristic graph search to match shape, color, and texture. The second process is global, also model-driven. It incorporates spatial relations as a global optimization problem solved by dynamic programming. Model input for this level comes from interactive designation of regions and objects, computing features, and updating the database. Symbolic information in the form of text is also a form of input.

The high-level system design includes a vision-production system with relational database.

Low-level segmentation is based on regions found by a shared, nearest-neighbor clustering modified by connectivity. Processing is approximately in order of decreasing size, using a pyramidal data structure. The edge pyramid has edges from a gradient operator. The pyramid thickens edges until, at the top level, all regions have been extinguished. Areas of the picture that are farthest from edges tend to be extinguished high in the pyramid. From a starting region, projecting down to the next level involves expanding 1 pixel into 4 pixels. Those marked as edges are not examined at this level but are looked at in the next level down. At this level, those not marked as edges are marked for clustering, using the nearest-neighbor algorithm.

Local template matching is used to match collections of adjacent regions against all stored object prototypes. Features are stored in three classes, according to decreasing importance in reducing search time. The first class includes the MBR and its area. "Intrinsic" features make up the second category: intensity, hue, saturation, and texture. The third category includes six moment invariants as a rough measure of shape and detailed shape from a set of Fourier coefficients for the outline, used only in final template evaluation.

The A* algorithm is used for graph search with an evaluation function. Nodes are regions, while arcs are region adjacency. The estimate of the cost to node n is the number of nodes expanded from the start.

Relational information is used in the optimal search stage, done with dynamic programming. Regions may be ordered either according to region area or decreasing maximal confidence value among interpretations. The orderings of model and data do not necessarily correspond; no mention is made of whether the algorithm accounts for the difference in order. The transition function is a linear weighting of differences between structural relations in the image model and observed relations. Relations include LEFT-OF, RIGHT-OF, ABOVE, BELOW, ADJACENT-TO, CONTAINS, and CONTAINED-BY.

The knowledge database or long-term memory (LTM) in the high-level system design is a management-type relational database with accessing operations that constitute a relational algebra. Operations such as JOIN, PROJECT, INTERSECT, UNION, and RESTRICT are available. The high-level system will be a data-driven production system. Thus far, it only deals with images, not three-dimensional scenes. The LTM has subworlds for outdoor scenes, office scenes, and so on. Objects in LTM have associated actions to be taken under conditions of the short-term memory (STM). A STM contains a list of regions and their interpretations. It resembles the "blackboard" of HEARSAY. Regions are interpreted sequentially, unless an action is involved that alters the sequence. For each region, there is a list ordered by decreasing confidence. Implicit actions are invoked by the system when a region matches an object in the LTM with a confidence above threshold. Explicit actions are invoked if there is only one interpretation for a region.

Limitations of this system are found throughout. Some come from the segmentation process, which relies on a gradient operator, with all its weaknesses. The intermediate level is viewpoint-dependent. Apparently, the top level will be built upon the intermediate level, and will also be viewpoint-dependent.

2.11. Parma, Hanson, and Riseman

Parma, Hanson, and Riseman (1980) take a color image of an outdoor scene and an image model with three-dimensional relations and build a symbolic model of the three-dimensional world shown in the image, in the form of names of objects and weak relations in three space.

The model contains image locations of objects, uncertainty radii, and size radii. They emphasize representation of knowledge structures and control of knowledge sources (KSs). Their knowledge structures are schema for a scene concept, (e.g., road scene or house scene), with control for invoking a subset of KSs. They believe that schemas provide a bridge between general-purpose and special-purpose systems. They raise two issues of control: (1) the basis for invoking KSs; and (2) the use of alternative hypotheses provided by KSs. The basis for invoking KSs is top-down control driven by schema. They identify a set of six experiments with varying generality. The first is a specific scene schema from a known viewpoint. Specific two-dimensional schema can be obtained; the example in this report was a particular house from a known viewpoint. The second is a general scene schema with known viewpoint. This is confusing. How can viewpoint be known for nonspecific scenes? The third is a specific scene schema with unknown viewpoint. The fourth is a general scene schema that is known, with an unknown viewpoint. In the fifth experiment, the general scene schema is unknown. The fifth has no scene schema. A partial three-dimensional surface/volume description is constructed. This is a subset of the general vision problem, since it does not use familiar information.

Two forms of segmentation were described: edge relaxation and region relaxation using histograms. Both were implemented in a simulation of "processing cones." Both use two complementary relaxation labeling processes: boundary formation, local differences; region formation, and global similarities. Edge relaxation finds local discontinuities in a feature (intensity or color) along horizontal and vertical edges between pixels. Iterative relaxation on small neighborhoods forms boundary segments. Region analysis proceeds by cluster detection of peaks in the histogram of one feature or in the joint density function of pairs of features. Connected sets of pixels are determined as regions.

Eleven modular KSs are included, implemented in a graph processing language built in ALISP. They include inference net KS; two-dimensional curve-fitting KS; two-dimensional shape KS; occlusion KS; spectral attribute matcher KS; three-dimensional shape KS; perspective KS; horizon KS; object size KS.

The authors use a database that includes a LTM of world knowledge that is not image-specific and that is organized into schemas, objects, volumes, surfaces, regions, line segments, and vertices (RSV: regions, segments, vertices). Nodes are those levels; arcs are relations, primarily AND/OR. Interlevel arcs exist. Interpretation is viewed as a set of instantiations of nodes in LTM put into STM. Short-term memory is image-specific; it is used for constructing an interpretation. Initially, it contains only the RSV levels.

Two-dimensional curve fitting uses splines with knots determined by places of high curvature measured as angle from a point to k-neighbors on either side. If straight line segments fit, they are used, else quadratic, else cubic.

In the system, two-dimensional shape classification is hierarchical. For straight line segments, quadrilaterals include trapezoids and parallelograms, which include rectangle and rhombus. Quadratics are used for ellipses and circles. Other types of curves are labeled as *blobs*.

Occlusion depends on continuous curve generalization of T junctions. It is not clear that it is used in the experiment described later.

Some natural objects have relatively invariant color and texture. Many objects, such as manufactured objects, vary in spectral characteristics. It will sometimes be right to guess which among the class of target objects have invariant spectra. In the example, below, of 21 regions assigned on the basis of color, 11 were correct. Of the remaining, 5 were wall assigned as sky, and 2 were roof assigned as grass (Table 1).

The authors describe problems with inference nets. Probabilities are assigned to nodes and conditional probabilities to arcs, providing weighted paths by which implications of local hypotheses may be propagated up and down through the layered network. They point out problems in consistency and loops when generalizing.

The three-dimensional shape KS uses blending functions of cubic splines, defining "quilted solids." It is stated that three-dimensional shape has not been integrated into the system used in the experiment described by Parma, Hanson, and Riseman. A specific three-dimensional schema can be transformed into a specific point of view and projected onto the corresponding image plane, with hidden lines removed. Those facilities were not available at the time of the experiment, but were available when the experiment was completed. Specific two-dimensional schema were used.

Two-dimensional schema and three-dimensional schema have for each region a centroid of the expected location of its center and a radius representing decreased likelihood of the region center appearing at that location.

The perspective KS assumes a horizontal ground plane, with surfaces either vertical or horizontal. The camera model includes angle of inclination, image distance, and height above the ground. It deals with elevation, height, width, and range. The assumption is sometimes made that an object stands on the ground. If the ground is planar, objects are on the ground, and if objects are identical, the horizon line can be determined. It is in the ground plane. Tilt is given by the angle of the horizon from the center of the image. If tilt of the observer were zero, the

Table 1.

Object	Spectral Character	Texture	Location	Shape	Size
Tree	Green	?irregular*	Above horizon Above bush	Tall	
Bush	Green	?irregular	Below horizon Above grass	Low	
Grass	Green	?irregular	Below horizon Below bush	Flat	
Sky	Light blue	?uniform	Above all		Large
House walls		?uniform	Above and below horizon ?adjacent roof ?adjacent grass	?vertical trapezoid	Large
Roof		?regular	Above horizon ?adjacent walls	Trapezoid Straight lines	Large
Shutter		?uniform	Above and below horizon In walls	Trapezoid	Small Known

* Question marks indicate properties and relations that Parma, Hanson, and Riseman (1980) do not use. They apparently do not use house walls adjacent to roof, house walls vertical, shutters symmetric, shutters inside house. They do not use occlusion or texture analysis.

horizon would fall in the center of the image. Range of objects is determined by projected distance to their feet. If other objects are the same height as the camera (e.g., eyes of other people) a third plane is defined by a least-root-mean-square fit; the plane goes through the horizon. It is not clear from the report whether those capabilities were implemented. Sky regions cannot be below the horizon line; grass regions cannot be above the horizon line. The ground is assumed to be planar, the horizon a level line in the horizon KS.

If the perspective KS gives an estimate of object size in three space, the object-size KS generates a list of object hypotheses ordered by confidence based on the region size. Perspective KS returns computed size and range of size. Default range is 5%.

There are sometimes boundaries with known characteristics (e.g., long and straight, bounding roof). Top-down control of KSs directs matching of schema regions to image regions and some schema line segments to image line segments. A heuristic weighted evaluation function is left unspecified.

Experiment one matches color and texture attributes to improve a fragmented segmentation, by the rule of merging adjacent regions with the same object labels. A spectral attribute matcher is used to get a list of object types for a region. The experiment uses only regions obtained from the region segmenter. The system uses local schema regions to direct semantic merging, including adjacent regions. That is, it uses spectral properties and location. The result is to merge tree regions together, bush regions together, and grass regions together.

The system uses long straight lines in two-dimensional schema, placing a rectangular mask around the selected schema edge. The system selects lines within the mask within tolerance of slope of schema line as candidates. It merges all colinear segments within the mask and matches all resulting segments to the schema line. It matches on slope, length, distance between center, and rms error. In the example, the procedure matches three sides of the roof. The roof region now matches a parallelogram.

Symbolic region shapes are matched via two-dimensional schemata. Some schema regions have distinctive two-dimensional shapes, including trapezoid, rectangle, and ellipse. Properties for matching include size, aspect ratio, and color (Table 1).

The system does reasonably well in making a crude segmentation of the image. Tree, roof, grass, bush, shutter, and sky are labeled appropriately. Major regions not labeled include much of the house and trees in the background.

The perspective KS uses the knowledge that bushes are vertical and stand on the ground plane to estimate the range of the bush and its size. Bush adjacent to grass implies that bush is probably not occluded. Computed size partially validates identification as bush.

The system has several interesting capabilities that belong in a general system. Its segmentation is limited. The quality of edges and regions holds back interpretation. Texture description is weak. Because it uses locations in an image, the system described is not only viewpoint-dependent but dependent on the specific scene. This system's capabilities seem better than that. The authors imply that general vision can be achieved by having many special schemata and selecting among them. I disagree.

2.12. Rubin

ARGOS uses color, texture, adjacency, occlusion, location, size, and shape factors. It generates two-dimensional models of the scene from various views. It attempts to generalize parts of the network.

Search is a form of dynamic programming with restricted transitions. Its first task is to find the view angle. Then it should name objects from known view. Without segmentation, its images were 75 × 100 pixels, with 7,500-level-deep search. Experiments shown are with hand-drawn segments. The system also uses Shafer's version of Ohlander's segmentation (Ohlander 1975; Shafer and Kanade 1980). View angle is determined to 51°.

ARGOS uses "adjacency first-order" Markov evaluation, which relates all surrounding nodes to the node under consideration. ARGOS has units called *primitive picture elements* (PPEs) that may be segments from Shafer and Kanade's system (1980) or that may be individual pixels. A PPE may be thought of as the largest region that is homogeneous in both signal and symbol. Both image models and test images are in the form of PPEs.

ARGOS mostly relies on adjacency relations. For example, images of Pittsburgh will have mountains between sky and buildings. There may be vertical or horizontal adjacency nodes between PPEs. PPEs may have within relations, but without a containment hierarchy. All relations are single-level and explicit. Networks tend to be large.

Much depends on spectral labeling. Median of blue gives 44% correct labeling. Rubin ends up choosing median red, median blue, median green, contrast red, contrast green, and contrast blue, where contrast is from Tamura, Mori, and Yamawaki 1977). ARGOS uses a weighted-Euclidean distance, weighted by an adjusted standard deviation. Statistics are obtained by computing mean and standard deviation for pixels in regions segmented by humans.

ARGOS uses locus search. It has a forward pass, keeping paths with values near the maximum value. Pruning heuristics are important. Since there is no unique order (two-dimensional), paths are recombined, using maximum over neighbors. The pruning threshold is dynamic, relative to the best value at a given depth. Transition likelihoods are the network knowledge constraints. They have only three values, 0.0, 0.1, 0.9. Likelihoods at a PPE (pixel) are normalized once computed.

In the backtrace, multiple beam pointers from the forward pass may disagree because the problem is two-dimensional. Some heuristics for conflict resolution were tried: throw a pixel away; carry along pointers when a pixel is left out; reject some possibilities based on adjacency rules; select by voting.

The internal model is a three-dimensional model of the city that is used to generate all possible views. A network of relations (predominatly adjacency relations) is constructed by multiple views. A region that appears in different views may be merged into one PPE, depending on adjacencies.

ARGOS does not segment; it labels. It works with pixels or regions. It can use absolute image location (i.e., mountains are usually found in the top of images). Each region has an MBR along horizontal and vertical axes. Proximity of MBRs is used to decide on merging two regions. Image location is used. Shape knowledge is difficult to incorporate, since segments may combine along self-transitions in the network. Four shape measures were used: fractional fill, compactness, orientation, and elongation.

ARGOS was found to work better without size knowledge (image size) than with size. No advantage was found in making a hierarchy of knowledge sources.

Rubin discusses some extensions to other city scenes and to noncity scenes. None of these has been implemented. Image knowledge should be divided into the scene level or schema level, viewpoint level, and object level. ARGOS does not address automatic model generation. It is assumed that all models are built by hand. Rubin discusses a knowledge hierarchy for use of more general schema, starting at the most general end of the hierarchy. He observes that lower levels of the knowledge hierarchy look alike.

Fifteen pictures taken from five different vantage points around Pittsburgh were segmented and labeled by untrained workers. Human labeling was done to define ground truth. Seven pictures were chosen as a training set and the remainder as a test set.

The networks were reduced to 10%. Weights for terms were determined on the training set. The beam size was 25 entries. Data were smoothed in three ways: (1) simple smoothing (i.e., clustering, changing labels of surrounded pixels); (2) throwing out any region with less than 8 pixels; and (3) filling unlabeled holes in regions.

The system was correct in 71% of labeled cells for the test set. The author does not say what fraction are labeled. Hand-segmented data were used to determine view angle; root means square error was 41°. Accuracy of labels was 67%. Automatically segmented data gave view angle error of 60° and accuracy of labeling of 59%.

A priori, the system would not generalize for both close-up and distant pictures. Since it depends on horizontal and vertical dimensions, these are inversely proportional to distance. To include both, a very large range of dimensions would be necessary, which would make very weak dimension constraints. Adjacencies also change, for example, buildings obscure mountains. Image location is not at all general. In summary, the system uses these types of information: spectral; adjacency; horizontal and vertical image dimensions; and absolute image location. Only spectral information is viewpoint-independent. The system has little potential as a general vision system.

3. Applications

A few projections for applications of vision systems for the short term, for the mid term (2–3 years), and for the long term (3–5 years) follow.

Industrial vision systems for the short term have a small market. Whether there is a profitable evolutionary niche or not remains to be seen. I believe that the major obstacle is not the lack of knowledge of users, although that is a factor, but the lack of capability of current industrial vision systems, which use a technology that is at least 15 years old. They use thresholding to obtain binary images, two-dimensional models, and trivial global descriptors such as moments of the boundary. Now, researchers are beginning to use local descriptors such as holes and corners to deal with obscuration. Adaptive thresholding is being developed to increase the flexibility of such systems, but that is greatly inadequate. As a consequence of thresholding, few features can be obtained, lighting must be carefully engineered, and the system is not rugged at all. In most cases, industrial vision systems do not work at all. If they do work, their applicability is limited and special-case engineering is required, raising costs and risks for users.

In the mid term, attaining larger markets is an important objective that involves going from an evolutionary niche to a major impact at the 10% level in automation. To achieve the objective, systems must be much more capable, lessening the extent of custom engineering needed. They must distinguish many kinds of flaws in inspection, especially cosmetic from essential flaws. Systems can accomplish those objectives by incorporating several mechanisms, including structured light, which begins to lead to three-dimensional vision systems. Gray-scale segmentation allows more internal detail and less sensitivity to lighting. Greater speed and better shape discrimination will improve two-dimensional systems to a useful level.

In the long term, three-dimensional systems for warehousing, handling unoriented parts, and inspection of nonlaminar parts will be important. The programming of vision problems will be a major issue; thus, a single system for many applications will be essential. While a system may deal with only one object at a time, over a large company and over many companies a system will require the generality to deal with many parts. Teaching and part programming will be difficult, requiring the ability to work from data bases of geometric models. Learning may also become important.

In cartography, current applications use automated stereo for terrain. These systems work only partially for terrain. Stereo mapping is very labor-intensive. As resolution requirements are increased by a factor x, the volume of effort increases by a factor of x^2.

For the mid term in cartography, automated stereo mapping for complex cultural sites is expected in research situations and subsequently in production prototypes. Limited feature classification of linear features may be demonstrated. Aids for measurement of dimensions and data entry are expected to be important.

For the long term, automated feature classification is expected to make a major impact in mapping.

In photointerpretation in the mid term, monitoring of selected objects in restricted situations such as aircraft, vehicles on roads, and rail traffic is expected to be demonstrated to be feasible for classification, identification, counting, and measurement.

In the long term, classification of a greater variety of objects with broader context and much greater detail is expected to be demonstrated.

Many other applications appear, some bordering on science fiction. They include guidance, medical image analysis for diagnosis, laboratory analysis, and aids to handicapped. There are a number of hazardous tasks and environments in which robots with vision are expected to be used, including (1) space craft servicing; (2) communications equipment servicing in space; (3) undersea oil exploration, mineral exploitation, and naval operations; (4) firefighting; (5) servicing nuclear reactors and other power generators; (6) servicing electric lines; (7) carrying TV cameras into hazardous environments for news; and (8) the battlefield.

My own favorite is the home robot for cooking and cleaning. The home environment is complex. I do not expect to see home robots for decades.

There are important applications in psychology in determining perceptual mechanisms. Perceptual mechanisms are important in epistemology—in determining what people can know and the limits of human perception. They also have potential applications in education—in determining how to teach people in ways that make greatest use of their natural perceptual mechanisms.

4. Objectives

The summary of applications leads to six objectives for a vision system: that it demonstrate high performance; that it be general, complete, intelligent, and easy to use; and that there be system support.

High performance relates to complex scenes with many objects and applications requirements for detail, accuracy, resolution, and speed.

Generality implies that the system should be generic with respect to object class. (i.e., it should easily handle similar applications such as a mix of models of small electric motors). Generality also implies that it be generic with respect to observation (i.e., viewpoint-insensitive and sensor-insensitive). A three-dimensional system is a primary means of achieving this objective. Generality also implies a standard system for research and applications, with a large, general core plus mechanisms for special-case implementations.

Completeness means spanning all applications tasks. Completeness can be achieved by integration of all data, knowledge, and information, including multisensor data, expert knowledge, geometric models, prediction mechanisms, mathematics, and physics. It also implies powerful perceptual mechanisms for observation, including strong use of shape, edge segmentation, texture and image organization, depth and stereo, shape from shading, and shape from shape.

Intelligent implies reasoning in the domains of images and surfaces (i.e., geometric reasoning), like a human observer or analyst. Mechanisms that make a system easy to use include standard user aids from computer science, an intelligent editor, automatic program synthesis, geometric models as a natural mode of communication common to human and machine, natural system structure to make the system intuitively clear to users at the system level, and bridges to natural language.

System support requires the existence of a large, critical mass effort with continuing development and a user base with collaborations.

5. System Design

Vision systems should integrate results of many image operators: region and edge segmentation; texture segmentation; surfaces from stereo, from motion parallax, and from object motion; shape from shape; surface interpolation; and shape from shading. Vision systems should combine such descriptions with general and domain-specific knowledge. Knowledge and observations relate geometric entities, including image, edges, structures of edges, surfaces, structures of surfaces, and objects. Thus, vision systems integrate inputs from many sources, relating several geometric types. In computer systems terms, integration requires matching input/output formats of procedures, which becomes clearer conceptually when defined in terms of data types. But vision involves geometric types with well-defined transformation properties, not just data types. Representations for geometric structures provide the basis for integrating these different data and knowledge included in images, image structures, surfaces, and objects. The fundamental scientific basis of vision systems is representation.

In building a vision system, whether through evolution or by design of a computer system, attempts are made to eliminate duplication, choose clean structures of data and control to eliminate inefficiencies of storage and computation, share data structures, and merge and streamline data types. These efforts go to decrease the size of the system (biological or computer), to increase its speed, and usually to simplify its conceptual and physical structure. The primary concern is with achieving adequate perceptual performance within limits of computational structure and power. In the human, these limits are imposed by wiring limitations, size, and power consumption. There are corresponding limits for computers. Adequate performance can be related to completeness of representation and completeness of perceptual maps, within complexity limits. These concerns for adequacy, simplicity, and efficiency are similar to those of the mathematician, who is concerned with completeness and equivalence of mathematical types or their simplest axiomatization, or who generalizes mathematical structures to treat many types uniformly; or to the worker in analysis of algorithms, who determines worst-case computational complexity. Not only is adequate representation a means of making efficient and manageable systems, but adequate representation allows the solving of hard problems by compact restatement with constructs that expose inherent complexity rather than apparent complexity. Any program or biological system is a formal system. The concepts are defined; they may not be general or well organized. The point is that analysis of generality and organization makes an important practical difference.

6. Representation

It is often useful to assume that in biological evolution there has been time for considerable optimization of the sort just described, for well-structured representations. A good starting place for exploring biological perception is from the standpoint of representation.

Representation means different things to different people. Much work deals with domain-independent representation, largely concerned with properties relevant to typed set theory, such as inheritance. Set theory is inadequate for vision and probably inadequate for most domains of artificial intelligence. Set theory or logic is general, but weak. Logic is valuable as a framework for embedding systems, but very little can actually be accomplished with such a weak theory. For vision, strong theories with limited domain are valid, for example, topology and geometry. If geometric proofs and calculations are formulated in logic or in informal reasoning systems based on set theory (e.g., production rules), their statement becomes clumsy and proofs are very long unless intermediate levels of mathematical theories are built up. Proofs are long and difficult because the language is weak. Mathematics is a compact and powerful language for expressing geometric concepts. It is important to represent these mathematical structures by building up an appropriate hierarchy of mathematical types.

In representation, we must concentrate on the problem domain and the task at hand. That does not mean that there is a separate representation for each domain and for each task. In physics, a small set of mathematical types and mathematical operations for solutions (a few hundred) is sufficient. Vector spaces, for example, are useful in many physics domains. Representation depends on the purpose, but a single representation may serve many purposes, and a few hundred representations serve all. There are few independent (inequivalent) mathematical structures and few independent (inequivalent) mathematical problems. Representations are open-ended and hierarchical, built from a few primitives and a few composition rules. Primitives at one level are compounded to become primitives one level higher. Applications tasks are built from a few fundamental mathematical tasks by composition. This promises a countable set of constructs, but not many have been constructed, and there are generalizing and compacting forces at work. Mathematics is concerned with equivalence of systems, an antidote to the process of inventing representations and names that turn out to be equivalent to other representations. Most representations are minor variations of others. A neat hierarchy has largely been defined by mathematicians.

In artificial intelligence, representation is a central concern. If representations are compounds, what are the fundamental representations that ultimately form their basis in a reductionist schema? I believe that the bases are fundamental mathematical, physical, and perceptual primitives. This does not mean mathematics and physics as taught in schools, but intuitive models that everyone apparently possesses to varying extent. Education does provide better models for some people but, on the whole, formal mathematics and physics depend on primitive, intuitive concepts. It is my belief that other domains are described by analogy with mathematics and physics. A current view is that language determines perception, a view largely discredited by experiment. The counter view is more tenable: that the representations of language are determined by perception.

Mathematicians use *representation* to mean a map from a codomain A of some mathematical structure onto a domain of type B, a map that preserves the structure of A. Frequently, the map is from an abstract to a more concrete type; for example, representation of the rotation group by the group of orthogonal matrices as transformations in Cartesian three space. This example is a homomorphism of a group onto the group of linear transformations of a vector space, hence matrices. More generally, a representation may map a group onto the transformation group of a vector space preserving composition. In artificial intelligence, the term *representation* refers to a map of any kind, regardless of structure of codomain and domain and regardless of whether the map preserves structure (even when there is obvious structure and when standard mathematical terminology might be used).

The central theme here is *structural isomorphism*. One important representation is the shape of structural elements of objects relevant to a task. At a crude level, an artist structures a human figure as torso, arms, legs, and head and represents these parts as ellipsoids or with slightly better approximations for parts. At this level, the artist focuses on describing gross body shape with regard to part/whole structure and articulation. For a more lifelike rendering of individual parts, the artist focuses on muscles and bones and their structural elements. Muscles are laminae that flex and extend. Since there are only a dozen or so muscles per limb, the representation at this level of detail is only slightly more complex than at the coarser level; that is, total complexity is only a small multiple of the complexity of the coarser level of detail. Representation of muscles is an obvious structure for the heart. At a tissue level, muscle fibers are natural structural elements. For biological objects, structure may be related to development. For manufactured objects, structural representations may be closely connected with fabrication and mechanical construction operations, which include milling: translation and turning; screw; extrusion; translation; and assembly operations, including insertion and screwing. Generalized cylinders are determined by the principle of generalized translational invariance related to many such fabrication operations.

In structural representations, it is important that form equal function. Generalized cylinders were intended to provide suitable abstractions of shape to make compact, well-defined representations of function. It is a tenet that object classes are defined in two ways: by function and by abstractions from perception. Both definitions of object class are typified by abstract shape; that is, generic shape elements and relations. Structural representations thus cover a very large part of relevant representation.

7. Criteria for Shape Representation

Criteria for three-dimensional shape representation were formulated in developing generalized cylinders and were described by Thomas and Binford 1974. Generalized cylinders were initially intended for use in visual interpretation of complex objects as a means for a natural semantics for part/whole segmentation. The idea of a segmentation is not new, but the choice of primitive element determines whether the resulting segmentation into parts is useful. Also, they were intended for a compact representation of complex shapes from which symbolic relations between surfaces could be computed easily. The criteria for three-dimensional shape representation apply, with appropriate changes, to the representation of surface and image elements. The design criteria that led to the formulation of generalized cones are described in the paragraphs that follow.

A representation of shape should aid in describing a very large possible class of objects, including many we have never seen. The representation should be locally generated, like splines from local primitives. It is not reasonable to enumerate rigid primitives like cube, sphere, cylinder. Part/whole segmentation describes one form of generation, but the primitives that go into the part/whole description must be locally generated. Volumes and surfaces should be determined from samples or boundary conditions, with interpolation and extrapolation constrained by general principles.

Defining senses of similarity is a central issue of perception. Each representation introduces a sense of similarity that is natural in the representation. Generalized cylinders were introduced in order to represent locally generated constructions from fundamental geometrical operations, for example, sweeping (Binford 1971). Generalized cylinders were to be augmented by spheres, which characterize constructions based on rotations. One interpretation of the phrase *natural semantic interpretation* is in terms of these fundamental operations. A representation of shape should aid in describing similarities of classes of similar objects, that is, it should be a generic representation. Each representation introduces a sense of similarity that is natural in the representation. Generalized cylinders were based on generalized translational invariance, which defines similarity in terms of a hierarchy of congruence transformations mapping one slice of a generalized cylinder into another (Binford 1971). Congruence transformations determine the set of similarities of parts, while part/whole relations define global similarity. Thus, in this framework, a stick is similar to a snake or a ring and, in another sense, to a screw.

A representation of shape should aid in symbolic, generic prediction of appearances—generic with respect to object class and generic with respect to observation (i.e., valid over a broad range of viewpoints, illumination, and so on). A representation of shape should aid in inferring volume description from image information. More generally, it should aid in symbolic, generic description—generic with respect to object class and with respect to observation.

A representation of shape should define levels of detail, coarse to fine, by defining a natural semantic segmentation, a part/whole decomposition intuitively natural to human beings. Parts should be part/whole structures themselves. This condition helps the system "communicate" with humans, which can help them debug programs and create understandable systems. Parts should be defined by continuity. A surface is not a part in "natural semantics" (e.g., a cube has six surfaces, yet a cube is thought of by most people as a single part). If we define parts by surface continuity, then only separate objects are parts, and a man standing on a floor is not separate from the floor. If, on the other hand, we define parts by surface tangent plane continuity, then a cube has six "parts." Parts are volumes. Primitive parts should be generated from elements that are disjoint and for which a small, finite set gives a good approximation. This adds intuitive clarity in description and in model building. Generalized cylinders correspond to stacking volume elements like slices of bread. Ribbon surfaces correspond to stacking surface elements. A representation should be local. If we want to describe an arm of a volume, we want to limit our attention to that part of the shape. Some splines have that property. The covering by a finite set implies that the elements are volumes. In the Blum transform (Blum 1967), which is a covering by a minimal set of maximal interior disks, the elements are overlapping circles, that is, not disjoint. In the Fourier representation, components or eigenfunctions form an overlapping set. Eigenfunctions for aircraft are roughly overlapping aircraft-shaped elements additively combined. It is much more natural to make disjoint combination of parts like fuselage, wings, and tail. The Fourier transform of a shape is global. Local changes have global consequences.

Parts should be locally realizable; that is, they should be closed and nonintersecting. Surfaces must be investigated totally before closure and intersection can be tested.

At the Stanford University Artificial Intelligence Laboratory, we aim to represent elements by mathematical entities and to relate these entities by maps within and between levels. Several of the levels correspond to entities of three dimensions (volumes), two dimensions (surfaces), one dimension (curves), and zero dimensions (points) embedded in spaces of three dimensions, two dimensions, and one dimension. We have maps that decrease dimension (projections) and maps that raise dimension (sweeping operations).

Our work has been based on the following paradigm. Descriptions are made of geometric entities formed by two processes. The first is grouping by a few geometric relational operations that are more or less independent of the geometric entity and that are common to all levels. These grouping operations correspond to neighborhoods of approximately uniform shape, elongated narrow neighborhoods in all directions corresponding to longitudinal projection, and transverse projection (Nevatia and Binford 1977). The second process is segmentation by tight constraints that are specific to the geometric entity.

8. Interpretation

One paradigm for interpretation is template matching of images. This assumes image invariance and has little place in three-dimensional image analysis. Template matching requires enormous computation for three-space scenes. Even that computational inefficiency is a minor fault compared to the fatal flaw: it produces a very weak sense of identity of objects. Another interpretation paradigm is graph endomorphism, or finding an embedding of a model element in a description of an image, where both are expressed as a graph of nodes and relations.

A distinction is made between total and local representations and between total and local matching. A further distinction is made between arbitrary and semantic segmentations. Key issues are (1) generic interpretation in terms of object classes, insensitive to viewpoint; (2) semantic interpretation, that is, an evaluation function that accounts for details of the scene and observation process; and (3) semantic search in matching, using semantic segmentations and indexing.

8.1. Total Image Matching

Most recognition schemes rely on total image matching and complete image congruence. The problem posed is to match one image with another, invariant to translation and rotation. This assumes image invariance; there must be no systematic differences between images. Any systematic differences between images will result in large, unpredictable biases in location of best match. The limitations of total image matching schemes do not depend on whether they match intensities or Fourier transforms or coefficients of other orthogonal expansions or eigenvalues of such expansions. These schemes sound more relevant than they are in reality, since they refer to plane figures as "objects," which implies three-space elements. The usual approach is to store a dense set of possible views (or coefficients describing them) so that any sensed image is "near enough" to one of the dense set of views. That rapidly becomes unmanageable. Consider three-space, articulated objects in arbitrary positions, orientations, and articulations. Assume that we do not know their shape exactly (the next person we see will be unlike any other). Objects are painted with irregular patterns that we do not know exactly either (people wear different clothes; different dogs have different spots). They will be in uneven illumination that we do not know exactly (this depends on atmospheric conditions and reflections from nearby objects), with shadows and obscurations. Images depend on many things, even on position within the retina, because of photometric and geometric nonuniformity (distortions and design). Sensors may have unusual response (SAR, infrared). One approach is to store a dense set of views of all possible combinations of objects in all positions, orientations, and articulations, with all possible illumination for all possible sensors. Any of these systematic effects can cause large, systematic errors in position of best match and interfere with estimation of accuracy. The complexity for three-dimensional objects with articulation and obscuration may be related to the power set of the plane with a certain granularity. We know a great deal about familiar objects and familiar scenes, but this is not the way to use that knowledge. Humans perceive scenes on postcards with ease without knowing surface pigmentation, illumination, or sensor characteristics. In a sense, humans are always seeing objects they have never seen before.

Even if total image matching could be made to work, it has little value, even for two-dimensional scenes, because it gives a trivial sense of object. Distinct views of an object in three space are separate and unrelated in such a scheme, linked only by their object name. This is not a useful sense of object. In two dimensions, any plane figure is a separate figure unrelated to any other. These schemes cannot identify shared image elements (i.e., partial image congruence), which they must do to perceive family relations.

8.2. Local Image Matching

Some concepts are defined here:

1. *Total representations* of an image depend on the full image, for example, Fourier transforms of an image are defined on the whole image. Total representations over a domain are defined on the total domain.
2. *Local or partial representations* are defined on proper subsets of the domain represented, for example, B splines are defined on a few adjacent nodes of a surface mesh. Locally generative representations like splines can be parameterized locally and composed globally to satisfy criteria such as continuity.
3. *Semantically segmented representations* of an image are local representations defined on image domains that are specific to image content. An example is a set of extended edges in an image. Semantically segmented representations of a domain (e.g., curve, surface) are local representations specific to the content of the domain. Another example is an approximation of curves by a B spline basis where nodes are chosen for optimal fit, corresponding to cusps. Local representations defined on an arbitrary tesselation of the domain are arbitrary segmented representations.
4. *Part/whole representations* are structured, semantically segmented representations with disjoint elements.
5. *Matching* is a map from two descriptions to a third description. The third description is usually a real number (distance or probability). In our work, we emphasize matches whose results are structured descriptions.
6. *Local matching* is a map from two local descriptions to a third local description.

One important generalization of interpretation is local image matching of semantically segmented descriptions that identify shared semantic image components, especially those which are locally generative like curves and ribbons in images. Local representations may be used for total matches, for example, least-squares matching of all observed curves to all model curves. There is little gain. Local or partial matching allows for identification in the presence of obscuration or physical differences between model and image. Some requirements of local matching include (1) sufficient support of local matching to generate adequate constraints and (2) semantic segmentations to limit combinatorics of matching.

For physical reasons, curves are a useful structural element in images. Many image curves and groupings of curves correspond to surface edges and inherent surface markings. Some correspond to illumination discontinuities that are also interesting. Curves are also useful for describing many strictly two-dimensional forms, for example, characters and drawings.

I suggest this principle for interpretation: incorporate models with explicit representation isomorphic to the domain of variation. In pattern recognition, this approach reduces cluster size by explicitly accounting for effects of "nuisance" variables. If the actual domain of variation is a subset of a larger domain, then representations of the larger domain can be restricted (e.g., we can find simplified special cases such as when objects are viewed in a few stable states from restricted viewpoints). Partial image matching can relate common image structure of distinctly different figures, but interprets different poses of a three-space object as different objects. If the principle just set forth is followed, three things will be represented explicitly in our models: three-space objects; the observation process; and illumination. Of course, if objects or viewpoint are restricted, then the representation is simplified. Use of image curves in image matching directly reduces some image variation caused by photometric effects (i.e., illumination, sensor differences, and sensor inhomogeneities). It is surprising how little we can do with image curves and structures of curves without three-space interpretation. Obscurations, surface markings, and edges of surfaces are three-space concepts. Image curve descriptions are compact and provide substantial reduction of combinatorics, however.

8.3. Three-Space Matching

In total three-space matching schemes, different articulations of a doll are separate objects, related only by their object name. Structured, partial matches do relate different articulations of an object as different aspects of the same object. While they seem gloriously general, partial three-space matches are not adequate either. Our usual sense of object is not determined by a three-dimensional shape but by a class of three-dimensional shapes. While this may seem a hopelessly general paradigm for perception, it is the usual perceptual problem, and mechanisms for generic interpretation are feasible. Interpretation by partial three-space matching would recognize different configurations of a Boeing 747 as distinct, unrelated objects; also different configurations of an F4 with different radar, fuel tanks, or armament; or a truck with different loads. It would have no idea that a 747B resembled a 747SP more than a truck. Without generic perception, there would be no cognitive basis for concepts of truck, vehicle, or passenger aircraft. Coffee cups vary from conical styrofoam throwaways to ceramic handcrafted treasures, from minimum forms to the extravagant. Chairs have great variety. We have not seen all such possible forms, we cannot enumerate all possible prototypes, and if we see another that is distinctly different, we probably will interpret it correctly. Similarity, not spatial congruence, is the paradigm of interpretation in nature. As stated above, humans are always seeing objects they have never seen before. No one has ever seen me before as I am now (in the sense of spatial congruence). They may have seen me as I was on one occasion yesterday or two years ago. That is the central perceptual problem. The paradigm is recognizing a friend after 10 years' aging, a 10-lb weight loss, in different clothes, and with less hair, or recognizing a tiger from verbal descriptions and warnings about them without having seen one before, even though no two tigers are identical. We have similar motivation for incorporating generic mechanisms for applications in manufacturing or photointerpretation to deal with the problem of programming a class of related tasks. Here, object classes may be generated by a variation of a design or manufacturing process, for example, a small motor product mix. Variation may be small within one task, but among a class of tasks the objects form a class with considerable variability yet strong similarity.

One usual approach is to characterize a class as a prototype with a distance measure or as the union of such classes or as some membership function on such sets, but that approach induces a weak sense of object class. Given fixed metrics based on three-dimensional distance for typical object classes, we conjecture that we can choose elements of these object classes that are very far apart in the metric, such that if the class diameter is relaxed to include usual members of the class, then it fails to discriminate against nonmembers.

The essential definition of object class is functional. Manufactured objects are designed for a function and living things have a teleology. Object classes have an associated three-dimensional form: form equals function. That is, an object's function is to be its form. Which aspect of its form? An object's function is often a geometric function. The function of a room is to be an enclosing volume. The function of a chair, desk, or table is to be a flat surface at a comfortable height for sitting, writing, eating. An object's function may constrain the choice of materials for its fabrication (e.g., a mattress versus a desk). Cost and available fabrication processes may constrain otherwise free choices. For example, a runway has its minimum length constrained by its function in the takeoff and landing of a class of aircraft and its maximum length constrained by cost. An important issue for interpretation is to identify which geometric parameters are causally determined such that their distributions are not just biases of the sample population (e.g., runway length). These essential characteristics enable tight discrimination, which is not possible if properties are treated only as statistical distributions. Causal relations come from function. Such reasoning allows classifying elements into natural subgroups. For example, runways can be classified according to the types of aircraft they serve, even when insufficient statistical information or none is available. This capability is important, since cases in which all distributions can be determined are probably few.

There is no great mystery about generic capability. The relevant geometric description may be at an abstract level. We must differentiate object form from function in suitable abstractions, extract descriptions of form in abstractions, and find a set of equivalences. Because there are only a few descriptors of generalized cones and thus only a few levels of abstractions, this scheme is feasible.

With statistical approaches, it is assumed that the choice of features and class definitions may be given externally; they concentrate on the manipulation of a priori and observed probabilities. I am passionately concerned about just what defines specific classes and which specific features should be used. In the light of our paradigm, general vision requires strong description and weak classification, since a central problem is defining object classes dynamically in a complex visual environment, that is, creating new object classes while living.

Because of computational limits and information limits we have limits on perception. Because of computational limits, we compute only the simplest few of the enormously many possible functions on an image. Because of information limits, we can consider only relatively simple underlying object interpretations for observations. These models represent a commitment or preconception to perceive what we can within those limits. Observations are represented as instantiations of these models.

A purely statistical approach, as opposed to a causal, structural approach, has limits that follow from those information limits. The number of possible scenes far exceeds the number of measurements. The number of possible parameter combinations also far exceeds the number of possible measurements. Some simplifications are essential. Locality and decomposability into primitives are central in structural approaches. In a sense, generalized cylinders are singly curved, hence separable in internal coordinates. By contrast, the Fourier transform is separable in external coordinates.

8.4. An Approach to Interpretation

One approach to the formalization of interpretation—to finding the "best match" between an observation and models—is graph embedding. In graph embedding, an isomorphism of one or more models with a subset of the observation is found (Barrow et al. 1977). This implies that models and observations have equivalent representations; for example, image models are compared with image observations (the most usual) or volume models are compared with volume observations. The chief problem lies in defining criteria for inexact matching, for which the usual approach is syntactic. For example, the best match has the fewest differences. This increases complexity of search greatly, but it also is a very unsatisfying match. In some cases we expect differences, for example, when limbs are obscured or not observable by the sensor used. Interpretation of significance of these differences is specific to the scene, to the observation process, to object class, and to articulation of the object.

Once a hypothesis has been made, predictions and measurements provide new information for the decision. Thus, the decision is not necessarily made on a fixed database; interpretation becomes a problem of knowledge acquisition. This raises the concept of "perceptual overkill." It does not seem a useful heuristic to determine the minimum information for classification as an approximation to the maximum-utility problem. In biological systems, many of the perceptual mechanisms are parallel, and there is nothing to be gained in ignoring them. In machine perception, overwhelming verification of a correct hypothesis is typically inexpensive compared to the computation required to get to the right hypothesis. These factors shift the utility balance toward getting data needed for a highly constrained decision. Very strong, relevant data are available if descriptive mechanisms can abstract them and interpretation mechanisms can use them. Object classes likewise have strong functional characterizations. A few structural relations characterize the class. Each relation can be tested.

The interpretation process is usually defined as statistical. Here, the definition is structural, detailed verification of criteria descriptions of class characteristics. All of this falls within the scope of decision theory, but usual applications of decision theory to interpretation trivialize the models from which conditional probabilities follow. The approach can be regarded as making explicit dependencies that might be glossed over in a statistical analysis. Noise is only one issue; systematic differences are primary.

The match of an observation to a model is the set of transformations necessary to map an abstract model to make it congruent to an abstracted, observed, and semantically segmented description, both specified at the level of essential volume or surface elements. Multiple interpretations are resolved when possible by new observations as required. Essential and optional characteristics are confirmed by new observations so that all criterial structures are verified. The mapping of a structured match to a real number (probability) can often be postponed; at a final decision, a real number is usually convenient to characterize an acceptable subspace, but there are many other ways to characterize a subspace. The distance of the class of transformations can be evaluated in the semantic evaluation sense described above.

This approach is closely related to the one Evans (1968) uses in solving analogy problems. It also follows directly the fundamental definition of generalized cylinders by generalized translational invariance. Generalized cylinders are not defined by a distance function but rather by a congruence map. This approach of a metric on transformations was pursued (Nevatia 1974). The outline of a simple distance measure can be specified based on some obvious semantics that are not complete or satisfactory. The distance measure is applied to the congruence transformation, which includes articulation, scaling, rotation, obscuration, observation errors, and object variations (growth, aging, missing parts). The cost assigned to variations is highly context-dependent. For example, articulations corresponding to usual postures and gaits have low cost. Articulations outside comfortable ranges have high cost. An obscuration interpretation must be consistent with observations of obscuring objects.

In summary, a key paradigm is similarity (not spatial congruence) and the matching of objects that are similar but not identical. There are several important mechanisms: (1) description of three-space form in terms of generic shared structural elements and their abstractions; (2) inference of causally determined parameters; (3) characterization of object classes; (4)

indexing of subclasses of similar forms; and (5) distance functions evaluated in context from congruence maps.

8.5. The Search Process

The search process in matching is important because potential for complexity is high. Search for graph endomorphism has high complexity for graphs of moderate size. There must be semantic simplifications. It is not reasonable in general vision to match against all models in visual memory. At Stanford, we introduced some concepts for indexing into subsets of objects similar to observed objects (Nevatia 1974). Those techniques were aimed at perception with a relatively large visual memory, even though we worked with only six objects. These indexing techniques relied on imposing a size (attachment) hierarchy on stick figures (i.e., on the part/whole graph). The reasoning for this was that small parts are attached to large parts. This led to comparisons with similar structures (e.g., comparison of a description of a doll with models of the class of objects that have two limbs at one end and three at the opposite end). Object classes were indexed by hash coding. We have considered a similar scheme in which object structures are arranged in a graph (based on topological and metric properties of stick figures) to be referenced by traversing the graph. These are mechanisms for generating hypotheses for subsequent verification. We focus on hypothesis generation because in vision it is a crucial step. In earlier work (Nevatia 1974), an attachment hierarchy allowed the structuring of model graphs and description graphs to facilitate indexing into a subset of similar shapes. Comparison of individual graphs was much abbreviated. This approach provides some capability for identification within a large visual memory.

It is my belief that general vision systems depend on the building of three-dimensional descriptions and that prediction, description, and interpretation take place largely in three dimensions. A recent article describes constraints that lead in the direction of incorporating these capabilities in ACRONYM (Binford 1981).

One paradigm for intelligent systems is *prediction–hypothesis–verification*. The paradigm can be useful or ineffectual, depending on how adequately prediction, hypotheses generation, and verification are conceived. We refer to hypotheses as descriptive maps, cueing, or bottom-up maps. Mapping occurs upward among structures in a geometric hierarchy, from image curves to surface edges, from structures of curves to surfaces, and from structures of surfaces to objects. We use the same terms to refer to prediction maps or top-down maps. We normally think of vision hypotheses as great leaps from images to objects and predictions as great leaps from object models to images. Those are not useful starting points. Vision systems have primarily been built on this basis, with only two levels of representation, name level and image level. *Image level* includes observations extracted from images and appearances of objects. This is too shallow a geometric structure. Instead, we have long thought of hypothesis–prediction–verification loops as steps between any two levels in a well-defined geometric hierarchy—a hierarchy that is deep, with small steps between levels. Hypothesis–prediction–verification relate nearby levels, especially, from image curve elements, to extended curves, to structures of curves (image organization, one level of Gestalt organization), to surfaces, through levels of surface organization. Each loop of prediction–hypothesis–verification is at once bottom-up and top-down. We claim an essential unity of bottom-up and top-down operations. If strong context and weak visual data are available in a situation, a system appears top-down; if the system has strong visual data and weak contextual information, it appears bottom-up. Usually, both context and visual data are available. Prediction is as effective at low levels of the geometric hierarchy as at the high level. Prediction is as general as description. If we have weak contextual information, if we do not know what objects are in the scene and we do not know our viewing conditions, we still know that we can represent objects by locally generative shape primitives (e.g., part/whole graphs of generalized cylinders), and we know that we can make generic predictions of the appearances of generalized cylinders, predictions that are insensitive to viewpoint, illumination, and sensor, general conditions on image areas and image curves corresponding to surfaces, limbs, and edges of surfaces. I remarked above that prediction–hypothesis–verification loops link primarily nearby levels in the geometric hierarchy. The nearer the levels, the more plausible the hypothesis. In ACRONYM, cueing (i.e., hypothesis generation) is based on powerful shape descriptions, image ribbons, surface ribbons, and generalized cylinders. We originally devised generalized cylinders as a natural way to use image cues about surfaces.

References

Ballard, D., Brown, C., and Feldman, J. 1978. An approach to knowledge-directed image analysis. *Computer vision systems*, ed. A. Hanson and E. Riseman. New York: Academic.

Barrow, H. G., et al. 1977. Interactive aids for cartography and photointerpretation: Progress report. *Proc. ARPA Image Understanding Workshop*, ed. L. Baumann. McLean, Va.: Science Applications, pp. 111–127.

Binford, T. O. 1971. Visual perception by computer. *Proc. IEEE Conf. Syst. Contr.*

Binford, T. O. 1981. Inferring surfaces from images. *Artificial Intell.* 17:205–245.

Blum, H. 1967. A transformation for extracting new descriptors of shape. *Models for the perception of speech and visual form*, ed. W. Dunn. Cambridge, Mass.: MIT Press, pp. 362–380.

Bolles, R. C. 1976. Verification vision within a programmable assembly system. AIM-295. Stanford, Calif.: Stanford University Artificial Intelligence Laboratory.

Brooks, R. 1981. Symbolic reasoning among 3-dimensional models and 2-dimensional images. *Artificial Intell.* 17:285–349.

Evans, T. A. 1968. A heuristic program to solve geometric analogy problems. *Semantic information processing*, ed. M. Minsky. Cambridge, Mass.: MIT Press.

Faugeras, O., and Price, K. 1980. Semantic description of aerial images using stochastic labeling. *Proc. ARPA Image Understanding Workshop*. McLean, Va.: Science Applications, pp. 89–94.

Garvey, T. D. 1976. Perceptual strategies for purposive vision. Tech. Note 117. Menlo Park, Calif.: SRI International, SRI Artificial Intelligence Center.

Hewitt, C. 1968. Planner. Memo 168. Cambridge, Mass.: Massachusetts Institute of Technology Artificial Intelligence Laboratory.

Horn, B. K. P. 1973. On lightness. Memo 295. Cambridge, Mass.: Massachusetts Institute of Technology Artificial Intelligence Laboratory.

Hueckel, M. 1973. A local visual operator which recognizes edges and lines. *J. Assoc. Comput. Mach.* 20:634.

Kanade, T., and Reddy, R. 1981. Image understanding at CMU. *Proc. ARPA Image Understanding Workshop*. McLean, Va.: Science Applications, pp. 199–207.

Land, E. H., and McCann, J. J. 1971. Lightness and retinex theory. *J. Optical Soc. Am.* 61:1–11.

Levine, M. 1978. A knowledge-based computer vision system. *Computer vision systems*, ed. A. Hanson and E. Riseman. New York: Academic.

Lowe, D. G., and Binford, T. O. 1981. The interpretation of geometric structure from image boundaries. *Proc. ARPA Image Understanding Workshop*, ed. L. Baumann. McLean, Va.: Science Applications, pp. 39–46.

Miyamoto, E., and Binford, T. O. 1975 (May). Display generated by a generalized cone representation. Paper delivered at Conf. Comput. Graphics Image Processing, Anaheim, Calif.

Moravec, H. P. 1980. Obstacle avoidance and navigation in the real world by a seeing robot rover. Ph.D. thesis, Stanford University. AIM 304-A. Stanford, Calif.: Stanford University Artificial Intelligence Laboratory.

Nagao, M., Matsuyama, T., and Ikeda, Y. 1978. Region extraction and shape analysis of aerial photographs. *Proc. 4th Int. Conf. Pattern Recognition*, p. 620.

Nagao, M., and Matsuyama, T. 1980. *A structural analysis of complex aerial photographs*. New York: Plenum.

Nevatia, R. 1974. Structured descriptors of complex curved objects for recognition and visual memory. Ph.D. thesis, Stanford University. AIM 250. Stanford, Calif.: Stanford University Artificial Intelligence Laboratory.

Nevatia, R., and Binford, T. O. 1977. Description and recognition of curved objects. *Artificial Intell.* 8:77–98.

Ohlander, R. B. 1975. Analysis of natural scenes. Pittsburgh: Carnegie-Mellon University Department of Computer Science.

Ohta, Y. 1980. A region-oriented image-analysis system by computer. Ph.D. thesis, Kyoto University Department of Information Science.

Parma, C. C., Hanson, A. M., and Riseman, E. M. 1980. Experiments in schema-driven interpretation of a natural scene. COINS Tech. Rept. 80-10. Amherst, Mass.: University of Massachusetts.

Rubin, S. 1978. The ARGOS image understanding system. *Proc. ARPA Image Understanding Workshop*. McLean, Va.: Science Applications, pp. 159–162. Ph.D. thesis, Carnegie-Mellon University.

Shafer, S., and Kanade, T. 1980. KIWI, a flexible system for region segmentation. Tech. Rept. (in preparation). Pittsburgh: Carnegie-Mellon University.
Shirai, Y. 1978. Recognition of man-made objects using edge cues. *Computer vision systems*, ed. A. Hanson and E. Riseman. New York: Academic.
Tamura, H., Mori, S., and Yamawaki, T. 1977. Psychological and computational measurements of basic textural features and their comparison. Tech. Rept. Electrotechnical Laboratory and Waseda University.
Thomas, A. J., and Binford, T. O. 1974. Information processing analysis of visual perception: A review. AIM-227; CS-408. Stanford, Calif.: Stanford University Artificial Intelligence Laboratory.

Several figures are reprinted from *A Structural Analysis of Complex Aerial Photographs* by Makoto Nagao and Takashi Matsuyama: Plenum Publishing Corporation 1980 with the permission of the authors and publisher; and from *Computer Vision Systems* edited by Allen R. Hanson and Edward M. Riseman: Academic Press, 1978 with the permission of the editors and publisher.

Low Level Image Segmentation: An Expert System

AHMED M. NAZIF AND MARTIN D. LEVINE, SENIOR MEMBER, IEEE

Reprinted from *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Volume PAMI-6, Number 5, September 1984, pages 555-577.

***Abstract*—A major problem in robotic vision is the segmentation of images of natural scenes in order to understand their content. This paper presents a new solution to the image segmentation problem that is based on the design of a rule-based expert system. General knowledge about low level properties of processes employ the rules to segment the image into uniform regions and connected lines. In addition to the knowledge rules, a set of control rules are also employed. These include metarules that embody inferences about the order in which the knowledge rules are matched. They also incorporate focus of attention rules that determine the path of processing within the image. Furthermore, an additional set of higher level rules dynamically alters the processing strategy. This paper discusses the structure and content of the knowledge and control rules for image segmentation.**

***Index Terms*—Artificial intelligence, computer vision, expert systems, image segmentation, rule-based systems.**

I. Introduction

A PRIMARY objective in contemporary computer vision research is the ability to analyze images originating from three-dimensional scenes in order to understand their content. This may be done by assigning appropriate interpretations to objects within the scene. Accordingly, an image must first be segmented into regions that roughly correspond to objects, surfaces, or parts of objects in the scene represented by that image. Two steps are thus apparent, the low level processing stage mainly concerned with segmentation, and the high level stage devoted to the interpretation of the segmented result.

The hierarchy suggested here assumes that a low level process that has no *a priori* knowledge about the objects in a scene, would be able to deliver a "plausible" output to the high level process. However, the option of receiving feedback from the latter for further processing in order to resolve high level ambiguities is left open. This research is concerned with the low level stage of an image understanding system, and is closely related to previous work on high level image interpretation [7]. It should be noted that the distinction between the two levels of analysis is primarily in terms of the knowledge available to each. Whereas the interpretation system uses domain specific knowledge about the contents of a scene, the low level segmentation stage employs general purpose models [25] that contain knowledge about images and grouping criteria that are independent of the class of scenes under analysis.

This paper presents a new paradigm for image segmentation, namely, the use of an expert rule-based system. Such a solution was motivated by a number of issues that needed to be addressed and studied. They can be classified under the following headings.

1) The presence of a large number of segmentation heuristics in the literature. A method is required for evaluating and organizing these to function together.

2) The absence of an explicit scheme for representing the knowledge embodied by these segmentation heuristics.

3) The lack of quantitative evaluations of a segmentation.

4) The need for a better understanding of the methods by which the segmentation heuristics should be applied to an image.

Following is a discussion of these issues and how the proposed solution affects each.

1) Integration of Knowledge Sources: Approaches to image segmentation in the past have relied on procedural algorithms for boundary detection and region growing [19]. These processes used different heuristics in their analysis, with varying degrees of success in obtaining output partitions that are compatible with human expectations. The diversity in the data structures, knowledge sources, and control mechanisms presents difficulties in finding a general framework that can integrate these efforts. A primary goal of this research was to design a complex system that not only is flexible enough to accommodate the wide variety of segmentation heuristics, but would also be capable of evaluating and selecting the best heuristics for different data situations. For example, both region analysis for grouping pixels based on the similarity of their features, and boundary analysis for partitioning the image based on discontinuities in the features, have been suggested as valid methods for segmenting an image. The proposed system is capable of doing both, with the additional potential of allowing interactions between these knowledge sources. Such an exchange of information between the various segmentation heuristics leads to a substantial improvement in the output delivered to the high level interpretation processes.

2) Explicit Knowledge Representation: The design of an expert segmentation system that blends knowledge from a wide variety of sources faces the problem of finding a suitable knowledge representation scheme. In vision systems developed so far, "explicit representations of knowledge have been reserved mainly for application domain knowledge, while general visual knowledge has been buried away in procedures" [22]. What is needed is a flexible mechanism capable of experiment-

Manuscript received June 21, 1983; revised January 4, 1984. This work was supported in part by the Natural Sciences and Engineering Research Council of Canada under Grant A4156, and by an FCAC Grant awarded by the Department of Education, Province of Quebec, under Grant EQ-633.

A. M. Nazif is with the Department of Electrical Engineering, University of Cairo, Cairo, Egypt.

M. D. Levine is with the Computer Vision and Robotics Laboratory, Department of Electrical Engineering, McGill University, Montreal, P.Q., Canada.

ing with different processing methodologies, and an expressive coding scheme that can accommodate all possible knowledge sources. The rule-based approach to control, which is proposed here, satisfies both requirements. Knowledge is detached from the application processes and coded into rules, which are modular entities that can be modified without affecting the structure of a system. An additional goal of this research was to investigate the use of the rule-based approach in general purpose image segmentation. This includes addressing control issues such as conflict resolution and focus of attention, as well as structural issues like the symbolic coding of segmentation heuristics into production rules.

3) Output Evaluation: Another aspect of the image segmentation problem is the nonuniqueness of the solution. Ideally, a complete segmentation should correspond to the objects to be interpreted. However, low level processes can only produce partitions on a nonsemantic basis, and these may not necessarily correspond to describable objects. Such partial segmentations are not unique even for humans examining a scene. This problem may not be of particular importance if the ultimate goal is to perform high level analysis with top-down feedback. Nevertheless, a method for evaluating the output is required. It provides the means for designing a system that produces the most appropriate partition, and hence minimizes the need for intervention by the high level stage. Therefore, another goal of this research was to establish design measures that indicate the distance from a known reference. The latter is taken to be a manually generated segmentation that corresponds to the objects in the image. These measures can then be used within the context of the rule-based system to "tune" the model by evaluating the rules and the control mechanisms.

The development of design measures has prompted us to search for other measures that estimate the quality of the output without the need for a reference partition. Consequently, these new measures can be used during actual processing and will be referred to as "real-time measures." Low level segmentation can now be posed as an optimization problem in which the goal is to maximize a set of performance parameters. By comparing an output partition to the input image, the real-time measures are used to modify the processing methodology in order to incrementally improve that output.

4) The Definition of a Control Strategy: For a system that employs a large number of heuristics to segment an image, two control issues must be addressed: the order in which different heuristics are applied, and the path within the image along which they are tested. Thus, a control strategy for image segmentation consists of rule-ordering and path selection components. Different strategies are available, and the best strategy to apply varies during processing. It depends on the state of the output segmentation at any given time. Consequently, a dynamic selection mechanism is used to execute the best strategy based on the data.

One of the early attempts at addressing these issues was not actually in image understanding, but rather studied the symbolic representation of visual images by humans [14]. In a system called VIS, Moran compiled a set of rules that simulated the behavior of a human describing a sequence of simple visual events. The first effort at using production systems in image

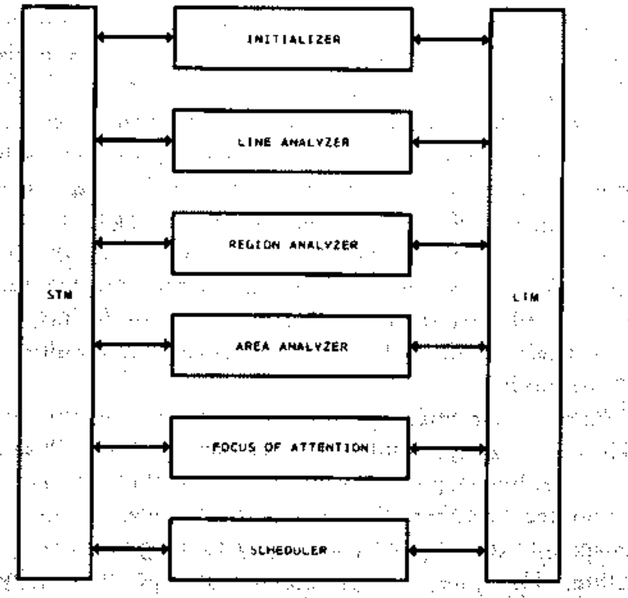


Fig. 1. The system block diagram.

understanding was reported in Sloan's [20]. The rule-based structure was limited to the interpretation stage and was clearly separated from the low level region analysis. Other interesting systems are reported in [1], [2], [10]. All the approaches have concentrated on the high level aspects of the vision problem. The rules represent specific domain knowledge that is application-dependent. What is also needed is a representational mechanism that can encompass general purpose knowledge about image formation and the laws of preceptual grouping. These information sources are independent of the specific application and the semantic content of the images. Such a formulation fills the gap between the procedural operators that measure and detect features in the image and the high level expert systems that interpret the results. This paper discusses the structure and type of low level knowledge implemented by such a rule-based system for image segmentation.

II. System Overview

The system is designed in the form of a modular set of processes and two associative memories, as shown in Fig. 1. The input image, the segmentation data, and at the end of processing, the output, are stored in a short term memory (STM). A long term memory (LTM) embodies the model representing the system knowledge about low level segmentation, as well as control strategies. Each of the system processes has access to the information stored in the LTM, and can also read and modify the data stored in the STM. In fact, this is the only way it can communicate with the other system processes. Thus any change in the data stored in the STM, brought about by one of the system processes, will be instantaneously available to the other system processes.

The basic control structure is that of a production system, in which general knowledge about independent low level properties of an image is formulated into condition-action rules. A system process matches rules in the LTM against the data stored in the STM, and when a match occurs, the rule fires. This triggers an action that is performed by that process, and usually involves modification of the data.

The segmentation of an image is defined by a set of regions that are connected and nonoverlapping, so that each pixel in the image acquires a unique region label that indicates the region it belongs to. In addition to the regions, discontinuities in the image array are defined by lines that are also connected and nonoverlapping. In this case, pixels in the image can either have a line label indicating the line they belong to, or they can have null labels to indicate that there is no line passing through them. This approach simultaneously uses both region information, based primarily on uniformity criteria in the image array, as well as line information, that represents discontinuity criteria in that array.

Initially, the image gradient is computed and thresholded. The resulting edge points are then grouped into lines to produce an initial line map for that image. An initial region map is also computed by either selecting an arbitrary segmentation of the image into regions, or by executing a fast region growing algorithm. The image array, its gradient, and the initial region and line maps are all stored in the STM. Low level features are then extracted and stored in the STM. These include the average color features for regions and lines, position features, and spatial relationships. The latter include ADJACENCY among regions, and relationships of IN FRONT OF, BEHIND, and PARALLEL TO involving lines. Regions to the LEFT and RIGHT OF a line, and lines TOUCHING or INTERSECTING a region, describe spatial relationships between lines and regions.

Other important data entries maintained and stored in the STM are the focus of attention areas. These are areas in the image defined primarily by their position and size. An area may correspond to a region, a line, or groups of regions and/or lines in the image segmentation. These areas are used for the purpose of directing the attention of the system to the more interesting and worthwhile parts of the image, in terms of processing need and richness of segmentation information. Three types of areas are defined: smooth, textured, and areas created by long lines that close, or almost close, forming loops. The latter are referred to as bounded areas. Initially, the process responsible for generating areas computes them on the basis of the segmentation data stored in the STM. Because the resulting areas would usually not cover the entire image, a subset of the regions and lines will not belong to a specific area. These are assigned to a default area which encompasses the balance of the image less the detected areas.

The information stored in the STM is continuously updated during processing, so that it reflects the state of the segmentation of the image at any point in time. The regions, lines, areas, plus their features at the end of processing, represent the output of the low level stage to be delivered to the high level interpretation system. The higher the correspondence between regions in the output segmentation and objects in the scene, the easier the task of the high level process. Lines corresponding to major discontinuities in the image, as well as smooth and textured areas, can also be used to guide the interpretation process.

Six processes are involved in producing actions, as shown in Fig. 1. The INITIALIZER generates the initial region and line maps, and uses them to produce initial focus of attention areas. It also computes and stores the features of these initial data elements in the STM. The REGION, LINE, and AREA ANALYZERS are the three main processing modules of the system. They are responsible for rule matching and data modification on their respective entities. The LINE ANALYZER, for example, matches the line analysis rules in the LTM to the data in the STM. If a rule fires, it will execute the action specified by that rule on the current line under analysis. The same applies to the REGION and AREA ANALYZERS. The FOCUS OF ATTENTION module matches its own rules to execute a defined path strategy that brings various data items to the attention of the system, in a particular order. Thus, when a focus of attention action is executed, this means that the current region, line, or area will be replaced by a new region, line, or area whose identity depends on the action specified by that rule. Finally, the SUPERVISOR acts as a monitor for system control purposes. It matches the strategy rules to select the appropriate control strategy. Consequently, a set of metarules is used to determine which set of knowledge rules, if any, is to be tested next.

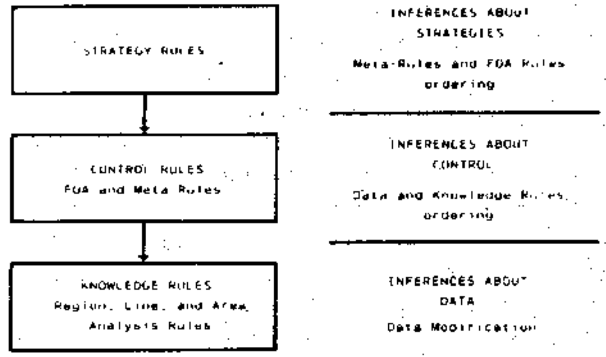


Fig. 2. Three levels of rules.

III. The Rule-Based Model

The model stored in the LTM is composed of three levels of production rules, as shown in Fig. 2. At the first level, the knowledge rules encode the information about properties of regions, lines, and areas in the form of sets of situation-action pairs. Each situation is coded into a number of logical predicates that compose the conditions of a rule. The latter are either logical comparisons or evaluations on the features of regions, lines, and areas in the segmented image. The conditions are ANDed together, so that when a specific situation occurs within the image, all the conditions will be met. In this case, a match is said to have occurred, and the rule fires. The rule action is then executed. This might be splitting of a region or merging of two regions, an addition, deletion, or extension of a line, a merging of two lines, or a creation or modification of a focus of attention area. Knowledge rules are classified by their actions, so that there are region analysis rules, line analysis rules, and area analysis rules. A region rule, for example, will contain conditions that match on features of regions, lines, and areas, but will always execute its action on the current region under analysis.

The second level of rules in the LTM contains the control rules, which can be further classified into two categories. First the focus of attention rules, which are responsible for finding the next data entry to be considered. They have actions that bring to the attention of the system a next region, next line, or an entire area. Using these rules, a strategy for visiting regions and lines within a focus of attention area, and for alternating from one area to another, can be defined and executed. This strategy will be data-driven since the conditions of these rules are also logical predicates evaluated on the STM data.

The second type of control rules are actually inferences about sets of knowledge rules, or in the spirit of a production system, they are termed metarules [3]. They differ from other rules, in that their actions do not modify the data in the STM. Instead, the metarules alter the matching order of different knowledge rule sets. Each process in the system is associated with a specific set of rules. The conditions of the metarules examine the data in the STM, and their actions specify the next process to be activated (and hence the next knowledge rule set). The metarules are also responsible for evaluating the stopping criteria of the system, and consequently terminating the processing. This approach renders the whole control process to be data-driven.

Control rules execute the system control strategy: focus of attention rules define the method by which data are selected for processing; the metarules specify the order in which the rule sets are matched. The system's control strategy is comprised of six basic elements, each of which can assume more than one specific state. The first three elements are the region path strategy, the line path strategy, and the region and line updating strategy. They determine the order in which the respective data items are tested and updated by the rules. Different path strategies are implemented by employing the appropriate set of focus of attention rules. The next three elements define strategies for determining process priority, region rule priority, and line rule priority. The first specifies the order in which the different rule sets are matched. The last two order the rules within the two processes. Each strategy state is achieved by invoking a specific set of control rules. Thus, one can effectively "program" the system into executing a desired strategy by putting together the appropriate combination of focus of attention rules and metarules.

The third and highest rule level in Fig. 2 contains the strategy rules. Their function is to select, based on the data, the set of control rules (focus of attention rules and metarules) that executes the most appropriate control strategy. Strategy determination is formulated as a dynamic decision-making process which results in the assignment of a specific state to each of the strategy elements.[1] In order to make this selection, a set of performance measurements is computed for each focus of attention area in the image [9]. These include values for the average uniformity of the regions within the area, the average contrast across these regions, the connectivity of the lines, and the average contrast across time. For example, if an area had regions of low average uniformity, the region rule priorities would be set so that rules which split regions were given priority over merging rules. Other constraints define the relation between the performance measurements and all the elements of strategy. The latter will therefore change with time, as well as spatially from one area to another.

To summarize, the system control strategy is defined by the strategy rules and executed by the control rules. Focus of attention rules specify the next data item to be tested, and metarules select the next rule set to be matched. Strategy rules, on the other hand, have actions that dynamically adjust the priorities of the metarules and the focus of attention rules.

The remaining sections of this paper describe the knowledge and control rules in more detail. The strategy rules and the dynamic strategy determination process are addressed separately in [9]. A more detailed account of the three rule levels is given in [16]. Before discussing the rules in detail, we will first define their basic structure in the next section.

IV. The Structure of the Rules

Knowledge representation will largely depend on the composition of the rules constituting the model. A rule has the following format:

CONDITION.AND.CONDITION ...... AND.CONDITION ACTIONS (1)

The left-hand side is composed of a set of CONDITIONS evaluated on the data. The ACTIONS on the right-hand side specify particular modifications to the data. The logical AND's indicate that the action of the rule will only be performed if *ALL* its conditions are satisfied. Note that there is no provision for a logical OR within a rule. This is because the latter can be accounted for by including another rule that encompasses the alternative situation.

Each rule depicts a certain situation that might be present in the data. A process will match a rule on the features of the regions, lines, or areas, or on some other data item stored in the STM. This is accomplished by a search conducted in the STM for the data configuration portrayed by the rule. If the search is successful, the rule will fire, and its actions will be executed. For this reason, rules have been termed situation-response tuples, or condition-action sets.

A RULE INTERPRETER interfaces the LTM rules to the processing modules, as well as to the experimenter. This two-way communication channel allows a designer to modify the rules, and provides the means for the rules to control the processing modules. As an input channel of the LTM, the INTERPRETER receives commands from a user to edit the rule-based model, adding, deleting, changing, and examining the rules. It monitors the formulation of the model, and signals any illegal syntactic combinations to ensure an error-free rule set. The output channel then translates the rules for the processing modules. The conditions are analyzed in order to specify the type of evaluations to be performed and identify the data items and features to be tested. The processing module then performs the matching operation accordingly. If a match occurs, the INTERPRETER provides pointers to the specific procedures that implement the rule actions. Fig. 3 is a schematic of the signal flow in and out of the model. The conditions and actions will now be discussed in more detail.

[1] Actually, the rule priorities associated with each of the possible states for each strategy element are adjusted.

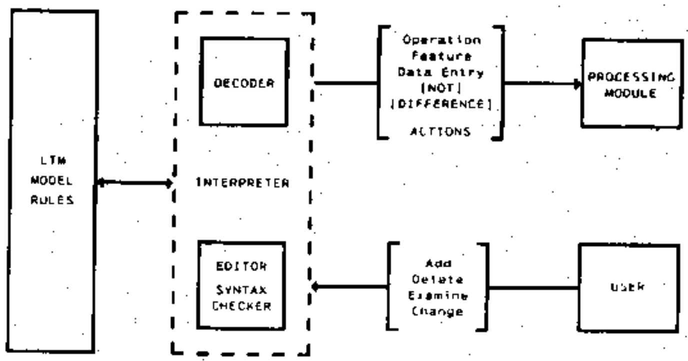


Fig. 3. The functions of the RULE INTERPRETER.

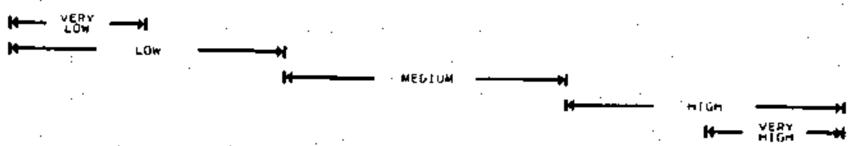


Fig. 4. Relative ranges of symbolic qualifiers.

A. The Rule Conditions

The conditions of a rule are logical entities, or equivalently, binary valued variables that can be instantiated to be either TRUE or FALSE. They correspond to logical evaluations or comparisons on the data. Each condition is composed of a logical predicate that may be preceded by the qualifier NOT, a reference to the logical complement of that predicate. The STM contains mostly numerical variables representing features of regions, lines, and areas in the image segmentation. The size of a region and the length of a line are typical examples. Some nonnumerical data are also stored. Examples of these include labels that indicate the presence or absence of a certain feature, and those that qualitatively describe a data entry (a line as being a loop, or an area as smooth).

In [16] the four classes of logical predicates that can exist in a rule condition were defined. These were classified according to the nature of the logical operation performed, as well as the type of variable that is tested. They are summarized as follows:

1) Logical comparisons on numerical variables.

LOWER LINE GRADIENT
EQUAL LINE DIRECTIONS
HIGHER REGION SIZE

2) Logical comparisons on nonnumerical variables.

SAME REGION LEFT

3) Logical evaluations on numerical variables.

VERY LOW REGION VARIANCE
MEDIUM REGION ADJACENCY
HIGH LINE LENGTH

Five symbols define different ranges over the scale of each feature. If the value of a feature lies in a given range, the corresponding logical evaluation will be TRUE. The relative position of the different ranges of symbols is represented schematically in Fig. 4. Note that the ranges for LOW and HIGH include the ranges for VERY LOW and VERY HIGH, respectively. This seems to conform with the linguistic definition of these qualifiers. Other ranges using the scale of Fig. 4 are accessible through combinations of qualifiers and the addition of the NOT qualifier (e.g., NOT LOW; HIGH.AND.NOT VERY HIGH). The choice of these symbolic qualifiers, their number, and their ranges are discussed in detail in [16].

4) Logical evaluations on non-numerical variables.

LINE IS LOOP
AREA IS NOT SMOOTH
PREVIOUS PROCESS WAS REGIONS

IS (ARE) and WAS in the examples above represent the keywords that distinguish this condition type.

Note that the employment of the qualifier NOT increases the flexibility of the four operations described above. Examples include NOT LOWER, NOT SAME, NOT VERY HIGH, and WAS NOT.

One aspect that relates to the numerical variables in type 1 and 3 conditions is the addition of a DIFFERENCE qualifier. This enables the system to perform all the logical operations cited above on differences in the values of two variables, instead of on the values themselves. Thus "LOW DIFFERENCE IN REGION FEATURE 1" indicates that the difference in the values of the first color feature (average red intensity level) of two regions must be in the LOW range for the condition to be satisfied (the predicate to be TRUE). Each numerical feature must thus have an additional scale as per Fig. 4, in order to specify the range of the symbolic qualifiers on the differences in that feature. For example, a line length of less than 50 pixels might be considered LOW. On the other hand, the limit for a LOW DIFFERENCE in the length of two lines will necessarily be less than that, maybe 10 pixels. The selection of these ranges is also discussed in [16].

We can now summarize the conditions of our rules and show that they include the following basic items.

1) A symbolic qualifier that depicts the type of logical operation to be performed on the data. The type of qualifier will depend on the type of feature to be examined, according to the classification given above.

2) A symbol denoting the data entry on which the condition is to be matched. By default, it refers to the current

TABLE I
POSSIBLE DATA ENTRIES

DATA ENTRY	SYMBOL
Current Region	REG
Current Line	LINE
Current Area	AREA
Region ADJACENT to current region	REGA
Region to the LEFT OF current line	REGL
Region to the RIGHT OF current line	REGR
Line NEAR current line	LINEN
Line IN FRONT OF current line	LINEF
Line BEHIND current line	LINEB
Line PARALLEL TO current line	LINEP
Line INTERSECTING current region	LINEI

TABLE II
THE FEATURES IN A CONDITION

NUMERICAL DESCRIPTIVE FEATURES

Feature 1	Feature 2	Feature 3
Variance 1	Variance 2	Variance 3
Intensity	Intensity Variance	Gradient
Gradient Variance	X-Centroid	Y-Centroid
Minimum X	Minimum Y	Maximum X
Maximum Y	Starting X	Starting Y
Ending X	Ending Y	Starting Direction
Ending Direction	Average Direction	Length
Start-End Distance	Size	Perimeter
Histogram Bimodality	Circularity	Aspect Ratio
Uniformity 1	Uniformity 2	Uniformity 3
Region Contrast 1	Region Contrast 2	Region Contrast 3
Line Contrast 1	Line Contrast 2	Line Contrast 3
Line Connectivity	Number of Regions	Number of Lines
Number of Areas		

NUMERICAL SPATIAL FEATURES

Number of ADJACENT Regions	Adjacency Values
Number of INTERSECTING Lines	Line Content between Regions
Distance to Line IN FRONT	Nearest Point on Line IN FRONT
Distance to Line BEHIND	Nearest Point on Line BEHIND
Distance to PARALLEL Line	Number of PARALLEL Points
Ajacency of LEFT Region	Adjacency of RIGHT Region
Number of Lines IN FRONT	Number of Lines BEHIND
Number of PARALLEL Lines	Number of Regions to the LEFT
Number of Regions to the RIGHT	

LOGICAL FEATURES

Histogram is bimodal	Region is bisected by line
Line is open	Line is closed
Line is loop	Line end is open
Line start is open	Line is clockwise
Area is smooth	Area is textured
Area is bounded	Area is new
One region to the LEFT	One region to the RIGHT
Same region to the LEFT and RIGHT OF line	
Same region LEFT OF line 1 and line 2	
Same region RIGHT OF line 1 and line 2	
Some region to the LEFT OF line 1 and RIGHT OF line 2	
Same region to the RIGHT OF line 1 and LEFT OF line 2	
Two lines are touching (8 connected)	
Areas are absent	Regions are absent
Lines are absent	System is starting
Process was Regions	Process was Lines
Process was Areas	Process was Focus
Process was Generate Areas	Process was active

region, line, or area considered by the system, as specified by the FOCUS OF ATTENTION module. This symbol can be omitted provided that no ambiguities result.[2] Other entries that are spatially related to the current ones may also be tested; for example, the features of an ADJACENT region or a PARALLEL line. Table I lists all such possible entries, together with the symbols that are used to express them.

3) A pointer to the feature pertaining to the data entry discussed above (e.g., size, length, and gradient). The value of that feature (a number or a label) is the operand of the logical operation. All possible features are listed in Table II. A detailed description of these is given in [16].

4) An optional NOT qualifier that negates the effect of the condition.

5) An optional DIFFERENCE qualifier that applies the operation to differences in feature values.

Fig. 5 summarizes the structure of a condition. Values in

[2] The tested operand can only belong to a region, a line, or an area; e.g., line length.

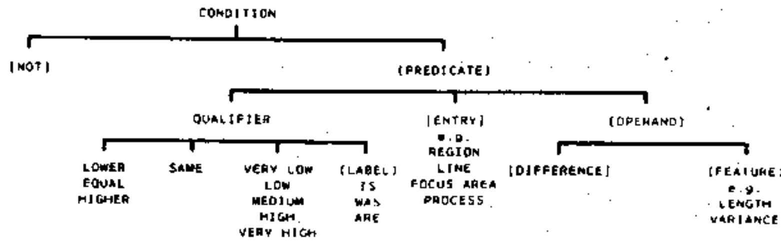


Fig. 5. The structure of a condition.

TABLE III
THE RULE ACTIONS

AREA ANALYZER ACTIONS

Create Smooth Area	Add to Smooth Area	Save Smooth Area
Create Texture Area	Add to Texture Area	Save Texture Area
Create Bounded Area	Add to Bounded Area	Save Bounded Area

Relabel Area to Smooth	Relabel Area to Texture
Relabel Area to Bounded	Delete Area

REGION ANALYZER ACTIONS

Split a Region by Histogram	Merge Two Regions
Split Region at Lines	

LINE ANALYZER ACTIONS

Extend Line Forward	Extend Line Backward
Join Lines Forward	Join Lines Backward
Insert Line Forward	Insert Line Backward
Merge Lines Forward	Merge Lines Backward
Delete Line	

FOCUS OF ATTENTION ACTIONS

Region with Highest Adjacency	Largest ADJACENT Region
Region with Lowest Adjacency	Smallest ADJACENT Region
Region with Higher Label	Next Scanned Region
Region to the LEFT OF Line	Region to the RIGHT OF Line
Closest Line IN FRONT	Closest Line BEHIND
Closest PARALLEL Line	Shortest Line that is near
Longest Line that is Near	Strongest Line that is near
Weakest Line that is Near	Line with Higher Label
Next Scanned Line	Line INTERSECTING Region
Defocus (Focus on Whole Image)	Focus on Areas
Clear Region List	Clear Line List
Freeze Area	Next Area (any)
Next Smooth Area	Next Texture Area
Next Bounded Area	

SUPERVISOR ACTIONS

Initialize Regions	Initialize Lines	Generate Areas
Match Region Rules	Match Line Rules	Match Area Rules
Match Focus Rules	Start	Stop

square brackets are optional, while those in parentheses are (variables) to be instantiated. Certain combinations of symbols are illegal, and these are flagged by the RULE INTERPRETER.

B. The Rule Actions

Each rule specifies to a processing module the action to be executed when all its conditions are met. Actions are selected from a finite list that represents the union of the capabilities of the processing modules in modifying the data in the STM. They provide the means for classifying the rules into sets according to the data entry on which each action is performed. A detailed description of how each action is accomplished is given in [16]. Table III provides a complete list of the actions sorted into classes. Following are brief definitions of the actions within each class.

1) Actions on Areas: Some actions create new areas, add regions to existing areas, and compute and store the features of the created areas. Three such actions are defined for each area type. Other actions performed by the AREA ANALYZER include changing the type of an area when its characteristics alter during processing, and deleting areas that are of no further use to the focus of attention mechanism.

2) Actions on Regions: The REGION ANALYZER can either merge two regions into one, or split a region into several. Two different methods for splitting a region are given. The first selects a threshold from the histogram of a feature, and finds the connected pixels that are above and below that value. The second bisects a region spatially along the lines that intersect it.

3) Actions on Lines: Actions on lines are more diverse. A line can be extended forward from its last point along the highest local gradient. The same can be done backwards from the line's starting point. Alternatively, a line could be extended forward (or backward) by joining it to another line that is IN FRONT OF (or BEHIND) it. A third method for extending lines forward (or backward) is by inserting the label of the line at pixels that are at the boundary of two regions. Two lines can be merged into one line with the same label in two ways: a forward merge will combine the current line with another IN FRONT OF it, and a backward merge will do the same for the current line and one that is BEHIND it. The two lines must be touching each other. The final action deletes a line completely from the segmentation.

4) Focus of Attention Actions: The focus of attention module possesses different methods for replacing the current region and line by others. The actions listed in Table III are self-explanatory. They should be interpreted as obtaining the next region (or line) that exhibits the particular feature with respect to a current region (or line). This includes, for example, fetching the region that is to the left of the current line, or the line that intersects the current region. Actions that focus on the next area execute a selection strategy that is discussed in detail in [9], [16]. These can be limited to a specific area type, or they can be selected from any of the available areas.

5) Supervisor Actions: The actions of the metarules are different from all of the others in that they do not modify the segmentation data in the STM. They specify which set of rules is to be matched next on the data, and thus indirectly activate the different processing modules. Other commands include those that trigger the initialization, commence processing, and halt the analysis.

Having described the structure of the rules and reviewed the available conditions and actions, we will now discuss the different types of rules that constitute the model for low level image segmentation.

V. The Knowledge Rules

The criteria that specify how an image should be segmented are at the heart of our rule-based model. Information about image intensities, region properties, and the existence of lines guide the analysis into creating an output that is in accordance with the model. By coding these knowledge sources into rules, and applying them to the data, a structured and uniform methodology will result. Other approaches to segmentation use a small number of heuristics in the analysis, as is evident by the abundance of efforts in the field, but rather because of the limitations imposed by the extremely rigid format in which the knowledge has been cast. A line detection program, for example, that is built on locating the discontinuities of features in the image array, will hardly produce a perfect (or even acceptable) line drawing. Clearly other heuristics are needed in order to account for deficiencies in the procedure. Methods for improving on the output of the above have been investigated, but they require the execution of other programs that apply new transformations to the image. One may imagine the application of several cascaded procedures to an image, with each one accounting for some knowledge heuristic that was found to enhance the output. This is not an efficient method of analysis. In the course of improving the result, previous accomplishments may be destroyed. Even if this does not happen, we still have to contend with a large number of image transformations that yield incremental results which are usually highly localized.

The answer to this problem is to combine all useful processing heuristics into a model, and use it to guide the analysis. This is what a rule-based system accomplishes. The appropriate piece of information can be brought into the analysis when it is most needed. Thus, a specific heuristic will only be used to update that part of the image to which it is applicable. Any number of knowledge sources can be used. The model can easily be tuned by testing, modifying, deleting, and adding information. In fact, the main question becomes which heuristics to encode into the rules? Guidelines are needed for selecting the knowledge. Almost half a century ago, psychologists described a set of principles for human visual perception. What has become known as the Gestalt principles amounts to a set of general rules for perceptual grouping [5]. Although intended for high level cognitive events, these premises also have their consequences in low level context-free applications. One of the factors that has so far limited the use of Gestalt psychology in computer vision is the lack of a framework to represent these logical assertions. The rule-based vision system provides the required mechanism. By modeling the rules after the Gestalt laws, we define guidelines for creating the former and a mechanism for testing the latter. The five basic principles for grouping visual entities are: similarity, proximity, uniform destiny, good continuity, and closure. Other related, although less general factors, include simplicity, symmetry, equilibrium, and good shape. For details on each, the reader is referred to [5], [6], [24]. Our main concern is to encode these logical grouping assertions into the low level model. Each of the segmentation rules may represent some or more of the above principles. In this section, we will present typical examples of each of the three types of knowledge rules, and discuss how the Gestalt criteria are incorporated into the model.

A. Region Analysis Rules

Rules belonging to this set are concerned with modifying the regions in a segmentation in order to conform with certain criteria. The REGION ANALYZER module applies these rules to the regions stored in the STM. When a match occurs, the process is instructed to either split a region, or merge it with an ADJACENT one. Thus, the function of this rule set is to specify the merging and splitting criteria to be applied to the present region configuration in order to produce a better partition of the image.

The dominant principles in region analysis are those of proximity and similarity. Pixels that are adjacent and have similar intensity (or color) features are grouped into regions. This is the basic principle behind most region growing programs [13]. A general rule merges two ADJACENT regions (each of which can be a single pixel) as follows [15]:

RULE (801):

IF: (1) There is a LOW DIFFERENCE in REGION FEATURE 1
(2) There is a LOW DIFFERENCE in REGION FEATURE 2
(3) There is a LOW DIFFERENCE in REGION FEATURE 3

THEN: (1) MERGE the two REGIONS

This implies that a low difference in the average values of all three color features between the two regions must exist. This region growing rule is responsible for most of the merging that takes place. Alone however, it cannot account for all the data situations that require region merging. Analyzing an image using only this rule as the merging criterion produces many incorrect data configurations. These result when nonuniform scene characteristics such as boundaries, shadows, and highlights are subjected to noise, as well as sampling and quantization errors during the image formation process. Based on our understanding of these phenomena, new rules can be added to deal with them on a case-by-case basis. Consider the following rule:

RULE (802):

IF: (1) The REGION SIZE is VERY LOW
(2) The ADJACENCY with another REGION is HIGH
(3) The DIFFERENCE in REGION FEATURE 1 is NOT HIGH
(4) The DIFFERENCE in REGION FEATURE 2 is NOT HIGH
(5) The DIFFERENCE in REGION FEATURE 3 is NOT HIGH

THEN: (1) MERGE the two REGIONS

The first two conditions describe the situation when a region is of very small size and is mostly surrounded (or totally contained) by an ADJACENT region. This is an indication that the first region resulted from some noise source. Therefore a relaxation of the merging criteria in Rule (801) is called for. The last three conditions provide the loosened version that restricts the differences in features to be of low or medium value.

Another aspect to be accounted for is the formation of "hybrid" regions at the boundary between two regions that have high differences in their average intensities (or colors). Due to the graded quantized transition, pixels in the middle acquire a range of intensities that does not allow them to merge with either of their neighbors. Because they are at a boundary, these intermediate regions exhibit a high average gradient, and therefore will be split longitudinally in a direction parallel to the border. This will result in very thin regions along some of the boundaries. Such regions are characterized by low size, a very high (or very low) aspect ratio, and a high average gradient. The merging criteria are again relaxed to eliminate these residual regions, as shown by the following rules.

RULE (803):

IF: (1) The REGION SIZE is LOW
(2) The REGION AVERAGE GRADIENT is HIGH
(3) The DIFFERENCE in REGION FEATURE 1 is NOT HIGH
(4) The DIFFERENCE in REGION FEATURE 2 is NOT HIGH
(5) The DIFFERENCE in REGION FEATURE 3 is NOT HIGH

THEN: (1) MERGE the two REGIONS

RULE (804):

IF: (1) The REGION SIZE is LOW
(2) The REGION ASPECT RATIO is VERY HIGH
(3) The DIFFERENCE in REGION FEATURE 1 is NOT HIGH
(4) The DIFFERENCE in REGION FEATURE 2 is NOT HIGH
(5) The DIFFERENCE in REGION FEATURE 3 is NOT HIGH

THEN: (1) MERGE the two REGIONS

A similar rule, Rule (805), exists for very low aspect ratio.

Because of the limited resolution of the image, faulty regions may also occur if a large number of regions intersect at the same spot. Rule (806) will abolish such errors allowing a merge with the most similar larger region.

RULE (806):

IF: (1) The REGION SIZE is LOW
(2) The NUMBER of ADJACENT regions is HIGH
(3) The DIFFERENCE in REGION FEATURE 1 is NOT HIGH
(4) The DIFFERENCE in REGION FEATURE 2 is NOT HIGH
(5) The DIFFERENCE in REGION FEATURE 3 is NOT HIGH
(6) The ADJACENT REGION SIZE is NOT LOW

THEN: (1) MERGE the two REGIONS

Two ADJACENT regions of very small size are also allowed to merge more easily because of diminished contrast sensitivity. The following rule portrays this concept.

RULE (807):

IF: (1) The REGION SIZE is VERY LOW
(2) The ADJACENT REGION SIZE is VERY LOW
(3) The DIFFERENCE in REGION FEATURE 1 is NOT HIGH
(4) The DIFFERENCE in REGION FEATURE 2 is NOT HIGH
(5) The DIFFERENCE in REGION FEATURE 3 is NOT HIGH

THEN: (1) MERGE the two REGIONS

The Gestalt principle of similarity is the main factor that motivates the splitting of a region. Then, the resulting regions must consist of pixels that are more similar to each other than the pixels belonging to the original region. Histograms of features are strong indicators of the presence of subgroups of pixels. A multimodal histogram signals the need for splitting to achieve a uniform unimodal distribution of the features in the resulting partition [23]. In [16], a method was introduced for determining whether a histogram is (at least) bimodal, and to what degree. The corresponding action to split the region was also described. The following pair of rules combine the measurement with the action.

RULE (901):

IF: (1) The REGION HISTOGRAM is BIMODAL

THEN: (1) SPLIT the REGION according to the HISTOGRAM

RULE (902):

IF: (1) The REGION HISTOGRAM BIMODALITY is NOT LOW

THEN: (1) SPLIT the REGION according to the HISTOGRAM

The second rule is seen to be more restrictive since it establishes a lower limit on the degree of bimodality below which splitting will not be allowed. The following rules take into account the size of a region in addition to its histogram:

RULE (903):

IF: (1) The REGION SIZE is HIGH
(2) The REGION HISTOGRAM BIMODALITY is HIGH

THEN: (1) SPLIT the REGION according to the HISTOGRAM

RULE (904):

IF: (1) The REGION SIZE is MEDIUM
(2) The REGION HISTOGRAM BIMODALITY is NOT LOW

THEN: (1) SPLIT the REGION according to the HISTOGRAM

The two rules are examples of how the different ranges of symbolic features can be utilized in knowledge representation. Rule (903) demands a highly bimodal histogram for large regions, while the restriction is eased in Rule (904) for medium size regions. Histogram splitting is unreliable (and therefore not allowed) for regions with small (LOW) size because of the increasing effect of the region boundary.

There are other indicators that a region should be split. Rule (905) depicts the case when the variance of the color features is large, indicating a large spread in the feature values from the average.

RULE (905):

IF: (1) The REGION VARIANCE 1 is HIGH
(2) The REGION VARIANCE 2 is HIGH
(3) The REGION VARIANCE 3 is HIGH
(4) The REGION HISTOGRAM is BIMODAL

THEN: (1) SPLIT the REGION according to the HISTOGRAM

The histogram must still be bimodal, although no restriction is made on the degree of bimodality. This implies that a small dip in the histogram will be sufficient. In fact, the dip is required by the rule action, since a threshold must be determined for histogram splitting. The next two rules are seen to use the average gradient over a region as the guide for splitting. A large gradient may be due to a large variance of the features, which is the case already covered by Rule (905). On the other hand, it may be caused by a local discontinuity in the feature values that might not reflect itself in the variances.

RULE (906):

IF: (1) The REGION SIZE is HIGH
(2) The REGION AVERAGE GRADIENT is NOT LOW
(3) The REGION HISTOGRAM is BIMODAL

THEN: (1) SPLIT the REGION according to the HISTOGRAM

RULE (907):

IF: (1) The REGION SIZE is NOT LOW
(2) The REGION AVERAGE GRADIENT is HIGH
(3) The REGION HISTOGRAM is BIMODAL

THEN: (1) SPLIT the REGION according to the HISTOGRAM

Lines may provide evidence for region splitting. Pixels bearing the same region label, but falling on opposite sides of a line passing through, may in fact belong to different regions. The REGION ANALYZER provides an action that splits a region along the lines that intersect it. Rule (908) illustrates how line information is used in processing regions.

RULE (908):

IF: (1) The REGION SIZE is NOT LOW
(2) REGION is BISECTED BY LINE
(3) The LINE LENGTH is NOT LOW
(4) The LINE AVERAGE GRADIENT is HIGH

THEN: (1) SPLIT the REGION at LINES

The use of line information in region analysis is again exemplified in Rule (809). Merging two regions can be inhibited by the presence of a line at their common boundary, even if they have identical average features. This is accomplished by adding another condition to Rule (801) to produce the following:

RULE (809):

IF: (1) There is a LOW DIFFERENCE in REGION FEATURE 1
(2) There is a LOW DIFFERENCE in REGION FEATURE 2
(3) There is a LOW DIFFERENCE in REGION FEATURE 3
(4) The value of LINES BETWEEN REGIONS is LOW

THEN: (1) MERGE the two REGIONS

Condition 4) above refers to the fraction of common boundary between the two regions that is covered by lines. The same condition can be added to other region merging rules. The next section introduces the rules used by the LINE ANALYZER.

B. Line Analysis Rules

Lines by their nature, provide a wider variety of data situations. They are also subject to a larger number of actions. In this section, we present examples of various line analysis rules. Unlike regions, similarity is not the main issue here. Instead, other Gestalt principles take on a more prominent role; namely, continuity and good closure. Proximity is of equal importance for lines as it was for regions.

These rules are attempting to enhance the initial line configuration that results from detecting the discontinuities in the image intensities. The latter usually produces incomplete lines, as well as faulty lines that are possibly due to noise and therefore must be eliminated. The task is then to discard illegitimate lines and to improve genuine ones. An important clue to both is the presence of a line with one (or both) ends open. Factors of both continuity and closure dictate the necessity to either expand the open end of a line until it encounters another line, or if this is not possible, delete the line.

A credible way to complete lines is by joining an open line to another that is closely IN FRONT of or BEHIND it. The situation is depicted by the following two rules.

RULE (1501):

IF: (1) The LINE END point is OPEN
(2) The DISTANCE to the LINE IN FRONT is LOW

THEN: (1) JOIN the LINES by FORWARD expansion

RULE (1601):

IF: (1) The LINE START point is OPEN
(2) The DISTANCE to the LINE BEHIND is LOW

THEN: (1) JOIN the LINES by BACKWARD expansion

The distance constraint is relaxed if the average gradient of the line is not low, or if both lines are colinear (have the same average direction). The corresponding rules are:

RULE (1502):

IF: (1) The LINE END point is OPEN
(2) The DISTANCE to the LINE IN FRONT is NOT HIGH
(3) The LINE AVERAGE GRADIENT is NOT LOW

THEN: (1) JOIN the LINES by FORWARD expansion

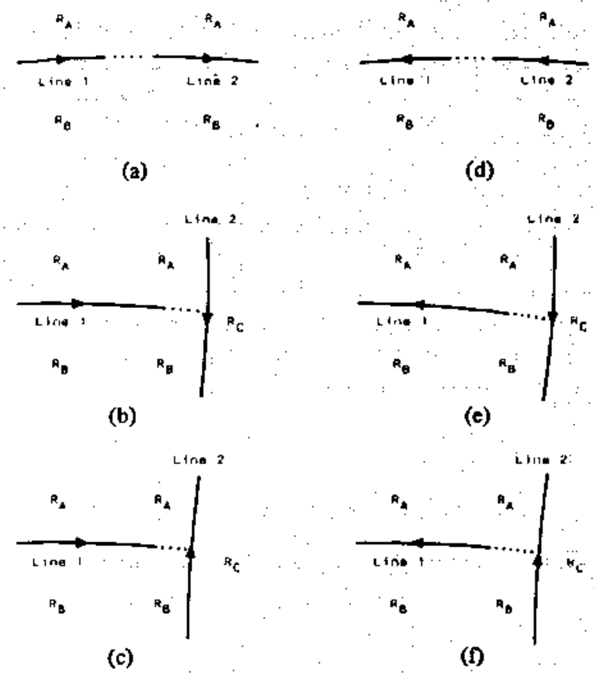


Fig. 6. Joining lines using region information.

RULE (1503):

IF: (1) The LINE END point is OPEN
(2) The DISTANCE to the LINE IN FRONT is NOT HIGH
(3) The LINES have EQUAL AVERAGE DIRECTION

THEN: (1) JOIN the LINES by FORWARD expansion

Similar rules exist for joining a line by backward expansion to a line that is BEHIND it.

Region information is also used to aid the joining of two lines. Other constraints can be relaxed if the lines share the same regions to their left and right. This is a strong indication that both lines are part of the same boundary. The following three rules correspond to the data configurations shown in Fig. 6.

RULE (1504): [Fig. 6(a)]

IF: (1) The LINE END point is OPEN
(2) The LINE GRADIENT is NOT VERY LOW
(3) The DISTANCE to the LINE IN FRONT is NOT VERY HIGH
(4) The two LINES have the SAME REGION to the LEFT
(5) The two LINES have the SAME REGION to the RIGHT

THEN: (1) JOIN the LINES by FORWARD expansion

RULE (1505): [Fig. 6(b)]

IF: (1) The LINE END point is OPEN
(2) The LINE GRADIENT is NOT VERY LOW
(3) The DISTANCE to the LINE IN FRONT is NOT VERY HIGH
(4) SAME REGION LEFT of LINE 1 and RIGHT of LINE 2

(5) The two LINES have the SAME REGION to the RIGHT

THEN: (1) JOIN the LINES by FORWARD expansion

RULE (1506): [Fig. 6(c)]

IF: (1) The LINE END point is OPEN
(2) The LINE GRADIENT is NOT VERY LOW
(3) The DISTANCE to the LINE IN FRONT is NOT VERY HIGH
(4) The two LINES have the SAME REGION to the LEFT
(5) SAME REGION RIGHT of LINE 1 and LEFT of LINE 2

THEN: (1) JOIN the LINES by FORWARD expansion

Joining by backward expansion produces three analogous rules for the cases in Fig. 6(d)-(f).

In the absence of a close neighbor, an open line can still be extended forward or backward by expanding the appropriate end point along the maximum local gradient at that position in the image. For this to happen, however, a single open line must exhibit strong survival characteristics, both in length and in strength (average gradient). The following rules represent the above situation.

RULE (1507):

IF: (1) The LINE END point is OPEN
(2) The LINE AVERAGE GRADIENT is HIGH

THEN: (1) EXTEND the LINE FORWARD

RULE (1508):

IF: (1) The LINE END point is OPEN
(2) The LINE AVERAGE GRADIENT is NOT LOW
(3) The LINE LENGTH is NOT LOW

THEN: (1) EXTEND the LINE FORWARD

Rules for extending a line backward from its starting point follow easily from the above.

The local gradient is also used to expand an open line that has a large number of regions on both sides, as shown in Fig. 7. The line is considered to be at the boundary of two textured areas, and the maximum local gradient is used to define the border. The rule that detects this situation is given by:

RULE (1509):

IF: (1) The LINE END point is OPEN
(2) The LINE GRADIENT is NOT LOW
(3) The NUMBER of REGIONS to the LEFT is NOT LOW
(4) The NUMBER of REGIONS to the RIGHT is NOT LOW

THEN: (1) EXTEND the LINE FORWARD

Rule (1609) will provide for the backward extension in a similar manner.

ADJACENT region information is also used to expand a line

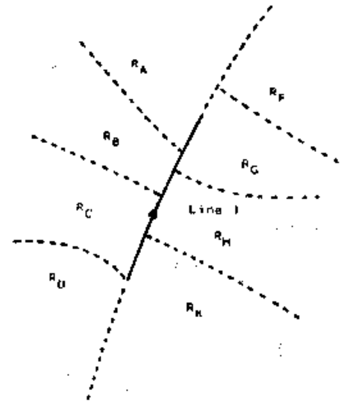


Fig. 7. Line at the boundary of two textured areas.

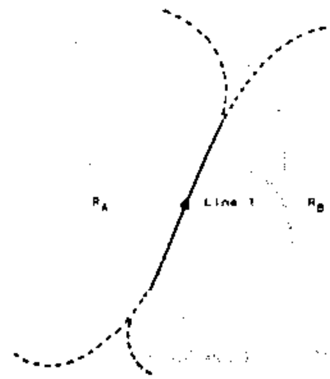


Fig. 8. Line at the boundary of two large regions.

by inserting additional points between two bordering regions. The configuration portrayed in Fig. 8 illustrates how the presence of two different regions, one on each side of an incomplete line, is a strong indication that the line is indeed part of a larger boundary. The following rule is based on this hypothesis.

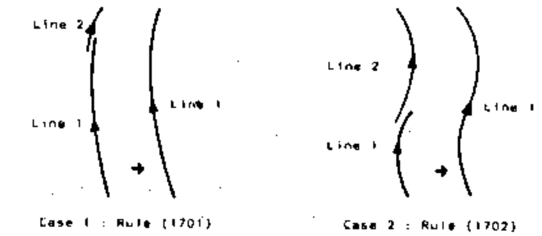
RULE (1510):

IF: (1) The LINE END point is OPEN
(2) The LINE LENGTH is NOT LOW
(3) There is ONE REGION to the LEFT of the LINE
(4) There is ONE REGION to the RIGHT of the LINE
(5) REGIONS to the LEFT and RIGHT are NOT the SAME

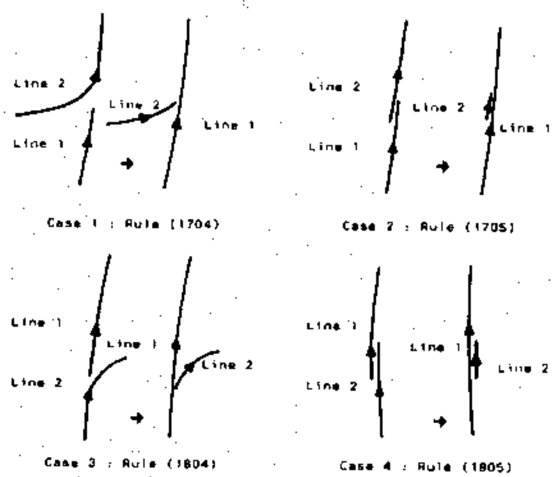
THEN: (1) Expand the LINE by INSERTING FORWARD

Points are inserted at the starting point of an open line if similar conditions exist.

As a result of applying the previous rules, incomplete lines will be extended, and will meet other lines. The resulting junctions may suggest the merging of two lines into one. This happens when both represent different parts of the same boundary, as shown in Fig. 9(a). In other cases, merging produces two new lines that form a more appropriate configuration in terms of the good continuity principle. This situation is depicted in Fig. 9(b). Rules may be constructed to perform forward and backward line merging, examples of which are:



(a)



(b)

Fig. 9. Rules for merging lines.

RULE (1701): [Fig. 9(a), case 1]

IF: (1) The LINE LENGTH is NOT LOW
(2) The LENGTH of the LINE IN FRONT is LOW
(3) The LINES are TOUCHING
(4) The closest POINT IN FRONT is LOW

THEN: (1) MERGE the LINES FORWARD

RULE (1702): [Fig. 9(a), case 2]

IF: (1) The LINE LENGTH is NOT LOW
(2) The LENGTH of the LINE IN FRONT is NOT LOW
(3) The LINES are TOUCHING
(4) The closest POINT IN FRONT is VERY LOW

THEN: (1) MERGE the LINES FORWARD

The previous two rules represent the situation in Fig. 9(a) where the closest point on the second line (the line IN FRONT) is near (or at) its starting point. The two rules account for different second line lengths, so that the constraint on the position of the closest point is more stringent if the line length is high.[3] A line can also be merged with one that is BEHIND it according to the following rules.

RULE (1801):

IF: (1) The LINE LENGTH is NOT LOW
(2) The LENGTH of the LINE BEHIND is LOW
(3) The LINES are TOUCHING
(4) The closest POINT BEHIND is HIGH

THEN: (1) MERGE the LINES BACKWARD

RULE (1802):

IF: (1) The LINE LENGTH is NOT LOW
(2) The LENGTH of the LINE BEHIND is NOT LOW
(3) The LINES are TOUCHING
(4) The closest POINT BEHIND is VERY HIGH

THEN: (1) MERGE the LINES BACKWARD

Merging based on similarity of lines is made possible by the following rule.

RULE (1703):

IF: (1) The LINES are TOUCHING
(2) The closest POINT IN FRONT is NOT HIGH
(3) The LINE IN FRONT has a HIGH GRADIENT VARIANCE
(4) There is a LOW DIFFERENCE in LINE FEATURE 1
(5) There is a LOW DIFFERENCE in LINE FEATURE 2
(6) There is a LOW DIFFERENCE in LINE FEATURE 3

THEN: (1) MERGE the LINES FORWARD

An analogous rule exists for merging a line with another that is BEHIND it. Note that condition 3) above justifies the splitting of the second line in order to merge part (or all) of it with the first.

Merging to improve the continuity of lines, as in Fig. 9(b), is achieved through the following rules.

RULE (1704): [Fig. 9(b), case 1]

IF: (1) The LINES are TOUCHING
(2) The closest POINT IN FRONT is MEDIUM
(3) The LINES END DIRECTIONS are EQUAL
(4) START and END DIR. of LINE IN FRONT are NOT EQUAL

THEN: (1) MERGE the LINES FORWARD

RULE (1705): [Fig. 9(b), case 2]

IF: (1) The LINES are TOUCHING
(2) The LENGTH of the LINE IN FRONT is NOT LOW
(3) The LINE START and END DIRECTIONS are EQUAL
(4) LINE IN FRONT START and END DIRECTIONS are EQUAL
(5) The closest POINT IN FRONT is LOW
(6) The DIFFERENCE in AVERAGE DIRECTION is VERY LOW

THEN: (1) MERGE the LINES FORWARD

[3] Note that the position of a point on the line is given as a fraction of the line length.

RULE (1804): [Fig. 9(b), case 3]

IF: (1) The LINES are TOUCHING
(2) The closest POINT BEHIND is MEDIUM
(3) The LINES START DIRECTIONS are EQUAL
(4) START and END DIR. of LINE BEHIND are NOT EQUAL

THEN: (1) MERGE the LINES BACKWARD

RULE (1805): [Fig. 9(b), case 4]

IF: (1) The LINES are TOUCHING
(2) The LENGTH of the LINE BEHIND is NOT LOW
(3) The LINE START and END DIRECTIONS are EQUAL
(4) The LINE BEHIND START and END DIRECTIONS are EQUAL
(5) The closest POINT BEHIND is HIGH
(6) The DIFFERENCE in AVERAGE DIRECTION is VERY LOW

THEN: (1) MERGE the LINES BACKWARD

There are a number of cases in which a line should be deleted from the segmentation. The simplest case is when the properties of the line do not justify its existence. Very short line segments that are not connected to any other lines and that exhibit a weak gradient value are considered to be due to noise factors and are consequently removed. This represents an indirect application of the principle of closure since lines are rarely assumed to end abruptly in an open space. In other words, if a line is not supported by others, and if it does not behave as a plausible independent entity, it will be deleted, as seen from the following rules.

RULE (1401):

IF: (1) The LINE LENGTH is VERY LOW
(2) The LINE AVERAGE GRADIENT is LOW

THEN: (1) DELETE the LINE

RULE (1402):

IF: (1) The LINE LENGTH is LOW
(2) The LINE AVERAGE GRADIENT is VERY LOW

THEN: (1) DELETE the LINE

RULE (1403):

IF: (1) The LINE is OPEN
(2) The LINE LENGTH is LOW
(3) The LINE AVERAGE GRADIENT is LOW

THEN: (1) DELETE the LINE

A line is also deleted if there is evidence of a multiple representation of a boundary. This commonly occurs in images of natural scenes where the edge between two regions can be several pixels wide. As a result, the process of edge location and boundary tracking will produce a number of PARALLEL lines at the position of the graded boundary. The following rule will eliminate such multiple line occurrences.

RULE (1404):

IF: (1) The LINE has LOWER LENGTH
(2) There is a LOW DIFFERENCE in the LINES GRADIENT
(3) The PARALLEL DISTANCE is VERY LOW

THEN: (1) DELETE the LINE

Thus, the shorter of two PARALLEL lines that are very close to each other will be deleted. Note that this rule does not apply to skewed lines (lines that are physically parallel, but have opposite directions). These lines result from the existence of a thin object on a darker or lighter background, and therefore, should not be eliminated.

The configuration of regions in the neighborhood of a line may dictate its removal. This is particularly true when the line falls within a large uniform region, and has a low local gradient as well. A rule that embodies this situation is given by:

RULE (1405):

IF: (1) The LINE is OPEN
(2) The LINE GRADIENT is LOW
(3) The SAME REGION to the LEFT and RIGHT

THEN: (1) DELETE the LINE

The third class of knowledge rules, those that analyze areas, is discussed in the next section.

C. *Area Analysis Rules*

These include rules that generate areas of attention, and others that update them during processing. The following three rules detect, add to, and save smooth areas in an image segmentation.

RULE (401):

IF: (1) The REGION SIZE is HIGH
(2) The REGION has a LOW VARIANCE 1
(3) The REGION has a LOW VARIANCE 2
(4) The REGION has a LOW VARIANCE 3

THEN: (1) CREATE SMOOTH AREA

RULE (402):

IF: (1) The AREA IS SMOOTH
(2) The REGION ADJACENCY is NOT VERY LOW
(3) The REGION SIZE is NOT LOW
(4) The REGION has a LOW VARIANCE 1
(5) The REGION has a LOW VARIANCE 2
(6) The REGION has a LOW VARIANCE 3

THEN: (1) ADD REGION TO SMOOTH AREA

RULE (403):

IF: (1) The AREA is SMOOTH
(2) The AREA SIZE is NOT LOW

THEN: SAVE SMOOTH AREA

Rule (401) will create the nucleus of a new smooth area from the first large smooth region encountered. Subsequent smooth ADJACENT regions (if any) are added to the area by Rule

(402). Finally, Rule (403) will save the area for further reference during processing, if its size is large enough.

Textured areas are detected in a similar fashion using the following set of rules.

RULE (501):

IF: (1) The REGION SIZE is LOW

THEN: (1) CREATE a TEXTURE AREA

RULE (502):

IF: (1) The AREA IS TEXTURE
(2) The REGION ADJACENCY is NOT VERY LOW
(3) The REGION SIZE is LOW

THEN: (1) ADD REGION TO TEXTURE AREA

RULE (503):

IF: (1) The AREA is TEXTURE
(2) The AREA SIZE is NOT LOW
(3) The NUMBER of REGIONS is NOT LOW
(4) The AREA VARIANCE 1 is NOT LOW
(5) The AREA VARIANCE 2 is NOT LOW
(6) The AREA VARIANCE 3 is NOT LOW

THEN: (1) SAVE TEXTURE AREA

The first two rules create a search for clusters of small ADJACENT regions. If the size of a cluster is large enough, and if it exhibits sufficient feature variance, it is saved as a texture area.

Bounded areas are generated by testing the lines in a segmentation. Long lines that close (or almost close) on themselves are sought in order to examine the encircled areas. Following are three criteria for detecting such occurrences.

RULE (601):

IF: (1) The LINE IS LOOP
(2) The LINE LENGTH is NOT LOW

THEN: (1) SAVE BOUNDED AREA

RULE (602):

IF: (1) The LINE LENGTH is HIGH
(2) The START-END DISTANCE is LOW

THEN: (1) SAVE BOUNDED AREA

RULE (603):

IF: (1) The LINE LENGTH is MEDIUM
(2) The START-END DISTANCE is VERY LOW

THEN: (1) SAVE BOUNDED AREA

Other area analysis rules monitor existing areas in order to modify their classification according to variations in their properties. Changes are brought about by the merging and splitting of regions, and the addition and deletion of lines. Since the boundaries of an area can be altered during processing, its physical properties may also change. It is the function of these rules to ensure that areas are consistently categorized according to their features. Examples of rules that change an area's type are:

RULE 701:

IF: (1) The AREA is SMOOTH
(2) The AREA VARIANCE 1 is NOT LOW
(3) The AREA VARIANCE 2 is NOT LOW
(4) The AREA VARIANCE 3 is NOT LOW

THEN: (1) RELABEL AREA TEXTURE

RULE (702):

IF: (1) The AREA IS TEXTURE
(2) The AREA VARIANCE 1 is LOW
(3) The AREA VARIANCE 2 is LOW
(4) The AREA VARIANCE 3 is LOW

THEN: (1) RELABEL AREA SMOOTH

Areas are locked out of processing if they are found to be stable enough, in terms of their performance characteristics [9]. This allows the system to concentrate on those areas that require further processing. Examples of rules that "freeze" areas are:

RULE (703):

IF: (1) The AREA is SMOOTH
(2) The NUMBER of REGIONS is VERY LOW
(3) LINES are ABSENT
(4) REGION UNIFORMITY 1 is HIGH
(5) REGION UNIFORMITY 2 is HIGH
(6) REGION UNIFORMITY 3 is HIGH

THEN: (1) FREEZE AREA

RULE (704):

IF: (1) The AREA is TEXTURE
(2) REGION CONTRAST 1 is HIGH
(3) REGION CONTRAST 2 is HIGH
(4) REGION CONTRAST 3 is HIGH
(5) LINE CONNECTIVITY is HIGH

THEN: (1) FREEZE AREA

RULE (705):

IF: (1) The AREA is BOUNDED
(2) LINE IS CLOCKWISE
(3) ONE REGION RIGHT OF LINE
(4) REGION UNIFORMITY 1 is HIGH
(5) REGION UNIFORMITY 2 is HIGH
(6) REGION UNIFORMITY 3 is HIGH

THEN: (1) FREEZE AREA

An analogous rule to Rule (705) exists for a counterclockwise line that has one region to its left. Note that a frozen area is still available to provide information about the part of image it represents (e.g., smooth or textured). An area is deleted from the STM only if it no longer carries useful segmentation information. The following rules will eliminate such areas.

RULE (707):

IF: (1) The AREA is SMOOTH
(2) The NUMBER of REGIONS is HIGH
(3) The AREA SIZE is NOT HIGH
(4) REGION CONTRAST 1 is HIGH
(5) REGION CONTRAST 2 is HIGH
(6) REGION CONTRAST 3 is HIGH

THEN: (1) DELETE AREA

RULE (708):

IF: (1) The AREA is TEXTURE
(2) The NUMBER OF REGIONS is LOW
(3) The AREA SIZE is NOT HIGH
(4) The REGION UNIFORMITY 1 is HIGH
(5) The REGION UNIFORMITY 2 is HIGH
(6) The REGION UNIFORMITY 3 is HIGH

THEN: (1) DELETE AREA

RULE (709):

IF: (1) The AREA is BOUNDED
(2) The NUMBER OF LINES is HIGH
(3) The LINE CONTRAST 1 is HIGH
(4) The LINE CONTRAST 2 is HIGH
(5) The LINE CONTRAST 3 is HIGH

THEN: (1) DELETE AREA

Regions and lines within an area are reassigned if that area is deleted. They are considered as belonging to a single area which does not include any of the specific focus of attention areas.

This concludes our discussion of the knowledge rules for low level image segmentation. From the analysis, we can conclude that the Gestalt principle of similarity plays an important role in region processing. On the other hand, closure and continuity are more prominent in line processing. Proximity is an essential factor in grouping both regions and lines. The knowledge rules presented in this section are typical examples of those used by the system. A complete listing of the knowledge rules is given in [16].

VI. The Control Rules

The focus of attention and the metarules differ from the knowledge rules in that they do not directly modify the segmentation data. Yet, their presence is essential to the functioning of the system. These control rules specify both the order in which the different sets of knowledge rules are matched, as well as the specific data entries to be tested. There exist numerous ways in which to execute any of these tasks. Each method corresponds to a particular control strategy. Elsewhere, we discuss a data-driven method for dynamically selecting the appropriate control strategy [9]. In this section, we describe how the focus of attention rules and the metarules are used to implement various strategies.

A. The FOCUS OF ATTENTION *Rules*

The FOCUS OF ATTENTION process performs two levels of data selection, as shown in Fig. 10. An area is selected, and

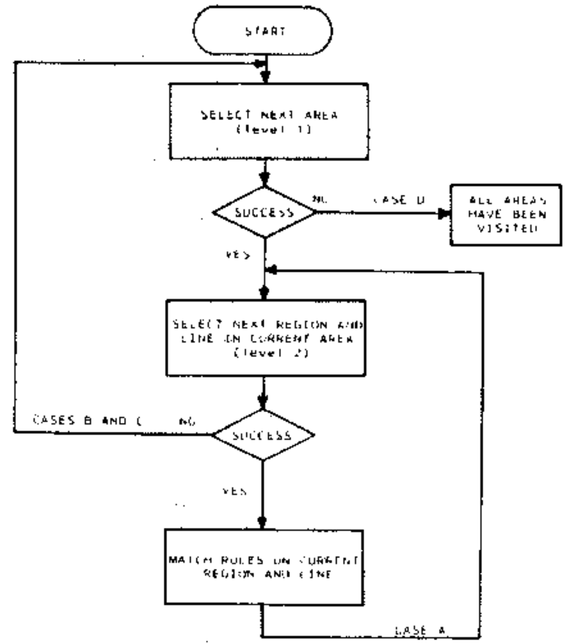


Fig. 10. Levels of data selection.

then the regions and lines within the area are chosen. When all have been visited, the process will move to a new area. The whole procedure is repreated until all the areas generated by the AREA ANALYZER are selected. When these are exhausted, the regions and lines in the image that do not belong to specific focus of attention areas are visited. This data selection method corresponds to a single pass over all the regions and lines in the image.

The transition from one area to the next is accomplished when the FOCUS OF ATTENTION process fails to select a new region or line in the current area. This failure is recorded by the system as part of the history stored in the STM. This particular cycle is then marked as INACTIVE. When this happens, the FOCUS OF ATTENTION process must be invoked again to obtain a new area. If a failure is repeated, this will signal that all the areas have been visited. An option is provided to either stop the processing, or revisit the areas.

By examining the history of processing in the previous two cycles (stored in the STM), different conclusions can be arrived at. Table IV lists the different cases and their interpretations (N/A correspond to don't care conditions). These are also indicated in Fig. 10.

In case A, the FOCUS OF ATTENTION process is invoked after a knowledge module has matched its rules on the current region or line. Therefore, a new region or line must now be fetched. This is accomplished by matching the following rule.

RULE ("1XX"):

IF: (1) The PREVIOUS PROCESS was NOT FOCUS

THEN: (1) "GET THE NEXT REGION"
(2) "GET THE NEXT LINE"

The quotations in the rule number and in the actions indicate that they are variables to be instantiated. Actions that correspond to different methods of obtaining the next region and the next line are listed in Table III. A specific strategy

TABLE IV
INTERPRETATION OF PROCESSING HISTORY

Case	Cycle	Process	State	Interpretation
A	Previous	NOT FOCUS	N/A	A knowledge module was invoked.
B	Next Previous	NOT FOCUS	N/A	A knowledge module was invoked.
	Previous	FOCUS	INACTIVE	Could not fetch a new region or line in current area.
C	Next Previous	FOCUS	ACTIVE	A new area was fetched.
	Previous	FOCUS	INACTIVE	None of the lines or regions in new area is selected.
D	Next Previous	FOCUS	INACTIVE	No more region or lines in current area.
	Previous	FOCUS	INACTIVE	No new area.

must select the method that is most suitable for the properties of the current area [9].

Cases *B* and *C* in Table IV correspond to the situation where the current area cannot contribute any new regions or lines, and therefore a new area is now called for. The following two rules are seen to be in accordance with the two cases

RULE (101): (Case *B*)

IF: (1) The PREVIOUS PROCESS was FOCUS
(2) The PREVIOUS PROCESS was NOT ACTIVE
(3) The NEXT PREVIOUS PROCESS was NOT FOCUS

THEN: (1) GET THE NEXT AREA

RULE (102): (Case *C*)

IF: (1) The PREVIOUS PROCESS was FOCUS
(2) The PREVIOUS PROCESS was NOT ACTIVE
(3) The NEXT PREVIOUS PROCESS was FOCUS
(4) The NEXT PREVIOUS PROCESS was ACTIVE

THEN: (1) GET THE NEXT AREA

The selection of the next area is also based on a data-driven decision-making methodology [9].

Case *D* in Table IV occurs when all the areas in the image have been visited. The next rule allows for an additional pass over the areas by erasing the history lists that record the regions and lines visited in the first path.

RULE (103): (Case *D*)

IF: (1) The PREVIOUS PROCESS was FOCUS
(2) The PREVIOUS PROCESS was NOT ACTIVE
(3) The NEXT PREVIOUS PROCESS was FOCUS
(4) The PREVIOUS PROCESS was NOT ACTIVE

THEN: (1) CLEAR REGION LIST
(2) CLEAR LINE LIST

In the next section, we will describe a metarule that uses the same conditions to terminate processing.

The previous rules permit the execution of a specific strategy for visiting the areas, regions, and lines in the image. In addition, other rules can override these and fetch a region or line other than those specified by the existing strategy. This is particularly useful when an interesting data configuration is detected that requires immediate investigation. The following is an example of such a rule.

RULE (201):

IF: (1) The LINE GRADIENT is HIGH
(2) The LINE LENGTH is HIGH
(3) SAME REGION LEFT and RIGHT of the LINE

THEN: (1) GET the REGION to the LEFT of the LINE

In this rule, a line that has a high gradient and length intersects a region. Thus, the latter should be examined to determine whether it should be split. Another interesting case occurs when a line encircles a region, as given by the following two rules.

RULE (202):

IF: (1) The LINE is LOOP
(2) The LINE is CLOCKWISE
(3) The RIGHT REGION ADJACENCY is HIGH

THEN: (1) GET the REGION to the RIGHT of the LINE

RULE (203):

IF: (1) The LINE is LOOP
(2) The LINE is NOT CLOCKWISE
(3) The LEFT REGION ADJACENCY is HIGH

THEN: (1) GET the REGION to the LEFT of the LINE

If the average gradient of a large region is high, this may be due to a line passing through it. The following rule brings any such line to the attention of the system.

RULE (204):

IF: (1) The REGION SIZE is HIGH
(2) The REGION AVERAGE GRADIENT is HIGH

THEN: (1) GET the LINE that INTERSECTS the REGION

PARALLEL lines also provide a configuration worth investigating, as is evident from the next rule.

RULE (205):

IF: (1) The PARALLEL DISTANCE is NOT VERY LOW

THEN: (1) GET the PARALLEL LINE

PARALLEL lines that are very close are subject to deletion according to Rule (1404) (see Section V-B).

Rules (201)-(205) are given higher priority than Rule ("1XX") in fetching the next region or line. If none of them matches, the strategy specified by Rule ("1XX") is executed.

B. The Metarules

In addition to specifying the method for data selection, the SUPERVISOR in Fig. 1 uses the metarules to coordinate the activities of all the other processing modules. The conditions of these meta-rules are matched against the processing history stored in the STM. Their actions establish the flow of control by specifying the next process to be activated. Because each process is associated with a particular rule set, the metarules effectively select the set of rules to match against the data. The simplest examples of metarules are those that ensure proper initialization, as follows:

METARULE (1):

IF: (1) REGIONS ARE ABSENT

THEN: (1) INITIALIZE REGIONS

METARULE (2):

IF: (1) LINES ARE ABSENT

THEN: (1) INITIALIZE LINES

METARULE (3):

IF: (1) AREAS ARE ABSENT

THEN: (1) GENERATE AREAS

METARULE (4):

IF: (1) The previous PROCESS was GENERATE AREAS
(2) The previous PROCESS was ACTIVE

THEN: (1) GENERATE AREAS

METARULE (5):

IF: (1) The previous PROCESS was GENERATE AREAS
(2) The previous PROCESS was NOT ACTIVE

THEN: (1) Match the FOCUS OF ATTENTION rules.

The first two rules will initialize the region and line maps according to specific procedures [16]. Areas of attention are generated when Metarule (3) matches. Metarule (4) will allow for the creation of all possible areas in the image, based on the initial region and line configurations, and the rules discussed in Section V. Metarule (5) specifies the action to be taken when all possible areas have been generated.

A complete set of control strategies are defined by the user and stored in the STM.[4] For example, the following sequence of three metarules alternatively invoke region analysis and the focus of attention

METARULE (9):

IF: (1) Previous PROCESS was FOCUS
(2) Previous PROCESS was ACTIVE

THEN: (1) Match the REGION analysis rules.

METARULE (10):

IF: (1) Previous PROCESS was REGIONS
(2) Previous PROCESS was ACTIVE

THEN: (1) Match the REGION analysis rules.

METARULE (11):

IF: (1) Previous PROCESS was REGIONS
(2) Previous PROCESS was NOT ACTIVE

THEN: (1) Match the FOCUS OF ATTENTION rules.

The effect of these is to successively match the region rules on all the regions in the current area of attention. A different strategy can be created by interchanging the processes in Metarules (9)-(11).

During processing, different metarules will invoke the FOCUS OF ATTENTION process whenever a new data entry is sought for examination. Because of the two levels of data selection (see Fig. 10), the FOCUS OF ATTENTION process must fail twice before the system can conclude that all data entries have been exhausted. This corresponds to case *D* in Table IV. Accordingly, Metarule (6) provides a default stopping criterion for the system.

METARULE (6):

IF: (1) Previous PROCESS was FOCUS
(2) Previous PROCESS was NOT ACTIVE
(3) Next previous PROCESS was FOCUS
(4) Next previous PROCESS was NOT ACTIVE

THEN: (1) STOP

Otherwise, a single failure of the FOCUS OF ATTENTION process to obtain a new entry signals the exhaustion of the regions and lines within the current area. The following rules are used to reinvoke the focus of attention rules in order to obtain a new area.

METARULE (7):

IF: (1) Previous PROCESS was FOCUS
(2) Previous PROCESS was NOT ACTIVE

[4] For automatic strategy determination, the system selects specific states for each strategy element. This results in the implementation of one of the stored control strategies. Dynamic strategy selection is based on measuring system performance at any point in time [9].

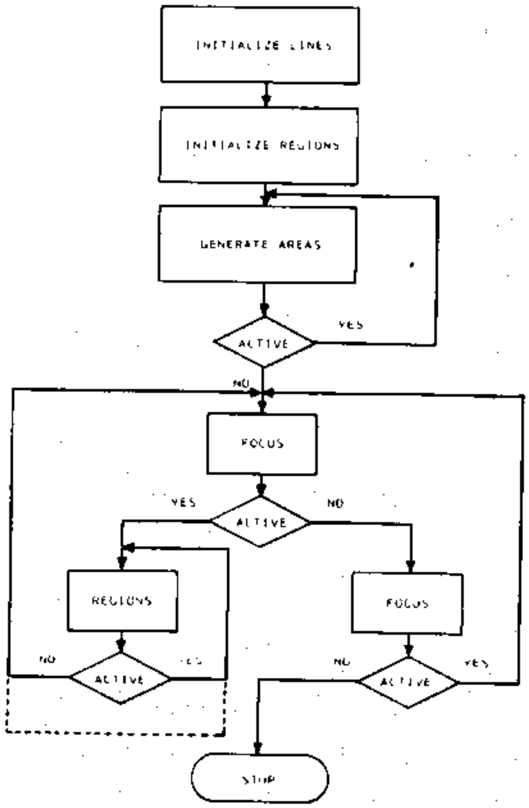


Fig. 11. The flowchart of a system strategy.

(3) Next previous PROCESS was NOT FOCUS

THEN: (1) Match the FOCUS OF ATTENTION rules.

METARULE (8):

IF: (1) Previous PROCESS was FOCUS
(2) Previous PROCESS was NOT ACTIVE
(3) Next previous PROCESS was FOCUS
(4) Next previous PROCESS was ACTIVE

THEN: (1) Match the FOCUS OF ATTENTION rules.

The previous three metarules are essential for the proper functioning of the system, irrespective of the processing strategy.

A specific control strategy can be represented by a flowchart, as shown in Fig. 11. Metarules (1)-(11) implement the particular strategy described in Fig. 11. Each region is successively modified by all the rules before moving to other regions. Replacing the crossed line by the dotted line in Fig. 11 results in an alternative strategy. In this case, the system moves to another region after a single modification of the current region by the first rule to fire. This is accomplished by replacing Metarule (10) by:

METARULE (12):

IF: (1) Previous PROCESS was REGIONS
(2) Previous PROCESS was ACTIVE

THEN: (1) Match the FOCUS OF ATTENTION rules.

As illustrated in the example of Fig. 11, strategy alteration is achieved by the substitution of metarules. This is an essential factor in implementing a dynamic strategy. The elements that constitute the system processing strategy and the choice of a particular strategy are discussed in detail in [16]. The same reference contains examples of other combinations of metarules that execute different strategies.

VII. Experimental Results

To demonstrate the advantages of using the rule-based system, it was compared to earlier approaches to segmentation. The segmentation outputs of the rule-based system were computed using an optimal set of rules [10] and dynamic strategy selection [11]. Two algorithms were chosen: Ohlander's histogram splitting method [18] and the split-and-merge algorithm [21]. The first method was chosen to represent the class of region splitting algorithms that is based on histogram analysis. The second method was selected because it employs both region merging and splitting, albeit in a very restricted data structure. Whereas cluster analysis in feature space is the basis for the first method, the second method uses a structural approach based on similarity grouping.

A number of parameters must be selected to employ these methods. For histogram segmentation, a fixed set of numerical criteria is used to define the peaks within the histogram. The split-and-merge algorithm requires the instantiation of two variables. The starting level of the "initial cutset" refers to the resolution of the square grid that forms the initial region partition. The second parameter is a tolerance level that defines the allowable range of grey level features within one region.

The region partitions that resulted from applying the three methods to an outdoor scene is shown in Fig. 12 and to a "blocks world" scene, in Fig. 13. Quantitatively, the latter is seen to exhibit a superior partition that corresponds more closely to the original objects. A quantitative analysis of the results using the segmentation error measures discussed in [9] confirms this.

The histogram splitting method is seen to produce high over-merging errors that correspond to the large regions of the image which are not segmented. This is because although these regions satisfy other criteria for splitting (such as high gradient or variance), their histograms fail to meet the necessary conditions for peak selection defined in [18]. This method is clearly more suitable for extracting contrasting objects from their background than it is for general purpose segmentation.

On the other hand, the split-and-merge algorithm produces low over-merging errors, but at the expense of high under-merging components. For example, in order to detect the top face of the upper block in Fig. 11(d) the tolerance level within regions had to be lowered. This produced too much detail in the foreground. This parameter dependency became evident when other images were segmented and the values used to obtain best results varied widely. The second parameter for the split-and-merge algorithm was the starting level within the pyramid data structure. The best partitions were obtained when processing started at the highest resolution level, so that no splitting took place. In addition to being more time consuming, this contradicted the original purpose of the algorithm, because it was now reduced to a simple region grower.

(a) (b) (c) (d)

Fig. 12. Segmentation of a natural scene. (a) Digitized color image of the scene. (b) Rule-based segmentation. (c) Histogram splitting. (d) Split-and-merge.

The split-and-merge algorithm was consistently faster than the others with an average cpu time of 370 s (Digital VAX 11/780). This is compared to 840 s for histogram segmentation and 1824 s for rule-based segmentation (an approximate ratio of 1:2.25:5). The rigidity of the data structure, the ease of applying the merging and splitting criteria, and the simplicity of the two basic actions were all factors that contributed to the speed of the split-and-merge process.

As the data structure becomes more flexible, more time is needed to compute and analyze the histograms of arbitrarily shaped regions and then split them accordingly. The rule-based system combined histogram analysis with other region and line analysis techniques in a formulation that maintained flexibility of data and control. In addition, its output conforms more closely to the human expectations of low level segmentation, with almost no over-merging errors and few undermerged regions. However, a price was paid in terms of the increased computation time required for its test and modify cycles.

VIII. Discussion and Conclusions

This section highlights the major accomplishments of the rule-based system.

1) Overall System Structure: The basic system structure follows closely that of the high level interpretation system of [7] in that it is composed of a modular set of independent processes that communicate and interact through a common database. What was presented as a single low level process in [7] is expanded to include the set of processes shown in Fig. 1. Whereas the high level model consisted mainlv of a set of constraints that drive a relaxation labeling process, the basic control paradigm for the low level segmenter is that of a production system. In fact, the system presented here introduces the rule-based approach to the image segmentation problem. Previous vision systems limited the use of explicit knowledge to the semantic interpretation level. Consequently, the heuristics used for low level image segmentation were always implemented in procedural form. The approach discussed in this paper is the first to employ domain independent

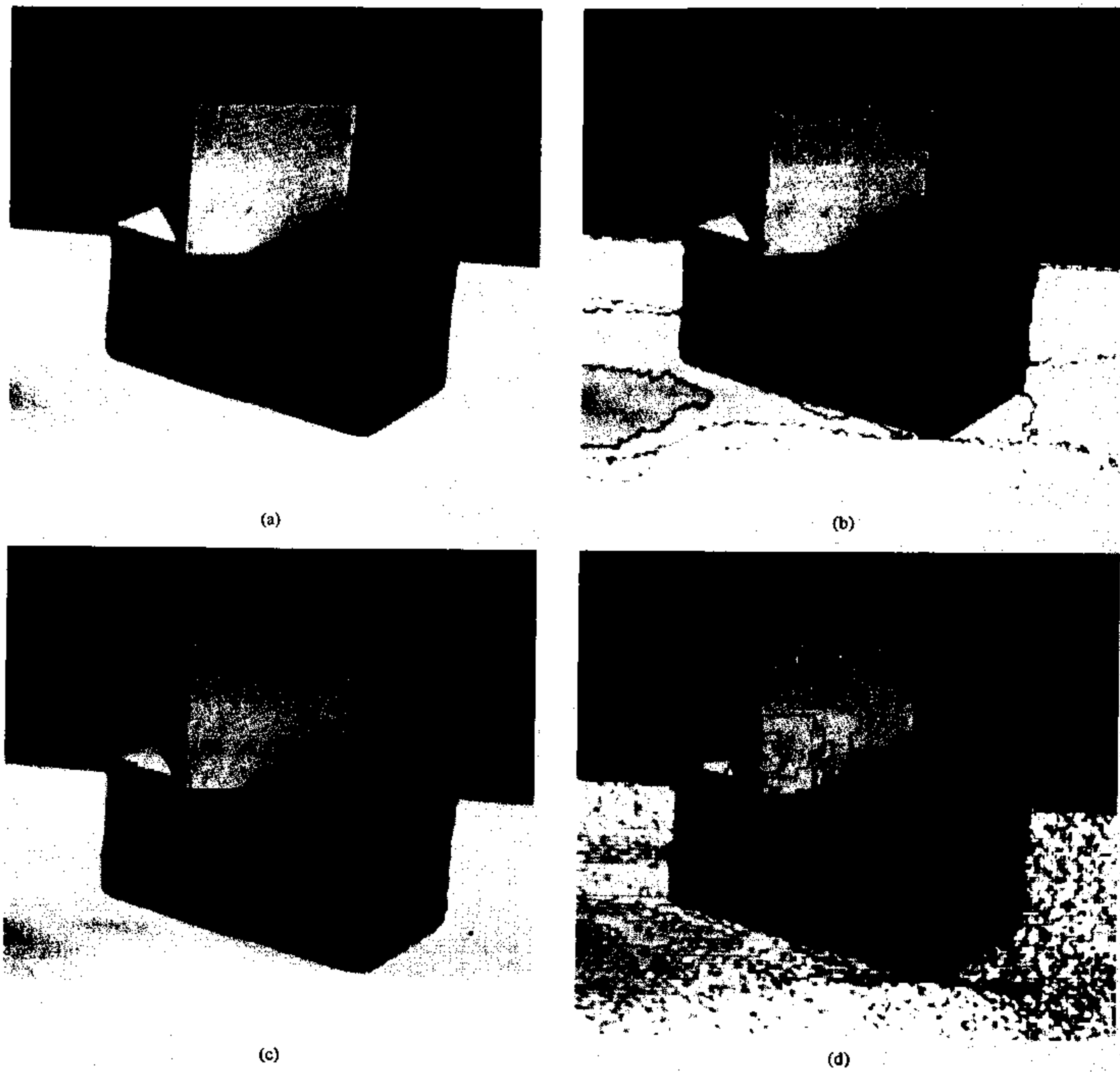


Fig. 13. Segmentation of a "blocks world" image. (a) The original image. (b) Rule-based segmentation. (c) Histogram splitting. (d) Split-and-merge.

knowledge in an explicit form. Knowledge is separated from processing modules by coding it into production rules which are stored in the LTM. In addition, system control is made more accessible by introducing a set of control rules into the model. This allows a user (or the system SUPERVISOR in Fig. 1 to interactively (or automatically) program different processing strategies. The separability of knowledge and control represents a unique approach to solving the segmentation problem.

2) Data Structure: Two new aspects are introduced into the data structure. First, regions and lines are combined and are simultaneously used in the analysis. Although other systems have employed both [4], each was processed separately, and the results combined only at the end. In this system, regions and lines share the same data structure and have common spatial features. The model includes rules that manipulate combinations of regions and lines. This allows uniformity and discontinuity information to blend together and cooperate in producing a better output. Experiments with the system prove that this type of interaction is beneficial.

The second aspect is the introduction of focus of attention areas as groupings of regions and lines that represent interesting parts of an image. In addition to providing valuable information such as texture to a high level process, these areas play an important role in the analysis by providing spatial boundaries across which the processing strategy is adjusted. This allows the system to execute the best strategy based on the individual properties of each area.

3) The Rule-Based Model: A multitude of segmentation criteria are coded in the rules. Heuristics that formed the basis of earlier segmentation techniques in the literature were extracted and organized within a uniform representation. In addition, new general purpose knowledge sources were employed, such as those driving from Gestalt principles for perceptual grouping.

The system also introduces a general symbolic coding scheme for the rules. The conditions are logical predicates evaluated on the STM data by using an automatic scaling mechanism [16], [17]. Low level symbolic processing is a step towards reducing the dependency of previous segmentation methods on numerical parameters. Thus, model learning through rule modification replaces the more ad hoc process of interactive parameter tuning.

The actions of the rules are independent entities that are carried out by the processing modules. They are designed to modify the regions, lines, and areas in finite ways, yet they have the flexibility to permit changes in different directions (e.g., merging and splitting of regions).

The conditions and actions create a "segmentation language" that provides for a wide range of data manipulation and modification. The ability to modify and expand the knowledge base is an important contribution that is a result of the symbolic coding scheme and the rule-based structure. The testing and tuning of the model [16] was only possible because of this powerful experimental feature. Furthermore, future additions and testing of new segmentation heuristics require minimum user interaction.

4) Measures of Segmentation: A primary concern of this research is the ability to evaluate intermediate and final output partitions. A set of error measures was devised that dynamically computes the distance between a test partition and a reference segmentation [8]. These are used to build the model by testing different rule combinations and selecting those that are the most effective in reducing the errors.

A second set of measures are unlike any developed so far in that they do not require a reference segmentation [9]. Performance is judged by comparing the segmentation to the original image. This enables the system to maintain "real-time" estimates of the segmentation as the processing evolves. These performance measures behaved consistently with the segmentation error measures throughout a wide variety of experiments with the system.

5) The Control Mechanism: Using the rule-based expert system discussed in this paper, a strategy determination process that varies with time and with image area has been introduced elsewhere [9], [11], [16]. The elements of control strategy were defined and their dependence on the real-time performance measures was experimentally verified. The experiments tested the effect of using different control strategies on the performance of the system, in terms of output quality and efficiency of computation. Analysis of the results led to conclusions about the best strategies to apply for different ranges of performance measures [16]. Such constraints are used in executing the dynamic strategy selection process.

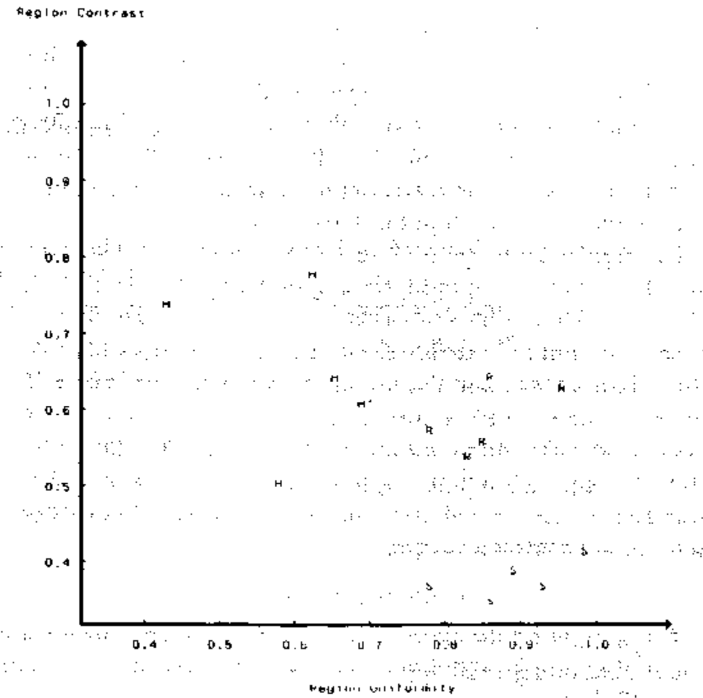


Fig. 14. Comparison of performance measures for three approaches to segmentation. *S*: Split-and-merge. *H*: Histogram splitting. *R*: Rule-based segmentation.

This dynamic strategy mechanism presents solutions to two control issues. First, for rule-based processing, conflict resolution is achieved by implementing a dynamic data-driven rule reordering process. Second, a focus of attention mechanism is created that is capable of adjusting its path of processing within the image according to the data. These factors result in a system that can select the most suitable segmentation heuristics and apply them to the parts of the image where they are most needed.

6) Experimental Results: The ability to quantitatively measure performance allowed us to conduct experiments with various knowledge rule combinations. A ranking of the rules was then established based on their effectiveness in maximizing the performance measures and their frequency of firing. The contribution of these experiments is the selection of an optimal set of rules over a large collection of segmentation heuristics [10], [16].

The performance of the system operating with dynamic strategy setting and the optimal set of rules was compared to other segmentation methods in the literature. The results show a considerable improvement in the quality of the output, in the segmentation error measures, and in the performance measures. The graph in Fig. 14 summarizes these results. It indicates the range of performance parameters measured on the final output partitions of several images for three different segmentation approaches. Algorithms that employ grouping based on similarity result in partitions that are highly uniform. Histogram-based partitions exhibit high contrast between the regions. Each sacrifices one measure to enhance the other. On the other hand, rule-based segmentation produces partitions that simultaneously maximize uniformity and contrast. The details of these results are presented in [16].

In this paper, we have described the knowledge and control rules of our rule-based segmentation system. The structure of the rules was analyzed. The conditions and actions that define our "segmentation language" were listed. The three types of knowledge rules were reviewed, showing how various segmentation heuristics are coded. Finally, the role of the focus of attention rules and the metarules in designing and implementing system control strategies was described.

This segmentation system is seen to be both knowledge-based and data-driven. The production system approach to control allows for knowledge separability, and thus provides an easy means for "tuning" the model used for low level segmentation. Rule classification, and the use of focus of attention rules and metarules permit easy access to the control mechanisms of the system, without compromising its modularity. A main objective of using such a design approach, is to assist us in understanding the nature and effect of various low level knowledge sources and control strategies.

Acknowledgment

The authors would like to thank W. Hong for implementing the split-and-merge algorithm used in the experiments.

References

[1] R. A. Brooks, R. Greiner, and T. O. Binford, "The ACRONYM model-based vision system," in *Proc. 4th IJCAI*, Kyoto, Japan, Nov. 1978, pp. 105-113.

[2] B. L. Bullock, "Unstructured control and communication processes in real world scene analysis," Hughes Res. Lab., Malibu, CA, Comput. Sci. Rep. CS-1, Aug. 1977.

[3] R. Davis, "Meta-rules: Reasoning about control," *Artificial Intelligence*, vol. 15, pp. 179-222, 1980.

[4] A. R. Hanson and E. M. Riseman, "Segmenting natural scenes," in *Computer Vision Systems*, A. Hanson and E. Riseman, Eds. New York: Academic, 1978.

[5] K. Koffka, *Principles of Gestalt Psychology*. New York: Harcourt, Brace & World, 1963.

[6] W. Kohler, "The task of Gestalt psychology," Princeton, NJ: Princeton Univ., 1969.

[7] M. D. Levine and S. I. Shaheen, "A modular computer vision system for picture segmentation and interpretation," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. PAMI-3, pp. 540-556, Sept. 1981.

[8] M. D. Levine and A. Nazif, "An experimental rule-based system for testing low level segmentation strategies," in *Multicomputers and Image Processing: Algorithms and Programs*, K. Preston and L. Uhr, Eds. New York: Academic, pp. 149-160, 1982.

[9] M. D. Levine and A. Nazif, "Performance measurement and strategy evaluation for rule-based image segmentation," Computer Vision and Robotics Lab., Dep. Elec. Eng., McGill University, Montreal, P.Q., Canada, TR-82-1, Mar. 1982.

[10] —, "An optimal set of image segmentation rules," Computer Vision and Robotics Lab., Dep. Elec. Eng., McGill University, Montreal, P.Q., Canada, TR-83-6, Apr. 1983.

[11] —, "Rule-based image segmentation: A dynamic control strategy appraoch," Computer Vision and Robotics Lab., Dep. Elec. Eng., McGill University, Montreal, P.Q., Canada, TR-83-9, June 1983.

[12] M. D. Levine, P. B. Noble, and Y. M. Youssef, "A rule-based system for characterizing blood cell motion," in *Image Sequence Processing and Dynamic Scene Analysis*, NATO ASI Series, Vol. F2, T. S. Huang, Ed. Berlin, Germany: Springer-Verlag, 1983, pp. 663-709.

[13] M. D. Levine, *Vision in Man and Machine*. New York: McGraw-Hill, to be published.

[14] T. P. Moran, "The symbolic nature of visual imagery," in *Proc. 3rd IJCAI*, Stanford, CA, Aug. 1973, pp. 472-477.

[15] J. L. Muerle and D. C. Allen, "Experimental evaluation of techniques for automatic segmentation of objects in a complex scene," in *Pictorial Pattern Recognition*, G. C. Cheng *et al.*, Eds. Washington, DC: Thompson, 1968, pp. 3-13.

[16] A. Nazif, "A rule-based expert system for image segmentation," Ph.D. dissertation, Dep. Elec. Eng., McGill University, Montreal, P.Q., Canada, Mar. 1983.

[17] A. Nazif and M. D. Levine, "Mapping numbers into symbols," Computer Vision and Robotics Lab., Elec. Eng., McGill University, Montreal, P.Q., Canada, TR-83-5, Apr. 1983.

[18] R. Ohlander, "Analysis of natural scenes," Ph.D. dissertation, Carnegie-Mellon Univ., Pittsburgh, PA, Apr. 1975.

[19] E. M. Riseman and M. A. Arbib, "Survey: Computational techniques in the visual segmentation of static scenes," *Computer Graphics and Image Processing*, vol. 6, pp. 221-276, 1977.

[20] K. R. Sloan, "World model driven recognition of natural scenes," Ph.D. dissertation, The Moore School of Electrical Engineering, Univ. Pennsylvania, Philadelphia, PA, June 1977.

[21] S. Tanimoto and T. Pavlidis, "A hierarchical data structure for picture processing," *Computer Graphics and Image Processing*, vol. 4, pp. 104-199, 1975.

[22] J. K. Tsotsos, "Knowledge of the visual process: Content, form, and use," in *Proc. 6th IJCPR*, Munich, Germany, Oct. 19-22, 1982, pp. 654-669.

[23] S. Tsuji and F. Tomita, "A structural analyzer for a class of textures," *Computer Graphics and Image Processing*, vol. 2, pp. 216-231, 1973.

[24] M. Wertheimer, "Laws of organization in perceptual forms," in *A Source Book of Gestalt Psychology*, W. Ellis, Ed. London, England: Kegan Paul, Trench, Trubner and Co, 1938.

[25] S. W. Zucker, A. Rosenfeld, and L. S. Davis, "General purpose models: Expectations about the unexpected," in *Proc. 4th IJCAI*, Tbilisi, Georgia, USSR, Sept. 1975, pp. 716-721.

Ahmed M. Nazif was born in Cairo, Egypt, on July 1952. He received the B.Sc. and M.Sc. degrees in electrical engineering from Cairo University in 1973 and 1975, respectively, and the Ph.D. degree from McGill University, Montreal, P.Q., Canada, in 1983.

From 1973 to 1976 he was a Demonstrator at Cairo University. From 1976 to 1983 he was a Research Assistant at the Computer Vision and Robotics Laboratory of McGill University. Since July 1983, he has been an Assistant Professor at the Department of Electrical Engineering, Cairo University.

Martin D. Levine (S'59-M'66-SM'74) was born in Montreal, P.Q., Canada, on March 30, 1938. He received the B.Eng. and M.Eng. degrees in electrical engineering in 1960 and 1963, respectively, from McGill University, Montreal, and the Ph.D. degree in electrical engineering in 1965 from the Imperial College of Science and Technology, University of London, London, England.

He is currently a Professor of Electrical Engineering in the Department of Electrical Engineering, McGill University. Recently, he was appointed a Senior Fellow in the Canadian Institute of Advanced Research. During 1972-1973 he was a member of Technical Staff at the Image Processing Laboratory of the Jet Propulsion Laboratory, Pasadena, CA. During the 1979-1980 academic session, he was a Visiting Professor in the Department of Computer Science, Hebrew University, Jerusalem, Israel. His research interests are computer vision, biomedical image processing, and robotics. He has authored the book *Vision in Man and Machine* to be published (New York: McGraw-Hill), and co-authored with P. Noble, the book *Computer Assisted Analyses of Cell Locomotion and Chemotaxis* to be published (CRC Press).

Dr. Levine is an Associate Editor of *Computer Vision, Graphics and Image Processing*, and the General Chairman of the Seventh International Conference on Pattern Recognition to be held in Montreal during the summer of 1983.

Chapter 8: Applications

Many of the computer vision techniques described in Chapters 1 through 7 were developed primarily to meet the needs of specific applications. The large variety of applications in which computer vision techniques have been used prevents us from mentioning all of these applications here. Instead, we identify in this chapter a representative set of papers in which applications of computer vision techniques are emphasized. These papers are not reprinted here, but are reprinted, by topic, in Chapter 8 of the companion book, *Computer Vision: Advances and Applications*. The five major topics are

(1) Aerial image analysis;
(2) Document image analysis;
(3) Medical image analysis;
(4) Industrial inspection and robotics; and
(5) Autonomous navigation.

Additional references covering these applications can be found in the Bibliography, which is also organized into these five topics. We would like to emphasize again that even the Bibliography for this chapter is far from being comprehensive. Readers still wanting additional references are advised to consult application-oriented journals (such as *Machine Vision and Applications*); the proceedings of several machine-vision-related conferences organized by SPIE (The Optical Engineering Society) and IAPR (International Association for Pattern Recognition); and application-oriented special issues of journals (such as *IEEE Transactions on Pattern Analysis and Machine Intelligence*, January and May 1988).

A list, by topic, of the papers that are reprinted in Chapter 8 of the companion book, *Computer Vision: Advances and Applications*, appears below.

Aerial image analysis

Harlow, C.A., M.M. Trivedi, R.W. Conners, and D. Philips, "Scene Analysis of High Resolution Aerial Scenes," *Optical Engineering*, Vol. 25, No. 3, 1986, pp. 347-355

Matsuyama, T., "Knowledge-based Aerial Image Understanding Systems and Expert Systems for Image Processing," *IEEE Trans. Geoscience and Remote Sensing*, Vol. 25, No. 3, 1987, pp. 305-316

McKeown, D.M., "Toward Automatic Cartographic Feature Extraction," in *Mapping and Spatial Modelling for Navigation*, L.F. Pau, ed., NATO ASI Series, Vol. F 65, Springer-Verlag, Berlin, Heidelberg, 1990

Document image analysis

Baird, H.S., and K. Thompson, "Reading Chess," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 6, 1990, pp. 552-559

Kasturi, R., S.T. Bow, W. El-Masri, J. Shah, J.R. Gattiker, and U.B. Mokate, "An Intelligent System for Interpretation of Line Drawings," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 10, 1990, pp. 978-992

Okazaki, A., T. Kondo, K. Mori, S. Tsunekawa, and E. Kawamoto, "An Automatic Circuit Diagram Reader with Loop-Structure-Based Symbol Recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 3, 1988, pp. 331-341

Wang, C.H., and S.N. Srihari, "A Framework for Object Recognition in a Visually Complex Environment and its Application to Locating Address Blocks on Mail Pieces," *Int'l J. Computer Vision*, Vol. 2, 1988, pp. 125-151

Medical image analysis

Gordon, D., and J.K. Udupa, "Fast Surface Tracking in Three-Dimensional Binary Images," *Computer Vision, Graphics, and Image Processing*, Vol. 45, 1989, pp. 196-214

Hibbard, L.S., J.S. McGlone, D.W. Davis, and R.A. Hawkins, "Three-Dimensional Representation and Analysis of Brain Energy Metabolism," *Science*, Vol. 236, 1987, pp. 1641-1646

Lifshitz, L.M., and S.M. Pizer, "A Multiresolution Hierarchical Approach to Image Segmentation Based on Intensity Extrema," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 6, 1990, pp. 529-540

Industrial inspection and robotics

Darwish, A.M., and A.K. Jain, "A Rule-Based Approach for Visual Pattern Inspection," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 1, 1988, pp. 56-68

Lougheed, R.M., and R.E. Sampson, "Three-Dimensional Imaging Systems and High-Speed Processing for Robot Control," *Machine Vision and Applications*, Vol. 1, 1988, pp. 41-57

Yoda, H., Y. Ohuchi, Y. Taniguchi, and M. Ejiri, "An Automatic Wafer Inspection System Using Pipelined Image Processing Techniques," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 1, 1988, pp. 4-16

Autonomous navigation

Dickmanns, E.D., and V. Graefe, "Applications of Dynamic Monocular Machine Vision," *Machine Vision and Applications*, Vol. 1, No. 4, 1988, pp. 241-261

Ishiguro, H., M. Yamamoto, and S. Tsuji, "Omni-Directional Stereo for Making Global Map," *Proc. Third Int'l Conf. Computer Vision*, 1990, pp. 540-547

Thorpe, C., M.H. Hebert, T. Kanade, and S.A. Shafer, "Vision and Navigation for the Carnegie-Mellon Navlab," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 3, 1988, pp. 362-373

Epilogue

Computer vision has been a very active research field in the last two decades. Because of both a better understanding of the important issues in the field and the tremendous growth in the availability of sensors and computing power, significant advances in this field have been made. Many new applications have been successful and many new application areas are emerging. The last few years have shown some new trends in computer vision research. In this section, we discuss some of these trends and the direction of research in computer vision.

The availability of range cameras encouraged many researchers to start addressing problems in surface characterization using explicit depth information. Though many early approaches were direct extensions of work in other areas, today researchers are studying differential-geometry-based approaches to better understand surface characteristics and to use them in segmentation. In many industries, these approaches will be increasingly applied to inspection and metrology of surfaces. In the near future, surface characterization techniques will be applied to data acquired using many different types of sensors. An encouraging trend in this direction is the increasing attention being given to the use of geometric models in computer vision. In the last few years, many new research projects have started to emphasize the role of geometric models in object recognition and inspection, although explicit three-dimensional reasoning using geometric models is still not very common.

Although the role of indexing in recognizing objects from a large set has been clear to researchers for at least two decades, it has not been given much attention. The problem of feature-based indexing will receive more attention in the near future. This indexing will be useful not only for recognizing objects, but also for organizing large image databases, such as those encountered in Earth Observation Systems (EOS).

The idea of integrating information from multiple sensors or multiple operators seems to be slowly maturing. After struggling with simple-minded approaches that try to combine information in image space, researchers are now starting to build incremental models in three dimensions. Volumetric approaches that represent voxel properties have become quite common in medical imaging and visualization. These techniques will become very common in computer vision. Techniques that try to combine information from multiple sources and sensors in three dimensions are likely to be very common soon. Some intrinsic surface characteristics are finally getting careful attention. Some activity in understanding color has occurred in the last few years; activity in understanding other images is also increasing. The near future will see increasing activity in these areas.

In the first few years of research in dynamic vision, papers addressed problems related to many aspects of dynamic vision. Later, for almost one complete decade, most effort was on myopic problems, such as recovering structure using a minimum number of frames or determining optical flow using two frames. Many other techniques in this area were based on first and second derivatives of optical flow and thus required a third derivative of intensity values; these techniques led to ineffective methods for real images. Some recent work on image sequence processing shows that many seemingly complex problems can be solved by using appropriate techniques—borrowed from systems engineering—that do not appear powerful when considered locally. Generally, more attention is being given to the analysis of long sequences of images to solve problems in dynamic vision. Techniques based on surface characterization and differential geometry in spatio-temporal space may facilitate motion detection, characterization of object and observer motion, and even determination of three-dimensional structure of objects in a sequence of images acquired by either a stationary or a moving camera.

Systems are now being considered that acquire images based on what needs to be done next. Although these systems do not do much reasoning yet, they represent a step in the right direction. Reasoning-based approaches are likely to pervade all aspects of computer vision systems in the next decade. A major hurdle in this direction is the explicit representation of knowledge about the operators used in different stages. Such knowledge will become increasingly available as researchers start more rigorous characterization of their operators by experimenting with images of disparate scenes acquired under different, but possibly controlled, conditions.

Increasing attention has been given to qualitative vision in the last few years. Approaches based on qualitative reasoning are a step towards analyzing phenomena that can only be captured at a qualitative level. Many current approaches try to recover very precise quantitative information; such approaches are very sensitive to noise. Many of these approaches are capable of giving good qualitative information about the scene. The effectiveness of these approaches in object recognition and navigation will result in their increasing acceptance and popularity.

Chapter 1: Image Formation
Selected Bibliography

Allen, P.K. and P. Michelman, "Acquisition and Interpretation of 3-D Sensor Data from Touch," *Proc. IEEE Workshop on Interpretation of 3D Scenes*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 33-40.

Alvertos, N., D. Brzakovic, and R.C. Gonzalez, "Camera Geometries for Image Matching in 3-D Machine Vision," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 9, 1989, pp. 897-915.

Arend, L. and A. Reeves, "Simultaneous Color Constancy," *J. Opt. Soc. Am. A*, Vol. 3, No. 10, 1986, pp. 1743-1751.

Asada, M., H. Ichikawa, and S. Tsuji, "Determining Surface Orientation by Projecting a Stripe Pattern," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 5, 1988, pp. 749-754.

Bajcsy, R., "Active Perception," *Proc. IEEE*, Vol. 76, No. 8, IEEE Press, New York, N.Y., 1988, pp. 996-1005.

Ballard, D.H., "Eye Movements and Visual Cognition," *Proc. Workshop on Spatial Reasoning and Multi-Sensor Fusion*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1987, pp. 188-200.

Ballard, D.H. and A. Ozcandarli, "Eye Fixation and Early Vision: Kinetic Depth," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 524-531.

Bastucheck, C.M., "Techniques for Real-Time Generation of Range Images," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 262-268.

Bergstrom, S.S., "Illumination, Color, and Three-Dimensional Form," in *Organization and Representation in Perception*, J. Beck, ed., Lawrence Erlbaum Assoc., Hillsdale, N.J., 1982.

Brelstaff, G. and A. Blake, "Detecting Specular Reflections Using Lambertian Constraints," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 297-302.

Brown, C., "Gaze Controls with Interactions and Delays," *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 20, No. 2, 1990, pp. 518-527.

Buchanan, T., "The Twisted Cubic and Camera Calibration," *Computer Vision, Graphics and Image Processing*, No. 42, 1988, pp. 130-132.

Chelberg, D.M., "Uncertainty in Interpretation of Range Imagery," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 654-657.

Clark, J.J. and N.J. Ferrier, "Modal Control of an Attentive Vision System," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif, 1988, pp. 514-523.

Collins, R.T. and R.S. Weiss, "Vanishing Point Calculation as a Statistical Inference on the Unit Sphere," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 400-405.

Drew, M.S. and B.V. Funt, "Calculating Surface Reflectance Using a Single-Bounce Model of Mutual Reflection," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 394-399.

Echigo, T., "A Camera Calibration Technique Using Three Sets of Parallel Lines," *Machine Vision and Applications*, Vol. 3, No. 3, 1990, pp. 159-167.

Forsyth, D.A., "A Novel Algorithm for Color Constancy," *Int'l J. Computer Vision*, Vol. 5, No. 1, 1990, pp. 5-36.

Forsyth, D.A. and A. Zisserman, "Mutual Illumination," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 466-473.

Gershon, R., "Aspects of Perception and Computation in Color Vision," *Computer Vision, Graphics and Image Processing*, No. 32, 1985, pp. 244-277.

Gershon, R., A.D. Jepson, and J.K. Tsotsos, "Ambient Illumination and the Determination of Material Changes," *J. Opt. Soc. Am. A*, Vol. 3, No. 10, 1986, pp. 1700-1707.

Healey, G., "A Color Reflectance Model and its Use For Segmentation," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 460-466.

Healey, G., "Color Discrimination by Computer," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, No. 6, 1989, pp. 1613-1617.

Ho, J., B.V. Funt, and M.S. Drew, "Separating a Color Signal into Illumination and Surface Reflectance Components: Theory and Applications," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 10, 1990, pp. 966-977.

Horn, B.K.P., "Understanding Image Intensities," *Artificial Intelligence*, Vol. 8, No. 2, 1977, pp. 201-231.

Hugli, H. and W. Frei, "Understanding Anisotropic Reflectance in Mountainous Terrain," *Photogrammetric Eng. and Remote Sensing*, No. 49, 1983, pp. 671-683.

Ikeuchi, K. and K. Sato, "Determining Reflectance Parameters Using Range and Brightness Images," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 400-405.

Izaguirre, A., P. Pu, and J. Summers, "A New Development in Camera Calibration: Calibrating a Pair of Mobile Cameras," *Int'l J. Robotics Research*, Vol. 6, No. 3, 1987, pp. 104-116.

Kamgar-Parsi, B. and Kamgar-Parsi B., "Evaluation of Quantization Error in Computer Vision," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 9, 1989, pp. 929-940.

Kanade, T. and M. Fuhrman, "A Noncontact Optical Proximity Sensor for Measuring Surface Shape," T. Kanade, ed., *Three Dimensional Machine Vision*, Kluwer, Boston, Mass., 1987., pp. 151-192.

Klinker, G.J., S.A. Shafer, and T. Kanade, "Using a Color Reflection Model to Separate Highlights from Object Color," *Proc. First Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 145-150.

Klinker, G.J., S.A. Shafer, and T. Kanade, "The Measurement of Highlights in Color Images," *Int'l J. Computer Vision*, Vol. 2, No. 1, 1988, pp. 7-32.

Koenderink, J.J., "Color Atlas Theory," *J. Opt. Soc. Am. A*, Vol. 4, No. 7, 1987, pp. 1314-1321.

Kumar, R. and A.R. Hanson, "Sensitivity of the Pose Refinement Problem to Accurate Estimation of Camera Parameters," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif, 1990, pp. 365-369.

Lenz, R.K. and R.Y. Tsai, "Calibrating a Cartesian Robot with Eye-on-Hand Configuration Independent of Eye-to-Hand Relationship," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 67-75.

Maloney, L.T., "Evaluation of Linear Models of Surface Spectral Reflectance with Small Numbers of Parameters," *J. Opt. Soc. Am. A*, Vol. 3, No. 10, 1986, pp. 1673-1683.

Matsuki, M. and T. Ueda, "A Real-Time Sectional Image Measuring System Using Time Sequentially Coded Grating Method," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 11, 1989, pp. 1225-1228.

Mori, T. and M. Yamamoto, "A Dynamic Depth Extraction Method," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 672-676.

Mundy, J. and G.B. Porter III, "A Three-Dimensional Sensor Based on Structured Light," in *Three Dimensional Machine Vision*, T. Kanade, ed., Kluwer, Boston, Mass., 1987, pp. 3-61.

Olsen, S.I., "Stereo Correspondence by Surface Reconstruction," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 3, 1990, pp. 309-314.

Park, J.-S. and J.T. Tou, "Highlight Separation and Surface Orientations for 3-D Specular Objects," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 331-335.

Pentland, A., et al., "A Simple Real-Time Range Camera," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 256-261.

Rioux, M. and F. Blais, "Compact Three-Dimensional Camera for Robotic Applications," *J. Opt. Soc. Am. A*, Vol. 3, No. 9, 1986, pp. 1518-1521.

Rioux, M., et al., "Range Imaging Sensors Development at NRC Laboratories," *Proc. IEEE Workshop on Interpretation of 3D Scenes*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 154-160.

Rubin, J.M. and W.A. Richards, "Color Vision and Image Intensities: When are Changes Material?," *Biological Cybernetics*, No. 45, 1982, pp. 215-226.

Shafer, S. and T. Kanade, "A Physical Approach to Color Image Understanding," *Int'l J. Computer Vision*, Vol. 4, No. 1, 1990, pp. 7-38.

Shmuel, A. and M. Werman, "Active Vision: 3D From an Image Sequence," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 48-54.

Srinivasan, V. and R. Lumia, "A Pseudo-Interferometric Laser Range Finder for Robot Applications," *IEEE Trans. Robotics and Automation*, Vol. 5, No. 1, 1989, pp. 98-105.

Suenaga, Y. and Y. Watanabe, "A Method for the Synchronized Acquisition of Cylindrical Range and Color Data," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 137-142.

Swain, M.J. and D.H. Ballard, "Indexing Via Color Histograms," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 390-393.

Tajima, J. and M. Iwakawa, "3D Data Acquisition by Rainbow Range Finder," *Proc. Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 309-313.

Tsukada, M. and Y. Ohta, "An Approach to Color Constancy Using Multiple Images," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 385-390.

Vuylsteke, P. and A. Oosterlinck, "Range Image Acquisition with a Single Binary-Encoded Light Pattern," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 2, 1990, pp. 148-164.

Wandell, B.A., "The Synthesis and Analysis of Color Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 1, 1987, pp. 2-13.

Wang, L.-L. and W.-H. Tsai, "Computing Camera Parameters Using Vanishing-Line Information from a Rectangular Parallelpiped," *Machine Vision and Applications*, Vol. 3, No. 3, 1990, pp. 129-141.

Wang, Y.F. and J.K. Aggarwal, "Integration of Active and Passive Sensing Techniques for Representing Three-Dimensional Objects," *IEEE Trans. Robotics and Automation*, Vol. 5, No. 5, 1989, pp. 701-710.

Will, P.M. and K.S. Pennington, "Grid Coding: A Preprocessing Technique for Robot and Machine Vision," *Artificial Intelligence*, Vol. 2, 1971, pp. 319-329.

Wolff, L.B., "Using Polarization to Separate Reflection Components," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 363-369.

Wolff, L.B. and T.E. Boult, "Polarization/Radiometric Based Material Classification," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 387-396.

Woodham, R. and M.H. Gray, "An Analytic Method for Radiometric Correction of Satellite Multispectral Scanner Data," *IEEE Trans. Geoscience and Remote Sensing*, Vol. 25, 1987, pp. 258-271.

Yi, S., R.M. Haralick, and L.G. Shapiro, "Automatic Sensor and Light Source Positioning for Machine Vision," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 55-59.

Chapter 2: Segmentation Selected Bibliography

Ahuja, N., "Dot Pattern Processing Using Voronoi Neighborhoods," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 4, No. 3, 1982, pp. 336-343.

Ahuja, N. and A. Rosenfeld, "Mosaic Models for Textures," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 3, No. 1, 1981, pp. 1-11.

Al-Hujazi, E. and A.K. Sood, "Range Image Segmentation with Applications to Robot Bin-Picking Using Vaccume Gripper," *IEEE Trans. on Systems, Man and Cybernetics*, Vol. 20, No. 6, 1990, pp. 1313-1325.

Babaud, J., et al., "Uniqueness of the Gaussian Kernel for Scale-Space Filtering," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 1, pp. 1986, 26-33.

Bajcsy, R. and L. Lieberman, "Texture Gradient as a Depth Cue," *Computer Graphics and Image Processing*, Vol. 5, No. 1, 1977, pp. 52-67.

Beaulieu, J.-M. and M. Goldberg, "Hierarchy in Picture Segmentation: A Stepwise Optimization Approach," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 2, 1989, pp. 150-163.

Bell, Z.W., "A Bayesian/Monte Carlo Segmentation Method for Images Dominated by Gaussian Noise," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 9, 1989, pp. 985-990.

Berzins, V., "Accuracy of Laplacian Edge Detectors," *Computer Vision, Graphics and Image Processing*, Vol. 27, 1984, pp. 195-210.

Bischof, W.F. and T. Caelli, "Parsing Scale-Space and Spatial Stability Analysis," *Computer Vision, Graphics and Image Processing*, Vol. 42, 1988, pp. 192-205.

Blostein, D. and N. Ahuja, "A Multiscale Region Detector," *Computer Vision, Graphics and Image Processing*, Vol. 45, No. 1, 1989, pp. 22-41.

Brooks, R.A., "Model-Based Three-Dimensional Interpretations of Two-Dimensional Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 5, No. 2, 1983, pp. 140-150.

Cannon, R.L., et al., "Segmentation of a Thematic Mapper Image Using Fuzzy C-means Clustering Algorithms," *IEEE Trans. on Geoscience and Remote Sensing*, Vol. 24, No. 3, 1986, pp. 400-408.

Carlotto, M.J., "Histogram Analysis Using a Scale-Space Approach," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1985, pp. 334-340.

Celenk, M., "A Recursive Clustering Technique for Color Picture Segmentation," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 437-444.

Cheevasuvit, F., H. Maitre, and D. Vidal-Madjar, "A Robust Method for Picture Segmentation Based on a Split-and-Merge Procedure," *Computer Vision, Graphics and Image Processing*, Vol. 34, 1986, pp. 268-281.

Chen, C.-C. and R.C. Dubes, "Experiments in Fitting Discrete Markov Random Fields to Textures," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 298-303.

Chen, J.S. and G. Medioni, "Detection, Location, and Estimation of Edges," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 2, 1989, pp. 191-198.

Chen, P.C. and T. Pavlidis, "Segmentation by Texture Using a Co-Occurrence Matrix and a Split-and-Merge Algorithm," *Computer Graphics and Image Processing* , Vol. 10, 1979, pp. 172-182.

Chu, C.-C. and J.K. Aggarwal, "The Integration of Region and Edge-Based Segmentation," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 117-120.

Clark, J.J., "Singularities of Contrast Functions in Scale Space," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, 1988, pp. 491-495.

Clark, J.J., "Authenticating Edges Produced by Zero-Crossing Algorithms," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 1, 1989, pp. 43-57.

Coggins, J.M. and A.K. Jain, "A Spatial Filtering Approach to Texture Analysis," *Pattern Recognition*, Vol. 3, 1985, pp. 195-203.

Cohen, F.S. and D.B. Cooper, "Simple Parallel Hierarchical and Relaxation Algorithms for Segmenting Non-Causal Markovian Random Fields," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 2, 1987, pp. 195-219.

Cohen, P. and H.H. Nguyen, "Unsupervised Bayesian Estimation for Segmenting Textured Images," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 303-309.

Cooper, D.H., "An Object Location Strategy Using Shape and Grey-Level Models," *Image and Vision Computing*, Vol. 7, 1989, pp. 50-56.

Daily, M.J., "Color Image Segmentation Using Markov Fields," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif, 1989, pp. 304-312.

Darrell, T., S. Sclaroff, and A. Pentland, "Segmentation by Minimal Description," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 112-115.

Davis, L.S. and A. Mitiche, "Edge Detection in Textures-Maxima Selection," *Computer Graphics and Image Processing*, Vol. 16, 1981, pp. 158-165.

De Micheli, E., B. Caprile, P. Ottonello, and V. Torre, "Localization and Noise in Edge Detection," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 10, 1989, pp. 1006-1117.

De Souza, P., "Edge Detection Using Sliding Statistical Tests," *Computer Vision, Graphics and Image Processing*, Vol. 23, No. 1, 1983, pp. 1-14.

Derin, H. and H. Elliott, "Modeling and Segmentation of Noisy and Textured Images Using Gibbs Random Fields," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 1, 1987, pp. 39-55.

Duncan, J.S. and T. Birkholzer, "Edge Reinforcement Using Parameterized Relaxation Labeling," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 19-27.

Eichel, P.H. and E.J. Delp, "Quantitative Analysis of a Moment-Based Edge Operator," *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 20, No. 1, 1990, pp. 59-66.

Eichel, P.H., et al., "A Method for a Fully Automatic Definition of Coronary Arterial Edges from Cineangiograms," *IEEE Trans. Medical Imaging*, Vol. 7, No. 4, 1988, pp. 313-320.

Eklundh, J.O., H. Yamamoto, and A. Rosenfeld, "A Relaxation Method for Multispectral Pixel Classification," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 2, No. 1, 1980, pp. 72-75.

Eom, K.B. and R.L. Kashyap, "Composite Edge Detection with Random Field Models," *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 20, No. 1, 1990, pp. 81-93.

Fletcher, L.A. and R. Kasturi, "Segmentation of Binary Images into Text Strings and Graphics," *Applications of Artificial Intelligence, Proc. SPIE*, Vol. 786, 1987, pp. 533-540.

Fletcher, L.A. and R. Kasturi, "A Robust Algorithm for Text String Separation from Mixed Text/Graphics Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 6, 1988, pp. 910-918.

Fogel, I. and D. Sagi, "Gabor Filters as Texture Discriminator," *Biological Cybernetics*, Vol. 61, 1989, pp. 103-113.

Geiger, D. and T. Poggio, "An Optimal Scale for Edge Detection," *Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufman Publishers, Inc., San Mateo, Calif., 1987, pp. 745-748.

Geman, D., et al., "Boundary Detection by Constrained Optimization," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 6, 1990, pp. 609-620.

Geman, S. and D. Geman, "Stochastic Relaxation, Gibbs Distributions, and Bayesian Restoration of Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 6, No. 6, 1984, pp. 721-741.

Godin, G.D. and M.D. Levine, "Structured Edge Map of Curved Objects in a Range Image," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 276-281.

Grosky, W.I. and R.C. Jain, "A Pyramid-Based Approach to Segmentation Applied to Region Matching," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 5, 1986, pp. 639-650.

Haddon, J.F. and J.F. Boyce, "Image Segmentation by Unified Region and Boundary Information," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 10, 1990, pp. 929-948.

Haralick, R.M., "Ridges and Valleys on Digital Images," *Computer Vision, Graphics and Image Processing*, Vol. 22, No. 1, 1983, pp. 28-38.

Haralick, R.M. and J.S.J. Lee, "Context Dependent Edge Detection," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 223-228.

Harlow, C.A., M.M. Trivedi, and R.W. Conners, "Use of Texture Operators in Scene Analysis," *Optical Eng.*, Vol. 25, No. 11, 1986, pp. 1200-1206.

Hsiao, J.Y. and A.A. Sawchuk, "Supervised Textured Image Segmentation Using Feature Smoothing and Probabilistic Relaxation Techniques," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 12, 1989, pp. 1279-1292.

Hu, G. and G. Stockman, "Representation and Segmentation of a Cluttered Scene Using Fusing Edge and Surface Data," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif, 1989, pp. 313-318.

Huertas, A. and G. Medioni, "Detection of Intensity Changes with Subpixel Accuracy Using Laplacian-Gaussian Masks," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 5, 1986, pp. 651-664.

Hummel, R.A., B. Kimia, and S.W. Zucker, "Deblurring Gaussian Blur," *Computer Vision, Graphics and Image Processing*, Vol. 38, No. 1, 1987, pp. 66-80.

Hwang, V.S.S., L.S. Davis, and T. Matsuyama, "Hypothesis Integration in Image Understanding Systems," *Computer Vision, Graphics and Image Processing*, Vol. 36, 1986, pp. 321-371.

Hwang, T.-L. and J.J. Clark, "A Spatio-Temporal Generalization of Canny's Edge Detector," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif, 1990, pp. 314-318.

Jain, A.K. and S.G. Nadabar, "Mrf Model-Based Segmentation of Range Images," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 667-671.

Julesz, B. and J.R. Bergen, "Textons, the Fundamental Elements in Preattentive Vision and the Perception of Textures," *Bell System Technical Journal*, Vol. 62, No. 6, 1983, pp. 1619-1644.

Kartikeyan, B. and A. Sarkar, "A Unified Approach for Image Segmentation Using Exact Statistics," *Computer Vision, Graphics and Image Processing*, Vol. 48, 1989, pp. 217-229.

Kass, M. and A. Witkin, "On Edge Detection," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 2, 1987, pp. 147-163.

Kass, M., A. Witkin, and D. Terzopoulos, "Snakes: Active Contour Models," *Int'l J. Computer Vision*, Vol. 1, No. 4, 1988, pp. 321-331.

Klinker, G.J., S.A. Shafer, and T. Kanade, "Image Segmentation and Reflection Analysis Through Color," *Proc. DARPA Image Understanding Workshop*, 1988, pp. 838-853.

Kocher, M. and R. Leonardi, "Adaptive Region Growing Technique Using Polynomial Functions for Image Approximation," *Signal Processing*, Vol. 11, No. 1, 1986, pp. 47-60.

Koenderink, J.J., "A Hitherto Unnoticed Singularity of Scale-Space," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 11, 1989, pp. 1222-1224.

Kohler, R., "A Segmentation System Based on Thresholding," *Comp. Graph. and Image Processing*, Vol. 15, No. 4, 1981, pp. 319-338.

Krumm, J. and S.A. Shafer, "Local Spatial Frequency Analysis of Image Texture," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 354-359.

Kube, P., "Polynomial Shift-Invariant Operators for Texture Segmentation," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 100-104.

Kundu, A., "Robust Edge Detection," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 11-18.

Lakshmanan, S. and H. Derin, "Simultaneous Parameter Estimation and Segmentation of Gibbs Random Fields Using Simulated Annealing," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 8, 1989, pp. 799-822.

Langridge, D.J., "Detection of Discontinuities in the First Derivatives of Surfaces," *Computer Vision, Graphics and Image Processing*, Vol. 27, 1984, pp. 291-308.

Laprade, R.H., "Split-and-Merge Segmentation of Aerial Photographs," *Computer Vision, Graphics and Image Processing*, Vol. 44, No. 1, 1988, pp. 77-86.

Le, Y.G., Image Segmentation Using Dynamic Programming, in *Advances in Computer Vision and Image Processing*, T.S. Huang, ed., Vol. 3, JAI Press Inc., 1988, pp. 39-62.

Leclerc, Y., "Capturing the Local Structure of Image Discontinuities in Two Dimensions," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1985, pp. 34-38.

Leclerc, Y.G., "Constructing Simple Stable Description for Image Partitioning," *Int'l J. Computer Vision*, Vol. 3, 1989, pp. 73-102.

Leclerc, Y.G. and S.W. Zucker, "The Local Structure of Image Discontinuities in One Dimension," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 3, 1987, pp. 341-355.

Lee, C., R.M. Haralick, and T.I. Phillips, "Image Segmentation Using Morphological Pyramid," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conference*, VII, 1095, 1989, pp. 208-221.

Lee, C.H. and A. Rosenfeld, "Albedo Estimation for Scene Segmentation," *Pattern Recognition*, Vol. 1, No. 3, 1983, pp. 155-160.

Lee, D., "Edge Detection, Classification, and Measurement," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 2-10.

Lee, D., "Coping with Discontinuities in Computer Vision: Their Detection, Classification, and Measurement," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 4, 1990, pp. 321-344.

Lee, D. and T. Pavlidis, "One-Dimensional Regularization with Discontinuities," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 6, 1988, pp. 822-829.

Lee, J.S.J., R.M. Haralick, and L.G. Shapiro, "Morphologic Edge Detection," *IEEE Trans. Robotics and Automation*, Vol. 3, No. 2, 1987, pp. 142-156

Leonardis, A., A. Gupta, and R. Bajcsy, "Segmentation as the Search for the Best Description of the Image in Terms of Primitives," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 121-125.

Levine, M.D. and A.M. Nazif, "Dynamic Measurement of Computer Generated Image Segmentations," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 2, 1985, pp. 155-164.

Li, S.Z., "Invariant Surface Segmentation through Energy Minimization with Discontinuties," *Int'l J. Computer Vision*, Vol. 5, No. 2, 1990, pp. 161-194.

Lindeberg, T., "Scale-Space for Discrete Signals," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 3, 1990, pp. 234-254.

Lindeberg, T. and J.-O. Eklundh, "Scale Detection and Region Extraction from a Scale-Space Primal Sketch," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 416-426.

Lunscher, W.H.H.J. and M.P. Beddoes, "Optimal Edge Detector Design," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 2, 1986, pp. 164-187.

Lyvers, E.P. and O.R. Mitchell, "Precision Edge Contrast and Orientation Estimation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 6, 1988, pp. 927-937.

Malik, J. and P. Perona, "A Computational Model of Texture Segmentation," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 326-332.

Malik, J. and P. Perona, "Preattentive Texture Discrimination with Early Vision Mechanisms," *J. Opt. Soc. Am. A*, Vol. 7, No. 5, May 1990, pp. 923-932.

Mallat, S.G., "Scale Change Versus Scale Space Representation," *Proc. First Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 592-596.

Matsuyama, T., "Expert Systems for Image Processing: Knowledge-Based Composition of Image Analysis Processes," *Computer Vision, Graphics and Image Processing*, Vol. 48, No. 1, 1989, pp. 22-49.

Mitiche, A. and J.K. Aggarwal, "Detection of Edges Using Range Information," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 5, No. 2, 1983, pp. 174-178.

Mohan, R. and R. Nevatia, "Segmentation and Description Based on Perceptual Organization," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 333-341.

Mohan, R. and R. Nevatia, "Using Perceptual Organization to Extract 3-D Structures," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 11, 1989, pp. 1121-1139.

Monga, O., "An Optimal Region Growing Algorithm for Image Segmentation," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 1, 1987, pp. 351-375.

Monga, O., "3D edge Detection Using Recursive Filtering: Application to Scanner Images," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 28-37.

Morgenthaler, D.G. and A. Rosenfeld, "Multidimensional Edge Detection by Hypersurface Fitting," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 3, No. 4, 1981, pp. 482-486.

Nalwa, V.S., "Edge-Detector Resolution Improvement by Image Interpolation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 3, 1987, pp. 446-451.

Nalwa, V.S. and E. Pauchon, "Edge Aggregation and Edge Description," *Computer Vision, Graphics and Image Processing*, Vol. 40, No. 1, 1987, pp. 79-94.

Nitzberg, M. and D. Mumford, "The 2.1-D Sketch," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif.,1990, pp. 138-145.

Pal, N.R. and S.K. Pal, "Entropic Thresholding," *Signal Processing,* Vol. 16, 1989, pp. 97-108.

Pappas, T.N. and N.S. Jayant, "An Adaptive Clustering Algorithm for Image Segmentation," *Proc. Second Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1988, pp. 310-315.

Perona, P. and J. Malik, "Scale-Space and Edge Detection Using Anisotropic Diffusion," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 12, No. 7, 1990, pp. 629-639.

Perona, P. and J. Malik, "Detecting and Localizing Edges Composed of Steps, Peaks, and Roofs," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 52-57.

Perry, A. and D.G. Lowe, "Segmentation of Textured Images," *Proc. IEEE Conf. Computer Vision and Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1989, pp. 319-325.

Pong, T.-C., et al., "Experiments in Segmentation Using a Facet Model Region Grower," *Computer Vision, Graphics and Image Processing,* Vol. 25, No. 1, 1984, pp. 1-23.

Raafat, H.M. and A.K.C. Wong, "A Texture Information-Directed Region Growing Algorithm for Image Segmentation and Region Classification," *Computer Vision, Graphics and Image Processing,* Vol. 43, No. 1, 1988, pp. 1-21.

Rao, A.R., *Taxonomy for Texture Description and Identification,* Springer-Verlag, New York, N.Y., 1990.

Rao, A.R. and R.C. Jain, "Analyzing Oriented Textures Through Phase Portraits," *Proc. Tenth Int'l Conf. Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 336-340.

Rao, A.R. and B.G. Schunck, "Computing Oriented Texture Fields," *Proc. IEEE Conf. Computer Vision and Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1989, pp. 61-69.

Rao, K. and R. Nevatia, "Computing Volume Descriptions from Sparse 3-D Data," *Int'l J. Computer Vision,* Vol. 2, No. 1, 1988, pp. 33-50.

Reed, T.R. and H. Wechsler, "Tracking of Nonstationarities of Texture Fields," *Signal Processing,* Vol. 14, 1988, pp. 95-102.

Reed, T.R. and H. Wechsler, "Segmentation of Textured Images and Gestalt Organization Using Spatial/Spatial-Frequency Representations," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 12, No. 1, 1990, pp. 1-12.

Reichenbach, S.E., S.K. Park, and R. Alter-Gartenberg, "Optimal Small Kernels for Edge Detection," *Proc. Tenth Int'l Conf. Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 57-63.

Rimey, R.D. and F.S. Cohen, "A Maximum-Likelihood Approach to Segmenting Range Data," *IEEE J. Robotics and Automation,* Vol. 4, No. 3, 1988, pp. 277-286.

Rosenfeld, A., "Image Analysis: Problems, Progress, and Prospects," *Pattern Recognition,* Vol. 17, No. 1, 1984, pp. 3-12.

Rosenfeld, A. and L.S. Davis, "Image Segmentation and Image Models," *Proc. IEEE,* Vol. 67, No. 5, IEEE Press, New York, N.Y., 1979, pp. 764-772.

Sahoo, P.K., et al., "A Survey of Thresholding Techniques," *Computer Vision, Graphics and Image Processing,* Vol. 41, 1988, pp. 233-260.

Shemlon, S., S.M. Dunn, and T. Liang, "Progressive Knowledge Use in Incremental Segmentation," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conference,* VII, 1095, 1989, pp. 239-250.

Sotak. Jr., G.E. and K.L. Boyer, "The Laplacian-of-Gaussian Kernel: A Formal Analysis and Design Procedure for Fast, Accurate Convolution and Full-Frame Output," *Computer Vision, Graphics and Image Processing,* Vol. 48, 1989, pp. 147-189.

Straub, B.J. and W.E. Blanz, "Combined Decision Theoretic and Syntactic Approach to Image Segmentation," *Machine Vision and Applications,* Vol. 2, No. 1, 1989, pp. 17-30.

Tan, H.L., S.B. Gelfand, and E.J. Delp, "A Cost Minimization Approach to Edge Detection Using Simulated Annealing," *Proc. IEEE Conf. Computer Vision and Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1989, pp. 86-91.

Tanaka, M. and T. Katayama, "Edge Detection and Restoration of Noisy Images by the Expectation-Maximization Algorithm," *Signal Processing,* Vol. 17, 1989, pp. 213-226.

Taxt, T., P.J. Flynn, and A.K. Jain, "Segmentation of Document Images as Statistical Classification task," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 11, No. 12, 1989, pp. 1322-1329.

Tenenbaum, J.M. and H.G. Barrow, "IGS: A Paradigm for Integrating Image Segmentation and Interpretation," *Proc. Third Int'l Conf. Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1976, pp. 435-444.

Toh, P.-S. and A.K. Forrest, "Occlusion Detection in Early Vision," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 126-132.

Tuceryan, M., A.K. Jain, and Y. Lee, "Texture Segmentation Using Voronoi Polygons," *Proc. IEEE Conf. Computer Vision and Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1988, pp. 94-99.

Van Vilet, L.J., I.T. Young, and G.L. Beckers, "A Nonlinear Laplace Operator as Edge Detector in Noisy Images," *Computer Vision, Graphics and Image Processing,* Vol. 45, 1989, pp. 167-195.

Vehel, J.L., "About Lacunarity, Some Links Between Fractal and Integral Geometry, and an Application to Texture Segmentation," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 380-384.

Vilnrotter, F.M., R. Nevatia, and K.E. Price, "Structural Analysis of Natural Textures," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 8, No. 1, 1986, pp. 76-89.

Vistnes, R., "Texture Models and Image Measures for Segmentation," *Int'l J. Computer Vision,* Vol. 3, No. 4, 1989, pp. 313-336.

Voorhees, H. and T. Poggio, "Detecting Blobs as Textons in Natural Images," *Proc. DARPA Image Understanding Workshop,* 1987, pp. 892-899.

Williams, D.J. and M.A. Shah, "Multiple Scale Edge Linking," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conference VII,* Vol. 1095, 1989, pp. 13-24.

Williams, L.R., "Perceptual Organization of Occluding Contours," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 133-137.

Wilson, R. and M. Spann, "Finite Prolate Spheroidal Sequences and Their Applications II: Image Feature Description and Segmentation,"

IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 10, No. 2, 1988, pp. 193-203.
Wong, A.K.C. and P.K. Sahoo, "A Gray-Level Threshold Selection Method Based on Maximum Entropy Principle," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, No. 4, 1989, pp. 866-871.
Yokoya, N. and M.D. Levine, "Range Image Segmentation Based on Differential Geometry: A Hybrid Approach," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 6, 1989, pp. 643-649.
Yonawitz, S.D. and A.M. Bruckstein, "A New Method for Image Segmentation," *Computer Vision, Graphics and Image Processing*, Vol. 46, No. 1, 1989, pp. 82-95.
Zhou, Y.T., V. Venkataswar, and R. Chellappa, "Edge Detection and Linear Feature Extraction Using a 2-D Random Field Model," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 1, 1989, pp. 84-95.
Zucker, S.W., "Early Orientation Selection: Tangent Fields and the Dimensionality of their Support," *Computer Vision, Graphics and Image Processing*, Vol. 32, No. 1, 1985, pp. 74-103.
Zucker, S.W., A. Dobbins, and L. Iverson, "Two Stages of Curve Detection Suggest Two Styles of Visual Computation," *Neural Computation*, Vol. 1, No. 1, 1989, pp. 68-81.

Chapter 3: Feature Extraction and Matching
Selected Bibliography

Aloimonos, J., "Visual Shape Computation," *Proc. IEEE*, Vol. 76, No. 8, IEEE Press, New York, N.Y., 1988, pp. 899-916.

Alvertos, N., D. Brzakovic, and R.C. Gonzalez, "Camera Geometries for Image Matching in 3-D Machine Vision," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 9, 1989, pp. 897-915.

Amini, A.A., T.E. Weymouth, and D.J. Anderson, "A Parallel Algorithm for Determining Two-Dimensional Object Positions Using Incomplete Information About Their Boundaries," *Pattern Recognition*, Vol. 22, No. 1, 1989, pp. 21-28.

Arcelli, C. and G.S. di Baja, "A Width-Independent Fast Thinning Algorithm," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 4, 1985, pp. 463-474.

Asada, M., "Map Building for a Mobile Robot from Sensory Data," *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 20, No. 6, 1990, pp. 1326-1336.

Bajcsy, R. and S. Kovacic, "Multiresolution Elastic Matching," *Computer Vision, Graphics and Image Processing*, Vol. 46, No. 1, 1989, pp. 1-21.

Ballard, D.H., "Strip Trees: A Hierarchical Representation for Curves," *Communications of the ACM*, Vol. 24, No. 5, 1981, pp. 310-321.

Bell, B. and L.F. Pau, "Contour Tracking and Corner Detection in a Logic Programming Environment," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 9, 1990, pp. 913-917.

Besl, P. and R.C. Jain, "Invariant Surface Characteristics for 3-D Object Recognition in Range Images," *Computer Vision, Graphics and Image Processing*, Vol. 33, No. 1, 1986, pp. 33-79.

Beveridge, J.R., R. Weiss, and E.M. Riseman, "Optimization of 2-D Model Matching," *Proc. DARPA Image Understanding Workshop*, 1989, pp. 815-830.

Beveridge, J.R., R. Weiss, and E.M. Riseman, "Combinatorial Optimization Applied to Variable Scale 2-D Model Matching," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 18-23.

Boldt, M., R. Weiss, and E. Riseman, "Token-Based Extraction of Straight Lines," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, No. 6, 1989, pp. 1581-1594.

Bolle, R.M., A. Califano, and R. Kjeldsen, "Data and Model Driven Focus of Foveation," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 1-7.

Bolles, R.C. and R.A. Cain, "Recognizing and Locating Partially Visible Objects: The Local-Feature-Focus Method," *Int'l J. Robotics Research*, Vol. 1, No. 3, 1982, pp. 57-82.

Borgefors, G., "Hierarchical Chamfer Matching: A Parametric Edge Matching Algorithm," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 6, 1988, pp. 849-865.

Brady, M., et al., "Describing Surfaces," *Computer Vision, Graphics and Image Processing*, Vol. 32, No. 1, 1985, pp. 1-28.

Brown, C.M., "Inherent Bias and Noise in the Hough Transform," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 5, No. 5, 1983, pp. 493-505.

Brown, M.K., "The Extraction of Curved Surface Features with Generic Range Sensors," *Int'l J. Robotics Research*, Vol. 5, No. 1, 1986, pp. 3-18.

Burns, J.B., A.R. Hanson, and E.M. Riseman, "Extracting Straight Lines," *Proc. Seventh Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1984, pp. 482-485.

Burt, P.J. and E.H. Adelson, "A Multiresolution Spline with Applications to Image Mosaics," *ACM Trans. on Graphics*, Vol. 2, No. 4, 1983, pp. 217-236.

Califano, A., R.M. Bolles, and R.W. Taylor, "Generalized Neighborhood: A New Approach to Complex Feature Extraction," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 192-199.

Canning, J., et al., "Symbolic Pixel Labeling for Curvilinear Feature Detection," *Pattern Recognition Letters*, Vol. 8, No. 5, 1988, pp. 299-310.

Cao, X. and F. Deravi, "An Efficient Method for Multiple-Circle Detection," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 744-747.

Casasent, D. and R. Krishnapuram, "Curved Object Location by Hough Transformations and Inversions," *Pattern Recognition*, Vol. 20, No. 2, 1987, pp. 181-188.

Cass, T.A., "Feature Matching for Object Localization in the Presence of Uncertainty," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 360-364.

Chakravarthy, C. and R. Kasturi, "Pose Clustering on Constraints for Object Recognition," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif, 1991, pp. 16-21.

Chen, D.S., "A Data-Driven Intermediate Level Feature Extraction Algorithm," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 7, 1989, pp. 749-758.

Chen, H.H., "Pose Determination from Line-to-Plane Correspondences: Existence Condition and Closed-Form Solutions," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 374-379.

Chen, M.H. and P.F. Yan, "A Multiscaling Approach Based on Morphological Filtering," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 7, 1989, pp. 694-700.

Cipolla, R. and A. Blake, "The Dynamic Analysis of Apparent Contours," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 616-625.

Coggins, J.M. and A.K. Jain, "A Spatial Filtering Approach to Texture Analysis," *Pattern Recognition*, Vol. 3, 1985, pp. 195-203.

Coleman, E.N., Jr. and R.C. Jain, "Obtaining 3-Dimensional Shape of Textured and Specular Surface Using Four Source Photometry," *Computer Graphics and Image Processing*, Vol. 18, No. 4, 1982, pp. 309-328.

Connelly, S. and A. Rosenfeld, "A Pyramid Algorithm for Fast Curve Extraction," *Computer Vision, Graphics and Image Processing*, Vol. 49, 1990, pp. 332-345.

Costa, M., et al., "Optimal Affine-Invariant Point Matching," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conf. VII*, Vol. 1095, 1989, pp. 515-530.

Cross, G.R. and A.K. Jain, "Markov Random Field Texture Models," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 5, No. 1, 1983, pp. 25-39.

Deriche, R. and G. Giraudon, "Accurate Corner Cetection: An Analytical Study," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 66-70.

Dom, B., W. Niblack, and J. Sheinvald, "Feature Selection with Stochastic Complexity," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 241-249.

Dougherty, E.R., "The Dual Representation of Gray-Scale Morphological Filters," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 172-177.

Dougherty, E.R. and C.R. Giardina, "Closed-Form Representation of Convolution, Dilation, and Erosion in the Context of Image Algebra," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 754-759.

Dougherty, E.R. and C.R. Giardina, "Morphology in Umbra Matrices," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 2, 1988, pp. 367-385.

Dougherty, E.R. and P. Sehdev, "A Robust Image Processing Language in the Context of Image Algebra," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 748-753.

Dudani, S., K.J. Breeding, and R.B. McGhee, "Aircraft Identification by Moment Invariants," *IEEE Trans. Computers*, Vol. C-26, No. 1, 1977, pp. 39-46.

Dudek, G. and J. Tsotsos, "Recognizing Planar Curves Using Curvature-Tuned Smoothing," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 130-135.

Fahn, C.S., J.F. Wang, and J.Y. Lee, "An Adaptive Reduction Procedure for the Piecewise Linear Approximation of Digitized Curves," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 9, 1989, pp. 967-973.

Ferrie, F.P. and J. Lagarde, "Curvature Consistency Improves Local Shading Analysis," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 70-76.

Fischler, M.A. and P. Barrett, "An Iconic Transform for Sketch and Shape Abstraction," *Computer Graphics and Image Processing*, Vol. 13, No. 3, 1980, pp. 334-360.

Fischler, M.A. and R.C. Bolles, "Random Sample Consensus: A Paradigm for Model Fitting with Application to Image Analysis and Automated Cartography," *Communications ACM*, Vol. 24, No. 6, 1981, pp. 381-395.

Fleck, M.M., "Multiple Widths Yield Reliable Finite Differences," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 58-61.

Freeman, W.T. and E.H. Adelson, "Steerable Filters for Early Vision, Image Analysis, and Wavelet Decomposition," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 406-415.

Friedberg, S.A., "Finding Axes of Skewed Symmetry," *Computer Vision, Graphics and Image Processing*, Vol. 34, No. 2, 1986, pp. 138-155.

Fua, P. and A.J. Hanson, "Objective Functions for Feature Discrimination," *Proc. Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufman Publishers, Inc., San Mateo, Calif., 1989, pp. 1596-1602.

Goldgof, D.B., T.S. Huang, and H. Lee, "A Curvature-Based Approach to Terrain Recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 11, 1989, pp. 1213-1217.

Grimson, W.E.L., "On the Recognition of Curved Objects," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 6, 1989, pp. 632-643.

Grimson, W.E.L., "On the Recognition of Parameterized 2-D Objects," *Int'l J. Computer Vision*, Vol. 2, No. 2, 1989, pp. 353-371.

Grimson, W.E.L., "The Effect of Indexing on the Complexity of Object Recognition," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 644-653.

Grimson, W.E.L. and D.P. Huttenlocher, "On the Sensitivity of Geometric Hashing," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 334-339.

Grimson, W.E.L. and D.P. Huttenlocher, "On the Sensitivity of the Hough Transform for Object Recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 3, 1990, pp. 255-274.

Grimson, W.E.L. and T. Lozano-Perez, "Localizing Overlapping Parts by Searching the Interpretation Tree," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 4, 1987, pp. 469-482.

Grossmann, P., "From 3-D Line Segments to Objects and Spaces," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 216-221.

Gutfinger, D., et al., "Robust Curve Detection by Temporal Geodesics," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 752-756.

Han, J.H., "Detection of Convex and Concave Discontinuous Points in a Plane Curve," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 71-74.

Haralick, R.M., "Statistical and Structural Approaches to Texture," *Proc. IEEE*, IEEE Press, New York, N.Y., Vol. 67, No. 5, 1979, pp. 786-804.

Haralick, R.M., L.T. Watson, and T.J. Laffey, "The Topographic Primal Sketch," *Int'l J. Robotics Research*, Vol. 2, No. 1, 1983, pp. 50-72.

Harlow, C.A., M.M. Trivedi, and R.W. Conners, "Use of Texture Operators in Scene Analysis," *Optical Eng.*, Vol. 25, No. 11, 1986, pp. 1200-1206.

Henderson, T.C. and W.S. Fai, "The 3-D Hough Shape Transform," *Pattern Recognition*, 1984, pp. 235-238.

Henikoff, J. and L.G. Shapiro, "Interesting Patterns for Model-Based Machine Vision," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 535-539.

Horn, B.K.P. and E.J. Weldon Jr, "Filtering Closed Curves," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 8, No. 5, 1986, pp. 665-668.

Hu, G., "Symmetry Detection of 2-D Figures," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conf. VIII,* Vol. 1293, 1990, pp. 516-523.

Hwang, V.S.S., "Recognizing and Locating Partially Occluded 2-D Objects: Symbolic Clustering Method," *IEEE Trans. Systems, Man, and Cybernetics,* Vol. 19, No. 6, 1989, pp. 1644-1656.

Illingworth, J. and J. Kittler, "A Survey on Hough Transform," *Computer Vision, Graphics and Image Processing,* Vol. 44, No. 1, 1988, pp. 87-116.

Imai, H. and M. Iri, "Computational-Geometric Methods for Polygonal Approximations of a Curve," *Computer Vision, Graphics and Image Processing,* Vol. 36, No. 1, 1986, pp. 31-41.

Joo, H., R.M. Haralick, and L.G. Shapiro, "Toward the Automatic Generation of Mathematical Morphology Procedures Using Predicate Logic," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 156-167.

Kalvin, A., et al., "Two-Dimensional, Model-Based, Boundary Matching Using Footprints," *Int'l J. Robotics Research,* Vol. 5, No. 4, 1986, pp. 38-55.

Kanatani, K., "Hypothesizing and Testing Geometric Attributes of Image Data," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 370-373.

Kass, M., A. Witkin, and D. Terzopoulos, "Snakes: Active Contour Models," *Int'l J. Computer Vision,* Vol. 1, No. 4, 1988, pp. 321-331.

Koenderink, J.J. and A.J. van Doorn, "Representation of Local Geometry in the Visual System," *Biological Cybernetics,* Vol. 55, 1987, pp. 367-375.

Korn, A.F., "Toward a Symbolic Representation of Intensity Changes in Images," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 10, No. 5, 1988, pp. 610-625.

Koshimizu, H. and M. Numada, "On the Extensive Reconstruction of Hough Transform," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 740-743.

Kovalevsky, V.A., "New Definition and Fast Recognition of Digital Straight Segments and Arcs," *Proc. Tenth Int'l Conf. Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 31-34.

Lee, J.C. and E.E. Milios, "Matching Range Images of Human Faces," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 722-726.

Li, Z.C., et al., "Harmonic Models of Shape Transformations in Digital Images and Patterns," *Proc. Tenth Int'l Conf. Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 1-7.

Liang, P., "A New Transform for Curve Detection," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 748-751.

Link, N.K. and S.W. Zucker, "Corner Detection in Curvilinear Dot Grouping," *Biological Cybernetics,* Vol. 59, 1988, pp. 247-256.

Lipari, C., M. Trivedi, and C. Harlow, "Geometric Modeling and Recognition of Elongated Regions in Aerial Images," *IEEE Trans. Systems, Man, and Cybernetics,* Vol. 19, No. 6, 1989, pp. 1600-1612.

Liu, H.-C. and M.D. Srinath, "Partial Shape Classification Using Contour Matching in Distance Transformation," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 12, No. 11, 1990, pp. 1072-1079.

Lowe, D.G., "Organization of Smooth Image Curves at Multiple Scales," *Int'l J. Computer Vision,* Vol. 3, No. 2, 1989, pp. 119-130.

Lu, S.Y. and K.S. Fu, "A Syntactic Approach to Texture Analysis," *Computer Graphics and Image Processing,* Vol. 7, 1978, pp. 303-330.

Mackworth, A.K. and F. Mokhtarian, "The Renormalized Curvature Scale Space and the Evolution Properties of Planar Curves," *Proc. IEEE Conf. Computer Vision and Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1988, pp. 318-327.

Mandler, E., and M.F. Oberlander, "One-Pass Encoding of Connected Components in Multi-Valued Images," *Proc. Tenth Int'l Conf. Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 64-69.

Maragos, P., "Morphology-Based Symbolic Image Modeling, Multi-Scale Nonlinear Smoothing, and Pattern Spectrum," *Proc. IEEE Conf. Computer Vision and Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1988, pp. 766-773.

Maragos, P., "Optimal Morphological Approaches to Image Matching and Object Detection," *Proc. Second Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1988, pp. 695-699.

Maragos, P., "A Representation Theory for Morphological Image and Signal Processing," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 11, No. 6, 1989, pp. 586-599.

Maragos, P., "Pattern Spectrum and Multiscale Shape Representation," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 11, No. 7, 1989, pp. 701-716.

Marimont, D.H., "A Representation for Image Curves," *Proc. Nat'l Conf. on Artificial Intelligence,* MIT Press, Cambridge, Mass., 1984, pp. 237-242.

Marshall, S., "Review of Shape Coding Techniques," *Image and Vision Computing,* Vol. 7, No. 4, 1989, pp. 281-294.

Medioni, G. and Y. Yasumoto, "Corner Detection and Curve Representation Using Cubic B-Splines," *Computer Vision, Graphics and Image Processing,* Vol. 39, 1987, pp. 267-278.

Mehrotra, R. and W.I. Grosky, "Shape Matching Utilizing Indexed Hypothesis Generation and Testing," *IEEE Trans. Systems, Man, and Cybernetics,* Vol. 19, No. 1, 1989, pp. 70-77.

Milios, E.E., "Shape Matching Using Curvature Processes," *Computer Vision, Graphics and Image Processing,* Vol. 47, 1989, pp. 203-226.

Mitchell, O.R. and T.A. Grogan, "Global and Partial Shape Discrimination for Computer Vision," *Optical Eng.,* Vol. 23, No. 5, 1984, pp. 484-491.

Mitiche, A. and J.K. Aggarwal, "Contour Registration by Shape-Specific Points for Shape Matching," *Computer Vision, Graphics and Image Processing,* Vol. 22, 1983, pp. 396-408.

Mohan, R. and R. Nevatia, "Using Perceptual Organization to Extract 3-D Structures," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 11, 1989, pp. 1121-1139.

Mokhtarian, F., "Fingerprint Theorems for Curvature and Torsion Zero-Crossings," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 269-275.

Mokhtarian, F. and A. Mackworth, "Scale-Based Description and Recognition of Planar Curves and Two-Dimensional Shapes," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 1, 1986, pp. 34-43.

Moravec, H.P., "Toward Automatic Visual Obstacle Avoidance," *Proc. Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1977, p. 584.

Mulgaonkar, P.G., L.G. Shapiro, and R.M. Haralick, "Matching 'Sticks, Plates, and Blobs' Objects Using Geometric and Relational Constraints," *Image and Vision Computing*, Vol. 2, 1984, pp. 85-98.

Nevatia, R. and R. Babu, "Linear Feature Extraction and Description," *Computer Graphics and Image Processing*, Vol. 13, No. 3, 1980, pp. 257-269.

Nevatia, R. and K.E. Price, "Locating Structures in Aerial Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 4, No. 5, 1982, pp. 476-484.

Neveu, C.F., C.R. Dyer, and R.T. Chin, "Two-Dimensional Object Recognition Using Multiresolution Models," *Computer Vision, Graphics and Image Processing*, Vol. 34, No. 1, 1986, pp. 52-65.

Noble, J.A., "Finding Corners," *Image and Vision Computing*, Vol. 6, 1988, pp. 121-128.

Noble, J.A., "Morphological Feature Detection," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 112-116.

O'Gorman, L., "An Analysis of Feature Detectability from Curvature Estimation," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 235-240.

O'Gorman, L., "K x K Thinning," *Computer Vision, Graphics, and Image Processing*, Vol. 51, 1990, pp. 195-215.

Okutomi, M. and T. Kanade, "A Locally Adaptive Window for Signal Matching," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 190-199.

Parent, P. and S.W. Zucker, "Trace Inference, Curvature Consistency, and Curve Detection," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 8, 1989, pp. 823-839.

Parvin, B. and G. Medioni, "Adaptive Multiscale Feature Extraction from Range Data," *Computer Vision, Graphics and Image Processing*, Vol. 45, 1989, pp. 346-356.

Pentland, A.P., "Fractal-Based Description of Natural Scenes," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 6, No. 6, 1984, pp. 661-374.

Perlant, F.P. and D.M. McKeown, "Scene Registration in Aerial Image Analysis," *Proc. DARPA Image Understanding Workshop*, 1989, pp. 309-331.

Pham, S., "Digital Straight Segments," *Computer Vision, Graphics and Image Processing*, Vol. 36, No. 1, 1986, pp. 10-30.

Porrill, J., "Fitting Ellipses and Predicting Confidence Envelopes Using a Bias Corrected Kalman Filter," *Image and Vision Computing*, Vol. 8, No. 1, 1990, pp. 37-41.

Princen, J., J. Illingworth, and J. Kittler, "A Hierarchical Approach to Line Extraction," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 92-97.

Princen, J., J. Illingworth, and J. Kittler, "Hypothesis Testing: A Framework for Analysing and Optimising Hough Transform Performance," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 427-435.

Qian, J. and R.W. Ehrich, "A Framework for Uncertainty Reasoning in Hierarchical Visual Evidence Space," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 119-124.

Rangarajan, K., M. Shah, and D. Van Brackle, "Optimal Corner Detector," *Computer Vision, Graphics and Image Processing*, Vol. 48, 1989, pp. 230-245.

Rao, K. and R. Nevatia, "From Sparse 3-D Data Directly to Volumetric Shape Descriptions," *Proc. DARPA Image Understanding Workshop*, 1987, pp. 360-369.

Rao, K. and R. Nevatia, "Shape Description from Imperfect and Incomplete Data," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 125-129.

Reisfeld, D., H. Wolfson, and Y. Yeshurun, "Detection of Interest Points Using Symmetry," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 62-65.

Rhodes, M.F., et al., "A Monolithic Hough Transform Processor Based on Restructurable VLSI," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 1, 1988, pp. 106-110.

Risse, T., "Hough Transform for Line Recognition: Complexity of Evidence Accumulation and Cluster Detection," *Computer Vision, Graphics and Image Processing*, Vol. 46, 1989, pp. 327-345.

Ritter, G.X., J.N. Wilson, and J.L. Davidson, "Image Algebra: An Overview," *Computer Vision, Graphics and Image Processing*, Vol. 49, No. 3, 1990, 297-331.

Rodriguez, J.J. and J.K. Aggarwal, "Matching Aerial Images to 3-D Terrain Maps," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 12, 1990, pp. 1138-1149.

Rodriguez, J.J. and J.K. Aggarwal, "Terrain Matching by Analysis of Aerial Images," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 677-683.

Rosin, P.L. and G.A.W. West, "Segmenting Curves Into Elliptic Arcs and Straight Lines," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 75-79.

Safaee-Rad, R., K.C. Smith, and B. Benhabib, "Accurate Estimation of Elliptical Shape Parameters from a Grey-Level Image," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 20-26.

Sander, P.T., "Generic Curvature Features from 3-D Images," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, No. 6, 1989, pp. 1623-1636.

Sander, P.T. and S.W. Zucker, "Singularities of Principle Directions Fields from 3-D Images," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 666-670.
Sanz, J.L.C. and T.T. Huang, "Image Representation by Sign Information," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 7, 1989, pp. 729-738.
Serra, J., ed., *Image Analysis and Mathematical Morphology 2: Technical Advances*, Academic Press, New York, N.Y., 1988.
Shahraray, B. and D.J. Anderson, "Optimal Estimation of Contour Properties by Cross-Validated Regularization," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 6, 1989, pp. 600-610.
Shapiro, L.G. and R.M. Haralick, "A Metric for Comparing Relational Descriptions," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 1, 1985, pp. 90-94.
Shapiro, L.G. and H. Lu, "Accumulator-Based Inexact Matching Using Relational Summaries," *Machine Vision and Applications*, Vol. 3, No. 3, 1990, pp. 143-158.
Shashua, A. and S. Ullman, "Structural Saliency: The Detection of Globally Salient Structures Using a Locally Connected Network," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 321-327.
Sherman, D. and S. Peleg, "Stereo by Incremental Matching of Contours," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 11, 1990, pp. 1102-1106.
Shih, C-C. and R. Kasturi, "Extraction of Graphic Primitives from Images of Paper-based Drawings," *Machine Vision and Applications*, Vol. 2, 1989, pp. 103-113.
Shih, F.Y. and O.R. Mitchell, "Automated Fast Recognition and Location of Arbitrarily Shaped Objects by Image Morphology," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 774-789.
Sinha, D. and C.R. Giardina, "Discrete Black and White Object Recognition via Morphological Functions," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 2, 1990, pp. 275-293.
Sinha, S.S. and B.G. Schunck, "Discontinuity Preserving Surface Reconstruction," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 229-234.
Sitaraman, R. and A. Rosenfeld, "Probabilistic Analysis of Two Stage Matching," *Pattern Recognition*, Vol. 22, 1989, pp. 331-343.
Skolnick, M.M., S. Kim, and R. O'Bara, "Morphological Algorithms for Computing Non-Planar Point Neighborhoods on Cellular Automata," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 106-111.
Staib, L.H. and J.S. Duncan, "Parametrically Deformable Contour Models," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 98-103.
Stark, L. and K.W. Bowyer, "Using Functional Features for 3-D Object Recognition," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conf. VIII*, Vol. 1293, 1990, 212-223.
Stein, F. and G. Medioni, "Efficient Fast Two-Dimensional Object Recognition," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 13-17.
Stevens, K.A. and A. Brookes, "Detecting Structure by Symbolic Constructions on Tokens," *Computer Vision, Graphics and Image Processing*, Vol. 37, 1983, pp. 238-260.
Stockman, G., "Object Recognition and Localization via Pose Clustering," *Computer Vision, Graphics, and Image Processing*, Vol. 40, 1987, pp. 361-387.
Stockman, G., G. Lee, and S.-W. Chen, "Reconstruction Line Drawings from Wings: The Polygonal Case," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 526-529.
Svalbe, I.D., "Natural Representation for Straight Lines and the Hough Transform on Discrete Arrays," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 9, 1989, pp. 941-950.
Tanaka, H.T. and D.T.L. Lee, "Representing Surface Curvature Discontinuities on Curved Surfaces," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 304-308.
Tanaka, H.T., O. Kling, and D.T.L. Lee, "On Surface Curvature Computation from Level Set," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 155-160.
Tang, Y.Y. and C.Y. Suen, "Nonlinear Shape Restoration by Transformation Models," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 14-19.
Taubin, G., R.M. Bolle, and D.B. Cooper, "Representing and Comparing Shapes Using Shape Polynomials," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 510-516.
Tehrani, S., T.E. Weymouth, and B.G. Schunck, "Interpolating Cubic Spline Contours by Minimizing Second Derivative Discontinuity," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 713-717.
Tenenbaum, J.M., M.A. Fischler, and H.G. Barrow, "Scene Modeling: A Structural Basis for Image Description," in *Image Modeling*, A. Rosenfeld, ed., Academic Press, New York, N.Y., 1980, pp. 371-389.
Tomita, F., Y. Shirai, and S. Tsuji, "Description of Texture by Structural Analysis," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 4, No. 2, 1982, pp. 183-191.
Trivedi, M.M., et al., "Object Detection Based on Gray Level Cooccurrence," *Computer Vision, Graphics and Image Processing*, Vol. 28, 1984, pp. 199-219.
Truve, S., "Image Interpretation Using Multi-relational Grammars," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 146-155.
Tsotsos, J.K., "The Complexity of Perceptual Search Tasks," *Proc. Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1989, pp. 1571-1577.
Van Gool, L., J. Wagemans, and A.J. Oosterlinck, "Regularity Detection as a Strategy in Object Modeling and Recognition," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conf. VII*, Vol. 1095, 1989, 138-149.
Van Gool, L., et al., "Similarity Extraction and Modelling," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 530-534.

Vermuri, B.C., A. Mitiche, and J.K. Aggarwal, "Curvature-Based Representations of Objects from Range Data," *Image and Vision Computing*, Vol. 4, No. 2, 1986, pp. 107-114.

Verri, A. and T. Poggio, "Motion Field and Optical Flow: Qualitative Properties," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 5, 1989, pp. 490-498.

Vincent, L., "Graphs and Mathematical Morphology," *Signal Processing*, Vol. 16, 1989, pp. 365-388.

Vossepoel, A.M., J.P. Buys, and G. Koelewijn, "Skeletons from Chain-Coded Contours," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 70-73.

Walters, D., "Selection of Image Primitives for General-Purpose Visual Processing," *Computer Vision, Graphics and Image Processing*, Vol. 37, 1987, pp. 261-298.

Wang, Y.F., "Computation of Intrinsic Surface Properties with Structured Lighting," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conf. VII*, Vol. 1095, 1989, 321-332.

Wang, Y.F. and P. Liang, "A New Method for Computing Intrinsic Surface Properties," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 235-240.

Watson, L.T., T.J. Laffey, and R.M. Haralick, "Topographic Classification of Digital Intensity Surfaces Using Generalized Splines and the Discrete Cosine Transformation," *Computer Vision, Graphics and Image Processing*, Vol. 29, 1985, pp. 143-167.

Weiss, I., "Line Fitting in a Noisy Image," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 3, 1989, pp. 325-328.

Weng, J., "A Theory of Image Matching," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 200-209.

Whitten, G., "A Framework for Adaptive Scale Space Tracking Solutions to Problems in Computational Vision," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 210-221.

Williams, D.J. and M. Shah, "A Fast Algorithm for Active Contours," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 592-597.

Wilson, H.R. and W.A. Richards, "Mechanisms of Contour Curvature Discrimination," *J. Opt. Soc. Am. A*, Vol. 6, No. 1, 1989, pp. 106-115.

Wilson, R. and M. Spann, "Finite Prolate Spheroidal Sequences and their Applications II: Image Feature Description and Segmentation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 2, 1988, pp. 193-203.

Yuen, H.K., J. Illingworth, and J. Kittler, "Detecting Partially Occluded Ellipses Using the Hough Transform," *Image and Vision Computing*, Vol. 7, 1989, pp. 31-37.

Yuen, H.K., et al., "Comparative Study of Hough Transform Methods for Circle Finding," *Image and Vision Computing*, Vol. 8, No. 1, 1990, pp. 71-77.

Yuille, A.L., D.S. Cohen, and P.W. Hallinan, "Feature Extraction from Faces Using Deformable Templates," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 104-109.

Zhong, S. and S. Mallat, "Compact Image Representation from Multiscale Edges," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 522-525.

Zucker, S.W., A. Dobbins, and L. Iverson, "Two Stages of Curve Detection Suggest Two Styles of Visual Computation," *Neural Computation*, Vol. 1, No. 1, 1989, pp. 68-81.

Chapter 4: Constraint Exploitation and Recovery of Shape
Selected Bibliography

Abbott, L.A. and N. Ahuja, "Surface Reconstruction by Dynamic Integration of Focus, Camera Vergence, and Stereo," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 532-543.

Abbott, L.A. and N. Ahuja, "Active Surface Reconstruction by Integrating Focus, Vergence, Stereo, and Camera Calibration," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 489-493.

Adorni, G., et al., "From Early Processing to Conceptual Reasoning: An Attempt to Fill the Gap," *Proc. Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1987, pp. 775-778.

Ahuja, N. and M. Tuceryan, "Extraction of Early Perceptual Structure in Dot Patterns: Integrating Regions, Boundary, and Component Gestalt," *Computer Vision, Graphics and Image Processing*, Vol. 48, 1989, pp. 304-356.

Aloimonos, J., "Shape from Texture," *Biological Cybernetics*, Vol. 58, No. 5, 1988, pp. 345-360.

Aloimonos, J., "Unifying Shading and Texture Through an Active Observer," *Proc. Royal Soc. Lond. B*, Vol. 238, 1989, pp. 25-37.

Aloimonos, J.Y. and A. Basu, "Combining Information in Low-Level Vision," *Proc. DARPA Image Understanding Workshop*, 1988, pp. 862-906.

Aloimonos, J.Y. and C. Brown, "Robust Computations of Intrinsic Images from Multiple Cues," *Advances in Computer Vision*, Erlbaum, Hillsdale, N.J., 1988, pp. 115-163.

Aloimonos, J.Y. and D. Shulman, *Integration of Visual Modules: An Extension of the Marr Paradigm*, Academic Press, Boston, Mass., 1989.

Aloimonos, J. and M. Swain, "Shape from Patterns: Regularization," *Int'l J. Computer Vision*, Vol. 2, 1988, pp. 171-187.

Amadasun, M. and R. King, "Textural Features Corresponding to Textural Properties," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, No. 12, 1989, pp. 1264-1274.

Amini, A.A., S. Tehrani, and T.E. Weymouth, "Using Dynamic Programming for Minimizing the Energy of Active Contours in the Presence of Hard Constraints," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 95-99.

Ayache, N. and O.D. Faugeras, "Building, Registering, and Fusing Noisy Visual Maps," *Proc. First Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 73-82.

Bajcsy, R . and L. Lieberman, "Texture Gradient as a Depth Cue," *Computer Graphics and Image Processing*, Vol. 5, No. 1, 1977, pp. 52-67.

Baldwin, R., et al., "Stereo Reconstruction Through Disparity Space," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 143-146.

Barnard, S.T., "Interpreting Perspective Images," *Artificial Intelligence*, Vol. 21, 1983, pp. 435-462.

Barnard, S.T., "Choosing a Basis for Perceptual Space," *Computer Vision, Graphics and Image Processing*, Vol. 29, 1985, pp. 87-99.

Barnard, S.T., "Stochastic Stereo Matching Over Scale," *Int'l J. Computer Vision*, Vol. 3, No. 1, 1989, pp. 17-32.

Barnard, S.T. and M.A. Fischler, "Computational Stereo," *ACM Computing Surveys*, Vol. 14, No. 4, 1982, pp. 553-572.

Barrow, H.G. and J.M. Tenenbaum, "Computational Vision," *Proc. IEEE*, Vol. 69, No. 5, IEEE Press, New York, N.Y., 1981, pp. 572-595.

Bertero, M., T.A. Poggio, and V. Torre, "Ill-Posed Problems in Early Vision," *Proc. IEEE*, Vol. 76, No. 8, IEEE Press, New York, N.Y., 1988, pp. 869-889.

Binford, T.O., "Inferring Surfaces from Images," *Artificial Intelligence*, Vol. 17, 1981, pp. 205-244.

Blake, A., "Specular Stereo," *Proc. Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1985, pp. 973-976.

Blake, A., "Comparison of the Efficiency of Deterministic and Stochastic Algorithms for Visual Reconstruction," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 1, 1989, pp. 2-12.

Blake, A. and G. Brelstaff, "Geometry from Specularities," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 394-403.

Blostein, S.D. and T.S. Huang, "Quantization Errors in Stereo Triangulation," *Proc First Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 325-334.

Bodington, R., G.D. Sullivan, and K.D. Baker, "Consistent Labeling of Image Features Using an Assumption-Based Truth Maintenance System," *Image and Vision Computing*, Vol. 7, 1989, pp. 43-49.

Boult, T.E. and L.-H. Chen, "Synergistic Smooth Surface Stereo," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 118-122.

Boyer, K.L., D.M. Wuescher, and S. Sarkar, "Dynamic Edge Warping: Experiments in Disparity Estimation Under Weak Constraints," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 471-475.

Bozma, H.I. and J.S. Duncan, "Admissibility of Constraint Functions in Relaxation Labeling," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 328-332.

Brady, J.M., "Computational Approaches to Image Understanding," *ACM Computing Surveys*, Vol. 14, No. 1, 1982, pp. 3-71.

Brady, J.M. and B.K.P. Horn, "Rotationally Symmetric Operators for Surface Interpolation," *Computer Vision, Graphics and Image Processing*, Vol. 22, No. 3, 1983, pp. 36-61.

Brady, M. and A. Yuille, "An Extremum Principle for Shape from Contour," in *Vision, Brain, and Cooperative Computation*, M.A. Arbib and A.R. Hanson, eds., MIT Press, Cambridge, Mass., 1987.

Brint, A.T. and M. Brady, "Stereo Matching of Curves," *Image and Vision Computing*, Vol. 8, No.1, 1990, pp. 50-56.

Brockelbank, D.C. and Y.H. Yang, "An Experimental Investigation in the Use of Color in Computational Stereopsis," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, No. 6, 1989, pp. 1365-1383.

Brown, L.G. and H. Shvaytser, "Surface Orientation from Projective Foreshortening of Isotropic Texture Autocorrelation," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 510-514.

Bruckstein, A.M., "On Shape from Shading," *Computer Vision, Graphics and Image Processing*, Vol. 44, 1988, pp. 139-154.

Bulthoff, H.H. and H.A. Mallot, "Integration of Depth Modules: Stereo and Shading," *J. Opt. Soc. Am. A*, Vol. 5, No. 10, 1988, pp. 1749-1758.

Cavanagh, P., "Reconstructing the Third Dimension: Interactions Between Color, Texture, Motion, Binocular Disparity, and Shape," *Computer Vision, Graphics and Image Processing*, Vol. 37, 1987, pp. 171-195.

Chou, P.B. and C.M. Brown, "The Theory and Practice of Bayesian Image Labeling," *Int'l J. Computer Vision*, Vol. 4, No. 3, 1990, pp. 185-210.

Clark, J.J. and A.L. Yuille, "Shape from Shading via the Fusion of Specular and Lambertian Image Components," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 88-92.

Cochran, S.D. and G. Medioni, "Accurate Surface Description from Binocular Stereo," *Proc. IEEE Workshop on Interpretation of 3-D Scenes*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 16-23.

Coleman Jr., E. North and R.C. Jain, "Obtaining 3-Dimensional Shape of Textured and Specular Surfaces Using Four-Source Photometry," *Computer Graphics and Image Processing*, Vol. 18, No. 4, 1982, pp. 309-328.

Cooper, D.B., Y.-P. Hung, and G. Taubin, "A New Model-Based Stereo Approach for 3-D Surface Reconstruction," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 74-83.

Cross, G.R. and A.K. Jain, "Markov Random Field Texture Models," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 5, No. 1, 1983, pp. 25-39.

Darrell, T. and K. Wohn, "Pyramid Based Depth from Focus," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 504-509.

Das, S. and N. Ahuja, "Integrating Multiresolution Image Acquisition and Coarse-to-Fine Surface Reconstruction from Stereo," *Proc. IEEE Workshop on Interpretation of 3-D Scenes*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 9-15.

Das, S. and N. Ahuja, "Multiresolution Image Acquisition and Surface Reconstruction," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 485-488.

Davis, L.S. and T.C. Henderson, "Hierarchical Constraint Processes for Shape Analysis," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 3, No. 3, 1981, pp. 265-277.

Davis, L.S. and A. Rosenfeld, "Cooperating Processes for Low-Level Vision: A Survey," *Artificial Intelligence*, Vol. 17, 1981, pp. 245-264.

Dhond, U.R. and J.K. Aggarwal, "Structure from Stereo - A Review," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, No. 6, 1989, pp. 1489-1510.

Draper, S.W., "The Use of Gradient and Dual Space in Line-Drawing Interpretation," *Artificial Intelligence*, Vol. 17, 1981, pp. 461-508.

Draper, B.A., et al., "The Schema System," *Int'l J. Computer Vision*, Vol. 2, No. 3, 1989, pp. 209-250.

Duncan, J.S. and W. Frei, "Relaxation Labeling Using Continuous Label Sets," *Pattern Recognition Letters*, Vol. 9, No. 1, 1989, pp. 7-37.

Durrant-Whyte, H.F., "Consistent Integration and Propagation of Disparate Sensor Observations," *Int'l J. Robotics Research*, Vol. 6, No. 3, 1987, pp. 3-24.

Eastman, R.D. and A.M. Waxman, "Using Disparity Functionals for Stereo Correspondence and Surface Reconstruction," *Computer Vision, Graphics and Image Processing*, Vol. 39, No. 1, 1987, pp. 73-101.

Eklundh, J.O., H. Yamamoto, and A. Rosenfeld, "A Relaxation Method for Multispectral Pixel Classification," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 2, No. 1, 1980, pp. 72-75.

Ferrie, F.P. and M.D. Levine, "Where and Why Local Shading Analysis Works," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 2, 1989, pp. 198-206.

Forsyth, D. and A. Zisserman, "Shape from Shading in the Light of Mutual Illumination," *Image and Vision Computing*, Vol. 8, No. 1, 1990, pp. 42-49.

Frankot, R.T. and R. Chellappa, "A Method for Enforcing Integrability in Shape from Shading Algorithms," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 4, 1988, pp. 439-451.

Gagalowicz, A., "Collaboration Between Computer Graphics and Computer Vision," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 733-739.

Gamble, E., et al., "Integration of Vision Modules and Labeling of Surface Discontinuities," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, No. 6, 1989, pp. 1576-1580.

Garding, J., "Shape from Texture and Contour by Weak Isotropy," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 324-330.

Gennert, M.A., "Brightness-Based Stereo Matching," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 139-143.

Giblin, P. and R. Weiss, "Reconstruction of Surfaces from Profiles," *Proc. First Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 136-144.

Gibson, J.J., *The Perception of the Visual World*, Riverside Press, Cambridge, Mass., 1950.

Govindaraju, V., S.N. Srihari, and D.B. Sher, "A Computational Model for Face Location," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 718-721.

Granlund, G.H. and H. Knutsson, "Contrast of Structured and Homogeneous Representations," in *Physical and Biological Processing of Images*, O.J. Braddick and A.C. Sleigh, eds., Springer-Verlag, Berlin, 1983, pp. 1-24.

Grimson, W.E.L., "An Implementation of a Computational Theory of Visual Surface Interpolation," *Computer Graphics and Image Processing*, Vol. 22, No. 1, 1983, pp. 39-69.

Grimson, W.E.L., "Surface Consistency Constraints in Vision," *Computer Vision, Graphics and Image Processing*, Vol. 24, No. 1, 1983, pp. 28-51.

Grimson, W.E.L., "Computational Experiments with a Feature Based Stereo Algorithm," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 1, 1985, pp. 17-34.

Grimson, W.E.L., "The Combinatorics of Local Constraints in Model-Based Recognition and Localization from Sparse Data," *J. Assoc. Computing Machinery*, Vol. 33, No. 4, 1986, pp. 658-686.

Grimson, W.E.L., "The Combinatorics of Object Recognition in Clustered Environments Using Constrained Search," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 218-227.

Griswold, N.C. and C.P. Yeh, "A New Stereo Vision Model Based Upon the Binocular Fusion Concept," *Computer Vision, Graphics and Image Processing*, Vol. 41, 1988, pp. 153-171.

Grossberg, S. and E. Mingolla, "Neural Dynamics of Surface Perception: Boundary Webs, Illuminants, and Shape-from-Shading," *Computer Vision, Graphics and Image Processing*, Vol. 37, 1987, pp. 116-165.

Grosso, E., G. Sandini, and M. Tistarelli, "3-D Object Reconstruction Using Stereo and Motion," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, No. 6, 1989, pp. 1465-1476.

Gusgen, H.W. and J. Hertzberg, "Some Fundamental Properties of Local Constraint Propagation," *Artificial Intelligence*, Vol. 36, 1988, pp. 237-247.

Haralick, R., "Monocular Vision Using Inverse Perspective Projection Geometry: Analytic Relations," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 370-378.

Haralick, R.M. and L.G. Shapiro, "The Consistent Labeling Problem: Part I," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 1, No. 2, 1979, pp. 173-184.

Haralick, R.M. and L.G. Shapiro, "The Consistent Labeling Problem: Part II," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 2, No. 3, 1980, pp. 193-203.

Harmon, S.Y., G.L. Bianchini, and B.E. Pinz, "Sensor Fusion Through a Distributed Blackboard," *Proc. IEEE Int'l Conf. Robotics and Automation*, IEEE CS Press, Los Alamitos, Calif., 1986, pp. 2002-2011.

Hartt, K. and M. Carlotto, "A Method for Shape-from-Shading Using Multiple Images Acquired Under Different Viewing and Lighting Conditions," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 53-60.

Healey, G. and T.O. Binford, "Local Shape from Specularity," *Computer Vision, Graphics and Image Processing*, Vol. 42, No. 1, 1988, pp. 62-86.

Hoff, W. and N. Ahuja, "Surfaces from Stereo: Integrating Feature Matching, Disparity Estimation, and Contour Detection," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 2, 1989, pp. 121-136.

Horaud, R., "Spatial Object Perception from an Image," *Proc. Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufmann Publishers, Inc, San Mateo, Calif., 1985, pp. 1116-1119.

Horaud, R. and T. Skordas, "Stereo Correspondence Through Feature Grouping and Maximal Cliques," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 11, 1989, pp. 1168-1180.

Horn, B.K.P., "Hill Shading and the Reflectance Map," *Proc. IEEE*, Vol. 69, No. 1, IEEE Press, New York, N.Y., 1981, pp. 14-47.

Horn, B.K.P., "Closed-Form Solution of Absolute Orientation Using Unit Quaternions," *J. Opt. Soc. Am. A*, Vol. 4, No. 4, 1987, pp. 629-642.

Horn, B.K.P., "Relative Orientation," *Int'l J. Computer Vision*, Vol. 4, no. 1, 1989, pp. 59-77.

Horn, B.K.P., "Height and Gradient from Shading," *Int'l J. Computer Vision*, Vol. 5, No. 1, 1990, pp. 37-75.

Horn, B.K.P. and M.J. Brooks, "The Variational Approach to Shape from Shading," *Computer Vision, Graphics and Image Processing*, Vol. 33, 1986, pp. 174-208.

Hu, G. and G. Stockman, "3-D Surface Solution Using Structured Light and Constraint Propagation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 4, 1989, pp. 390-402.

Huffman, D.A., "Impossible Interpreting Pictures of Polyhedral Scenes," *Artificial Intelligence*, Vol. 4, 1973, pp. 121-137.

Hummel, R.A. and S.W. Zucker, "On the Foundations of Relaxation Labeling Processes," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 5, No. 3, 1983, pp. 267-287.

Hutchinson, J., et al., "Computing Motion Using Analog and Binary Resistive Networks," *Computer*, Vol. 21, No. 3, 1988, pp. 52-63.

Ikeuchi, K., "Shape from Regular Patterns," *Artificial Intelligence*, Vol. 22, No. 1, 1984, pp. 49-75.

Ikeuchi, K., "Determining a Depth Map Using a Dual Photometric Stereo," *Int'l J. Robotics Research*, Vol. 6, No. 1, 1987, pp. 15-31.

Ikeuchi, K., "Determining Surface Orientation of Specular Surfaces by Using the Photometric Stereo Method," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 3, No. 6, 1981, pp. 661-669.

Ikeuchi, K., et al., "Determining Grasp Configurations Using Photometric Stereo and the PRISM Binocular Stereo System," *Int'l J. Robotics Research*, Vol. 5, 1986, pp. 46-65.

Ishiguro, H., M. Yamamoto, and S. Tsuji, "Omni-directional Stereo for Making Global Map," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 540-547.

Iwahori, Y., H. Sugie, and N. Ishii, "Reconstructing Shape From Shading Images Under Point Light Source Illumination," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 83-87.

Jain, R.C., S. Bartlett, and N. O'Brien, "Motion Stereo Using Ego-Motion Complex Logarithmic Mapping," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 3, 1987, pp. 356-369.

Jamison, T.A. and R.J. Schalkoff, "Image Labeling: A Neural Network Approach," *Image and Vision Computing*, Vol. 6, 1988, pp. 203-214.

Jau, Y.C. and R.T. Chin, "Shape from Texture Using the Wigner Distribution," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 515-523.

Jepson, A.D. and M.R.M. Jenkin, "The Fast Computation of Disparity from Phase Differences," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif. 1989, pp. 398-403.

Jou, J.Y. and A.C. Bovik, "Improved Initial Approximation and Intensity-Guided Discontinuity Detection in Visible-Surface Reconstruction," *Computer Vision, Graphics and Image Processing*, Vol. 47, 1989, pp. 292-326.

Kanade, T., "A Theory of Origami World," *Artificial Intelligence*, Vol. 13, Vol. 1-3, 1980, pp. 279-311.

Kanade, T., "Recovering of the Three-Dimensional Shape of an Object from a Single View," *Artificial Intelligence*, Vol. 17, 1981, pp. 409-460.

Kanade, T., "Geometrical Aspects of Interpreting Images as a Three-Dimensional Scene," *Proc. IEEE*, Vol. 71, No. 7, IEEE Press, New York, N.Y., 1983, pp. 789-802.

Kanade, T. and J.P. Kender, "Mapping Image Properties into Shape Constraints: Skewed Symmetry, Affine-Transformable Patterns, and the Shape-from-Texture Paradigm," in *Human and Machine Vision*, J. Beck, B. Hope, A. Rosenfeld, eds., Academic Press, New York, N.Y., 1983.

Kanatani, K., "Camera Rotation Invariance of Image Characteristics," *Computer Vision, Graphics and Image Processing*, Vol. 39, No. 3, 1987, pp. 328-354.

Kanatani, K., "Constraint on Length and Angle," *Computer Vision, Graphics and Image Processing*, Vol. 41, No. 1, 1988, pp. 28-42.

Kanatani, K., "Reconstruction of Consistent Shape from Inconsistent Data: Optimization of 2 1/2 D Sketches," *Int'l J. Computer Vision*, Vol. 3, No. 4, 1989, pp. 261-291.

Kass, M., "Linear Image Features in Stereopsis," *Int'l J. Computer Vision*, Vol. 1, 1988, pp. 357-368.

Kass, M. and A. Witkin, "Analyzing Oriented Patterns," *Computer Vision, Graphics and Image Processing*, Vol. 37, 1987, pp. 362-385.

Kayaalp, A., A.R. Rao, and R.C. Jain, "Scanning Electron Microscope-Based Stereo Analysis," *Machine Vision and Applications*, Vol. 3, No. 4, 1990, pp. 231-246.

Kehtarnavaz, N. and R.J.P. deFigueiredo, "A Framework for Surface Reconstruction from 3-D Contours," *Computer Vision, Graphics and Image Processing*, Vol. 42, No. 1, 1988, pp. 32-47.

Kender, J.R, *Shape from Texture*, PhD thesis, Carnegie-Mellon Univ., 1980.

Kender, J.R., "Surface Constraints from Linear Extents," *Proc. DARPA Image Understanding Workshop*, 1983, pp. 49-53.

Kim, B. and P. Burger, "Calculation of Surface Position and Orientation Using the Photometric Stereo Method," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 492-497.

Kim, Y.C. and J.K. Aggarwal, "Positioning 3-D Objects Using Stereo Images," *IEEE Trans. Robotics and Automation*, Vol. 3, No. 4, 1987, pp. 361-373.

Kittler, J. and E.R. Hancock, "Combining Evidence in Probabilistic Relaxation," *Int'l. J. Pattern Recognition and Artificial Intelligence*, Vol. 3, No. 1, 1989, pp. 29-51.

Kittler, J. and J. Illingworth, "Relaxation Labeling Algorithms - A Review," *Image and Vision Computing*, Vol. 3, No. 4, 1985, pp. 206-216.

Koenderink, J.J. and A.J. van Doorn, "Photometric Invariants Related to Solid Shape," *Optica Acta*, Vol. 27, No. 7, 1980, pp. 981-996.

Koenderink, J.J. and A.J. van Doorn, "The Shape of Smooth Objects and the Way Contours End," *Perception*, Vol. 11, Pion Limited, London, U.K., 1982, pp. 129-137.

Krotkov, E.P., *Active Computer Vision by Cooperative Focus and Stereo*, Springer-Verlag, New York, N.Y., 1989.

Krotkov, E., Henriksen, and R. Kories, "Nonlinear Multiresolution: A Shape-from Shading Example," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 12, 1990, pp. 1206-1210.

Le Bras-Mehlman, et al., "How the Delaunay Triangulation Can Be Used for Representing Stereo Data," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 54-59.

Lee, D., "Algorithms for Shape from Shading and Occluding Boundaries," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 478-485.

Lee, D., "Some Computational Aspects of Low-Level Computer Vision," *Proc. IEEE*, Vol. 76, No. 8, IEEE Press, New York, N.Y., 1988, pp. 890-898.

Lee, D. and T. Pavlidis, "One-Dimensional Regularization with Discontinuities," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 6, 1988, pp. 822-829.

Lee, S.J., R.M. Haralick, and L.G. Shapiro, "Understanding Objects with Curved Surfaces from a Single Perspective View of Boundaries," *Artificial Intelligence*, Vol. 26, 1985, pp. 145-169.

Li, S.Z., "Reconstruction without Discontinuities," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 709-712.

Liu, H.H., T.Y. Young, and A. Das, "A Multilevel Parallel Processing Approach to Scene Labeling," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 4, 1988, pp. 586-590.

Lucas, B.D. and T. Kanade, "Optical Navigation by the Method of Differences," *Proc. Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1985, pp. 981-984.

Luo, R.C., M.H. Lin, and R.S. Scherp, "Dynamic Multi-Sensor Data Fusion Systems for Intelligent Robots," *IEEE Trans. Robotics and Automation*, Vol. 4, No. 4, 1988, pp. 386-396.

Luo, W. and H. Matre, "Using Surface Model to Correct and Fit Disparity Data in Stereovision," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 60-64.

Mackworth, A.K., "Interpreting Pictures of Polyhedral Scenes," *Artificial Intelligence*, Vol. 4, No. 1, 1973, pp. 121-137.

Mackworth, A.K., "Consistency in Networks of Relations," *Artificial Intelligence*, Vol. 8, No. 1, 1977, pp. 121-137.

Mackworth, A.K. and E.C. Freuder, "The Complexity of Some Polynomial Network Consistency Algorithms for Constraint Satisfaction Problems," *Artificial Intelligence*, Vol. 25, No. 1, 1985, pp. 65-74.

Malik, J., "Interpreting Line Drawings of Curved Objects," *Int'l J. Computer Vision*, Vol. 1, 1987, pp. 73-103.

Malik, J. and D. Maydan, "Recovering Three-Dimensional Shape from a Single Image of Curved Objects," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 6, 1989, pp. 555-566.

Malik, J. and P. Perona, "Preattentive Texture Discrimination with Early Vision Mechanisms," *J. Opt. Soc. Am. A*, Vol. 7, No. 5, 1990, pp. 923-932.

March, R., "A Regularization Model for Stereo Vision with Controlled Continuity," *Pattern Recognition Letters*, Vol. 10, 1989, pp. 259-263.

Marinos, C. and A. Blake, "Shape from texture: The Homogeneity Hypothesis," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 350-353.

Marr, D. and T. Poggio, "Analysis of a Cooperative Stereo Algorithm," *Biological Cybernetics*, Vol. 28, 1978, pp. 223-239.

Marroquin, J., S. Mitter, and T. Poggio, "Probabilistic Solution of Ill-Posed Problems in Computational Vision," *J. American Statistical Assoc.*, Vol. 82, (397) 1987, pp. 76-89.

Matthies, L. and S.A. Shafer, "Error Modeling in Stereo Navigation," *IEEE Trans. Robotics and Automation*, Vol. 3, No. 3, 1987, pp. 239-248.
Mayhew, J.E.W. and J.P. Frisby, "Psychophysical and Computational Studies Towards a Theory of Human Stereopsis," *Artificial Intelligence*, Vol. 17, 1981, pp. 349-385.
McKeown Jr., D.M., "Building Knowledge-Based System for Detecting Man-Made Structures from Remotely Sensed Imagery," *Proc. Royal Soc. Lond. B*, Vol. A324, 1988, pp. 423-435.
Mingolla, E. and J.T. Todd, "Perception of Solid Shape from Shading," *Biological Cybernetics*, Vol. 53, 1986, pp. 137-151.
Mitiche, A. and J.K. Aggarwal, "Multiple Sensor Integration/Fusion Through Image Processing: A Review," *Optical Eng.*, Vol. 25, No. 3, 1986, pp. 379-386.
Moerdler, M.L., "Multiple Shape-from-Texture into Texture Analysis and Surface Segmentation," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 316-320.
Moerdler, M.L. and T.E. Boult, "The Integration of Information from Stereo and Multiple Shape-from-Texture Cues," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 524-529.
Mohan, R., G. Medioni, and R. Nevatia, "Stereo Error Detection, Correction, and Evaluation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 2, 1989, pp. 113-120.
Mulgaonkar, P.G., L.G. Shapiro, and R.M. Haralick, "Shape from Perspective: A Rule-Based Approach," *Computer Vision, Graphics and Image Processing*, Vol. 36, 1986, pp. 298-320.
Naeve, A. and J.-O. Eklundh, "On Projective Geometry and the Recovery of 3-D Structure," *Proc. First Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 128-135.
Naito, S. and A. Rosenfeld, "Shape from Random Planar Features," *Computer Vision, Graphics and Image Processing*, Vol. 42, No. 3, 1988, pp. 345-370.
Nalwa, V.S., "Line-Drawing Interpretation: Straight Lines and Conic Sections," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 4, 1988, pp. 514-529.
Nalwa, V.S., "Line-Drawing Interpretation: A Mathematical Framework," *Int'l J. Computer Vision*, Vol. 2, 1988, pp. 103-124.
Nalwa, V.S., "Line-Drawing Interpretation: Bilateral Symmetry," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 10, 1989, pp. 1117-1120.
Nayar, S.K., K. Ikeuchi, and T. Kanade, "Shape from Interreflections," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 2-11.
Nishihara, H.K., "Practical Real-Time Imaging Stereo Matcher," *Optical Eng.*, Vol. 23, 1984, pp. 536-545.
Ohta, Y., M. Watanabe, and K. Ikeda, "Improving Depth Map by Trinocular Stereo," *Proc. Eighth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1986, pp. 519-521.
Oliensis, J., "Existence and Uniqueness in Shape from Shading," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 341-345.
Olsen, S.I., "Stereo Correspondence by Surface Reconstruction," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 3, 1990, pp. 309-314.
Olsen, T.J. and R.D. Potter, "Real-Time Vergence Control," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 404-409.
Onn, R. and A. Bruckstein, "Integrability Disambiguates Surface Recovery in Two-Image Photometric Stereo," *Int'l J. Computer Vision*, Vol. 5, No. 1, 1990, pp. 105-113.
Parent, P. and S.W. Zucker, "Radial Projection: An Efficient Update Rule for Relaxation Labeling," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 8, 1989, pp. 886-889.
Park, J.-S. and J.T. Tou, "Highlight Separation and Surface Orientations for 3-D Specular Objects," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 331-335.
Penna, M.A., "A Shape from Shading Analysis for a Single Perspective Image of a Polyhedron," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 6, 1989, pp. 545-554.
Penna, M.A., "Local and Semi-Local Shape from Shading for a Single Perspective Image of a Smooth Object," *Computer Vision, Graphics and Image Processing*, Vol. 46, No. 3, 1989, pp. 346-366.
Pentland, A.P., "Local Shading Analysis," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 6, No. 2, 1984, pp. 170-187.
Pentland, A.P., "Shading into Texture," *Artificial Intelligence*, Vol. 29, No. 2, 1986, pp. 147-170.
Pentland, A.P., "Shape Information from Shading: A Theory About Human Perception," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 404-413.
Pentland, A.P., "A Possible Neural Mechanism for Computing Shape from Shading," *Neural Computation*, Vol. 1, No. 2, 1989, pp. 208-217.
Poggio, T., V. Torre, and C. Koch, "Computational Vision and Regularization Theory," *Nature*, Vol. 317, No. 26, 1985, pp. 314-319.
Pong, T.C. and B.G. Kaiser, "A Hierarchical Approach to the Correspondence Problem," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, 1989, pp. 271-276.
Pong, T.C., R.M. Haralick, and L.G. Shapiro, "Matching Topographic Structures in Stereo Vision," *Pattern Recognition Letters*, Vol. 9, 1989, pp. 127-136.
Porrill, J., S.B. Pollard, and J.E.W. Mayhew, "Optimal Combination of Multiple Sensors Including Stereo Vision," *Image and Vision Computing*, Vol. 5, 1987, pp. 174-180.
Price, K.E., "Relaxation Matching Techniques: A Comparison," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 5, 1985, pp. 617-623.
Quam, L.H., "Hierarchical Warp Stereo," *Proc. DARPA Image Understanding Workshop*, 1984, pp. 149-155.
Quan, L. and R. Mohr, "Matching Perspective Images Using Geometric Constraints and Perceptual Grouping," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 679-684.

Rao, A.R. and B.G. Schunck, "Computing Oriented Texture Fields," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 61-69.

Rao, A.R. and R.C. Jain, "Analyzing Oriented Textures Through Phase Portraits," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 336-340.

Richards, W. and D.D. Hoffman, "Codon Constraints on Closed 2D Shapes," *Computer Vision, Graphics and Image Processing*, Vol. 31, No. 3, 1985, pp. 265-281.

Richards, W.A., J.J. Koenderink, and D.D. Hoffman, "Inferring Three-Dimensional Shapes from Two-Dimensional Silhouettes," *J. Opt. Soc. Am. A*, Vol. 4, No. 7, 1987, pp. 1168-1175.

Roan, S.J., J.K. Aggarwal, and W.N. Martin, "Multiple Resolution Imagery and Texture Analysis," *Pattern Recognition*, Vol. 20, No. 1, 1987, pp. 17-31.

Ron, G. and S. Peleg, "Multiresolution Shape from Shading," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 350-355.

Samal, A. and T. Henderson, "Parallel Split-Level Relaxation," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 2, 1988, pp. 425-442.

Sato, H., S.K. Nayar, and K. Ikeuchi, "Extracting Shape and Reflectance of Glossy Surfaces by Using 3-D Photometric Sampling Method," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 133-136.

Saund, E., "Representation and the Dimensions of Shape Deformation," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 684-689.

Shafer, S.A. and T. Kanade, "Using Shadows in Finding Surface Orientations," *Computer Vision, Graphics and Image Processing*, Vol. 22, 1983, pp. 145-176.

Shafer, S.A., T. Kanade, and J. Kender, "Gradient Space Under Orthography and Perspective," *Computer Vision, Graphics and Image Processing*, Vol. 24, 1983, pp. 182-199.

Shah, Y.C., R. Chapman, and R.B. Mahani, "A New Technique to Extract Range Information from Stereo Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 7, 1989, pp. 768-773.

Shakunaga, T. and H. Kaneko, "Perspective Angle Transform: Principle of Shape from Angles," *Int'l J. Computer Vision*, Vol. 3, No. 3, 1989, pp. 239-254.

Shao, M., T. Simchony, and R. Chellappa, "New Algorithms for Reconstruction of a 3-D Depth Map from One or More Images," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 530-535.

Shapira, R., "The Use of Objects Faces in Interpreting Line Drawings," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 6, No. 6, 1984, pp. 789-794.

Shapira, R., "More About Polyhedra - Interpretation Through Constructions in the Image Plane," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 1, 1985, pp. 1-16.

Sherman, D. and S. Peleg, "Stereo by Incremental Matching of Contours," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 11, 1990, pp. 1102-1106.

Shrikhande, N. and G. Stockman, "Surface Orientation from a Projected Grid," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 6, 1988, pp. 650-655.

Silverman, J.F. and D.B. Cooper, "Bayesian Clustering for Unsupervised Estimation of Surface and Texture Models," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 4, 1988, pp. 482-495.

Skifstad, K. and R.C. Jain, "Range Estimation from Intensity Gradient Analysis," *Machine Vision and Applications*, Vol. 2, No. 1, 1989, pp. 81-102.

Smith, G.B., "Stereo Integral Equations," *Proc. Nat'l Conf. Artificial Intelligence*, MIT Press, Cambridge, Mass., 1986, pp. 689-694.

Stevens, K.A., "The Visual Interpretation of Surface Contours," *Artificial Intelligence*, Vol. 17, No. 1, 1981, pp. 47-73.

Stevens, K.A. and A. Brookes, "Depth Reconstruction from Stereopsis," *Proc. First Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 682-686.

Stevens, K. A. and A. Brookes, "Integrating Stereopsis with Monocular Interpretations of Planar Surfaces," *Vision Research*, Vol. 28, No. 3, 1988, pp. 371-386.

Stevenson, R.L. and E.J. Delp, "Invariant Reconstruction of Visual Surfaces," *Proc. IEEE Workshop on Interpretation of 3-D Scenes*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 131-137.

Stevenson, R.L. and E.J. Delp, "Viewpoint Invariant Recovery of Visual Surfaces from Sparse Data," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 309-312.

Stewart, C.V. and C.R. Dyer, "The Trinocular General Support Algorithm: A Three-Camera Stereo Algorithm for Overcoming Binocular Matching Errors," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 134-138.

Strat, T.M. and M.A. Fischler, "One-Eyed Stereo: A General Approach to Modeling Scene Geometry," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 6, 1986, pp. 730-741.

Subbarao, M., "Parallel Depth Recovery by Changing Camera Parameters," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 149-155.

Subirana, B., S. Vilanova, and J. Brian, "Curved Inertia Frames and the Skeleton Sketch: Finding Salient Frames of Reference," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 702-708.

Sugihara, K., "Mathematical Structures of Line Drawings of Polyhedrons - Toward Man-Machine Communication by Means of Line Drawings," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 4, No. 5, 1982, pp. 458-469.

Sugihara, K., "An Algebraic Approach to Shape-from-Image Problems," *Artificial Intelligence*, Vol. 23, No. 1, 1984, pp. 59-95.

Tagare, H.D. and R.J.P. deFigueiredo, "A Theory of Photometric Stereo for General Class of Reflectance Maps," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 38-45.

Tagare, H.D. and R.J.P. de Figueiredo, "Simultaneous Estimation of Shape and Reflectance Maps from Photometric Stereo," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 340-343.

Terzopoulos, D., "Multilevel Computational Processes for Visual Surface Reconstruction," *Computer Vision, Graphics and Image Processing*, Vol. 24, No. 1, 1983, pp. 52-96.

Terzopoulos, D., "Image Analysis Using Multigrid Relaxation Methods," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 2, 1986, pp. 129-139.

Terzopoulos, D., "Regularization of Inverse Visual Problems Involving Discontinuities," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 4, 1986, pp. 413-424.

Terzopoulos, D., "The Computation of Visible Surface Representations," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 4, 1988, pp. 417-438.

Terzopoulos, D. and K. Waters, "Analysis of Facial Images Using Physical and Anatomical Models," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 727-732.

Terzopoulos, D. and A. Witkin, "Physically Based Models with Rigid and Deformable Components," *IEEE Computer Graphics and Applications*, Vol. 8, No. 6, 1988, pp. 41-51.

Terzopoulos, D., A. Witkin, and M. Kass, "Symmetry-Seeking Models and 3-D Object Reconstruction," *Int'l J. Computer Vision*, Vol. 1, No. 3, 1987, pp. 211-221.

Thirion, E. and L. Quan, "Geometrical Learning from Multiple Stereo Views Through Monocular Based Feature Grouping," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 481-484.

Tirumalai, A.P., B.G. Schunck, and R.C. Jain, "Dynamic Stereo with Self-Calibration," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 466-470.

Treisman, A., "Preattentive Processing in Vision," *Computer Vision, Graphics and Image Processing*, Vol. 31, No. 2, 1985, pp. 156-177.

Tsotsos, J.K., "A Complexity Level Analysis of Immediate Vision," *Int'l J. Computer Vision*, Vol. 1, 1988, pp. 303-320.

Ullman, S., "Visual Routines," *Cognition*, Vol. 18, 1984, pp. 97-159.

Ulupinar, F. and R. Nevatia, "Using Symmetries for Analysis for Shape from Contours," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 414-426.

Ulupinar, F. and R. Nevatia, "Inferring Shape from Contour for Curved Surfaces," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 147-154.

Ulupinar, F. and R. Nevatia, "Shape from Contour: Straight Homogeneous Generalized Cones," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 582-586.

Vaillant, R. and O.D. Faugeras, "Using Occluding Contours for Recovering Shape Properties of Objects," *Proc. IEEE Workshop on Interpretation of 3-D Scenes*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 26-32.

Van Gool, L., P. Dewaele, and O. Oosterlinck, "Texture Analysis Anno 1983," *Computer Vision, Graphics, and Image Processing*, Vol. 29, 1985, pp. 336-357.

Verri, A. and A. Yuille, "Some Perspective Projection Invariants," *J. Opt. Soc. Am. A*, Vol. 5, No. 3, 1988, pp. 426-431.

Walker, E.L. and M. Herman, "Geometric Reasoning for Constructing 3-D Scene Descriptions from Images," *Artificial Intelligence*, Vol. 37, 1988, pp. 275-290.

Waltz, D., "Understanding Line Drawing of Scenes with Shadows," in *The Psychology of Computer Vision*, P. H. Winston, ed., McGraw-Hill, New York, N.Y., 1975.

Wang, Y.F. and J.K. Aggarwal, "Surface Reconstruction and Representation of 3-D Scenes," *Pattern Recognition*, Vol. 19, No. 3, 1986, pp. 197-207.

Wang, Y.-F. and J.-F. Wang, "Surface Reconstruction Using Deformable Models with Interior and Boundary Constraints," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 300-303.

Wang, Y.F., A. Mitiche, and J.K. Aggarwal, "Computation of Surface Orientation and Structure of Objects Using Grid Coding," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 1, 1987, pp. 129-137.

Watanabe, M. and Y. Ohta, "Cooperative Integration of Multiple Stereo Algorithms," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 476-480.

Weinshall, D., "Application of Qualitative Depth and Shape from Stereo," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 144-148.

Weymouth, T.E. and S. Moezzi, "Wide Base-Line Dynamic Stereo: Approximation and Refinement," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 183-188.

Whaite, P. and E.P. Ferrie, "From Uncertainty to Visual Exploration," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 690-697.

Wildes, R.P., "An Analysis of Stereo Disparity for the Recovery of Three-Dimensional Scene Geometry," *Proc. IEEE Workshop on Interpretation of 3-D Scenes*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 2-8.

Witkin, A.P., "Recovering Surface Shape and Orientation from Texture," *Artificial Intelligence*, Vol. 17, No. 1, 1981, pp. 17-45.

Witkin, A.P. and J.M. Tenenbaum, "On the Role of Structure in Vision," in *Human and Machine Vision*, J. Beck, B. Hope, and A. Rosenfeld, eds., Academic Press, New York, N.Y., 1983, pp. 481-543,

Wolff, L.B., "Shape Understanding from Lambertian Photometric Flow Fields," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 46-52.

Wolff, L.B., "Using Polarization to Separate Reflection Components," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 363-369.

Wolff, L.B., "A Photometric Invariant and Shape Constraints at Parabolic Points," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 344-349.

Wolff, L.B. and T.E. Boult, "Polarization/Radiometric Based Material Classification," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 387-396.

Wolff, L.B. and T.E. Boult, "Using Line Correspondence Stereo to Measure Surface Orientation," *Proc. Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1989, pp. 1655-1660.

Woodham, R.J., "Analyzing Images of Curved Surfaces," *Artificial Intelligence*, Vol. 17, 1981, pp. 117-140.

Worrall, A.D., K.D. Baker, and G.D. Sullivan, "Roll Angle Consistency Constraints," *Image and Vision Computing*, Vol. 8, No. 1, 1990, pp. 78-84.

Xu, J. and Y.-H. Yang, "Generalized Multidimensional Orthogonal Polynomials with Applications to Shape Analysis," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 9, 1990, pp. 906-913.

Yachida, M., Y. Kitamura, and M. Kimachi, "Trinocular Vision: New Approach for Correspondence Problem," *Proc. Eighth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1986, pp. 1041-1044.

Zheng, Y., et al., "SWITCHER: A Stereo Algorithm for Ground Plane Obstacle Detection," *Image and Vision Computing*, Vol. 8, 1990, pp. 57-62.

Zhuang, X., R.M. Haralick, and H. Joo, "A Simplex-Like Algorithm for the Relaxation Labeling Process," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 12, 1989, pp. 1316-1321.

Zucker, S.W., "Early Orientation Selection: Tangent Fields and the Dimensionality of Their Support," *Computer Vision, Graphics and Image Processing*, Vol. 32, 1985, pp. 74-103.

Chapter 5: Three-Dimensional Object Recognition Selected Bibliography

Acampora, A.S. and J.H. Winters, "Three-Dimensional Ultrasonic Vision for Robotic Applications," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 3, 1989, pp. 291-303.

Arbter, K., et al., "Application of Affine-Invariant Fourier Descriptors to Recognition of 3-D Objects," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 7, 1990, pp. 640-647.

Bajcsy, R. and F. Solina, "Three Dimensional Object Representation Revisited," *Proc. First Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 231-240.

Ballard, D.H. and D. Sabbah, "Viewer Independent Recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 5, No. 6, 1983, pp. 653-660.

Barr, A.H., "Superquadrics and Angle-Preserving Transformations," *IEEE Computer Graphics and Applications*, Vol. 1, No. 1, 1981, pp. 11-23.

Barr, A.H., "Global and Local Deformations of Solid Primitives," *ACM Computer Graphics, SIGGRAPH*, Vol. 18, No. 3, ACM, Inc., New York, N.Y., 1984, pp. 21-30.

Barry, M., et al., "A Multi-Level Geometric Reasoning System for Vision," *Artificial Intelligence*, Vol. 37, 1989, pp. 291-332.

Basri, R. and S. Ullman, "The Alignment of Objects with Smooth Surfaces," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 482-488.

Bastuscheck, C.M., et al., "Object Recognition by Three-Dimensional Curve Matching," *Int'l J. of Intelligence Systems*, Vol. 1, 1986, pp. 105-132.

Beausmans, J.M.H., D.D. Hoffman, and B.M. Bennett, "Description of Solid Shape and its Inference from Occluding Contours," *J. Opt. Soc. Am. A*, Vol. 4, No. 7, 1987, pp. 1155-1167.

Ben-Arie, J., "The Probabilistic Peaking Effect of Viewed Angles and Distances with Applications to 3-D Object Recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 8, 1990, pp. 760-774.

Ben-Arie, J. and A. Zvi Meiri, "3-D Objects Recognition by Optimal Matching Search of Multinary Relations Graph," *Computer Vision, Graphics and Image Processing*, Vol. 37, 1987, pp. 345-361.

Besl, P.J., "Geometric Modeling and Computer Vision," *Proc. IEEE*, Vol. 76, No. 8, IEEE Press, New York, N.Y., 1988, pp. 936-958.

Besl, P. and R.C. Jain, "Invariant Surface Characteristics for 3-D Object Recognition in Range Images," *Computer Vision, Graphics and Image Processing*, Vol. 33, No. 1, 1986, pp. 33-79.

Bhanu, B. and C. Ho, "CAD-based 3-D Object Representation for Robot Vision," *Computer*, Vol. 20, No. 8, 1987, pp. 19-36.

Bhanu, B. and J.C. Ming, "Recognition of Occluded Objects: A Cluster-Structure Algorithm," *Pattern Recognition*, Vol. 20, No. 2, 1987, pp. 199-211.

Bhanu, B. and L.A. Nuttall, "Recognition of 3-D Objects in Range Images Using a Butterfly Multiprocessor," *Pattern Recognition*, Vol. 22, No. 1, 1989, pp. 49-64.

Biederman, I., "Human Image Understanding: Recent Research and Theory," *Computer Vision, Graphics and Image Processing*, Vol. 32, No. 1, 1985, pp. 29-73.

Biederman, I., "Recognition-by-Components: A Theory of Human Image Understanding," *Psychological Review*, Vol. 94, No. 2, 1987, pp. 115-147.

Binford, T.O., "Survey of Model-Based Image Analysis," *Int'l J. Robotics Research*, Vol. 1, No. 1, 1982, pp. 18-64.

Boissonnat, J., "Geometric Structures for Three-Dimensional Shape Representation," *ACM Trans. on Graphics*, Vol. 3, No. 4, 1984, pp. 266-286.

Bolle, R.M. and D.B. Cooper, "On Optimally Combining Pieces of Information, with Application to Estimating 3-D Complex-Object Position from Range Data," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 5, 1986, pp. 619-638.

Bolle, R.M., et al., "Active 3-D Object Models," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 329-333.

Bolle, R.M., et al., "Visual Recognition Using Concurrent and Layered Parameter Networks," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 625-631.

Bolles, R.C. and P. Horaud, "3DPO: A Three-Dimensional Part Orientation System," *Int'l J. Robotics Research*, Vol. 5, 1986, pp. 3-26.

Bowyer, K., et al., "Developing the Aspect Graph Representation for Use in Image Understanding," *Proc. DARPA Image Understanding Workshop*, 1989, pp. 831-849.

Brady, J.P., N. Nandhakumar, and J.K. Aggarwal, "Recent Progress in the Recognition of Objects from Range Data," *Image and Vision Computing*, 1988, 295-307.

Bresler, Y., J.A. Fessler, and A. Macovski, "A Bayesian Approach to Reconstruction from Incomplete Projections of a Multiple Objects 3-D Domain," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 8, 1989, pp. 840-858.

Breuel, T.M., "Adaptive Model Base Indexing," *Proc. DARPA Image Understanding Workshop*, 1989, pp. 805-814.

Brooks, R.A., "Model-Based Three-Dimensional Interpretations of Two-Dimensional Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 5, No. 2, 1983, pp. 140-150.

Brou, P., "Using the Gaussian Image to Find the Orientations of Objects," *Int'l J. Robotics Research*, Vol. 3, No. 4, 1984, pp. 89-125.

Burns, B.J. and L.J. Kitchen, "Recognition in 2-D Images of 3-D Objects from Large Model Bases Using Prediction Hierarchies," *Proc. Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1987, pp. 763-766.

Burns, J.B. and L.J. Kitchen, "Rapid Object Recognition from a Large Model Based Using Prediction Hierarchies," *Proc. of DARPA Image Understanding Workshop*, 1988, pp. 711-719.

Callahan, J. and R. Weiss, "A Model for Describing Surface Shape," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1985, pp. 240-245.

Canny, J., Z. Gigus, and R. Seidel, "Efficiently Computing and Representing Aspect Graphs of Polyhedral Objects," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 30-39.

Cappellini, V., et al., "From Multiple Views to Object Recognition," *IEEE Trans. Circuits and Systems*, Vol. 34, 1987, pp. 1344-1350.

Cernuschi-Frias, B., et al., "Toward a Model-Based Bayesian Theory for Estimating and Recognizing Parameterized 3-D Objects Using Two or More Images Taken from Different Positions," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 10, 1989, pp. 1028-1052.

Chen, C.H. and A.C. Kak, "A Robot Vision System for Recognizing 3-D Objects in Low-Order Polynomial Time," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, No. 6, 1989, pp. 1564-1575.

Chen, H.H., "Pose Determination from Line-to-Plane Correspondences: Existence Condition and Closed-Form Solutions," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990 pp. 374-379.

Chen, S.W. and G. Stockman, "Object Wings - 2 1/2-D Primitives for 3-D Recognition," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 535-440.

Chen, S.W. and G. Stockman, "Wing Representation for Rigid 3-D Objects," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 398-402.

Chien, C.H. and J.K. Aggarwal, "Identification of 3-D Objects from Multiple Silhouettes Using Quadtrees/Octrees," *Computer Vision, Graphics and Image Processing*, Vol. 36, 1986, pp. 256-273.

Chien, C.H and J.K. Aggarwal, "Model Construction and Shape Recognition from Occluding Contours," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 4, 1989, pp. 372-389.

Chin, R.T. and C.R. Dyer, "Model-Based Recognition in Robot Vision," *ACM Computing Surveys*, Vol. 18, No. 1, 1986, pp. 67-108.

Chu, N.T. and L.G. Shapiro, "Experiments in Model-Based Matching Using a Relational Pyramid Representation," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conference VIII*, Vol. 1293, 1990, 236-247.

Cohen, L.D. and I. Cohen, "A Finite Element Method Applied to New Active Contour Models and 3-D Reconstruction from Cross Sections," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 587-591.

Connell, J.H. and M. Brady, "Generating and Generalizing Models of Visual Objects," *Artificial Intelligence*, Vol. 31, No. 2, 1987, pp. 159-183.

Cooper, P.R., "Parallel Structure Recognition with Uncertainty: Coupled Segmentation and Matching," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1900, pp. 287-291.

Dhome, M., et al., "Determination of the Attitude of 3-D Objects from a Single Perspective View," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 12, 1989, pp. 1265-1278.

Dickinson, S.J., A.P. Pentland, and A. Rosenfeld, "Qualitative 3-D Shape Reconstruction Using Distributed Aspect Graph Matching," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 257-262.

Draper, B.A. and E.M. Riseman, "Learning 3-D Object Recognition Strategies," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 320-324.

Ettinger, G.J., "Large Hierarchical Object Recognition in Robot Vision," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 32-41.

Fan, T.J., G. Medioni, and R. Nevatia, "Recognizing 3-D Objects Using Surface Descriptions," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 11, 1989, pp. 1140-1157.

Faugeras, O.D. and M. Hebert, "The Representation, Recognition, and Locating of 3-D Objects," *Int'l J. Robotics Research*, Vol. 5, 1986, pp. 27-52.

Feldman, J.A., "Connectionist Models and Parallelism in High Level Vision," *Computer Vision, Graphics and Image Processing*, Vol. 31, 1985, pp. 178-200.

Fisher, R.B., "Using Surfaces and Object Models to Recognize Partially Obscured Pbjects," *Proc. Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1983, pp. 989-995.

Fisher, R.B., "Determining Back-Facing Curved Model Surfaces by Analysis at the Boundary," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 296-299.

Flynn, P.J. and A.K. Jain, "Bonsai: 3-D Object Recognition Using Constrained Search," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 263-267.

Flynn, P.J. and A.K. Jain, "CAD-Based Vision," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 13, No. 2, 1991, 114-132.

Forsyth, D., et al., "Invariance - A New Framework for Vision," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 598-605.

Ganapathy, S., "Decomposition of Transformation Matrices for Robot Vision," *Proc. IEEE Int'l Conf. Robotics*, IEEE CS Press, Los Alamitos, Calif., 1984, pp. 130-139.

Gerig, G., "Linking Image-Space and Accumulator-Space: A New Approach for Object-Recognition," *Proc. First Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 112-117.

Goad, C., "Fast 3-D Model Based Vision," in *From Pixels to Predicates: Recent Advances in Computational and Robot Vision*, Ablex, Norwood, N.J., 1986, pp. 371-391

Grimson, W.E.L., "Sensing Strategies for Disambiguating Among Multiple Objects in Known Poses," *IEEE Trans. Robotics and Automation*, Vol. 2, No. 4, 1986, pp. 196-213.

Grimson, W.E.L., "The Combinatorics of Local Constraints in Model-Based Recognition and Localization from Sparse Data," *J. Assoc. of Computing Machinery*, Vol. 33, No. 4, 1986, pp. 658-686.

Grimson, W.E.L., "The Combinatorics of Object Recognition in Clustered Environments Using Constrained Search," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 218-227.

Grimson, W.E.L., "On the Recognition of Curved Objects," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 11, No. 6, 1989, pp. 632-643.
Grimson, W.E.L., "On the Recognition of Parameterized 2-D Pbjects," *Int'l J. Computer Vision,* Vol. 2, No. 2, 1989, pp. 353-371.
Grimson, W.E.L., "The Effect of Indexing on the Complexity of Object Recognition," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 644-653.
Grimson, W.E.L. and D.P. Huttenlocher, "On the Sensitivity of the Hough Transform for Object Recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 12, No. 3, 1990, pp. 255-274.
Grimson, W.E.L. and D.P. Huttenlocher, "On the Sensitivity of Geometric Hashing," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 334-339.
Grimson, W.E.L. and T. Lozano-Perez, "Localizing Overlapping Parts by Searching the Interpretation Tree," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 9, No. 4, 1987, pp. 469-482.
Gupta, A., L. Bogoni, and R. Bajcsy, "Quantitative and Qualitative Measures for the Evaluation of the Superquadric Models," *Proc. IEEE Workshop on Interpretation of 3-D Scenes,* IEEE CS Press, Los Alamitos, Calif., 1989, pp. 162-169.
Hanson, A.J., "Hyperquadrics: Smoothly Deformable Shapes with Convex Polyhedral Bounds," *Computer Vision, Graphics and Image Processing,* Vol. 44, 1988, pp. 191-210.
Haralick, R.M., et al., "Pose Estimation from Correspondence Point Data," *IEEE Trans. Systems, Man, and Cybernetics,* Vol. 19, No. 6, 1989, pp. 1426-1446.
Heel, J., "Temporally Integrated Surface Reconstruction," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 292-295.
Herman, M., "Matching Three-Dimensional Symbolic Descriptions Obtained from Multiple Views of a Scene," *Proc. IEEE Conf. Computer Vision and Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1985, pp. 585-590.
Hoffman, D.D. and W. Richards, "Parts of Recognition," *Cognition,* Vol. 18, 1984, pp. 65-96.
Hoffman, R. and A.K. Jain, "Learning Rules for 3-D Object Recognition," *Proc. IEEE Conf. Computer Vision and Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1988, pp. 885-892.
Hoffman, R., H.R. Keshavan, and F. Towfiq, "CAD-Driven Machine Vision," *IEEE Trans. Systems, Man, and Cybernetics,* Vol. 19, No. 6, 1989, pp. 1477-1488.
Hong, L. and D. Brzakovic, "An Approach to 3-D Scene Reconstruction from Noisy Binocular Image Sequences Using Information Fusion," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 658-661.
Hong, K.S., K. Ikeuchi, and K.D. Gremban, "Minimum Cost Aspect Classification: A Module of a Vision Algorithm Compiler," *Proc. Tenth Int'l Conf. Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 65-69.
Horaud, R., "New Methods for Matching 3-D Objects with Single Perspective Views," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 9, No. 3, 1987, pp. 401-412.
Horn, B.K.P., "Extended Gaussian Images," *Proc. IEEE,* Vol. 72, No. 11, IEEE Press, New York, N.Y., 1984, pp. 1656-1678.
Huang, C.L., "Contour Generation and Shape Restoration of the Straight Homogeneous Generalized Cylinder," *Proc. Tenth Int'l Conf. Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 409-413.
Hutchinson, S.A., R.I. Cromwell, and A.C. Kak, "Applying Uncertainty Reasoning to Model Based Object Recognition," *Proc. IEEE Conf. Computer Vision and Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1989, pp. 541-548.
Huttenlocher, D.P. and S. Ullman, "Object Recognition Using Alignment," *Proc. First Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1987, pp. 102-111.
Huttenlocher, D.P. and S. Ullman, "Recognizing Solid Objects by Alignment with an Image," *Int'l J. Computer Vision,* Vol. 5, No. 2, 1990, pp. 195-212.
Idesawa, M., "Multi-Precision Position Measuring Method with r-hpsd Scheme," *IAPR Workshop on Machine Vision Applications,* 1990, pp. 129-132.
Ikeuchi, K. and K.S. Hong, "Determining Linear Shape Change: Toward Automatic Generation of Object Recognition Programs," *Proc. IEEE Conf. Computer Vision and Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1989, pp. 450-457.
Ikeuchi, K. and T. Kanade, "Modeling Sensors: Toward Automatic Generation of Object Recognition Program," *Computer Vision, Graphics and Image Processing,* Vol. 48, No. 1, 1989, pp. 50-79.
Jain, A.K. and R. Hoffman, "Evidence-Based Recognition of 3-D Objects," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 10, No. 6, 1988, pp. 783-802.
Jain, R.C. and A.K. Jain, "Report on Range Image Understanding Workshop, East Lansing, Michigan, March 21-23, 1988," *Machine Vision and Applications,* Vol. 2, 1989, pp. 5-60.
Kanatani, K., "Hypothesizing and Testing Geometric Attributes of Image Data," *Proc. Third Int'l Conf. Computer Vision,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 370-373.
Kapur, D. and J.L. Mundy, " Wu's Method and its Application to Perspective Viewing," *Artificial Intelligence,* Vol. 37, No. 1, 1988, pp. 15-36.
Kender, J.R. and D.G. Freudenstein, "What is a `Degenerate' View?," *Proc. Int'l Joint Conf. Artificial Intelligence,* Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1987, pp. 801-804.
Kim, Y.C. and J.K. Aggarwal, "Rectangular Parallelepiped Coding: A Volumetric Representation of Three-Dimensional Objects," *J. Opt. Soc. Am. A,* Vol. 2, No. 3, 1986, pp. 127-134.
Kim, Y.C. and J.K. Aggarwal, "Positioning Three-Dimensional Objects Using Stereo Images," *IEEE Trans. Robotics and Automation,* Vol. 3, No. 4, 1987, pp. 361-373.
Knoll, T. and R.C. Jain, "Recognizing Partially Visible Objects Using Feature Indexed Hypotheses," *IEEE Trans. Robotics and Automation,* Vol. 2, No. 1, 1986, pp. 3-13.
Koch, M.W. and R.L. Kashyap, "Using Polygons to Recognize and Locate Partially Occluded Objects," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 9, No. 4, 1987, pp. 483-494.

Koenderink, J.J., *Solid Shape*, MIT Press, Cambridge, Mass., 1989.

Kriegman, D.J. and J. Ponce, "On Recognizing and Positioning Curved 3-D Objects from Image Contours," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 12, 1990, pp. 1127-1137.

Krishnapuram, R. and D. Casasent, "Determination of Three-Dimensional Object Location and Orientation from Range Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 11, 1989, pp. 1158-1167.

Kuno, Y., Y. Okamoto, and S. Okada, "Object Recognition Using a Feature Search Strategy Generated from a 3-D Model," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 626-635.

Lamdan, Y., J.T. Schwartz, and H.J. Wolfson, "Object Recognition by Affine Invariant Matching," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 335-344.

Lee, S. and H.S. Hahn, "Object Recognition and Localization Using Optical Proximity Sensor System: Polyhedral Case," *Proc. IEEE Workshop on Interpretation of 3-D Scenes*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 75-81.

Lin, W.C. and K.S. Fu, "A Syntactic Approach to 3-D Object Representation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 6, No. 3, 1984, pp. 351-364.

Linnainmaa, S., D. Harwood, and L.S. Davis, "Pose Determination of a Three-Dimensional Object Using Triangle Pairs," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 5, 1988, pp. 634-647.

Lowe, D.G., "The Viewpoint Consistency Constraint," *Int'l J. Computer Vision*, Vol. 1, 1987, pp. 57-72.

Lu, H., L.G. Shapiro, and O.I. Camps, "A Relational Pyramid Approach to View Class Determination," *Proc. IEEE Workshop on Interpretation of 3-D Scenes*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 177-183.

Lysak, D.B. Jr. and R. Kasturi, "Interpretation of Line Drawings with Multiple Views," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 220-222.

Magee, M. and M. Nathan, "A Viewpoint Independent Modeling Approach to Object Recognition," *IEEE Trans. Robotics and Automation*, Vol. 3, 1987, pp. 351-356.

Magee, M. and M. Nathan, "Spatial Reasoning, Sensor Repositioning and Disambiguation in 3-D Model Based Recognition," *Workshop Spatial Reasoning and Multi-Sensor Fusion*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1987, pp. 262-271.

Magee, M.J., et al., "Experiments in Intensity Guided Range Sensing Recognition of Three-Dimensional Objects," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 6, 1985, pp. 629-637.

Marefat, M. and R.L. Kashyap, "Geometric Reasoning for Recognition of Three-Dimensional Object Features," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 10, 1990, pp. 949-965.

Martin, W.N. and J.K. Aggarwal, "Volumetric Description of Objects from Multiple Views," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 5, No. 2, 1983, pp. 150-158.

Mundy, J.L. and A.J. Heller, "The Evolution and Testing of a Model-Based Object Recognition System," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 268-282.

Mundy, J., A.J. Heller, and D.W. Thompson, "The Concept of an Effective Viewpoint," *Proc. DARPA Image Understanding Workshop*, 1988, pp. 651-659.

Murase, H., "Surface Shape Reconstruction of an Undulating Transparent Object," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 313-319.

Murray, D.W. and D.B. Cook, "Using the Orientation of Fragmentary 3-D Edge Segments for Polyhedral Object Recognition," *Int'l J. Computer Vision*, Vol. 2, No. 2, 1988, pp. 153-169.

Nackman, L.R., "Two-Dimensional Critical Point Configuration Graphs," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 6, No. 4, 1984, pp. 442-450.

Nasrabadi, N.M., W. Li, and C.Y. Choo, "Object Recognition by a Hopfield Neural Network," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 325-328.

Nitzan, D., "Three-Dimensional Vision Structure for Robot Applications," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 3, 1988, pp. 291-309.

Oh, C., N. Nandhakumar, and J.K. Aggarwal, "Integrated Modeling of Thermal and Visual Image Generation," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 356-362.

Oshima, M. and Y. Shirai, "Object Recognition Using Three-Dimensional Information," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 5, No. 4, 1983, pp. 353-361.

Pasquariello, G., et al., "A System for 3-D Workpiece Recognition," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 280-284.

Pentland, A.P., "On Describing Complex Surface Shapes," *Image and Vision Computing*, Vol. 3, 1986, 153-162.

Pentland, A.P., "Perceptual Organization and the Representation of Natural Form," *Artificial Intelligence*, Vol. 28, No. 3, 1986, pp. 293-331.

Pinker, S., "Visual Cognition: An Introduction," *Cognition*, 1984, pp. 1-63.

Plantinga, H. and C.R. Dyer, "Visibility, Occlusion and the Aspect Graph," *Int'l J. Computer Vision*, Vol. 5, No. 2, 1990, pp. 137-160.

Pollard, S.B., et al., "Matching Geometrical Descriptions in Three-Space," *Image and Vision Computing*, Vol. 5, 1987, pp. 73-78.

Ponce, J. and O. Faugeras, "An Object Centered Hierarchical Representation for 3-D Objects: The Prism Tree," *Computer Vision, Graphics and Image Processing*, Vol. 38, 1987, pp. 1-28.

Ponce, J. and D. Kriegman, "On Recognizing and Positioning Curved 3-D Objects from Image Contours," *Proc. IEEE Workshop on Interpretation of 3-D Scenes*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 61-67.

Ponce, J., D. Chelberg, and W.B. Mann, "Invariant Properties of Straight Homogeneous Generalized Cylinders and Their Contours," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 9, 1989, pp. 951-966.

Potmesil, M., "Generating Octree Models of 3-D Objects from Their Silhouettes in a Sequence of Images," *Computer Vision, Graphics and Image Processing*, Vol. 40, No. 1, 1987, pp. 1-29.

Reeves, A.P. and R.W. Taylor, "Identification of Three-Dimensional Objects Using Range Information," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 4, 1989, pp. 403-410.

Richetim, M., M. Dhome, and J.T. Lapreste, "Inverse Perspective Transform from Zero-Curvature Curve Points Application to the Location of Some Generalized Cylinders," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 517-522.

Rosenfeld, A., "Recognizing Unexpected Objects: A Proposed Approach," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 1, 1987, pp. 71-84.

Sabata, B., F. Arman, and J.K. Aggarwal, "Segmentation of 3-D Range Images Using Pyramidal Data Structures," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 662-666.

Sakaguchi, Y., et al., "Generation of 3-D Models Based on Image Fusion of Range Data," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 147-150,.

Sallam, M., J. Stewman, and K. Bowyer, "Computing the Visual Potential of an Articulated Assembly of Parts," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 636-643.

Schwartz, J.T. and M. Sharir, "Identification of Partially Obscured Objects in Two and Three Dimensions by Matching Noisy Characteristic Curves," *Int'l J. Robotics Research*, Vol. 6, No. 2, 1987, pp. 29-44.

Seales, W.B. and C.R. Dyer, "Modeling the Rim Appearance," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 698-701.

Shapiro, L.G. and R.M. Haralick, "A Metric for Comparing Relational Descriptions," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 1, 1985, pp. 90-94.

Shapiro, L.G. and H. Lu, "Accumulator-Based Inexact Matching Using Relational Summaries," *Machine Vision and Applications*, Vol. 3, No. 3, 1990, pp. 143-158.

Shoham, D. and S. Ullman, "Aligning a Model to an Image Using Minimal Information," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 259-263.

Shvaytser, H., "Towards a Computational Theory of Model Based Vision and Perception," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 283-286.

Stark, L., D. Eggert, and K. Bowyer, "Aspect Graphs and Nonlinear Optimization in 3-D Object Recognition," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 501-507.

Stockman, G., "Object Recognition and Localization via Pose Clustering," *Computer Vision, Graphics and Image Processing*, Vol. 40, 1987, pp. 361-387.

Stockman, G.C. and B. Flinchbaugh, "Recognition via Alignment Using Aspect Models," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conference VIII*, Vol. 1293, 1990, 224-235.

Subrahmonia, J., Y.P. Hung, and D.B. Cooper, "Model-based Segmentation and Estimation of 3-D Surfaces from Two or More Intensity Images Using Markov Random Fields," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 390-397.

Suenaga, Y. and Y. Watanabe, "A Method for the Synchronized Acquisition of Cylindrical Range and Color Data," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 137-142.

Taylor, R.W. and A.P. Reeves, "Classification Quality Assessment for a Generalized Model-Based Object Identification System," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, 1989, pp. 846-853.

Terzopoulos, D. and D. Metaxas, "Dynamic 3-D Models with Local and Global Deformations: Deformable Superquadrics," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 606-615.

Trivedi, M.M., C. Chen, and D.H. Cress, "Object Detection by Step-Wise Analysis of Spectral, Spatial and Topographic Features," *Computer Vision, Graphics and Image Processing*, Vol. 51, 1990, pp. 235-255.

Umeyama, S., T. Kasvand, and M. Hospital, "Recognition and Positioning of Three-Dimensional Objects by Combining Matchings of Primitive Local Patterns," *Computer Vision, Graphics and Image Processing*, Vol. 44, No. 1, 1988, pp. 58-76.

Verly, J.G. and R.L. Delanoy, "Appearance-Model-Based Representation and Matching of 3-D Objects," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 248-256.

Vemuri, B.C. and J.K. Aggarwal, "Representation and Recognition of Objects from Dense Range Maps," *IEEE Trans. Circuits and Systems*, Vol. 34, 1987, pp. 1351-1363.

Vemuri, B.C., A. Mitiche,, and J.K. Aggarwal, "Curvature-Based Representations of Objects from Range Data," *Image and Vision Computing*, Vol. 4, No. 2, 1986, 107-114.

Wesley, G. and M.A. Markowsky, "Fleshing Out Projections," *IBM J. Research and Development*, Vol. 25, No. 6, 1981, pp. 934-954.

Wong, A.K.C., S.W. Lu, and M. Rioux, "Recognition and Shape Synthesis of 3-D Objects Based on Attributed Hypergraphs," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 3, 1989, pp. 279-290.

Yang, H.S. and A.C. Kak, "Determination of the Identity, Position and Orientation of the Topmost Object in a Pile," *Computer Vision, Graphics and Image Processing*, Vol. 36, 1986, pp. 229-255.

Yokoya, N. and M.D. Levine, "Volumetric Description of Solids of Revolution in a Range Image," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 303-308.

Chapter 6: Dynamic Vision
Selected Bibliography

Abidi, M.A. and R.C. Gonzalez, "Motion Detection in Radar Images," *Proc. Seventh Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1984, pp. 787-790.

Adelson, E.H. and J.R. Bergen, "Spatiotemporal Energy Models for the Perception of Motion," *Optical Society of America*, Vol. 2, No. 2, 1985, pp. 284-299.

Adiv, G., "Determining 3-D Motion and Structure from Optical Flow Generated by Several Moving Objects," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 4, 1985, pp. 384-401.

Adiv, G., "Inherent Ambiguities in Recovering 3-D Motion and Structure from a Noisy Flow Field," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 5, 1989, pp. 477-489.

Aggarwal, J.K., "Motion and Time-Varying Imagery," *Computer Graphics*, 1984, pp. 20-21.

Aggarwal, J.K. and M.J. Magee, "Determining Motion Parameters Using Intensity Guided Range Sensing," *Pattern Recognition*, Vol. 19, No. 2, 1986, pp. 169-180.

Aggarwal, J.K. and A. Mitiche, "Structure and Motion from Images: Fact and Fiction," *Proc. Third IEEE Workshop on Computer Vision: Representation and Control*, IEEE CS Press, Los Alamitos, Calif., 1985, pp. 127-128.

Aggarwal, J.K., L.S. Davis, and W.N. Martin, "Correspondence Processes in Dynamic Scene Analysis," *Proc. IEEE*, Vol. 69, No. 5, IEEE Press, New York, N.Y., 1981, pp. 562-572.

Ahuja, N. and C. Nash, "Octree Representations of Moving Objects," *Computer Vision, Graphics and Image Processing*, Vol. 26, 1984, pp. 207-216.

Aisbett, J., "An Iterated Estimation of Motion Parameters of a Rigid Body from Noisy Displacement Vectors," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 11, 1990, pp. 1092-1098.

Allmen, M. and C.R. Dyer, "Cyclic Motion Detection using Spatiotemporal Surfaces and Curves," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 365-370.

Allmen, M. and C.R. Dyer, "Computing Spatiotemporal Surface Flow," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 47-51.

Aloimonos, J., "Purposive and Qualitative Active Vision," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 346-360.

Aloimonos, J.Y. and C.M. Brown, "The Relationship Between Optical Flow and Surface Orientation," *Proc. Seventh Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1984, pp. 542-545.

Aloimonos, J.Y. and C.M. Brown, "On the Kinetic Depth Effect," *Biological Cybernetics*, Vol. 60, 1989, pp. 445-455.

Anandan, P., "A Computational Framework and an Algorithm for the Measurement of Visual Motion," *Int'l J. Computer Vision*, Vol. 2, No. 3, 1989, pp. 283-310.

Anstis, S.M., "The Perception of Apparent Movement," *Phil. Trans. Royal Soc. London B*, Vol 290, 1980, pp. 153-168.

Aoki, M., "Detection of Moving Objects Using Line Image Sequence," *Proc. Seventh Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1984, pp. 784-786.

Arnspang, J., "Optic Acceleration," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 364-373.

Arnspang, J., "Direct Determination of a Non Accelerating Greylevel Scene," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 319-323.

Asada, M., M. Kimura, and Y. Shirai, "Dynamic Integration of Height Maps into a 3-D World Representation From Range Image Sequences," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 548-557.

Baker, H. H., "Surface Reconstruction from Image Sequences," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 334-343.

Baker, H. H. and R.C. Bolles, "Generalizing Epipolar-Plane Image Analysis on the Spatiotemporal Surface," *Int'l J. Computer Vision*, Vol. 3, No. 1, 1989, pp. 33-49.

Ballard, D.H. and C.M. Brown, *Computer Vision*, Prentice-Hall, Englewood Cliffs, N.J., 1982.

Ballard, D.H. and O.A. Kimball, "Rigid Body Motion from Depth and Optical Flow," *Computer Vision, Graphics and Image Processing*, Vol. 22, 1983, pp. 95-115.

Barron, J.L., et al., "Determination of Egomotion and Environmental Layout from Noisy Time-Varying Image Velocity in Binocular Image Sequences," *Proc. Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1987, pp. 822-825.

Barron, J.L., A.D. Jepson, and J.K. Tsotsos, "The Sensitivity of Motion and Structure Computations," *Proc. Nat'l Conf. on Artificial Intelligence*, MIT Press, Cambridge, Mass., 1987, pp. 700-705.

Barron, J.L., A.D. Jepson, and J.K. Tsotsos, "The Feasibility of Motion and Structure Computations," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 651-657.

Bergen, J.R. et al, "Computing Two Motions from Three Frames," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 27-32.

Bergholm, F., "A Theory on Optical Velocity Fields and Ambiguous Motion of Curves," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 165-176.

Bergholm, F., "Motion from Flow Along Contours: A Note on Robustness and Ambiguous Cases," *Int'l J. Computer Vision*, Vol. 2, No. 4, pp. 395-415.

Bergholm, G., "Decomposition Theory and Transformations of Visual Directions," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 85-90.

Bhanu, B. and W. Burger, "Approximation of Displacement Fields Using Wavefront Region Growing," *Computer Vision, Graphics and Image Processing*, Vol. 41, 1988, pp. 306-322.

Black, M.J. and P. Anandan, "A Model for the Detection of Motion Over Time," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 33-37.

Bolles, R.C., H.H. Baker, and D.H. Marimont, "Epipolar-Plane Image Analysis: An Approach to Determining Structure from Motion," *Int'l J. Computer Vision*, Vol. 1, pp. 7-55.

Bouthemy, P., "A Maximum Likelihood Framework for Determining Moving Edges," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 5, 1989, pp. 499-511.

Bray, A.J., "Tracking Objects Using Image Disparities," *Image and Vision Computing*, Vol. 8, No. 1, 1990, pp. 4-9.

Broida, T.J. and R. Chellappa, "Estimation of Object Motion Parameters from Noisy Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 1, 1986, pp. 90-99.

Broida, T.J. and R. Chellappa, "Performance Bounds for Estimating Three-Dimensional Motion Parameters from a Sequence of Noisy Images," *J. Opt. Soc. Am. A*, Vol. 6, No. 6, 1989.

Broida, T.J. and R. Chellappa, "Experiments and Uniqueness Results on Object Structure and Kinematics from a Sequence of Monocular Images," *Proc. Workshop on Visual Motion*, IEEE CS Press, Los Alamitos, Calif, 1989, pp. 21-30.

Burger, W. and B. Bhanu, "Qualitative Motion Understanding," *Proc. Int'l Joint Conf. Artificial Intelligence*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1987, pp. 819-821.

Burger, W. and B. Bhanu, "Estimating 3-D Egomotion from Perspective Image Sequences," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 11, 1990, pp. 1040-1058.

Burt, P.J. et al, "Object Tracking with a Moving Camera," *Proc. Workshop on Visual Motion*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 2-12.

Buxton, B.F. and H. Buxton, "Monocular Depth Perception from Optical Flow by Space Time Signal Processing," *Proc. Royal Soc. London B*, 1983, pp. 27-47.

Buxton, B.F and H. Buxton, "Computation of Optical Flow from the Motion of Edge Features in Image Sequences," *Image & Vision Computing*, Vol. 2, No. 2, 1984, pp. 59-75.

Campani, M. and A. Verri, "Computing Optical Flow from an Overconstrained System of Linear Algebraic Equations," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 22-26.

Cappelini, V., A. del Bimbo, and P. Nesi, "Object Motion Identification for Object Recognition," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 189-194.

Carlsson, S., "Information in the Geometric Structure of Retinal Flow Fields," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 629-633.

Chang, Y.-L. and J.K. Aggarwal, "Reconstructing 3-D Lines from a Sequence of 2-D Projections: Representation and Estimation," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990. pp. 101-105.

Charnley, D. and R. Blissett, "Surface Reconstruction from Outdoor Image Sequences," *Image and Vision Computing*, Vol. 7, 1989, pp. 10-16.

Chen, C.W. and T.S. Huang, "Epicardial Motion and Deformation Estimation from Coronary Artery Bifurcation Points," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 456-459.

Chen, H.H., "Motion and Depth from Binocular Orthographic Views," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 634-640.

Chen, H.H. and T.S. Huang, "Matching 3-D Line Segments with Applications to Multiple-Object Motion Estimation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 10, 1990, pp. 1002-1008.

Chharbra, A.K. and T.A. Grogan, "Uniqueness, the Minimum Norm Constraint, and Analog Networks for Optical Flow Along Contours," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 80-84.

Chu, H.C. and E.J. Delp, "Estimating Displacement Vectors from an Image Sequence," *J. Opt. Soc. Am. A*, Vol. 6, No. 6, 1989.

Cipolla, R. and M. Yamamoto, "Stereoscopic Tracking of Bodies in Motion," *Image and Vision Computing*, Vol. 8, No. 1, 1990, pp. 85-90.

Costabile, M.F., C. Guerra, and G.G. Pieroni, "Matching Shapes: A Case Study in Time-Varying Images," *Computer Vision, Graphics and Image Processing*, Vol. 29, 1985, pp. 296-310.

Crowley, J.L., P. Stelmaszyk, and C. Discours, "Measuring Image Flow by Tracking Edge-Lines," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 658-664.

Cui, N., J. Weng, and P. Cohen, "Extended Structure and Motion Analysis from Monocular Image Sequences," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 222-229.

D'Haeyer, J., "Determining Motion of Image Curves from Local Pattern Changes," *Computer Vision, Graphics and Image Processing*, Vol. 34, 1986, pp. 166-188.

Daugman, J.G., "Pattern and Motion Vision Without Laplacian Zero Crossings," *J. Opt. Soc. Am. A*, Vol. 5, No. 7, 1988, pp. 1142-1148.

Davis, L.S., Z. Wu, and H. Sun, "Contour-Based Motion Estimation," *Computer Vision, Graphics and Image Processing*, Vol. 23, 1983, pp. 313-326.

Debrunner, C.H. and N. Ahuja, "A Direct Data Approximation Based Motion Estimation Algorithm," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 384-389.

Dickmanns, E.D., "Object Recognition and Real-Time Relative State Estimation Under Egomotion," in *Real-Time Object Measurement and Classification*, A.K. Jain, ed., Springer-Verlag, Berlin, 1988.

Dickmanns, E.D. and V. Graefe, "Dynamic Monocular Machine Vision," *Machine Vision and Applications*, Vol. 1, No. 4, 1988, pp. 223-240.

Dickmanns, E.D. and V. Graefe, "Applications of Dynamic Monocular Machine Vision," *Machine Vision and Applications*, Vol. 1, No. 4, 1988, pp. 241-261.

Dickmanns, E.D., B. Mysliwetz, and T. Christians, "An Integrated Spatio-Temporal Approach for Automatic Visual Guidance of Autonomous Vehicles," *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 20, No. 6, 1990, pp. 1273-1284.

Dietz, T.E., K.R. Diller, and J.K. Aggarwal, "Automated Computer Evaluation of Time-Varying Cryomicroscopical Images," *Cryobiology*, Vol. 21, 1984, pp. 200-208.

Duncan, J.H. and T.C. Chou, "Temporal Edges: The Detection of Motion and the Computation of Optical Flow," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 374-382.

Dutta, R. and M.A. Snyder, "Robustness of Correspondence-Based Structure from Motion," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 106-110.

Fang, J.-Q. and T.S. Huang, "Some Experiments on Estimating the 3-D Motion Parameters of a Rigid Body from Two Consecutive Image Frames," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 6, No. 5, 1984, pp. 545-554.

Fang, J.Q. and T.S. Huang, "Solving Three-Dimensional Small-Rotation Motion Equations: Uniqueness, Algorithms, and Numerical Results," *Computer Vision, Graphics and Image Processing*, Vol. 26, 1984, pp. 183-206.

Fleet, D.J. and A.D. Jepson, "Computation of Component Image Velocity from Local Phase Information," *Int'l J. Computer Vision*, Vol. 5, No. 1, 1990, pp.77-104.

Fogel, S.V., "A Nonlinear Approach to the Motion Correspondence Problem," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 619-628.

Fogel, S.V., "Implementation of a Nonlinear Approach to the Motion Correspondence Problem," *Proc. IEEE Workshop on Visual Motion*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 87-98.

Fuh, C.S. and P. Maragos, "Region-Based Optical Flow Estimation," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 130-35.

Girosi, F., A. Verri, and V. Torre, "Constraints for the Computation of Optical Flow," *Proc. IEEE Workshop on Visual Motion*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 116-124.

Giusto, D.D. and G. Vernazza, "Optical Flow Calculation from Feature Space Analysis Through an Automatic Segmentation Process," *Signal Processing*, Vol. 16, 1989, pp. 41-51.

Gould, K. and M. Shah, "The Trajectory Primal Sketch: A Multi-Scale Scheme for Representing Motion Characteristics," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 79-85.

Goutsias, J. and J.M. Mendel, "Simultaneous Optimal Segmentation and Model Estimation of Nonstationary Noisy Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 9, 1989, pp. 990-998.

Grzywacz, N.M. and E.C. Hildreth, "Incremental Rigidity Scheme for Recovering Structure from Motion: Position-Based Versus Velocity-Based Formulations," *J. Opt. Soc. Am. A*, Vol. 4, No. 3, 1987, pp. 503-518.

Hadani, I. and E. Barta, "The Hybrid Constraint Equation for Motion Extraction," *Image and Vision Computing*, Vol. 7, 1989, pp. 217-224.

Haralick, R.M. and X. Zhuang, "A Note on 'Rigid Body Motion from Depth and Optical Flow'," *Computer Vision, Graphics and Image Processing*, Vol. 34, 1986, pp. 372-387.

Hayashi, B.Y. and S. Negahdaripour, "Direct Motion Stereo: Recovery of Observer Motion and Scene Structure," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 446-450.

Haynes, S.M. and R.C. Jain, "Time-Varying Edge Detection," *Computer Graphics and Image Processing*, Vol. 21, 1983, pp. 345-367.

Haynes, S.M. and R.C. Jain, "Event Detection and Correspondence," *Optical Engineering*, Vol. 25, No. 3, 1986, pp. 387-393.

Haynes, S.M. and R.C. Jain, "A Qualitative Approach for Recovering Depths in Dynamic Scenes," *IEEE Workshop on Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 66-71.

Heeger, D.J., "Model for the Extraction of Image Flow," *J. Opt. Soc. Am. A*, Vol. 4, No. 8, 1987, pp. 1455-1471.

Heeger, D.J. and G. Hager, "Egomotion and the Stabilized World," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 435-440.

Heeger, D.J. and A. Jepson, "Simple Method for Computing 3-D Motion and Depth," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 96-100.

Heitz, F. and P. Bouthemy, "Multimodal Motion Estimation and Segmentation Using Markov Random Fields," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 378-383.

Herman, M. and T. Kanade, "Incremental Reconstruction of 3-D Scenes from Multiple, Complex Images," *Artificial Intelligence*, Vol. 30, 1986, pp. 289-341.

Hoffman, D.D. and B.M. Bennett, "Inferring the Relative Three-Dimensional Positions of Two Moving Points," *J. Opt. Soc. Am. A*, Vol. 2, No. 2, 1985, pp. 350-353.

Hoffman, D.D. and B.M. Bennett, "The Computation of Structure from Fixed-Axis Motion: Rigid Structures," *Biological Cybernetics*, Vol. 54, 1986, pp. 71-83.

Horn, B.K.P., "Motion Fields are Hardly Ever Ambiguous," *Int'l J. Computer Vision*, Vol. 1, 1987, pp. 259-274.

Horn, B.K.P., "Relative Orientation," *Int'l J. Computer Vision*, Vol. 4, No. 1, 1990, pp. 59-78.

Horn, B.K.P. and B.G. Schunck, "Determining Optical Flow," *Artificial Intelligence*, Vol. 17, 1981, pp. 185-203.

Horn, B.K.P. and E.J. Weldon, "Direct Methods for Recovering Motion," *Int'l J. Computer Vision*, Vol. 2, No. 1, 1988, pp. 151-75.

Huang, T.S., "Modeling Analysis, and Visalization of Nonrigid Object Motion," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 361-364.

Huang, T.S. and O.D. Faugeras, "Some Properties of the E Matrix in Two-View Motion Estimation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 12, 1989, pp. 1310-1312.

Huang, T.S. and C.H. Lee, "Motion and Structure from Orthographic Projection," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 5, 1989, pp. 536-540.

Hutchinson, J., et al., "Computing Motion Using Analog and Binary Resistive Networks," *Computer*, Vol. 21, No. 3, 1988, pp. 52-63.

Jacobson, L. and H. Wechsler, "Derivation of Optical Flow Using a Spatiotemporal-Frequency Approach," *Computer Vision, Graphics and Image Processing*, Vol. 38, No. 1, 1987, pp. 29-65.

Jain, R.C., "Extraction of Motion Information from Peripheral Processes," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 3, No. 5, 1981, pp. 489-503.

Jain, R.C., "Dynamic Vision," *Proc. Ninth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 226-235.
Jain, R.C., S. Bartlett, and N. O'Brien, "Motion Stereo Using Ego-Motion Complex Logarithmic Mapping," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 3, 1987, pp. 356-369.
Jain, R.C., Y. Roth-Tabak, and K. Skifstad, "Hyperpyramids for Vision-Driven Navigation," *Proc. SPIE Conf. on Applications of Artificial Intelligence VI*, Vol. 937, 1988, pp. 630-637.
Jasinschi, R.S., "Space-Time Sampling with Motion Uncertainty: Constraints on Space-Time Filtering," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 428-434.
Jasinschi, R. and A. Yuille, "Nonrigid Motion and Regge Calculus," *J. Opt. Soc. Am. A*, Vol. 6, 1989, pp. 1088-1095.
Jayaramamurthy, S.N. and R.C. Jain, "An Approach to the Segmentation of Textured Dynamic Scenes," *Computer Vision, Graphics and Image Processing*, Vol. 21, No. 2, 1983, pp. 239-261.
Jezouin, J.L. and N. Ayache, "3-D Structure from a Monocular Sequence of Images," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 441-445.
Kanatani, K., "Tracing Planar Surface Motion from a Projection without Knowing the Correspondence," *Computer Vision, Graphics and Image Processing*, Vol. 29, No. 1, 1985, pp. 1-12.
Kanatani, K., "Structure and Motion from Optical Flow Under Perspective Projection," *Computer Vision, Graphics and Image Processing*, Vol. 38, No. 2, 1987, pp. 122-146.
Kanatani, K., "Transformation of Optical Flow by Camera Rotation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 2, 1988, pp. 131-143.
Kearney, J.K., W.B. Thompson, and D.L. Boley, "Optical Flow Estimation: An Error Analysis of Gradient-Based Methods with Local Optimization," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 2, 1987, pp. 229-244.
Kehtarnavaz, N. and S. Mohan, "A Framework for Estimation of Motion Parameters from Range Images," *Computer Vision, Graphics and Image Processing*, Vol. 46, 1989, pp. 88-105.
Kim, Y.C. and J.K. Aggarwal, "Determining Object Motion in a Sequence of Stereo Images," *IEEE Trans. Robotics and Automation*, Vol. 3, No. 6, 1987, pp. 599-614.
Koenderink, J.J. and A.J. van Doorn, "Facts on Optic Flow," *Biological Cybernetics*, Vol. 56, 1987, pp. 247-254.
Koenderink, J.J., A.J. van Doorn, and W.A. van de Grind, "Spatial and Temporal Parameters of Motion Detection in the Peripheral Visual Field," *J. Opt. Soc. Am. A*, Vol. 2, No. 2, 1985, pp. 252-259.
Konrad, J. and E. Dubois, "Multigrid Bayesian and Estimation of Image Motion Fields Using Stochastic Relaxation," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 354-362.
Landy, M.S., "Parallel Model of the Kinetic Depth Effect Using Local Computations," *J. Opt. Soc. Am. A*, Vol. 4, No. 5, 1987, pp. 864-877.
Lawton, D.T., "Processing Translational Motion Sequences," *Computer Graphics and Image Processing*, Vol. 22, No. 1, 1983, pp. 116-144.
Lee, C.H., "Structure and Motion from Two Perspective Views Via Planar Patch," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 158-164.
Lee, D., A. Papageorgiou, and G.W. Wasilkowski, "Computing Optical Flow," *Proc. Workshop on Visual Motion*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 99-106.
Lee, S. and Y. Kay, "A Kalman Filter Approach for Accurate 3-D Motion Estimation from a Sequence of Stereo Images," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 104-108.
Legters, G.R. and T.Y. Young, "A Mathematical Model for Computer Image Tracking," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 4, No. 6, 1982, pp. 583-594.
Levine, M.D., P.B. Noble, and Y.M. Youssef, "Understanding Blood Cell Motion," *Computer Vision, Graphics and Image Processing*, Vol. 21, No. 1, 1983, pp. 58-84.
Lin, X. and Z. Zhu, "Detecting Height from Constrained Motion," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 503-506.
Little, J.J. and A. Verri, "Analysis of Differential and Matching Methods for Optical Flow," *Proc. Workshop on Visual Motion*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 173-180.
Little, J.J., H.H. Bulthoff, and T. Poggio, "Parallel Optical Flow Using Local Voting," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 454-459.
Loomis, J.M. and D.W. Eby, "Perceiving Structure from Motion: Failure of Shape Constancy," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 383-391.
Lowe, D.G., "Integrated Treatment of Matching and Measurement Errors for Robust Model-Based Motion Tracking," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 436-440.
Magee, M.J. and J.K. Aggarwal, "Determining Vanishing Points from Perspective Images," *Computer Vision, Graphics and Image Processing*, Vol. 26, 1984, pp. 256-267.
Markandey, V. and B.E. Flinchbaugh, "Multispectral Constraints for Optical Flow Computation," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 38-41.
Mase, K., "An Application of Optical Flow - Extraction of Facial Expression" *IAPR Workshop on Machine Vision Applications*, 1990, pp. 195-198.
Matthies, L., R. Szeliski, and T. Kanade, "Kalman Filter-Based Algorithms for Estimating Depth from Image Sequences," *Int'l J. Computer Vision*, Vol. 3, No. 3, 1989, pp. 209-237.
Maybank, S.J., "Rigid Velocities Compatible with Five Image Velocity Vectors," *Image and Vision Computing*, Vol. 8, No. 1, 1990, pp. 18-23.
McIvor, A.M., "Edge Recognition in Dynamic Vision," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 118-123.
Mecocci, A., "Moving Object Recognition and Classification in External Environments," *Signal Processing*, Vol. 18, 1989, pp. 183-194.

Meygret, A. and M. Thonnat, "Segmentation of Optical Flow and 3-D Data for the Interpretation of Mobile Objects," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 238-245.

Mitiche, A., "On Lineopsis and Computation of Structure and Motion," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 1, 1986, pp. 109-112.

Mitiche, A., "Three-Dimensional Space From Optical Flow Correspondence," *Computer Vision, Graphics and Image Processing*, Vol. 42, 1988, pp. 306-317.

Mitiche, A. and P. Bouthemy, "Tracking Modeled Objects Using Binocular Images," *Computer Vision, Graphics and Image Processing*, Vol. 32, 1985, pp. 384-396.

Mitiche, A., S. Seida, and J.K. Aggarwal, "Using Constancy of Distance to Estimate Position and Displacement in Space," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 4, 1988, pp. 594-599.

Mori, T., "An Active Method of Extracting Egomotion Parameters from Optical Flow," *Biological Cybernetics*, Vol. 52, 1985, pp. 405-407.

Mukawa, N., "Estimation of Shape, Reflection Coefficients, and Illuminant Direction from Image Sequence," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 507-512.

Murray, D.W., "Algebraic Polyhedral Constraints and 3-D Structure from Motion," *Image and Vision Computing*, Vol. 8, No. 1, 1990, pp. 24-31.

Murray, D.W. and B.F. Buxton, "Scene Segmentation from Visual Motion Using Global Optimization," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 2, 1987, pp. 220-228.

Murray, D.W., D.A. Castelow, and B.F. Buxton, "From Image Sequences to Recognized Moving Polyhedral Objects," *Int'l J. Computer Vision*, Vol. 3, No. 3, 1989, pp. 181-207.

Mutch, K.M. and W.B. Thompson, "Analysis of Accretion and Deletion at Boundaries in Dynamic Scenes," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 2, 1985, pp. 133-138.

Nagel, H.H., "On a Constraint Equation for the Estimation of Displacement Rates in Image Sequences," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol 11, No. 1, 1989, pp. 13-30.

Nagel, H.H. and W. Enkelmann, "An Investigation of Smoothness Constraints for the Estimation of Displacement Vector Fields from Image Sequences," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 5, 1986, pp. 565-593.

Navab, N., R. Deriche, and O.D. Faugeras, "Recovering 3-D Motion and Structure from Stereo and 2-D Token Tracking Cooperation," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 513-516.

Negahdaripour, S., "Critical Surface Pairs and Triplets," *Int'l J. Computer Vision*, Vol. 3, No. 4, 1989, pp. 293-311.

Negahdaripour, S., "Multiple Interpretations of the Shape and Motion of Objects from Two Perspective Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 11, 1990, pp. 1025-1039.

Nelson, R.C. and J.Y. Aloimonos, "Obstacle Avoidance Using Flow Field Divergence," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 10, 1989, pp. 1102-1106.

Nevatia, R., "Depth Measurement by Motion Stereo," *Computer Graphics and Image Processing*, Vol. 5, 1976, pp. 203-214.

Ohta, N., "Movement Vector Detection with Reliability," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 177-180.

Peleg, S. and H. Rom, "Motion Based Segmentation," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 109-113.

Pentland, A., "Photometric Motion," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 178-189.

Prager, J.M. and M.A. Arbib, "Computing the Optic Flow: The Match Algorithm and Prediction," *Computer Vision, Graphics and Image Processing*, Vol. 24, 1983, pp. 271-304.

Prazdny, K., "Egomotion and Relative Depth Map from Optical Flow," *Biological Cybernetics*, Vol. 36, 1980, pp. 87-102.

Prazdny, K., "On the Information in Optical Flows," *Computer Vision, Graphics and Image Processing*, Vol. 22, 1983, pp. 239-259.

Prazdny, K., "Detection of Binocular Disparities," *Biological Cybernetics*, Vol. 52, 1985, pp. 93-99.

Prazdny, K., "Studies of Some New Phenomena of Motion Perception," *Biological Cybernetics*, Vol. 52, 1985, pp. 187-194.

Price, K., "Multi-Frame Feature-Based Motion Analysis," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 114-118.

Reiger, J.H. and D.T. Lawton, "Processing Differential Image Motion," *J. Opt. Soc. Am. A*, Vol. 2, No. 2, 1985, pp. 354-359.

Richards, W., "Structure from Stereo and Motion," *J. Opt. Soc. Am. A*, Vol. 2, No. 2, 1985, pp. 343-349.

Rink, R.E., T.M. Caelli, and V.G. Gourishankar, "Recovery of the 3-D Location and Motion of a Rigid Object Through Camera Image (An Extended Kalman Filter Approach)," *Int'l J. Computer Vision*, Vol. 2, No. 4, 1989, pp. 373-393.

Sawhney, H.S., J. Oliensis, and A.R. Hanson, "Description and Reconstruction from Image Trajectories of Rotational Motion," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 494-498.

Schalkoff, R.J., "Dynamic Imagery Modeling and Motion Estimation Using Weak Formulations," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 4, 1987, pp. 578-584.

Schunck, B.G., "Image Flow: Fundamentals and Algorithms," in *Motion Understanding: Robot and Human Vision*, W. N. Martin and J. K. Aggarwal, eds., Kluwer, 1988.

Schunck, B.G., "Motion Segmentation and Estimation by Constraint Line Clustering," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 10, 1989, pp. 1010-1027.

Scott, G.L., "'Four-Line' Method of Locally Estimating Optic Flow," *Image and Vision Computing*, Vol. 5, 1987, pp. 67-72.

Sethi, I.K. and R.C. Jain, "Finding Trajectories of Feature Points in a Monocular Image Sequences," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 1, 1987, pp. 56-73.

Shahraray, B. and M.K. Brown, "Robust Depth Estimation from Optical Flow," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 641-650.

Shigang, L., S. Tsuji, and M. Imai, "Determining of Camera Rotation from Vanishing Points of Lines on Horizontal Planes," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 499-502.

Shiraishi, K., M. Terauchi, and K. Onaga, "Recognition of Human Motion Based on Interpretation of 2-D Pattern Deformation," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 185-189.

Shulman, D. and J.Y. Herve, "Regularization of Discontinuous Flow Fields," *Proc. Workshop on Visual Motion*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 81-86.

Silven, O., "Estimating the Pose and Motion of a Known Object for Real-Time Robotic Tracking," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 357-361.

Singh, A., "An Estimation-Theoretic Framework for Image-Flow Computation," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 168-177.

Spetsakis, M. and J.Y. Aloimonos, "Optimal Computing of Structure from Motion Using Point Correspondences in Two Frames," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 449-453.

Spetsakis, M.E. and J.Y. Aloimonos, "Structure from Motion Using Line Correspondences," *Int'l J. Computer Vision*, Vol. 4, No. 3, 1990, pp. 171-183.

Spoerri, A. and S. Ullman, "The Early Detection of Motion Boundaries," *Proc. First Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 209-218.

Stephens, R.S., "Real-Time 3-D Object Tracking," *Image and Vision Computing*, Vol. 8, No. 1, 1990.

Subbarao, M., "Interpretation of Image Flow: Rigid Curved Surfaces in Motion," *Int'l J. Computer Vision*, Vol. 2, No. 1, 1988, pp. 77-96.

Subbarao, M. and A.M. Waxman, "Closed Form Solutions to Image Flow Equations for Planar Surfaces in Motion," *Computer Vision, Graphics and Image Processing*, Vol. 36, 1986, pp. 208-228.

Szeliski, R., "Estimating Motion from Sparse Range Data Without Correspondence," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 207-216.

Taalebinezhaad, M.A., "Direct Recovery of Motion and Shape in the General Case by Fixation," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 451-455.

Tan, C.L. and W.N. Martin, "A Distributed System for Analyzing Time-Varying Multiresolution Imagery," *Computer Vision, Graphics and Image Processing*, Vol. 36, 1986, pp. 162-174.

Terzopoulos, D., A.P. Witkin, and M. Kass, "Constraints on Deformable Models: Recovering 3-D Shape and Nonrigid Motion," *Artificial Intelligence*, Vol. 36, 1988, pp. 91-123.

Thompson, W.B., "Dynamic Occlusion Analysis in Optical Flow Fields," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 4, 1985, pp. 374-383.

Tomasi, C. and T. Kanade, "Shape and Motion Without Depth," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 91-95.

Topa, L.C. and R.J. Schalkoff, "Edge Detection and Thinning in Time-Varying Image Sequences Using Spatio-Temporal Templates," *Pattern Recognition*, Vol. 22, 1989, pp 143-154.

Tsai, R.Y. and T.S. Huang, "Estimating Three-Dimensional Motion Parameters of a Rigid Planar Patch," *IEEE Trans. Acoustics, Speech, and Signal Processing*, Vol. 29, No. 6, 1981, pp. 1147-1152.

Tsai, R.Y. and T.S. Huang, "Uniqueness and Estimation of 3-D Motion Parameters of Rigid Objects with Curved Surfaces," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 6, No. 1, 1984, pp. 13-27.

Tsai, R.Y., T.S. Huang, and W.L Zhu, "Estimating Three-Dimensional Motion Parameters of a Rigid Planar Patch, II: Singular Value Decomposition," *IEEE Trans. Acoustics, Speech, and Signal Processing*, Vol. 30, No. 4, 1982, pp. 525-534.

Tseng, G. and A.K. Sood, "Analysis of Long Image Sequence for Structure and Motion Estimation," *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, 1989, pp. 1511-1526.

Tsukune, H. and J.K. Aggarwal, "Analyzing Orthographic Projection of Multiple 3-D Velocity Vector Fields in Optical Flow," *Computer Vision, Graphics, And Image Processing*, Vol. 42, 1988, pp. 157-191.

Tziritas, G., "Recursive And/Or Iterative Estimation of the Two-Dimensional Velocity Field and Reconstruction of Three-Dimensional Motion," *Signal Processing*, Vol. 16, 1989, pp. 53-72.

Ullman, S., "Analysis of Visual Motion by Biological and Computer Systems," *Computer*, Vol. 14, No. 8, 1984, pp. 97-160.

Verri, A. and T. Poggio, "Against Quantitative Optical Flow," *Proc. First Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 171-180.

Vieville, T. and O.D. Faugeras, "Feed-Forward Recovery of Motion and Structure from a Sequence of 2D-Lines Matches," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990. pp. 517-521.

Wang, G., R.M. Inigo, and E.S. McVey, "A Single-Pixel Target Detection & Tracking System," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 99-103.

Waxman, A.M. and J.H. Duncan, "Binocular Image Flows: Steps Toward Stereo-Motion Fusion," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 6, 1986, pp. 715-729.

Waxman, A.M. and S.S. Sinha, "Dynamic Stereo: Passive Ranging to Moving Objects from Relative Image Flows," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 4, 1986, pp. 406-412.

Waxman, A.M. and K. Wohn, "Contour Evolution, Neighborhood Deformation and Image Flow: Textured Surfaces in Motion," in *Image Understanding*, W. Richards and S. Ullman, eds., Chap. 4, 1985-86, Ablex, 1987.

Waxman, A.M. and K. Wohn, "Image Flow Theory: A Framework for 3-D Inference from Time-Varying Imagery," in *Advances in Computer Vision*, C.M. Brown, ed., Lawrence Erlbaum, Hillsdale, N.J., 1988.

Waxman, A.M., B. Kamgar-Parsi, and M. Subbarao, "Closed-Form Solutions to Image Flow Equations for 3-D Structure and Motion," *Int'l J. Computer Vision*, Vol. 1, 1987, pp. 239-258.

Waxman, A.M., J. Wu, and F. Bergholm, "Convected Activation Profiles and the Measurement of Visual Motion," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 717-723.

Weinshall, D., "Direct Computation of Qualitative 3-D Shape and Motion Invariants," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 230-237.

Weng, J., T.S. Huang, and N. Ahuja, "Motion and Structure from Two Perspective Views: Algorithms, Error Analysis, and Error Estimation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 5, 1989, pp. 451-476.

Weng, J., T.S. Huang, and N. Ahuja, "Estimating Motion and Structure from Line Matches: Performance Obtained and Beyond," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 168-172.

Werkhoven, P., A. Toet, and J.J. Koenderink, "Displacement Estimates Through Adaptive Affinities," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 7, 1990, pp. 658-663.

Westphal, H. and H.H. Nagel, "Toward the Derivation of Three-Dimensional Descriptions from Image Sequences for Nonconvex Moving Objects," *Computer Vision, Graphics and Image Processing*, Vol. 34, 1986, pp. 302-320.

Williams, L.R. and A.R. Hanson, "Translating Optical Flow into Token Matching and Depth from Looming," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 441-448.

Woodham, R.J., "Multiple Light Source Optical Flow," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 42-46.

Wu, J., R. Brockett, and K. Wohn, "A Contour-Based Recovery of Image Flow: Iterative Method," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 124-129.

Xu, G., S. Tsuji, and M. Asada, "A Motion Stereo Method Based on Coarse-To-Fine Control Strategy," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 2, 1987, pp. 332-336.

Yamamoto, M., "A General Aperture Problem for Direct Estimation of 3-D Motion Parameters," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 5, 1989, pp. 528-536.

Yamamoto, M. et al, "Direct Estimation of Deformable Motion Parameters from Range Image Sequence," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 460-465.

Young, G.-S. and R. Chellappa, "Statistical Analysis of Inherent Ambiguities in Recovering 3-D Motion from a Noisy Flow Field," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 371-377.

Young, G.-S. J. and R. Chellappa, "3-D Motion Estimation Using a Sequence of Noisy Stereo Images: Models, Estimation, and Uniqueness Results," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 8, 1990, pp. 735-759.

Yuille, A.L. and N. Grzywacz, "A Mathematical Analysis of the Motion Coherence Theory," *Int'l J. Computer Vision*, Vol. 3, No. 2, 1989, pp. 155-175.

Zhang, Z. and O.D. Faugeras, "Tracking and Grouping 3-D Line Segments," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 577-581.

Zhang, Z., O.D. Faugeras, and N. Ayache, "Analysis of a Sequence of Stereo Scenes Containing Multiple Moving Objects Using Rigidity Constraints," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 177-186.

Zhao, W.Z., F.H. Qi, and T.Y. Young, "Dynamic Estimation of Optical Flow Field Using Objective Functions," *Image and Vision Computing*, Vol. 7, No. 4, 1989, pp. 259-267.

Zheng, J.Y. and S. Tsuji, "Panoramic Representation of Scenes for Route Understanding," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 161-167.

Zucker, S.W. and L. Iverson, "From Orientation Selection to Optical Flow," *Computer Vision, Graphics and Image Processing*, Vol. 37, 1987, pp. 196-220.

Chapter 7: Knowledge-based Vision Selected Bibliography

Alexandrov, V.V. and N.D. Gorsky, "Expert Systems Simulating Human Visual Perception," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 3, 1989, pp. 19-28.

Ballard, D.H., C.M. Brown, and J.A. Feldman, "An Approach to Knowledge-Directed Image Analysis," in *Computer Vision Systems*, A.R. Hanson and E.M. Riseman, eds., Academic Press, New York, N.Y., 1978, pp. 271-281.

Barr, A. and E.A. Feigenbaum, *The Handbook of Artificial Intelligence*, William Kaufmann, Los Altos, Calif., 1982.

Bobick, A.F. and R.C. Bolles, "Representation Space: An Approach to the Integration of Visual Information," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 492-499.

Bogdanowicz, J.F., "An Evolving System for Image Understanding," *Proc. SPIE Conf. Digital Image Processing*, Vol. 528, 1985, pp. 110-116.

Bolle, R.M., A. Califano, and R. Kjeldsen, "Data and Model Driven Focus of Foveation," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 1-7.

Edelman, S. and T. Poggio, "Representations in High-Level Vision: Reassessing the Inverse Optics Paradigm," *Proc. DARPA Image Understanding Workshop*, 1989, pp. 944-949.

Hanson, A. and E. Riseman, "The VISIONS Image Understanding System," in *Advances in Computer Vision*, C. Brown, ed., 1988, Erlbaum, Hillsdale, N.J., pp. 1-114.

Herman, M. and T. Kanade, "The 3-D MOSAIC Scene Understanding System: Incremental Reconstruction of 3-D Scenes from Multiple Complex Images," *Artificial Intelligence*, Vol. 30, No. 3, 1986, pp. 289-341.

Hopkins, S., G.J. Michaelson, and A.M. Wallace, "Parallel Imperative and Functional Approaches to Visual Scene Labeling," *Image and Vision Computing*, Vol. 7, No. 3, 1989, pp. 178-193.

Kak, A.C., "Spatial Reasoning," *AI Magazine*, Vol. 9, No. 2, 1988, pp. 23.

Koons, D.B. and B.H. McCormick, "A Model of Visual Knowledge Representation," *Proc. First Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 365-372.

Kuan, D. et al, "A Constraint-Based System for Interpretation of Aerial Imagery," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 601-609.

Lawton, D.T. and T.S. Levitt, "Knowledge Based Vision for Terrestrial Robots," *Proc. DARPA Image Understanding Workshop*, 1989, pp. 128-133.

Levine, M.D. and A.M. Nazif, "Dynamic Measurement of Computer Generated Image Segmentations," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 2, 1985, pp. 155-164.

Levitt, T.S. et al, "Probability-Based Control for Computer Vision," *Proc. DARPA Image Understanding Workshop*, 1989, pp. 355-369.

Marefat, M. and R.L. Kashyap, "Geometric Reasoning for Recognition of Three-Dimensional Object Features," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 10, Oct. 1990, pp. 949-965.

McKeown Jr., D.M., "Building Knowledge-Based System for Detecting Man-Made Structures from Remotely Sensed Imagery," *Proc. Royal Soc. London B*, Vol. A324, 1988, pp. 423-435.

McKeown Jr., D.M., W.A. Harvey Jr., and J. McDermott, "Rule-Based Interpretation of Aerial Imagery," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 5, 1985, pp. 570-585.

Modestino, J.W. and J. Zhang, "A Markov Random Field Model-Based Approach to Image Interpretation," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 458-465.

Morris, D.T. and A. Narendra-Nathan, "A Rule-Based System for Dimensional Analysis of Glass Containers," *Image and Vision Computing*, Vol. 7, No. 4, 1989, pp. 274-280.

Mulder, J.A., A.K. Mackworth, and W.S. Havens, "Knowledge Structuring and Constraint Satisfaction: The Mapsee Approach," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 6, 1988, pp. 866-879.

Nandhakumar, N. and J.K. Aggarwal, "Integrated Analysis of Thermal and Visual Images for Scene Interpretation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 4, 1988, pp. 469-481.

Nazif, A.M. and M.D. Levine, "Low Level Image Segmentation: An Expert System," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 6, No. 5, 1984, pp. 555-577.

Niemann, H. et al, "A Knowledge-Based Vision System for Industrial Applications," *Machine Vision and Applications*, Vol. 3, No. 4, 1990, pp. 201-229.

Niemann, H. et al, "Ernest: A Semantic Network System for Pattern Understanding," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 9, 1990, pp. 883-905.

Oh, C., N. Nandhakumar, and J.K. Aggarwal, "Integrated Modeling of Thermal and Visual Image Generation," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 356-362.

Olin, K.E., et al., "Knowledge-Based Vision Technology Overview for Obstacle Detection and Avoidance," *Proc. DARPA Image Understanding Workshop*, 1989, pp. 134-143.

Pentland, A.P., "Perceptual Organization and the Representation of Natural Form," *Artificial Intelligence*, Vol. 28, No. 3, 1986, pp. 293-331.

Provan, G.M., "The Visual Constraint Recognition System: Analyzing the Role of Reasoning in High Level Vision," *Proc. Workshop on Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1987, pp. 170-175.

Reiter, R. and A.K. Mackworth, "A Logical Framework for Depiction and Image Interpretation," *Artificial Intelligence*, Vol. 41, No. 2, 1989, pp. 125-156.

Rich, E., *Artificial Intelligence*, McGraw-Hill, New York, N.Y., 1983.

Rosenfeld, A., "'Expert' Vision Systems: Some Issues," *Computer Vision, Graphics and Image Processing*, Vol. 34, No. 1, 1986, pp. 99-117.
Shvaytser, H., "Towards a Computational Theory of Model Based Vision and Perception," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 283-286.
Srihari, S.N. and Z. Xiang, "Spatial Knowledge Representation," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 3, 1989, pp. 67-84.
Tehrani, S., T.E. Weymouth, and G.B.L. Mancini, "Knowledge-Guided Left Ventricular Boundary Detection," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 342-347.
Trivedi, M.M., "Analysis of High Resolution Aerial Images," in *Image Analysis Applications*, R. Kasturi and M.M. Trivedi, eds., Marcel Dekker, New York, N.Y., 1990, pp. 281-305.
Tsotsos, J.K., "Knowledge and the Visual Process: Content, Form and Use," *Pattern Recognition*, Vol. 17, No. 1, 1984, pp. 13-27.
Tsotsos, J.K., "Knowledge Organization and Its Role in Representation and Interpretation for Time-Varying Data: The ALVEN System," *Computational Intelligence*, Vol. 1, 1985, pp. 16-32.
Wallace, A.M., "A Comparison of Approaches to High-Level Image Interpretation," *Pattern Recognition*, Vol. 21, 1988, pp. 241-259.
Wesley, L.P., "Evidential Knowledge-Based Computer Vision," *J. Opt. Soc. Am. A*, Vol. 25, No. 3, 1986, pp. 363-379.
Woods, P.W., D. Pycock, and C.J. Taylor, "A Frame-Based System for Modeling and Executing Visual Tasks," *Image and Vision Computing*, Vol. 7, No. 2, 1989, pp. 102-108.
Zhang, J. and J.W. Modestino, "A Model-Fitting Approach to Cluster Validation with Application to Stochastic Model-Based Image Segmentation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 10, 1990, pp. 1009-1017.

Chapter 8: Applications
Selected Bibliography

Aerial Image Analysis:

Conners, R.W., M.M. Trivedi, and C.A. Harlow, "Segmentation of a Complex Urban Scene Using Texture Operators," *Computer Vision, Graphics, and Image Processing*, Vol. 25, 1984, pp. 273-310.

Fischler, M.A., J.M. Tenenbaum, and H.C. Wolf, "Detection of Roads and Linear Structures in Low-Resolution Aerial Imagery Using a Multisource Knowledge Integration Technique," *Computer Graphics and Image Processing*, Vol. 15, No. 3, 1981, pp. 201-223.

Harlow, C.A., R.W. Conners, and M.M. Trivedi, "Developing a Computer Vision System for the Analysis of Aerial Scenes," *Proc. Seventh Int'l Conf. Pattern Recognition*, IEEE, CS Press, Los Alamitos, Calif., 1984, pp. 407-410.

Harlow, C.A. et al, "Scene Analysis of High Resolution Aerial Scenes," *Optical Engineering*, Vol. 25, No. 3, 1986, pp. 347-355.

Hsieh, Y.C., F. Perlant, and D.M. McKeown, "Recovering 3-D Information from Complex Aerial Imagery," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE, CS Press, Los Alamitos, Calif., 1990, pp. 136-146.

Huertas, A. and R. Nevatia., "Detecting Buildings in Aerial Images," *Computer Vision, Graphics, and Image Processing*, Vol. 41, 1988, pp. 131-152.

Kuan, D. et al, "A Constraint-Based System for Interpretation of Aerial Imagery," *Proc. Second Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1988, pp. 601-609.

Landgrabe, D.A., "Analysis Technology for Land Remote Sensing," *Proc. IEEE*, Vol. 69, No. 5, IEEE Press, New York, N.Y., 1981, pp. 628-642.

Laprade, R.H., "Split-and-Merge Segmentation of Aerial Photographs," *Computer Vision, Graphics, and Image Processing*, Vol. 44, No. 1, 1988, pp. 77-86.

Matsuyama, T., "Knowledge-Based Aerial Image Understanding Systems and Expert Systems for Image Processing," *IEEE Trans. on Geoscience and Remote Sensing*, Vol. 25, No. 3, 1987, pp. 305-316.

McKeown, D.M., "Toward Automatic Cartographic Feature Extraction," in *Mapping and Spatial Modeling for Navigation*, L.F. Pau, ed., NATO ASI Series, Vol. F 65, Springer-Verlag, Berlin, Heidelberg, 1990, pp. 149-180.

McKeown, D.M., W.A. Harvey, and J.M. McDermott., "Rule-Based Interpretation of Aerial Imagery," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 7, No. 5, 1985, pp. 570-584.

Sevingny, L.G. et al, "Discrimination and Classification of Vehicles in Natural Scenes from Thermal Imagery," *Computer Vision, Graphics, and Image Processing*, Vol. 24, 1983, pp. 229-243.

Trivedi, M.M., "Analysis of High Resolution Aerial Images," in *Image Analysis Applications*, R. Kasturi and M.M. Trivedi, eds., Marcel Dekker, New York, N.Y., 1990, pp. 281-305.

Document Image Analysis:

Abdulla, W.H., A.O.M. Saleh, and A.H. Morad, "A Preprocessing Algorithm for Hand-Written Character Recognition Letters," *Pattern Recognition*, Vol. 7, No. 1, 1988, pp. 13-18.

Ahmed, P. and C.Y. Suen, "Computer Recognition of Totally Unconstrained Handwritten Zip Codes," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 1, 1987, pp. 1-15.

Akiyama, T. and N. Hagita, "Automated Entry System for Printed Documents," *Pattern Recognition*, Vol. 23, 1990, pp. 141-154.

Al-Emami, S. and M. Usher, "On-Line Recognition of Handwritten Arabic Characters," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 7, 1990, pp. 704-710.

Almuallim, H. and S. Yamaguchi, "A Method of Recognition of Arabic Cursive Handwriting," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 9, No. 5, 1987, pp. 715-722.

Ammar, M., Y. Yoshida, and T. Fukumura, "Off-Line Preprocessing and Verification of Signatures," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 2, 1988, pp. 589-602.

Amin, T.J. and R. Kasturi, "Map Data Processing: Recognition of Lines and Symbols," *Optical Engineering*, Vol. 26, 1987, pp. 354-358.

Antoine, D., S. Collin, and K. Tombre, "Analysis of Technical Documents: The REDRAW System," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition*, Murray Hill, N.J., 1990, pp. 1-20.

Baird, H.S., "Feature Identification for Hybrid Structural/Statistical Pattern Classification," *Computer Vision, Graphics, and Image Processing*, Vol. 42, 1988, pp. 318-33.

Baird, H.S., "Document Image Defect Models," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition*, Murray Hill, N.J., 1990, pp. 38-46.

Baird, H.S., "Anatomy of a Page Reader," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 483-486.

Baird, H.S. and K. Thompson, "Reading Chess," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 6, 1990, pp. 552-559.

Bapista, G. and K.M. Kulkarni, "A High Accuracy Algorithm for Recognition of Handwritten Numerals," *Pattern Recognition*, Vol. 21, 1988, pp. 287-291.

Belaid, A., J.J. Brault, and Y. Chenevoy, "Knowledge-Based System for Structured Document Recognition," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 465-469.

Bixler, J.P. and J.P. Sanford, "A Technique for Encoding Lines and Regions in Engineering Drawings," *Pattern Recognition*, Vol. 18, 1985, pp. 367-377.

Bixler, J.P., L.T. Watson, and J.P. Sanford, "Spline-Based Recognition of Straight Lines and Curves in Engineering Line Drawings," *Image and Vision Computing*, Vol.6, 1988, pp. 262-269.

Bow, S.T. and R. Kasturi, "A Graphics Recognition System for Interpretation of Line Drawings," in *Image Analysis Applications*, Marcel Dekker, 1990, pp. 37-72.

Bozinovic, R.M. and S.N. Srihari, "Off-Line Cursive Script Word Recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 1, 1989, pp. 68-83.

Brossman, C. and G.R. Cross, "Model-Based Recognition of Characters in Trademark Artwork," *Pattern Recognition Letters*, Vol. 11, 1990, pp. 363-370.

Brown, R.M., T.H. Fay, and C.L. Walker, "Handprinted Symbol Recognition System," *Pattern Recognition*, Vol. 21, 1988, pp. 91-118.

Cabrelli, C.A. and U.M. Molter, "Automatic Representation of Binary Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 11, 1990, pp. 1190-1196.

Campbell-Grant, I.R. and P.J. Robinson, "An Introduction to ISO DIS 8613, 'Office Document Architecture', and Its Application to Computer Graphics," *Computer & Graphics*, Vol. 11, 1987, pp. 325-341.

Casey, R.G. and D.R. Ferguson, "Intelligent Forms Processing," *IBM Systems Journal*, Vol. 29, 1990, pp. 435-450.

Cash, G.L. and M. Hatamian, "Optical Character Recognition by the Method of Moments," *Computer Vision, Graphics, and Image Processing*, Vol. 39, 1987, pp. 29-310.

Chen, K.J., K.C. Li, and Y.L. Chang, "A System for On-Line Recognition of Chinese Characters," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 2, 1988, pp. 139-148.

Chen, P.N., Y.S. Chen, and W.H. Hsu, "Stroke Relation Coding - A New Approach to the Recognition of Multi-Font Printed Chinese Characters," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 2, 1988, pp. 149-160.

Cheng, F.H., W.H. Hsu, and M.Y. Chen, "Recognition of Handwritten Chinese Characters by Modified Hough Transform Techniques," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 4, 1989, pp. 429-439.

Cheng, Y.Q., Y.L. Cao, and J.Y. Yang, "An Automatic Recognition System of Assembly Drawings," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 211-214.

Collin, S. and D. Colnet, "Analysis of Dimension in Mechanical Engineering Drawings," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 105-108.

Davis, R.H. and J. Lyall, "Recognition of Handwritten Characters - A Review," *Image and Vision Computing*, Vol. 4, 1986, pp. 208-218.

de Jesus, E.O., "High Level Loader and Recognizer of Electrical and Electronic Images Diagrams," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 101-103.

Dengel, A., "Document Image Analysis - Expectation-Driven Text Recognition," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition*, 1990, pp. 78-87.

Dengel, A. and G. Barth, "High Level Document Analysis Guided by Geometric Aspects," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 2, 1988, pp. 641-655.

Dinan, R.F., L.D. Painter, and R.R. Rodite, "Image Plus High Performance Transaction System," *IBM Systems Journal*, Vol. 29, 1990, pp. 421-434.

Dori, D., "Self Structural Syntax Directed Pattern Recognition of Dimensioning Components in Engineering Drawings," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition*, 1990, pp. 88-112.

Dori, D. and A. Pnueli, "The Grammar of Dimensions in Machine Drawings," *Computer Vision, Graphics, and Image Processing*, Vol. 42, No. 1, 1988, pp. 1-18.

Downton, A.C. and C.G. Leedham, "Preprocessing and Presorting of Envelope Images for Automatic Sorting Using OCR," *Pattern Recognition*, Vol. 23, 1990, pp. 347-362.

El-Dabi, S.S., R. Ramis, and A. Kamel, "Arabic Character Recognition System: A Statistical Approach for Recognizing Cursive Typewritten Text," *Pattern Recognition*, Vol. 23, 1990, pp. 485-495.

El-Khaly, and M.A. Sid-Ahmed, "Machine Recognition of Optically Captured Machine Printed Arabic Text," *Pattern Recognition*, Vol. 23, 1990, pp. 1207-1214.

El-Sheikh, T.S. and S.G. El-Taweel, "Real-Time Arabic Handwritten Character Recognition," *Pattern Recognition*, Vol. 23, 1990, pp. 1323-1332.

Elliman, D.G. and I.T. Lancaster, "A Review of Segmentation and Contextual Analysis Techniques for Text Recognition," *Pattern Recognition*, Vol. 23, 1990, pp. 337-346.

Espelid, R. et al, "Automatic Digitizing of the Colour-Layer of Thematic Maps," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 299-302.

Fahn, C.S., J.F. Wang, and J.Y. Lee, "A Topology-Based Component Extractor for Understanding Electronic Circuit Diagrams," *Computer Vision, Graphics, and Image Processing*, Vol. 44, 1988, pp. 119-138.

Fletcher, L.A. and R. Kasturi, "A Robust Algorithm for Text String Separation from Mixed Text/Graphics Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 6, 1988, pp. 910-918.

Freeman, H. and J. Ahn, "On the Problem of Placing Names in a Geographic Map," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 1, 1987, pp. 121-140.

Fujisawa, H. and Y. Nakano, "A Top-Down Approach for the Analysis of Document Images," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition*, 1990, pp. 113-122.

Futatsumata, T. et al, "Development of an Automatic Recognition System for Plant Diagrams," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 207-210.

Futrelle, R.P., "Strategies for Diagram Understanding: Generalized Equivalence, Spatial/Object Pyramids, and Animate Vision," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 403-408.

Goodson, K.J. and P.H. Lewis, "A Knowledge-Based Line Recognition System," *Pattern Recognition Letters*, Vol. 11, 1990, pp. 295-304.

Govindan, V.K. and A.P. Shivaprasad, "Character Recognition - A Review," *Pattern Recognition*, Vol. 23, 1990, pp. 671-683.

Groen, F.C.A., A.C. Sanderson, and J.F. Schlag, "Symbol Recognition in Electrical Diagrams Using Probabilistic Graph Matching," *Pattern Recognition,* Vol. 3, 1985, pp. 343-350.

Hayakawa, T. et al, "Recognition of Roads in an Urban Map by Using the Topological Road-Network," *Proc. IAPR Workshop on Machine Vision Applications,* 1990, pp. 215-221.

Ho, T.K., J.J. Hull, and S.N. Srihari, "Combination of Structural Classifiers," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition,* 1990, pp. 123-136.

Hori, O. and A. Okazaki, "High Quality Vectorization Based on a Generic Object Model," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition,* 1990, pp. 137-153.

Hrechak, A.K. and J.A. McHugh, "Automated Fingerprint Recognition Using Structural Matching," *Pattern Recognition,* Vol. 23, 1990, pp. 893-904.

Ilg, M. and R. Ogniewicz, "Knowledge-Based Interpretation of Road Maps Based on Symmetrical Skeletons," *Proc. IAPR Workshop on Machine Vision Applications,* 1990, pp. 161-164.

Joseph. S.H., "Processing of Engineering Line Drawings for Automatic Input to CAD," *Pattern Recognition,* Vol. 22, 1989, pp. 1-11.

Joseph, S.H. and T.P. Pridmore, "A System for the Interpretation of Images of Graphics," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition,* 1990, pp. 154-164.

Kanai, J., "Text-Line Extraction Using Character Prototypes," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition,* 1990, pp. 182-191.

Kasturi, R., "Image Analysis Techniques for Geographic Information Systems", in *Image Analysis Applications,* Marcel Dekker, 1990, pp. 127-163.

Kasturi, R. and J. Alemany, "Information Extraction from Images of Paper-based Maps for Query Processing," *IEEE Trans. Software Engineering* (special section on Image Databases), Vol. 14, 1988, pp. 671-675.

Kasturi, R., S. Siva, and L. O'Gorman, "Techniques for Line Drawing Interpretation: An Overview," *Proc. IAPR Workshop on Machine Vision Applications,* 1990, pp. 151-160.

Kasturi, R. et al, "Map Data Processing in Geographical Information Systems," *Computer,* Vol. 22, No. 12, 1989, pp. 10-21.

Kasturi, R. et al, "Document Image Analysis: An Overview of Techniques for Graphics Recognition," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition,* 1990, pp. 192-230.

Kasturi, R. et al, "A System for Interpretation of Line Drawings," *IEEE Trans. Pattern Analysis and Machine Intelligence,* Vol. 12, No. 10, 1990, pp. 978-992.

Kato, H. and S. Inokuchi, "The Recognition System for Printed Piano Music Using Musical Knowledge and Constraints," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition,* 1990, pp. 231-248.

Kerrick, D.D. and A.C. Bovik, "Microprocessor-Based Recognition of Handprinted Characters from a Tablet Input," *Pattern Recognition,* Vol. 21, 1988, pp. 525-537.

Kise, K., et al., "Model Based Understanding of Document Images," *Proc . IAPR Workshop on Machine Vision Applications,* 1990, pp. 471-474.

Kita, N., "Handwriting Model Adjustable to Writers," *Proc. IAPR Workshop on Machine Vision Applications,* 1990, pp. 431-440.

Kultanen, P., E. Oja, and L. Xu, "Randomized Hough Transform (RHT) in Engineering Drawing Vectorization System," *Proc. IAPR Workshop on Machine Vision Applications,* 1990, pp. 173-180.

Kumar, R.E., A. Agarwal, and A.K. Pujari, "Off-Line Shorthand Recognition System," *Proc. IAPR Workshop on Machine Vision Applications,* 1990, pp. 437-444.

Kurtzberg, J.M., "Feature Analysis for Symbol Recognition by Elastic Matching," *IBM J. Res. Develop.,* Vol. 31, No. 1, 1987, pp. 91-95.

Lam, L. and C.Y. Suen, "Structural Classification and Relaxation Matching of Totally Unconstrained Handwritten Zip-code Numbers," *Pattern Recognition,* Vol. 21, No. 1, 1988, pp. 19-31.

Lee, D.S., S.W. Lam, and S.N. Srihari, "A Structural Approach to Recognize Hand-printed and Degraded Machine-printed Characters," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition,* 1990, pp. 256-272.

Lee, S.W., J.H. Kim, and F.C.A. Groen, "Translation-, Rotation-, and Scale-Invariant Recognition of Hand-Drawn Electrical Circuit Symbols with Attributed Graph Matching," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition,* 1990, pp. 273-292.

Lee, S.W., J.H. Kim, and F.C.A. Groen, "Translation-, Rotation-, and Scale- Invariant Recognition of Hand-Drawn Symbols in Schematic Diagrams," *Int'l J. Pattern Recognition and Artificial Intelligence,* Vol. 4, 1990, pp. 1-25.

Leedham, C.G. and A.C. Downton, "Automatic Recognition and Transcription of Pitman's Handwritten Shorthand - An Approach to Shortforms," *Pattern Recognition,* Vol. 20, 1987, pp. 341-348.

Leung, C.H., Y.S. Cheung, and Y.L. Wong, "A Knowledge-Based Stroke-Matching Method for Chinese Character Recognition," *IEEE Trans. Systems, Man, and Cybernetics,* Vol. 17, No. 6, 1987, pp. 993-1003.

Li, H.F., R. Jayakumar and M. Youssef, "Parallel Algorithms for Recognizing Handwritten Characters Using Shape Features," *Pattern Recognition,* Vol. 22, 1989, pp. 641-652.

Luo, Q., et al., "Recognition of Document Structure on the Basis of Spatial and Geometric Relationships between Document Items," *Proc. IAPR Workshop on Machine Vision Applications,* 1990, pp. 461-464.

Lysak, D.B. Jr. and R. Kasturi, "Interpretation of Line Drawings with Multiple Views," *Proc. Tenth Int'l Conf. on Pattern Recognition,* IEEE CS Press, Los Alamitos, Calif., 1990, pp. 220-222.

Maderlechner, G., "'Symbolic Subtraction' of Fixed Formatted Graphics and Text from Filled-in Forms," *Proc. IAPR Workshop on Machine Vision Applications,* 1990, pp. 457-459.

Mantas, J., "An Overview of Character Recognition Methodologies," *Pattern Recognition,* Vol. 19, 1986, pp. 425-430.

Marukawa, K. et al, "A High Speed Word Matching Algorithm for Handwritten Chinese Character Recognition," *Proc. IAPR Workshop on Machine Vision Applications,* 1990, pp. 445-449.

Mehtre, B.M. and B. Chatterjee, "Segmentation of Fingerprint Images - A Composite Method," *Pattern Recognition,* Vol. 22, 1989, pp. 381-385.

Mehtre, B.M. and A.K. Jain, "Automatic Classification of Fingerprint Images," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 287-290.

Mehtre, B.M., N.N. Murthy, and S. Kapoor, "Segmentation of Fingerprint Images Using the Directional Image," *Pattern Recognition*, Vol. 20, 1987, pp. 429-435.

Miligram, M., M. Jobert, and B. Lamy, "A Segmentation Free Approach to Symbol Extraction and Recognition from Image Document," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 475-478.

Mitchell, B.T. and A.M. Gillies, "A Model-Based Computer Vision System for Recognizing Handwritten ZIP Codes," *Machine Vision and Applications*, Vol. 2, No. 4, 1989, pp. 231-243.

Moon, Y.S. and W.K. Hui, "High Quality Chinese Fonts Generation for Desktop Publishing - A Computer Vision Approach," *Pattern Recognition Letters*, Vol. 9, 1989, pp. 147-151.

Morishita, T., M. Ooura, and Y. Ishii, "A Kanji Recognition Method which Detects Writing Errors," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 2, 1988, 181-195.

Murase, H. and T. Wakahara, "Online Hand-Sketched Figure Recognition," *Pattern Recognition*, Vol. 19, 1986, pp. 147-160.

Musavi, M.T. et al, "A Vision-Based Method to Automate Map Processing," *Pattern Recognition*, Vol. 21, 1988, pp. 319-326.

Nagasamy, V. and N.A. Langrana, "Engineering Drawing Processing and Vectorization System," *Computer Vision, Graphics, and Image Processing*, Vol. 49, 1990, pp. 379-397.

Nagy, G. "Towards a Structured-Document-Image Utility," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition*, 1990, pp. 293-309.

Nakano, Y. et al, "An Algorithm for the Skew Normalization of Document Image," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 8-13.

Namane, A. and M.A. Sid-Ahmed, "Character Scaling by Contour Method," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 6, 1990, pp. 600-606.

Nouboud, F. and R. Plamondon, "On-Line Recognition of Handprinted Characters: Survey and Beta Tests," *Pattern Recognition*, Vol. 23, 1990, pp. 1031-1044.

Okamoto, M. and A. Miyazawa, "An Experimental Implementation of Document Recognition System for Papers Containing Mathematical Expressions," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition*, 1990, pp. 335-350.

Okazaki, A. et al, "An Automatic Circuits Diagram Reader with Loop-Structure-Based Symbol Recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 3, 1988, pp. 331-341.

Parizeau, M. and R. Plamondon, "A Comparative Analysis of Regional Correlation, Dynamic Time Warping, and Skeletal Tree Matching for Signature Verification," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 7, 1990, pp. 710-716.

Pavlidis, T., "A Vectorizer and Feature Extractor from Document Recognition," *Computer Vision, Graphics, and Image Processing*, Vol. 35, 1986, pp. 111-127.

Pham, B., "Conic B-Splines for Curve Fitting: A Unifying Approach," *Computer Vision, Graphics, and Image Processing*, Vol. 45, 1989, pp. 117-125.

Plamondon, R. and G. Lorette, "Automatic Signature Verification and Writer Identification - The State of the Art," *Pattern Recognition*, Vol. 22, 1989, pp. 107-131.

Plesums, C.A. and R.W. Bartels, "Large-Scale Image Systems: USAA Case Study," *IBM Systems Journal*, Vol. 29, 1990, pp. 343-355.

Rao, P.V.S., "Word-Based Recognition of Cursive Script," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 441-445.

Risse, T., "Hough Transform for Line Recognition: Complexity of Evidence Accumulation and Cluster Detection," *Computer Vision, Graphics, and Image Processing*, Vol. 46, 1989, pp. 327-345.

Roach, J.W. and J.E. Tatem, "Using Domain Knowledge in Low-Level Visual Processing to Interpret Handwritten Music: An Experiment," *Pattern Recognition*, Vol. 21, No. 1, 1988, pp. 33-44.

Sabourin, R., R. Plamondon, and G. Lorette, "Off-Line Identification with Handwritten Signature Images: Survey and Perspectives," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition*, 1990, pp. 377-391.

Satoh, S. and M. Sakauchi, "Descriptive Ability of Drawing Image Understanding Framework Using State Transition Models," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 199-202.

Seemuller, W.W., "The Extraction of Ordered Vector Drainage Networks from Elevation Data," *Computer Vision, Graphics, and Image Processing*, Vol. 47, No. 1, 1989, pp. 45-58.

Shih, C-C. and R. Kasturi, "Extraction of Graphic Primitives from Images of Paper-based Drawings," *Machine Vision and Applications*, Vol. 2, 1989, pp. 103-113.

Shlien, S., "Multifont Character Recognition for Typeset Documents," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 2, 1988, pp. 603-620.

Shridhar, M. and A. Badreldin, "Recognition of Isolated and Simply Connected Handwritten Numerals," *Pattern Recognition*, Vol. 19, 1986.

Simon, J.C. and O. Baret, "Regularities and Singularities in Line Pictures," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition*, 1990, pp. 423-439.

Sinha, R.M.K., "Rule Based Contextual Post-Processing for Devanagari Text Recognition," *Pattern Recognition*, Vol. 20, 1987, pp. 475-485.

Sinha, R.M.K. and B. Prasada, "Visual Text Recognition Through Contextual Processing," *Pattern Recognition*, Vol. 21, 1988, pp. 463-479.

Sinha, R.M.K. and H.C. Karnick, "Plang Based Specification of Patterns with Variations for Pictorial Data Bases," *Computer Vision, Graphics, and Image Processing*, Vol. 43, 1988, pp. 98-110.

Srihari, S.N. and V. Govindaraju, "Analysis of Textual Images Using the Hough Transform," *Machine Vision and Application*, Vol. 2, 1989, pp. 141-153.

Srinivasan, V.S., "Identification of Core and Delta Points in Fingerprint Images," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 263-266.

Stringa, L., "Efficient Classification of Totally Unconstrained Handwritten Numerals with a Trainable Multilayer Network," *Pattern Recognition Letters*, Vol. 10, 1989, pp. 273-280.

Suzuki, S. and T. Yamada, "Maris: Map Recognition Input System," *Pattern Recognition*, Vol. 23, 1990, pp. 919-933.

Tappert, C.C., C.Y. Suen, and T. Wakahara, "The State of the Art in On-Line Handwriting Recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 8, 1990, pp. 787-808.

Taxt, T., P.J. Flynn, and A.K. Jain, "Segmentation of Document Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 12, 1989, pp. 1322-1329.

Taxt, T., J.B. Olafsdottir, and M. Dehlen, "Recognition of Handwritten Symbols," *Pattern Recognition*, Vol. 23, 1990, pp. 1155-1166.

Thibadeau, R.H. and D.M. McNulty, "Two Systems for Converting Raster Data to Numerical Control Data," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 227-231.

Tsuji, Y. et al, "Document Recognition System with Layout Structure Generator," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 479-482.

Vaxiviere, P. and K. Tombre, "Interpretation of Mechanical Engineering Drawings for Paper-CAD Conversion," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 203-205.

Viseshsin, S. and S. Murai, "Automated Height Information Acquisition from Topographic Map," *Proc. IAPR Workshop on Machine Vision Applications*, 1990, pp. 219-221.

Viswanathan, M., "Analysis of Scanned Documents - A Syntactic Approach," *Proc. IAPR Workshop on Syntactic and Structural Pattern Recognition*, 1990, pp. 450-459.

Wang, C.H. and S.N. Srihari, "A Framework for Object Recognition in a Visually Complex Environment and its Application to Locating Address Blocks on Mail Pieces," *Int'l J. Computer Vision*, Vol. 2, 1988, pp. 125-151.

Wolberg, G., "A Syntactic Omni-Font Character Recognition System," *Int'l J. Pattern Recognition and Artificial Intelligence*, Vol. 1, 1987, pp. 303-322.

Xia, Y. and C. Sun, "Recognizing Restricted Handwritten Chinese Characters by Structure Similarity Method," *Pattern Recognition Letters*, Vol. 11, No. 1, 1990, pp. 67-73.

Yeh, P.S. et al, "Address Location on Envelopes," *Pattern Recognition*, Vol. 20, 1987, pp. 213-227.

Yong, Y., "Handprinted Chinese Character Recognition Via Neural Networks," *Pattern Recognition Letters*, Vol. 7, No. 1, 1988, pp. 19-25.

Medical Image Analysis:

Abdel, A., O. Hasekioglu, and J.J. Bloomer, "Image Segmentation via Motion Vector Estimates," *SPIE Medical Imaging IV*, 1990, pp. 366-373.

Adam, D., O. Hareuveni, and S. Sideman, "Semiautomated Border Tracking of Cine-Echocardiographic Ventricular Images," *IEEE Trans. on Medical Imaging*, 1987, pp. 266-271.

Ahn, C.B. and Z.H. Cho, "A New Phase Correction Method in NMR Imaging Based on Autocorrection and Histogram Analysis," *IEEE Trans. on Medical Imaging*, 1987, pp. 32-36.

Amamoto, D.Y., R. Kasturi and A. Mamourian, "Tissue-type Discrimination in Magnetic Resonance Images," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 603-607.

Apicella, A., J.S. Kippenhan, and J.H. Nagel, "Fast Multi-Modality Image Matching," *Proc. SPIE Medical Imaging III*, Vol. 1090, 1989, pp. 252-263.

Armadillo, R. et al, "Modeling and Shape Decomposition of Anatomical Organs by Using Superquadric Primitives," *Eleventh Ann. IEEE Engineering in Medical and Biology Conf.*, 1989, pp. 610-611.

Barth, K.L., B. Eicker, and J. Seissl, "Automated Biplane Vessel Recognition in Digital Coronary Angiograms," *Proc. of SPIE Medical Imaging I*, 1990, pp. 266-277.

Bartoo, G.T., "Multi-Modality Image Registration Using Centroid Mapping," *Eleventh Ann. IEEE Engineering in Medical and Biology Conf.*, 1989, pp. 550-552.

Besson, G.M., "Vascular Segmentation Using Snake Transforms and Region Growing," *Proc. SPIE Medical Imaging III*, Vol. 1090, 1989, pp. 429-435.

Biederman, "Human Visual Pattern Recognition," *Proc. SPIE Medical Imaging IV*, Vol. 1231, 1990, pp. 2-9.

Bow, S.T. and X.-F. Wang, "Applications of Pattern Recognition and AI Technique to the Cytoscreening of Vaginal Smears by Computer," *Proc. SPIE Medical Imaging III*, Vol. 1090, 1989, pp. 551-555.

Chaudhuri, S. et al, "Detection of Blood Vessels in Retinal Images Using Two-Dimensional Matched Filters," *IEEE Trans. on Medical Imaging*, 1989, pp. 263-269.

Chen, C.-T., "Edge and Surface Searching in Medical Images," *Proc. of SPIE Medical Imaging II*, Vol. 914, 1988, pp. 594-599.

Chen, S.Y., "Sensor Integration for Tomographic Image Segmentation," *Eleventh Ann. IEEE Engineering in Medical and Biology Conf.*, 1988, pp. 1387-1388.

Chen, S.Y. and W.-C. Lin, "Expert Vision System for Medical Image Segmentation," *Proc. SPIE Medical Imaging III*, Vol. 1090, 1989, pp. 162-172.

Chu, C.H., E.J. Delp, and A.J. Buda, "Detecting Left Ventricular Endocardial and Epicardial Boundaries by Digital 2-D Echocardiography," *IEEE Trans. Medical Imaging*, 1988, pp. 81-90.

Cios, K.J. and A. Sarieh, "An Edge Extraction Technique for Noisy Images," *IEEE Trans. on Biomedical Engineering*, 1990, pp. 520-524.

Dalton, B.L. and G. du Boulay, "Medical Image Matching," *Proceeding of SPIE Medical Imaging II*, Vol. 914, 1988, pp. 456-464.

Dann, R. and J. Hoford, "3-D Computerized Brain Atlas for Elastic Matching: Creation and Initial Evaluation," *Proc. of SPIE Medical Imaging II*, Vol. 914, 1988, pp. 600-608.

Davis, D.H., D.R. Dance, and C.H. Jones, "Automatic Detection of Microcalcifications in Digital Mammograms," *Proc. SPIE Medical Imaging IV*, Vol. 1231, 1990, pp. 185-193.

Dhawan, A.P. and S. Juvvadi, "Knowledge-Based Analysis and Understanding of 3-D Medical Images," *Proc. of SPIE Medical Imaging II*, Vol. 914, 1988, pp. 422-428.

Dunn, S.M., "Biological Image Understanding," *Proc. SPIE Medical Imaging III*, Vol. 1090, 1989, pp. 480-491.

Egbert, D.D., V.G. Kaburlasos, and P.H. Goodman, "Invariant Feature Extraction for Neurocomputer Analysis of Biomedical Images," *Second IEEE Symp. Computer-Based Medical Systems*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 69-75.

Ehricke, H., "Problems and Approaches for Tissue Segmentation in 3-D MR Imaging," *Proc. SPIE Medical Imaging IV*, Vol. 1231, 1990, pp. 128-137.

Evans, A.C. et al, "Anatomical-Functional Correlative Analysis of the Human Brain Using 3-D Imaging System," *Proc. SPIE Medical Imaging III*, Vol. 1090, 1989, pp. 264-274.

Faber, T.L. and E.M. Stokely, "Feature Detection in 3-D Medical Images Using Shape Information," *IEEE Trans. on Medical Imaging*, 1987, pp. 8-13.

Friendland, N. and D. Adam, "Automatic Ventricular Cavity Boundary Detection from Sequential Ultrasound Images Using Simulated Annealing," *IEEE Trans. on Medical Imaging*, 1989, pp. 344-353.

Giger, M.L., K. Doi, and H. MacMahon, "Computerized Detection of Lung Nodules in Digital Chest Radiographs," *Proc. of SPIE Medical Imaging II*, Vol. 914, 1987, pp. 384-386.

Gordon, D. and J.K. Udupa, "Fast Surface Tracking in Three-Dimensional Binary Images," *Computer Vision, Graphics, and Image Processing*, Vol. 45, 1989, pp. 196-214.

Hibbard, L.S. et al, "Three-Dimensional Representation and Analysis of Brain Energy Metabolism," *Science*, Vol. 236, 1987, pp. 1641-1646.

Ji, Z. and J. Yang, "The Development of Automatic Recognition System for DNA," *Tenth Ann. IEEE Engineering in Medical and Biology Conf.*, 1988, pp. 366-367.

Kennedy, D.N., P.A. Filipek, and V.S. Caviness, Jr, "Anatomic Segmentation and Volumetric Calculations in Nuclear Magnetic Resonance Imaging," *IEEE Trans. on Medical Imaging*, 1989, pp. 1-7.

Kim, N.H., A.C. Bovik, and S.J. Aggarwal, "Shape Description of Biological Objects vis Stereo Light Microscopy," *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 20, No. 2, 1990, pp. 475-489.

Klingler Jr., J.W. et al, "Segmentation of Echocardiographic Image Using Mathematical Morphology," *IEEE Trans. Biomedical Engineering*, 1988, pp. 925-934.

Kowarski, D., "Expert System and Image and Text Database," *Third IEEE Symp. Computer-Based Medical Systems*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 298-305.

Lee, R.H. and R.M. Leahy, "Multispectral Tissue Classification of MR Images Using Sensor Fusion Approaches," *Proc. SPIE Medical Imaging IV*, Vol. 1231, 1990, pp. 149-159.

Lifshitz, L.M. and S.M. Pizer, "A Multiresolution Hierarchical Approach to Image Segmentation Based on Intensity Extrema," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 6, June, 1990, pp. 529-540.

Lilly, P., J. Jenkins, and P. Bourdillon, "Automatic Contour Definition on Left Ventriculograms by Image Evidence and a Multiple Template-Based Model," *IEEE Trans. on Medical Imaging*, 1989, pp. 173-185.

Luo, R.C. and Y. Kim, "Representation and Recognition of 3-D Curved Objects Using Complete 3-D Range Data," *Proc. SPIE Medical Imaging IV*, Vol. 1231, 1990, pp. 103-115.

McGlone, J.S. et al, "A Computerized System for Measuring Cerebral Metabolism," *IEEE Trans. Bio-Medical Engineering*, Vol. 34, 1987, pp. 704-712.

Merickel, M.B. et. al, "Multi-Dimensional MRI Pattern Recognition of Atherosclerosis," *Eighth Ann. IEEE Engineering in Medical and Biology Conf.*, 1986, pp. 1142-1145.

Michael, D.J. and A.C. Nelson, "Handx: A Model-Based System for Automatic Segmentation of Bones from Digital Hand Radiographs," *IEEE Trans. on Medical Imaging*, 1989, pp. 64-69.

Minato, K et al, "Automatic Contour Detection Using a 'Fixed-Point Hachimura-Kuwahara Filter' for Spect Attenuation," *IEEE Trans. on Medical Imaging*, 1987, pp. 126-133.

Prasad, B. et al, "A Knowledge-Based System for Tutoring Bronchial Asthma Diagnosis," *Second IEEE Symp. Computer-Based Medical Systems*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 40-45.

Ro, D.W. et al, "Computed Masks in Coronary Subtraction Imaging," *IEEE Trans. on Medical Imaging*, 1987, pp. 297-300.

Smets, C., P. Suetens, and A.J. Oosterlinck, "Knowledge-Based System for the Delineation of the Coronary Arteries," *Proc. SPIE Medical Imaging III*, Vol. 1090, 1989, pp. 214-219.

Sun, Y., "Automated Identification of Vessel Contours in Coronary Arteriograms by an Adaptive Tracking Algorithm," *IEEE Trans. on Medical Imaging*, 1989, pp. 78-88.

Sun, Y., "Automated Biplane Vessel Recognition in Digital Coronary Angiograms," *Proc. SPIE Medical Imaging IV*, Vol. 1231, 1990, pp. 257-265.

Tehrani, S., T.E. Weymouth, and G.B.J. Mancini, "Knowledge-Guided Left Ventricular Boundary Detection," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 342-347.

Trivedi, S.S., G.T. Herman, and J.K. Udupa, "Segmentation into Three Classes Using Gradients," *IEEE Trans. on Medical Imaging*, 1986, pp. 116-119.

Unser, M. et al, "Automated Extraction of Serial Myocardial Borders from M-mode Echocardiograms," *IEEE Trans. on Medical Imaging*, 1989, pp. 96-103.

van der Stelt, P.F. and W.G.M. Geraets, "Automated Recognition of Bone Structure in Osteoporotic Patients," *Proc. SPIE Medical Imaging III*, Vol. 1090, 1989, pp. 376-382.

Vandermeulen, D. et al, "Knowledge-Based 3-D Segmentation of Blood Vessels on a Spatial Sequence of MRI and Ultrasound Images," *Proc. SPIE Medical Imaging III*, Vol. 1090, 1989, pp. 142-152.

Watson, A.B. and A.J. Ahumada, "A Hexagonal Orthogonal-Oriented Pyramid as a Model of Image Representation on Visual Cortex," *IEEE Trans. Biomedical Engineering*, 1989, pp. 97-106.

Yan, H. and J.C. Gore, "Optimized MR Image Segmentation for Tissue Characterization," *Tenth Ann. IEEE Engineering in Medical and Biology Conf.*, 1988, pp. 338-339.

Industrial Inspection and Robotics:

Barnett, K. and M.M. Trivedi, "Analysis of Thermal and Visual Images for Industrial Inspection Tasks," *Proc. Applications of Artificial Intelligence*, VII, 1989, 482-488.

Bartlett, S.J. et al, "Automatic Solder Joint Inspection," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 1, 1988, pp. 31-43.

Boerner, H. and H. Strecker, "Automated X-Ray Inspection of Aluminum Castings," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 1, 1988, pp. 79-91.

Chen, C., M.M. Trivedi, and C. Bidlack, "Design and Implementation of Autonomous Spill Cleaning Robotic System," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conf. VIII*, Vol. 1293, 1990, pp. 691-703.

Chen, C., M.M. Trivedi, and S.B. Marapane, "Extending Capabilities of a Robotic Vision System," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conf. VII*, Vol. 1095, 1989, pp. 579-580.

Chin, R.T., *Algorithms and Techniques for Automated Visual Inspection*, Academic Press, New York, N.Y., 1986, pp. 587-612.

Chin, R.T. and C.A. Harlow, "Automated Visual Inspection: A Survey," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 4, No. 6, 1982, pp. 557-573.

Courtney, J.W., M.J. Magee, and J.K. Aggarwal, "Robot Guidance Using Computer Vision," *Pattern Recognition*, Vol. 17, No. 6, 1984, pp. 585-592.

Darwish, A.M. and A.K. Jain, "A Rule-Based Approach for Visual Pattern Inspection," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 1, 1988, pp. 56-68.

He, S., N. Abe, and T. Kitahashi, "Understanding Assembly Illustrations in an Assembly Manual without any Model of Mechanical Parts," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 573-576.

Jarvis, J.F., "A Method for Automating the Visual Inspection of Printed Wiring Boards," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 2, No. 1, 1980, pp. 77-82.

Kak, A.C. et al, "A Knowledge-Based Robotic Assembly Cell," *IEEE EXPERT*, Vol. 1, No. 1, 1986, pp. 63-83.

Lavin, M.A. and L.I. Lieberman, "AML/V: An Industrial Machine Vision Programming System," *Int'l J. Robotics Research*, Vol. 1, No. 3, 1982, pp. 42-56.

Lougheed, R.M. and R.E. Sampson, "3-D Imaging Systems and High-Speed Processing for Robot Control," *Machine Vision and Applications*, Vol. 1, 1988, pp. 41-57.

Mandeville, J.R., "Novel Method for Analysis of Printed Circuit Images," *IBM J. Res. Develop.*, Vol. 29, No. 1, 1985, pp. 73-86.

Maruyama, T. et al, "Hand-Eye System with Three-Dimensional Vision and Microgripper for Handling Flexible Wire," *Machine Vision and Applications*, Vol. 3, No. 4, 1990, pp. 189-199.

McIntosh, W.E., "Automating the Inspection of Printed Circuit Boards," *Robotics Today*, 1983, pp. 75-100.

Niemann, H. et al, "Interpretation of Industrial Scenes by Semantic Networks," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 39-42.

Nishihara, K.H. and P.A. Crossley, "Measuring Photolithographic Overlay Accuracy and Critical Dimensions by Correlating Binarized Laplacian of Gaussian Convolutions," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 1, 1988, pp. 17-30.

Pau, L.F., "Integrated Testing and Algorithms for Visual Inspection of Integrated Circuits," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 5, No. 6, 1983, pp. 602-608.

Piironen, T. et al, "Automated Visual Inspection of Rolled Metal Surfaces," *Machine Vision and Applications*, Vol. 3, No. 4, 1990, pp. 247-254.

Rosenfeld, A., "Machine Vision for Industry: Tasks, Tools, and Techniques," *Image and Vision Computing*, Vol. 3, 1985, pp. 122-135.

Sanderson, A.C., L.E. Weiss, and S.K. Nayar, "Structured Highlight Inspection of Specular Surfaces," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 1, 1988, pp. 44-55.

Sanz, J.L.C. and D. Petkovic, "Machine Vision Algorithms for Automated Inspection of Thin-Film Disk Heads," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 6, 1988, pp. 830-848.

Sanz, J.L.C., F. Merkle, and K.Y. Wong, "Automated Digital Visual Inspection with Dark-Field Microscopy," *J. Opt. Soc. Am. A*, Vol. 2, 1985, pp. 1857-1862.

Shneier, M.O., R. Lunia, and M. Herman, "Prediction-Based Vision for Robot Control," *Computer*, Vol. 20, No. 8, 1987, pp. 46-55.

Shu, D.B. et al, "A Line Extraction Method for Automated SEM Inspection of VLSI Resist," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 1, 1988, pp. 117-121.

Shuttleworth, P.J. and M. Robinson, "3-D Vision for Robot Manipulator Control," *Proc. SPIE/IEEE Applications of Artificial Intelligence Conf. VIII*, Vol. 1293, 1990, pp. 344-353.

Sood, R.K. and E. Al-Hujazi, "An Integrated Approach to Segmentation of Range Images of Industrial Parts," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 27-30.

Trivedi, M.M. and C. Chen, "Sensor-Driven Intelligent Robotics," *Advances in Computers*, Vol. 32, 1991, pp. 173-216.

Trivedi, M.M., C. Chen, and S.B. Marapane, "A Vision System for Robotic Inspection and Manipulation," *Computer*, Vol. 22, No. 6, 1989, pp. 91-97.

Trivedi, M.M. et al, "Developing Robotic Systems with Multiple Sensors," *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 20, No. 6, 1990, pp. 1285-1300.

Urban, J.-P., G. Motyle, and J. Gallice, "A Visual Servoing Approach Applied to Robotic Tasks," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 351-356.

Yoda, H. et al, "An Automatic Wafer Inspection System Using Pipelined Image Processing Techniques," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 1, 1988, pp. 4-16.

Autonomous Navigation:

Bares, J. et al, "Ambler- An Autonomous Rover for Planetary Exploration," *Computer*, Vol. 22, No. 6, 1989, pp. 18-26.

Brooks, R.A., "Visual Map Making for a Mobile Robot," *Proc. IEEE Int'l Conf. Robotics and Automation*, IEEE CS Press, Los Alamitos, Calif., 1985, pp. 824-829.

Bruss, A.R. and B.K.P. Horn, "Passive Navigation," *Computer Vision, Graphics, and Image Processing*, Vol. 21, No. 1, 1983, pp. 3-20.

Chattergy, R., "Some Heuristics for the Navigation of a Robot," *Int'l J. Robotics Research*, Vol. 4, No. 1, 1985, pp. 59-66.

Dhome, M. et al, "Localization of Autonomous Mobile Robots by Monocular Vision in Modelled Sites: Application to a Nuclear Power Plant," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 337-342.

Dickmanns, E.D. and V. Graefe, "Dynamic Monocular Machine Vision," *Machine Vision and Applications*, Vol. 1, No. 4, 1988, pp. 223-240.

Dickmanns, E.D. and V. Graefe, "Applications of Dynamic Monocular Machine Vision," *Machine Vision and Applications*, Vol. 1, No. 4, 1988, pp. 241-261.

Dickmanns, E.D., B. Mysliwetz, and T. Christians, "An Integrated Spatio-Temporal Approach for Automatic Visual Guidance of Autonomous Vehicles," *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 20, No. 6, 1990, pp. 1273-1284.

Elfes, A., "Sonar-Based Real-World Mapping and Navigation," *IEEE Trans. Robotics and Automation*, Vol. 3, No. 3, 1987, pp. 249-265.

Fennema, C., A. Hanson, and E. Riseman, "Towards Autonomous Mobile Robot Navigation," *Proc. DARPA Image Understanding Workshop*, 1989, pp. 219-231.

Flynn, A.M., "Combining Sonar and Infrared Sensors for Mobile Robot Navigation," *Int'l J. Robotics Research*, Vol. 7, No. 6, 1988, pp. 5-14.

Hanson, A.R. and C. Fennema, "Experiments in Autonomous Navigation," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp 24-31.

Hoshino, J., T. Uemura, and I. Masuda., "Region-Based Reconstruction of an Indoor Scene Using an Integration of Active and Passive Sensing Techniques," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 568-572.

Ishiguro, H., M. Yamamoto, and S. Tsuji, "Omni-Directional Stereo for Making Global Map," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 540-547.

Kahn, P., L. Kitchen, and E.M. Riseman, "A Fast Line Finder for Vision-Guided Navigation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 12, No. 11, 1990, pp. 1098-1102.

Keirsey, D. et al, "Autonomous Vehicle Control Using AI Technique," *IEEE Trans. on Software Engineering*, Vol. 11, 1985, pp. 986-992.

Koch, E. et al, "Simulation of Path Planning for a System with Vision and Map Updating," *Proc. IEEE Int'l Conf. on Robotics and Automation*, IEEE CS Press, Los Alamitos, Calif., 1985, pp. 1-15.

Kriegman, D.J., E. Triendl, and T.O. Binford, "Stereo Vision and Navigation in Buildings for Mobile Robots," *IEEE Trans. Robotics and Automation*, Vol. 5, 1989, pp. 792-804.

Kuan, D., G. Phipps, and A.C. Hsueh, "Autonomous Robotic Vehicle Road Following," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 5, 1988, pp. 648-658.

McDermott, D. and E. Davis, "Planning Routes through Uncertain Territory," *Artificial Intelligence*, Vol. 22, 1984, pp. 107-156.

McVey, E.S., K.C. Drake, and R.M. Inigo, "Range Measurements by a Mobile Robot Using a Navigation Line," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 1, 1986, pp. 105-109.

Miller, D.P. et al, "Robot Navigation," *Proc. Int'l Joint Conf. Artificial Intelligence*, 1989, pp. 1672-1674.

Rao, N.S.V., "Algorithmic Framework for Learned Robot Navigation in Unknown Terrains," *Computer*, Vol. 22, No. 6, 1989, pp. 37-43.

Rodriguez, J.J. and J.K. Aggarwal, "Navigation Using Image Sequence Analysis and 3-D Terrain Matching," *Proc. IEEE Workshop on Interpretation of 3-D Scenes*, IEEE CS Press, Los Alamitos, Calif., 1989, pp. 200-207.

Rosenfeld, A. and L.S. Davis, "Image Understanding Techniques for Autonomous Vehicle Navigation," *Proc. DARPA Image Understanding Workshop*, 1985, pp. 1-3.

Roth-Tabak, Y. and T. Weymouth, "Using and Generating Environment Models for Indoor Mobile Robots," *IAPR Workshop on Machine Vision Applications*, 1990, pp. 343-346.

Sharma, U.K. and D. Kuan, "Real-Time Model-Based Geometric Reasoning for Vision-Guided Navigation," *Machine Vision and Applications*, Vol. 2, 1989, pp. 31-44.

Sugihara, K., "Some Location Properties for Robot Navigation Using Single Camera," *Computer Vision, Graphics, and Image Processing*, Vol. 42, 1988, pp. 112-129.

Thorpe, C. et al, "Vision and Navigation for the Carnegie-Mellon Navlab," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 3, 1988, pp. 362-373.

Thorpe, C. and T. Kanade, "Carnegie Mellon Navlab Vision," *Proc. DARPA Image Understanding Workshop*, 1989, pp. 273-282.

Turk, M.A. et al, "VITS - A Vision System for Autonomous Land Vehicle Navigation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 10, No. 3, 1988, pp. 342-360.

Weisbin, C.R. et al, "Autonomous Mobile Robot Navigation and Learning," *Computer*, Vol. 22, No. 6, 1989, pp. 29-35.

Zhang, Z. and O. Faugeras, "Building a 3-D World Model with a Mobile Robot: 3-D Line Segment Representation and Integration," *Proc. Tenth Int'l Conf. Pattern Recognition*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 38-42.

Zheng, J.Y., M. Barth, and S. Tsuji, "Qualitative Route Scene Description Using Autonomous Landmark Detection," *Proc. Third Int'l Conf. Computer Vision*, IEEE CS Press, Los Alamitos, Calif., 1990, pp. 558-562.

The following list of books, special issues, and conferences are relevant to computer vision. We have limited the selections to those published since 1980. A bibliography of journal and conference papers on topics covered in each chapter are included in the companion book, *Computer Vision: Principles.* Additional references may be found in the annual bibliographies of *Computer Vision, Graphics, and Image Processing* compiled by A. Rosenfeld and published by Academic Press.

Books and Edited Volumes

Ahuja, N. and B.J. Schachter, *Pattern Models*, John Wiley & Sons, New York, N.Y., 1983.
Allen, P.K., *Robotic Object Recognition Using Vision and Touch*, Kluwer, Boston, 1987.
Aloimonos, J.Y. and D. Shulman, *Integration of Visual Modules: An Extension of the Marr Paradigm*, Academic Press, Boston, Mass., 1989.
Arbib, M.A. and A.R. Hanson, eds., *Vision, Brain, and Cooperative Computation*, MIT Press, Cambridge, Mass., 1987.
Baird, H.S., *Model-Based Image Matching Using Location*, MIT Press, Cambridge, Mass., 1984.
Ballard, D.H. and C.M. Brown, *Computer Vision*, Prentice-Hall, Englewood Cliffs, N.J., 1982.
Barr, A. and E.A. Feigenbaum, *The Handbook of Artificial Intelligence*, William Kaufmann, Los Altos, Calif., 1982.
Baxes, G.A., *Digital Image Processing: A Practical Primer*, Prentice-Hall, Englewood Cliffs, N.J., 1984.
Beck, J., B. Hope, and A. Rosenfeld, eds., *Human and Machine Vision*, Academic Press, New York, N.Y., 1983.
Besl, P., *Surfaces in Range Image Understanding*, Springer-Verlag, New York, N.Y., 1988.
Blake, A. and T. Troscianko, eds., *AI and the Eye*, John Wiley & Sons, New York, N.Y., 1990.
Blake, A. and A. Zisserman, *Visual Reconstruction*, MIT Press, Cambridge, Mass., 1987.
Bow, S.T., *Pattern Recognition: Applications to Large Data-Set Problems*, Marcel-Dekker, New York, N.Y., 1984.
Boyle, R. and R.C. Thomas, *Computer Vision: A First Course*, Blackwell Scientific Publications, Boston, Mass., 1988.
Braddick, O.J. and A.C. Sleigh, *Physical and Biological Processing of Images*, Springer-Verlag, Berlin, 1983.
Brady, J.M., ed., *Computer Vision*, North-Holland Publishing Co., Amsterdam, 1981.
Brady, J.M. and R. Paul, eds., *Robotics Research: The First Int'l Symposium*, MIT Press, Cambridge, Mass., 1984.
Brooks, R., *Model-Based Computer Vision*, UMI Research Press, Ann Arbor, Mich., 1984.
Brown, C., ed., *Advances in Computer Vision*, Erlbaum Lawrence Associates, Hillsdale, N.J., 1988, (2 volumes).
Cappellini, V., ed., *Time-Varying Image Processing and Moving Object Recognition*, Elsevier Science Publishing, New York, N.Y., 1987.
Cappellini, V., ed., *Time-Varying Image Processing and Moving Object Recognition* (2), Elsevier Science Publishing, New York, N.Y., 1990.
Chang, S.K., *Principles of Pictorial Information Systems Design*, Prentice-Hall, Englewood Cliffs, N.J., 1989.
Chellappa, R. and A.A. Sawchuk, eds., *Digital Image Processing and Analysis: Volume I: Digital Image Processing*, IEEE CS Press, Los Alamitos, Calif., 1985.
Chellappa, R. and A.A. Sawchuk, eds., *Digital Image Processing and Analysis: Volume II: Digital Image Analysis*, IEEE CS Press, Los Alamitos, Calif., 1986.
Chen, S.S., ed., *Image Understanding in Unstructured Environment*, (Erice-Trapani, Sicily, January 5-25, 1987), World Scientific, Singapore, 1988.
Devijver, P.A. and J. Kittler, eds., "Pattern Recognition Theory and Applications", *Proc. NATO Advanced Study Institute*, 1986, Springer-Verlag, Berlin, 1987.
Dew, P.M., R.A. Earnshaw, and T.R. Heywood, eds., *Parallel Processing for Computer Vision and Display*, Addison-Wesley, Reading, Mass., 1989.
Dougherty, E.R. and C.R. Giardina, *Image Processing - Continuous to Discrete*, Prentice-Hall, Englewood Cliffs, N.J., 1987.
Dougherty, E.R. and C.R. Giardina, *Matrix Structured Image Processing*, Prentice-Hall, Englewood Cliffs, N.J., 1986.
Dougherty, E.R. and C.R. Giardina, *Morphological Methods in Image and Signal Processing*, Prentice-Hall, Englewood Cliffs, N.J., 1987.
Duff, M.J.B. and S. Levialdi, *Languages and Architectures for Image Processing*, Academic Press, New York, N.Y., 1981.
Ekstorm, M.P., *Digital Image Processing Techniques*, Academic Press, Orlando, Florida, 1984.
Fairhurst, M., *Computer Vision for Robotic Systems - An Introduction*, Prentice-Hall, New York, N.Y., 1988.
Fan, T.-J., *Describing and Recognizing 3-D Objects Using Surface Properties*, Springer-Verlag, New York, N.Y., 1990.
Faugeras, O.D., ed., *Fundamentals in Computer Vision*, Cambridge Univ. Press, Cambridge, Mass., 1983.
Fischler, M.A. and O. Firschein, eds., *Readings in Computer Vision: Issues, Problems, Principles, and Paradigms*, Morgan Kaufmann, Publishers, Inc., San Mateo, Calif., 1987.
Fisher, R.B., *From Surfaces to Objects: Computer Vision and Three Dimensional Scene Analysis*, John Wiley & Sons, New York, N.Y., 1989.
Freeman, H. and G.G. Pieroni, eds., "Map Data Processing," *Proc. NATO Advanced Study Institute*, 1979, Academic Press, New York, N.Y., 1980.
Freeman, H., ed., "Machine Vision - Algorithms, Architectures, and Systems," *Proc. Workshop Machine Vision: Where are we Going?*, 1987, Academic Press, Boston, Mass., 1988.
Freeman, H., ed., *Machine Vision for Inspection & Measurement*, Academic Press, San Diego, Calif., 1989.
Freeman, H., ed., *Machine Vision for Three-dimensional Scenes*, Academic Press, Boston, Mass., 1990.
Frisby, J., *Seeing: Illusion, Brain, and Mind*, Oxford Univ. Press, Oxford, UK, 1980.
Fu, K.S., *Applications of Pattern Recognition*, CRC Press, Boca Raton, Florida, 1982.
Fu, K.S., *Syntactic Pattern Recognition and Applications*, Prentice-Hall, Englewood Cliffs, N.J., 1982.
Fu, K.S., R.C. Gonzalez, and C.S.G. Lee, *Robotics: Control, Sensing, Vision, and Intelligence*, McGraw Hill, 1987.
Fu, K.S. and T.L. Kunii, eds., *Picture Eng.*, Springer-Verlag, New York, N.Y., 1982.
Galbiati Jr., L.J., *Machine Vision and Digital Image Processing Fundamentals*, Prentice-Hall, Englewood Cliffs, N.J., 1990.

Gale, A.G., M.H. Freeman, C.M. Haslegrave, P. Smith, and S.P. Taylor, eds., *Vision in Vehicles II*, North-Holland, Amsterdam, 1988.
Gelsema, E.S. and L.N. Kanal, eds., "Pattern Recognition in Practice," *Proc. of an Int'l Workshop*, North-Holland, Amsterdam, 1980.
Gelsema, E.S. and L.N. Kanal, eds., Pattern Recognition in Practice II," *Proc. of an Int'l Workshop*, North-Holland, Amsterdam, 1986.
Gonzalez, R.C. and P. Wintz, *Digital Image Processing*, Addison-Wesley, Reading, Mass., Second edition, 1987.
Green, W.B., *Digital Image Processing: A Systems Approach*, Van Nostrand Reinhold, New York, N.Y., Second edition, 1989.
Grimson, W.E.L., *From Images to Surfaces: A Computational Study of the Human Early Visual System*, MIT Press, Cambridge, Mass., 1981.
Grossberg, N., *Neural Networks and Natural Intelligence*, MIT Press, Cambridge, Mass., 1988.
Haralick, R.M., ed., "Pictorial Data Analysis," *Proc. NATO Advanced Study Institute on Pictorial Data Analysis*, Springer-Verlag, Berlin, 1983.
Haralick, R.M. and J.C. Simon, eds., Issues in Digital Image Processing," *Proc. NATO Advanced Study Institute on Digital Image Processing and Analysis*, Sijthoff & Noordoff, Groningen, 1980.
Henderson, T.C., *Discrete Relaxation Techniques*, Oxford Univ. Press, New York, N.Y., 1989.
Hildreth, E.C., *The Measurement of Visual Motion*, MIT Press, Cambridge, Mass., 1983.
Hord, R.M., *Remote Sensing - Methods and Applications*, John Wiley & Sons, New York, N.Y., 1986.
Horn, B.K.P., *Robot Vision*, McGraw-Hill, New York, N.Y., 1986.
Horn, B.K.P. and M.J. Brooks, eds., *Shape from Shading*, MIT Press, Cambridge, Mass., 1989.
Huang, T.S., ed., *Image Sequence Processing and Dynamic Scene Analysis*, Springer-Verlag, New York, N.Y., 1983.
Huang, T.S., ed., *Advances in Computer Vision and Image Processing: Image Reconstruction from Incomplete Observation*, JAI Press, Greenwich, Conn., 1984.
Huang, T.S., ed., *Advances in Computer Vision and Image Processing: Image Enhancement and Restoration*, JAI Press, Greenwich, Conn., 1986.
Huang, T.S., ed., *Advances in Computer Vision and Image Processing: Time-Varying Imagery Analysis*, JAI Press, Greenwich, Conn., 1987.
Ingle, D.J., M.A. Goodale, and R.J.W. Mansfield, eds., *Analysis of Visual Behavior*, MIT Press, Cambridge, Mass., 1982.
Jain, A.K., *Fundamentals of Digital Image Processing*, Prentice-Hall, Englewood Cliffs, N.J., 1989.
Jain, A.K., ed., *Real-Time Object Measurement and Classification*, Springer-Verlag, Berlin, 1988.
Jain, R.C. and A.K. Jain, eds., *Analysis and Interpretation of Range Images*, Springer-Verlag, New York, N.Y., 1990.
Kak, A. and S.S. Chen, eds., Spatial Reasoning and Multi-Sensor Fusion," *Proc. 1987 Workshop*, Morgan Kaufmann Publishers, Inc., San Mateo, Calif., 1987.
Kak, A.C. and M. Slaney, eds., *Principles of Computerized Tomographic Imaging*, IEEE Press, New York, N.Y., 1988.
Kanade, T., ed., *Three-Dimensional Machine Vision*, Kluwer Academic, Norwell, Mass., 1987.
Kanal, L.N. and A. Rosenfeld, eds., *Progress in Pattern Recognition*, Vol. 1, North Holland, New York, N.Y., 1981.
Kanal, L.N. and A. Rosenfeld, eds., *Progress in Pattern Recognition 2*, Noth Holland, New York, N.Y., 1985.
Kasturi, R. and M.M. Trivedi, eds., *Image Analysis Applications*, Marcel Dekker Inc., New York, N.Y., 1990.
Kender, J., *Shape from Texture*, Morgan Kaufman, Los Altos, Calif., 1986.
Kittler, J., K.S. Fu, and L.F. Pau, eds., "Pattern Recognition Theory and Applications," *Proc. NATO Advanced Study Institute*, D. Reidel, Dordrecht, Holland, 1982.
Koenderink, J.J., *Solid Shape*, MIT Press, Cambridge, Mass., 1989.
Kovalevsky, V.A., *Image Pattern Recognition*, Springer-Verlag, New York, N.Y., 1980.
Krotkov, E.P., *Active Computer Vision by Cooperative Focus and Stereo*, Springer-Verlag, New York, N.Y., 1989.
Krzyzak, A., T. Kasvand, and C.Y. Suen, eds., "Computer Vision and Shape Recognition," *Canadian Conf. Pattern Recognition and Picture Processing: Vision Interface '88*, World Scientific, Singapore, 1989.
Kumar, V., P.S. Gopalakrishnan, and L.N. Kanal, eds., *Parallel Algorithms for Machine Intelligence and Vision*, Springer-Verlag, New York, N.Y., 1990.
Lancaster, P. and K.S.Salkaukas, *Curve & Surface Fitting: An Introduction*, Academic Press, London, U.K., 1986.
Levialdi, S., ed., *Multicomputer Vision*, Academic Press, San Diego, Calif., 1988.
Levine, M.D., *Vision in Man and Machine*, McGraw-Hill, New York, N.Y., 1985.
Lowe, D., *Perceptual Organization and Visual Recognition*, Kluwer, Boston, Mass., 1985.
Marr, D., *Vision: A Computational Investigation into the Human Representation and Processing of Visual Information*, W. H. Freeman & Co., San Francisco, Calif., 1982.
Martin, W.N., J.K. Aggarwal, *Motion Understanding: Robot & Human Vision*, Kluwer, Boston, Mass., 1988.
McCafferty, J.D., *Human and Computer Vision: Computing Perceptual Organisation*, Ellis Horwood, New York, N.Y., 1990.
Murray, D.W. and B.F. Buxton, *Experiments in the Machine Interpretation of Visual Motion*, MIT Press, Cambridge, Mass., 1990.
Nagao, M. and T. Matsuyama, *A Structural Analysis of Complex Aerial Photographs*, Plenum Press, New York, N.Y., 1980.
Nevatia, R., Machine *Perception*, Prentice-Hall, Englewood Cliffs, N.J., 1982.
Niblack, W., *An Introduction to Digital Image Processing*, Prentice-Hall, Englewood Cliffs, N.J., 1986.
Ohta, Y., *Knowledge-Based Interpretation of Outdoor Natural Color Scenes*, Pitman, Mass., 1985.
Offen, R.J., *VLSI Image Processing*, McGraw-Hill, New York, N.Y., 1985.
Page, I., ed., *Parallel Architectures and Computer Vision*, Oxford Univ. Press, New York, N.Y., 1988.
Pao, Y.H. and G.W. Ernst, eds., *Context-Directed Pattern Recognition and Machine Intelligence Techniques for Information Processing*, IEEE Press, New York, N.Y., 1982.
Pau, L.F., *Computer Vision for Electronics Manufacturing*, Plenum Press, New York, N.Y., 1989.
Pavlidis, T., *Algorithms for Graphics and Image Processing*, Computer Science Press, Rockville, Maryland, 1982.
Pentland, A.P., ed., *From Pixels to Predicates: Recent Advances in Computational and Robot Vision*, Ablex, Norwood, N.J., 1986.
Pieroni, G.G., ed., *Issues on Machine Vision*, Springer-Verlag, New York, N.Y., 1989.

Pugh, A., ed., *Robot Vision*, IFS (Publications) Ltd., U.K., 1983.
Rao, A.R., *Taxonomy for Texture Description and Identification*, Springer-Verlag, New York, N.Y., 1990.
Rich, E., *Artificial Intelligence*, McGraw-Hill, New York, N.Y., 1983.
Richards, W. and S. Ullman, eds., *Image Understanding 1985-1986*, Ablex, Norwood, N.J., 1987.
Rioux, M. and L. Cournoyer, *The NRCC Three-Dimensional Image Data Files*, Nat'l Research Council Canada, Ottawa, Canada, 1989.
Rock, I., *The Logic of Perception*, MIT Press, Cambridge, Mass., 1983.
Ronse, C. and P.A. Devijver, *Connected Components in Binary Images: The Detection Problem*, Research Studies Press, Letchworth, Hertfordshire, England, 1984.
Rosenfeld, A., ed., *Multiresolution Image Processing & Analysis*, Springer-Verlag, New York, N.Y., 1984.
Rosenfeld, A., ed., *Techniques for 3-D Machine Perception*, Elsevier Science Publisher, Amsterdam, Holland, 1986.
Rosenfeld, A. and A. Kak, *Digital Picture Processing*, Volumes 1 & 2, Academic Press, New York, N.Y., Second edition, 1982.
Sanz, J.L.C., ed., *Advances in Machine Vision*, Springer-Verlag, New York, N.Y., 1989.
Sanz, J.L.C., E.B. Hinkle, and A.K. Jain, *Radon and Projection Transform-based Computer Vision: Algorithms, a Pipeline Architecture, and Industrial Applications*, Springer-Verlag, New York, N.Y., 1988.
Schalkoff, R.J., *Digital Image Processing and Computer Vision*, John Wiley & Sons, New York, N.Y., 1989.
Serra, J., *Image Analysis and Mathematical Morphology*, Academic Press, New York, N.Y., 1982.
Serra, J., ed., *Image Analysis and Mathematical Morphology 2: Technical Advances*, Academic Press, New York, N.Y., 1988.
Shafer, S.A., *Shadows and Silhouettes in Computer Vision*, Kluwer Academic Press, Boston, Mass., 1985.
Shani, U., *Understanding Three-Dimensional Images: Recognition of Abdominal Anatomy from CAT Scans*, UMI Research Press, Ann Arbor, Mich., 1984.
Shirai, Y., *Three-Dimensional Computer Vision*, Springer-Verlag, New York, N.Y., 1987.
Simon, J.C., "From Pixels to Features", *Proc. of a Workshop*, North Holland, Amsterdam, 1989.
Simon, J.C. and R.M. Haralick, eds., Digital Image Processing," *Proc. NATO Advanced Study Institute*, D. Reidel, Dordrecht, Holland, 1981.
Suen, C.Y. and R. DeMori, eds., *Computer Analysis and Perception*, Vol. 1, Visual Signals, CRC Press, Boca Raton, Florida, 1982.
Sugihara, K., *Machine Interpretation of Line Drawings*, MIT Press, Cambridge, Mass., 1986.
Szeliski, R., *Bayesian Modeling of Uncertainty in Low-level Vision*, Kluwer, Boston, Mass., 1989.
Tanimoto, S.L., *Elements of Artificial Intelligence*, Computer Science Press, 1990.
Tanimoto, S. and A. Klinger, eds., *Structured Computer Vision: Machine Perception through Hierarchical Computational Structures*, Academic Press, New York, N.Y., 1980.
Trivedi, M.M., ed., *Selected Papers on Digital Image Processing*, Milestone series Vol. 17, SPIE Press, 1990.
Uhr, L., ed., *Parallel Computer Vision*, Academic Press, Boston, Mass., 1987.
Vogt, R.C., *Automatic Generation of Morphological Set Recognition Algorithms*, Springer-Verlag, New York, N.Y., 1989.
Watanabe, S., *Pattern Recognition: Human and Mechanical*, John Wiley & Sons, New York, N.Y., 1985.
Wechsler, H., *Computational Vision*, Academic Press, Boston, Mass., 1990.
Wilson, R. and M. Spann, *Image Segmentation and Uncertainty*, John Wiley & Sons, New York, N.Y., 1988.
Winston, P.H., *Artificial Intelligence*, second edition, Addison-Wesley, Reading, Mass., 1984.
Wong, A.K.C. and A. Pugh, eds., *Machine Intelligence and Knowledge Eng. for Robotic Applications*, Springer-Verlag, Berlin, 1987.
Woodwark, J., ed., *Geometric Reasoning*, Oxford Univ. Press, New York, N.Y., 1989.
Yaroslavsky, L.P., *Digital Picture Processing, An Introduction*, Springer-Verlag, Berlin, 1985.
Yaroslavsky, L.P., A. Rosenfeld, and W. Wilhelmi, eds., "Computer Analysis of Images and Patterns," *Proc. of CAIP '87, Second Conf. on Automatic Image Processing*, Akademie-Verlag, Berlin, 1987.
Young, T.Y. and K.S. Fu, eds., *Handbook of Pattern Recognition and Image Processing*, Academic Press, Orlando, FL, 1986.
Zuech, N. and R.K. Miller, *Machine Vision*, Fairmont Press, Lilburn, GA, 1987.

Conference and Workshop Proceedings

IEEE Conference on Computer Vision and Pattern Recognition, 1983-1991, published by IEEE Computer Society Press.
IEEE International Conference on Computer Vision, 1987-1990, published by IEEE Computer Society Press.
First European Conference on Computer Vision, published by Springer-Verlag, New York, N.Y.
International Conference on Pattern Recognition, 1980-1990, published by IEEE Computer Society Press.
Annual DARPA Image Understanding Workshop, 1980-1989, sponsored by Defense Advanced Research Projects Agency, Information Science and Technology Office.
Scandinavian Conference on Image Analysis (SCIA), 1980-1989,
International Joint Conference on Artificial Intelligence, 1981-1991, sponsored by International Joint Conferences on Artificial Intelligence, Inc., published by Morgan Kaufmann Publishers, Inc., San Mateo, California.
National Conference on Artificial Intelligence, 1980-1990, sponsored by The American Association for Artificial Intelligence, published by Morgan Kaufmann Publishers, Inc., San Mateo, California.
IEEE Conference on Artificial Intelligence Applications (CAIA), 1984-1989, published by the IEEE Computer Society Press.
International Conference on Image Analysis and Processing (ICIAP), 1980-1989.
IEEE International Conference on Image Processing 1989.
IEEE International Conference on Robotics and Automation, 1984-1990, sponsored by IEEE Council on Robotics and Automation, published by IEEE Computer Society Press.
International Conference on Robot Vision and Sensory Controls (ICRVSC), 1981-1988, organized by IFS (Conferences) Ltd., Bedford, U.K. and other co-sponsors.
IEEE Workshop on Computer Vision: Representation and Control, 1982-1987.
IEEE Workshop on Motion: Representation and Analysis, 1986.
IEEE Workshop on Visual Motion, 1989.
IEEE Workshop on Interpretation of 3D Scenes, 1989.
IEEE Workshop on Robust Computer Vision, 1990.
IEEE Workshop on Directions in Automated CAD-Based Vision, 1991.
IAPR Workshop on Computer Vision - Special Hardware and Industrial Applications, 1988.
IAPR Workshop on Machine Vision Applications, proceedings published for IAPR by M. Takagi, Univ. of Tokyo, Japan, 1990.
IAPR Workshop on Syntactic and Structural Pattern Recognition, 1990, proceedings edited by H. Baird, AT&T Bell Laboratories.
SPIE Conference on Applications of Artificial Intelligence, 1984-1990, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Conference on Intelligent Robots and Computer Vision, 1984-1989, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Conference on Medical Imaging, 1987-1990, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Conference on Mobile Robots, 1986-1989, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Conference on Optics, Illumination, and Image Sensing for Machine Vision, 1986-1990, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Conference on Visual Communications and Image Processing, 1986-1990, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Conference on Applications of Digital Image Processing, 1982-1990, A.G. Tescher, editor, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Critical Review Series Conferences, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.:
  Robotics and Robot Sensing Systems, Vol. 442, D. Casasent and E.L. Hall, editors, 1983,
  Remote Sensing, Vol. 475, P.N. Slater, editor, 1984.
  Digital Image Processing, Vol. 528, A.G. Tescher, editor, 1985.
  Image Pattern Recognition, Vol. 755, F.J. Corbett, editor, 1987.
SPIE Conference on Techniques and Applications of Image Understanding, Vol. 281, J.J. Pearson, editor, 1981, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Conference on 3-D Machine Perception, Vol. 283, B.R. Altschuler, editor, D.C., 1981, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Conference on Processing of Images and Data from Optical Sensors, Vol. 292, W.H. Carter, editor, 1981, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Conference on Design of Digital Image Processing Systems, Vol. 301, J.L. Mannos, editor, 1981, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Conference on Robot Vision, Vol. 336, A. Rosenfeld, editor, 1982, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Conference on Image Understanding and Man-Machine Interface, Vol. 758, J.J. Pearson and E. Barrett, editors, 1987, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.
SPIE Parallel Architectures for Image Processing, Vol. 1246, J. Ghosh and C.G. Harrison, editors, 1990, published by SPIE-The International Society for Optical Eng., Bellingham, Washington, U.S.A.

Special issues

Advances in mathematical morphology, J. Serra, ed., *Signal Processing*, Vol. 16, April 1989.
Advances in syntactic pattern recognition, H. Bunke and A. Sanfeliu, eds., *Pattern Recognition*, Vol. 19, 1986.
Artificial intelligence and signal processing in underwater acoustics and geophysics problems, C.H. Chen, ed., *Pattern Recognition*, Vol. 18, No. 6, 1985.
Autonomous intelligent machines, S.S. Iyengar and R.L. Kashyap, eds., *Computer*, Vol. 22, June 1989.
CAD-based robot vision, B. Bhanu, ed., *Computer*, Vol. 20, August 1987.
Computer analysis of time-varying images, W.E. Snyder, ed., *Computer*, Vol. 14, August 1981.
Computational geometry, R. Forrest, L. Guibas, and J. Nievergelt, eds., ACM Trans. Graphics, Vol. 3, October 1984.
Computational geometry, C.K. Yap, ed., *Algorithmica*, Vol. 4, 1989.
Computational geometry, C. K. Yap, ed., *Journal of Computer and System Sciences*, Vol. 39, October 1989.
Computer graphics in medicine and biology, J.M.S. Prewitt, ed., *IEEE Computer Graphics and Applications*, Vol. 3, August 1983.
Computer vision, R.M. Haralick, ed., *Computer Vision, Graphics and Image Processing*, 22, April 1983.
Computer vision, M. Brady, ed., *Artificial Intelligence*, Vol. 17, No. 1 and No. 3, 1981.
Computer vision, H. Li and J.R. Kender, eds., *Proceedings of the IEEE*, Vol. 76, August 1988.
Computer vision, M.M. Trivedi and A. Rosenfeld, eds., *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 19, December 1989.
Computerized tomography, G.T. Herman, ed., *Proceedings of the IEEE*, Vol. 71, March 1983.
Connectionist models and their applications, J.A. Feldman, ed., *Cognitive Science*, 9, January-March 1985.
Current issues and trends in computer vision, L. Shapiro and A. Kak, eds., *Computer Vision, Graphics and Image Processing*, 36, November-December 1986.
Digital image processing and application, A.N. Venetsanopoulos, ed., *IEEE Trans. Circuits and Systems*, Vol. 34, November 1987.
Factory automation and robotics (special section), H.J. Bernstein, ed., *Comm. ACM*, Vol. 29, June 1986.
Frontier in computer graphics and applications: selections from intergraphics '83, T.L. Kunii, ed., *IEEE Computer Graphics and Applications*, Vol. 3, December 1983.
Geometric reasoning, D. Kapur and J. Mundy, eds., *Artificial Intelligence*, Vol. 37, December 1988.
Human and machine vision, A. Rosenfeld, ed., *Computer Vision, Graphics and Image Processing*, 31-32, August-October 1985.
Image analysis and processing, S. Levialdi, ed., *Signal Processing*, Vol. 3, July 1981.
Image database management (special section), S.S. Iyengar and R.L. Kashyap, eds., *IEEE Trans. Software Engineering*, Vol. 14, May 1988.
Image database management, Grosky W. and R. Mehrotra, eds., *Computer*, Vol. 22, December 1989.
Image processing, H. Freitag, ed., *Proceedings of the IEEE*, Vol. 69, May 1981.
Image restoration & reconstruction, M.I. Sezan and A.M. Tekalp, eds., *Optical Eng.*, Vol. 29, May 1990.
Industrial machine vision and computer vision technology part I and II, J.L.C. Sanz, ed., *IEEE Trans. Pattern* Analysis *and Machine Intelligence*, January and May 1988.
Knowledge based image analysis, N. Niemann and Y.T. Chien, eds., *Pattern Recognition*, Vol. 17, August 1984.
Machine Vision mensuration, R.M. Haralick, ed., *Computer Vision, Graphics and Image Processing*, Vol. 40, December 1987.
Machine vision and image understanding, O. Firschein, ed., *IEEE Control Systems Magazine*, Vol. 8, June 1988.
Memorial issue for Professor King-Sun Fu, T. Pavlidis, ed., *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, No. 3, May 1986.
Modeling of natural phenomena, A. Fournier and W.T. Reeves, eds., *ACM Trans. Graphics*, Vol. 6, July 1987.
Multiresolution representation (special section), S.L. Tanimoto, ed., *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, July 1989.
Optical pattern recognition, B.V.K.V. Kumar, ed., *Optical Eng.*, Vol. 29, September 1990.
Papers from Third International Conference on Pattern Recognition of the British Pattern Recognition Assoc., D. Rutovitz, ed., *Pattern Recognition Letters*, Vol. 5, No. 2, Feb. 1987, Vol. 6, No. 1 and No. 2, June, July 1987.
Pattern recognition of cell images, J.W. Bacus and P.H. Bartels, eds., *Pattern Recognition*, Vol. 13, No. 1 and No. 4, 1981.
Perceiving Earth's resources from space, D.A. Landgrebe, ed., *Proceedings of the IEEE*, Vol. 73, June 1985.
Sensor data fusion, J.M. Brady, ed., *Int'l J. of Robotic Research*, Vol. 6, December 1988.
Shape analysis in image processing, *Pattern Recognition*, Vol. 13, No. 2, 1981.
Spatial reasoning, A. Kak, ed., *AI Magazine*, Vol. 9, Summer 1988.
Time-varying imagery, J.K. Aggarwal, ed., *Computer Vision, Graphics and Image Processing*, 21, January 1983.
Visual communications systems, A.N. Netravali and B. Prasada, ed., *Proceedings of the IEEE*, Vol. 73, April 1985.
Visual motion, W.B. Thompson, ed., *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, May 1989.

INDEX

The following index was created by searching for terms in the chapter introductions and in the titles and abstracts of reprinted papers; terms in the main body of the papers are not indexed.

About the authors

Rangachar Kasturi was born in Bangalore, India in 1949. He received his BE degree in electrical engineering from Bangalore University in 1968 and his MSEE and PhD from Texas Tech University, Lubbock, in 1980 and 1982, respectively.

Professor Kasturi is the acting director of the Computer Engineering Program and an associate professor of electrical and computer engineering at the Pennsylvania State University, where he was an assistant professor from 1982 to 1986. From 1989 to 1990, he was a visiting scholar at the Artificial Intelligence Laboratory of the University of Michigan. From 1978 to 1982, he was a research assistant at Texas Tech University in the areas of multiplex holography and digital image processing. From 1976 to 1978, he was the engineering officer at the Visvesvaraya Industrial and Technological Museum, Bangalore, and from 1969 to 1976 he was with Bharat Electronics Ltd., Bangalore, as a research and development engineer.

Professor Kasturi's current research interests are in the applications of image analysis and computer vision techniques. He is a contributing author and a co-editor of the book, *Image Analysis Applications*, Marcel Dekker, 1990. He is a senior member of the IEEE, and a member of the Optical Society of America, the International Society for Optical Engineering (SPIE), American Society for Photogrammetry and Remote Sensing, Eta Kappa Nu, and Sigma Xi. He is the chairman of the Technical Committee on Graphics Recognition (TC-10) of the International Association for Pattern Recognition (IAPR). He was a general chairman of the 1990 IAPR Workshop on Machine Vision Applications. He is an associate editor of *IEEE Transactions on Pattern Analysis and Machine Intelligence*. During 1987-1990, Professor Kasturi delivered lectures on his research at many chapters of the IEEE Computer Society through its Distinguished Visitor Program.

Ramesh Jain received his BE from Nagpur University, India in 1969 and his PhD from IIT, Kharagpur, India, in 1975. He is currently a Professor of electrical engineering and computer science and the Director of the Artificial Intelligence Laboratory at the University of Michigan. He has been affiliated with Stanford University, IBM Alamaden Research Labs, General Motors Research Labs, Wayne State University, University of Texas at Austin, University of Hamburg, West Germany, and Indian Institute of Technology, Kharagpur, India.

Professor Jain's current research interests are in computer vision and artificial intelligence. Some of the projects he has completed include: semiconductor wafer inspection using scanning electron microscopes and optical microscopes, automatic visual inspection of solder joints for IBM, laser range image processing for CAD-based vision systems, robotic navigation and rotorcraft navigation using machine vision, and applications of expert systems in inspection systems. He is a consultant in the areas of computer vision, artificial intelligence, and computer graphics.

Professor Jain is a senior member of IEEE and a member of ACM, AAAI, Pattern Recognition Society, Cognitive Science Society, Optical Society of America, the International Society for Optical Engineering (SPIE), and the Society of Manufacturing Engineers. He has been involved in organizing several professional conferences and workshops. Currently, he is on the editorial boards of *IEEE Expert*, *Machine Vision and Applications*, *Computer Vision Graphics and Image Processing*, the *Bulletin of Approximate Reasoning*, and *Image and Vision Computing*.

OTHER IEEE COMPUTER SOCIETY PRESS TITLES

MONOGRAPHS

Analyzing Computer Architectures
Written by J.C. Huck and M.J. Flynn
(ISBN 0-8186-8857-2); 206 pages

Desktop Publishing for the Writer: Designing, Writing, and Developing
Written by Richard Ziegfeld and John Tarp
(ISBN 0-8186-8840-8); 380 pages

Digital Image Warping
Written by George Wolberg
(ISBN 0-8186-8944-7); 340 pages

Integrating Design and Test—CAE Tools for ATE Programming
Written by K.P. Parker
(ISBN 0-8186-8788-6); 160 pages

JSP and JSD—The Jackson Approach to Software Development (Second Edition)
Written by J.R. Cameron
(ISBN 0-8186-8858-0); 560 pages

National Computer Policies
Written by Ben G. Matley and Thomas A. McDannold
(ISBN 0-8186-8784-3); 192 pages

Physical Level Interfaces and Protocols
Written by Uyless Black
(ISBN 0-8186-8824-2); 240 pages

Protecting Your Proprietary Rights in Computer and High-Technology Industries
Written by Tobey B. Marzouk, Esq.
(ISBN 0-8186-8754-1); 224 pages

TUTORIALS

Advanced Computer Architecture
Edited by D.P. Agrawal
(ISBN 0-8186-0667-3); 400 pages

Advances in Distributed System Reliability
Edited by Suresh Rai and Dharma P. Agrawal
(ISBN 0-8186-8907-2); 352 pages

Computer and Network Security
Edited by M.D. Abrams and H.J. Podell
(ISBN 0-8186-0756-4); 448 pages

Computer Architecture
Edited by D.D. Gajski, V.M. Milutinovic, H. Siegel, and B.P. Furht
(ISBN 0-8186-0704-1); 602 pages

Computer Arithmetic I
Edited by Earl E. Swartzlander, Jr.
(ISBN 0-8186-8931-5); 398 pages

Computer Arithmetic II
Edited by Earl E. Swartzlander, Jr.
(ISBN 0-8186-8945-5); 412 pages

Computer Communications: Architectures, Protocols and Standards (Second Edition)
Edited by William Stallings
(ISBN 0-8186-0790-4); 448 pages

Computer Graphics Hardware: Image Generation and Display
Edited by H.K. Reghbati and A.Y.C. Lee
(ISBN 0-8186-0753-X); 384 pages

Computer Graphics: Image Synthesis
Edited by Kenneth Joy, Nelson Max, Charles Grant, and Lansing Hatfield
(ISBN 0-8186-8854-8); 380 pages

Computer Networks (Fourth Edition)
Edited by M.D. Abrams and I.W. Cotton
(ISBN 0-8186-0568-5); 512 pages

Computers for Artificial Intelligence Applications
Edited by B. Wah and G.J. Li
(ISBN 0-8186-0706-8); 656 pages

Database Management
Edited by J.A. Larson
(ISBN 0-8186-0714-9); 448 pages

Digital Image Processing and Analysis: Volume 1—Digital Image Processing
Edited by R. Chellappa and A.A. Sawchuk
(ISBN 0-8186-0665-7); 736 pages

Digital Image Processing and Analysis: Volume 2—Digital Image Analysis
Edited by R. Chellappa and A.A. Sawchuk
(ISBN 0-8186-0666-5); 680 pages

Digital Private Branch Exchanges (PBXs)
by Edwin Coover
(ISBN 0-8186-0829-3); 394 pages

Distributed Computing Network Reliability
Edited by Suresh Rai and Dharma Agrawal
(ISBN 0-8186-8908-0); 357 pages

Distributed Software Engineering
Edited by Sol Shatz and Jia-Ping Wang
(ISBN 0-8186-8856-4); 294 pages

DSP-Based Testing of Analog and Mixed Signal Circuits
Edited by Matthew Mahoney
(ISBN 0-8186-0785-8); 272 pages

Fault Tolerant Computing
Edited by V. Nelson and B. Carroll
(ISBN 0-8186-8677-4); 428 pages

Formal Verification of Hardware Design
Edited by Michael Yoeli
(ISBN 0-8186-9017-8); 340 pages

Hard Real-Time Systems
Edited by J.A. Stankovic and K. Ramamritham
(ISBN 0-8186-0819-6); 624 pages

Human Factors in Software Development (Second Edition)
Edited by Bill Curtis
(ISBN 0-8186-0577-4); 736 pages

Integrated Services Digital Networks (ISDN) (Second Edition)
Edited by William Stallings
(ISBN 0-8186-0823-4); 406 pages

Local Network Technology (Third Edition)
Edited by William Stallings
(ISBN 0-8186-0825-0); 512 pages

Microprogramming and Firmware Engineering
Edited by V. Milutinovic
(ISBN 0-8186-0839-0); 416 pages

Modeling and Control of Automated Manufacturing Systems
Edited by A. A. Desrochers
(ISBN 0-8186-8916-1); 384 pages

Nearest Neighbor Pattern Classification Techniques
Edited by Belur V. Dasarathy
(ISBN 0-8186-8930-7); 464 pages

For Further Information Call 1-800-CS-BOOKS or Write:

IEEE Computer Society Press, 10662 Los Vaqueros Circle, PO Box 3014, Los Alamitos, California 90720-1264, USA

IEEE Computer Society, 13, avenue de l'Aquilon, B-1200 Brussels, BELGIUM

IEEE Computer Society, Ooshima Building, 2-19-1 Minami-Aoyama, Minato-ku, Tokyo 107, JAPAN

New Paradigms for Software Development
Edited by William Agresti
(ISBN 0-8186-0707-6); 304 pages

Object-Oriented Computing, Volume 1: Concepts
Edited by Gerald E. Petersen
(ISBN 0-8186-0821-8); 214 pages

Object-Oriented Computing, Volume 2: Implementations
Edited by Gerald E. Petersen
(ISBN 0-8186-0822-6); 324 pages

Parallel Architectures for Database Systems
Edited by A.R. Hurson, L.L. Miller, and S.H. Pakzad
(ISBN 0-8186-8838-6); 478 pages

Programming Productivity: Issues for '80s (Second Edition)
Edited by C. Jones
(ISBN 0-8186-0681-9); 472 pages

Reduced Instruction Set Computers (RISC) (Second Edition)
Edited by William Stallings
(ISBN 0-8186-8943-9); 448 pages

Software Design Techniques (Fourth Edition)
Edited by P. Freeman and A.I. Wasserman
(ISBN 0-8186-0514-6); 736 pages

Software Engineering Project Management
Edited by R. Thayer
(ISBN 0-8186-0751-3); 512 pages

Software Maintenance and Computers
Edited by D.H. Longstreet
(ISBN 0-8186-8898-X); 304 pages

Software Management (Third Edition)
Edited by D.J. Reifer
(ISBN 0-8186-0678-9); 526 pages

Software Quality Assurance: A Practical Approach
Edited by T.S. Chow
(ISBN 0-8186-0569-3); 506 pages

Software Reusability
Edited by Peter Freeman
(ISBN 0-8186-0750-5); 304 pages

Software Reuse—Emerging Technology
Edited by Will Tracz
(ISBN 0-8186-0846-3); 400 pages

Software Risk Management
Edited by B.W. Boehm
(ISBN 0-8186-8906-4); 508 pages

Standards, Guidelines and Examples on System and Software Requirements Engineering
Edited by Merlin Dorfman and Richard H. Thayer
(ISBN 0-8186-8922-6); 626 pages

System and Software Requirements Engineering
Edited by Richard H. Thayer and Merlin Dorfman
(ISBN 0-8186-8921-8); 740 pages

Test Access Port and Boundary-Scan Architecture
Edited by C. M. Maunder and R. E. Tulloss
(ISBN 0-8186-9070-4); 400 pages

Test Generation for VLSI Chips
Edited by V.D. Agrawal and S.C. Seth
(ISBN 0-8186-8786-X); 416 pages

Visual Programming Environments: Paradigms and Systems
Edited by Ephraim Glinert
(ISBN 0-8186-8973-0); 680 pages

Visual Programming Environments: Applications and Issues
Edited by Ephraim Glinert
(ISBN 0-8186-8974-9); 704 pages

Visualization in Scientific Computing
Edited by G.M. Nielson, B. Shriver, and L. Rosenblum
(ISBN 0-8186-8979-X); 304 pages

VLSI Testing and Validation Techniques
Edited by H. Reghbati
(ISBN 0-8186-0668-1); 616 pages

Volume Visualization
Edited by Arie Kaufman
(ISBN 0-8186-9020-8); 494 pages

REPRINT COLLECTIONS

Dataflow and Reduction Architectures
Edited by S.S. Thakkar
(ISBN 0-8186-0759-9); 460 pages

Distributed Computing Systems: Concepts and Structures
Edited by A. Ananda and B. Srinivasan
(ISBN 0-8186-8975-0); 416 pages

Expert Systems: A Software Methodology for Modern Applications
Edited by Peter Raeth
(ISBN 0-8186-8904-8); 476 pages

Logic Design for Testability
Edited by C.C. Timoc
(ISBN 0-8186-0573-1); 324 pages

Milestones in Software Evolution
Edited by Paul W. Oman and Ted G. Lewis
(ISBN 0-8186-9033-X); 332 pages

Object-Oriented Databases
Edited by Ez Nahouraii and Fred Petry
(ISBN 0-8186-8929-3); 256 pages

Validating and Verifying Knowledge-Based Systems
Edited by Uma G. Gupta
(ISBN 0-8186-8995-1); 400 pages

ARTIFICIAL NEURAL NETWORKS TECHNOLOGY SERIES

Artificial Neural Networks—Concept Learning
Edited by Joachim Diederich
(ISBN 0-8186-2015-3); 160 pages

Artificial Neural Networks—Electronic Implementation
Edited by Nelson Morgan
(ISBN 0-8186-2029-3); 144 pages

Artificial Neural Networks—Theoretical Concepts
Edited by V. Vemuri
(ISBN 0-8186-0855-2); 160 pages

SOFTWARE TECHNOLOGY SERIES

Computer Algorithms
Edited by Jun-ichi Aoe
(ISBN 0-8186-2123-0); 154 pages

Computer-Aided Software Engineering (CASE)
Edited by E.J. Chikofsky
(ISBN 0-8186-1917-1); 110 pages

Software Reliability Models: Theoretical Development, Evaluation and Applications
Edited by Y.K. Malaiya and P.K. Srimani
(ISBN 0-8186-2110-9); 136 pages

COMMUNICATIONS TECHNOLOGY SERIES

Multicast Communication in Distributed Systems
Edited by Mustaque Ahamad
(ISBN 0-8186-1970-8); 110 pages

ROBOTICS TECHNOLOGY SERIES

Multirobot Systems
Edited by Rajiv Mehrotra and Murali R. Varanasi
(ISBN 0-8186-1977-5); 122 pages

Offices of the IEEE Computer Society

Headquarters Office
1730 Massachusetts Avenue, N.W.
Washington, DC 20036-1903
Phone: (202) 371-0101 — Fax: (202) 728-9614

Publications Office
P.O. Box 3014
10662 Los Vaqueros Circle
Los Alamitos, CA 90720-1264
Membership and General Information: (714) 821-8380
Publication Orders: (800) 272-6657 — Fax: (714) 821-4010

European Office
13, avenue de l'Aquilon
B-1200 Brussels, BELGIUM
Phone: 32-2-770-21-98 — Fax: 32-3-770-85-05

Asian Office
Ooshima Building
2-19-1 Minami-Aoyama, Minato-ku
Tokyo 107, JAPAN
Phone: 81-3-408-3118 — Fax: 81-3-408-3553

IEEE Computer Society

IEEE Computer Society Press Publications

Monographs: A monograph is an authored book consisting of 100-percent original material.
Tutorials: A tutorial is a collection of original materials prepared by the editors, and reprints of the best articles published in a subject area. Tutorials must contain at least five percent of original material (although we recommend 15 to 20 percent of original material).
Reprint collections: A reprint collection contains reprints (divided into sections) with a preface, table of contents, and section introductions discussing the reprints and why they were selected. Collections contain less than five percent of original material.
Technology series: Each technology series is a brief reprint collection — approximately 126-136 pages and containing 12 to 13 papers, each paper focusing on a subset of a specific discipline, such as networks, architecture, software, or robotics.
Submission of proposals: For guidelines on preparing CS Press books, write the Editorial Director, IEEE Computer Society Press, PO Box 3014, 10662 Los Vaqueros Circle, Los Alamitos, CA 90720-1264, or telephone (714) 821-8380.

Purpose

The IEEE Computer Society advances the theory and practice of computer science and engineering, promotes the exchange of technical information among 100,000 members worldwide, and provides a wide range of services to members and nonmembers.

Membership

All members receive the acclaimed monthly magazine *Computer*, discounts, and opportunities to serve (all activities are led by volunteer members). Membership is open to all IEEE members, affiliate society members, and others seriously interested in the computer field.

Publications and Activities

***Computer* magazine:** An authoritative, easy-to-read magazine containing tutorials and in-depth articles on topics across the computer field, plus news, conference reports, book reviews, calendars, calls for papers, interviews, and new products.
Periodicals: The society publishes six magazines and five research transactions. For more details, refer to our membership application or request information as noted above.
Conference proceedings, tutorial texts, and standards documents: The IEEE Computer Society Press publishes more than 100 titles every year.
Standards working groups: Over 100 of these groups produce IEEE standards used throughout the industrial world.
Technical committees: Over 30 TCs publish newsletters, provide interaction with peers in specialty areas, and directly influence standards, conferences, and education.
Conferences/Education: The society holds about 100 conferences each year and sponsors many educational activities, including computing science accreditation.
Chapters: Regular and student chapters worldwide provide the opportunity to interact with colleagues, hear technical experts, and serve the local professional community.