Pattern Recognition and Image Processing

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Abstract—Extensive research and development has taken place over the last 20 years in the areas of pattern recognition and image processing. Areas to which these disciplines have been applied include business (e.g., character recognition), medicine (diagnosis, abnormality detection), automation (robot vision), military intelligence, communications (data compression, speech recognition), and many others. This paper presents a very brief survey of recent developments in basic pattern recognition and image processing techniques.

Index Terms—Decision-theoretic recognition, image processing, image recognition, pattern recognition, syntactic recognition.

I. INTRODUCTION

DURING the past twenty years, there has been a considerable growth of interest in problems of pattern recognition and image processing. This interest has created an increasing need for theoretical methods and experimental software and hardware for use in the design of pattern recognition and image processing systems. Over twenty books have been published in the area of pattern recognition [5], [8], [10], [11], [15], [16], [35], [41], [47], [79], [82], [86], [89], [110], [111], [118], [122], [123], [136], [137]. In addition, a number of edited books, conference proceedings, and journal special issues have also been published [40], [43], [45], [46], [57], [65], [67], [69], [77], [80], [96], [113], [121], [127], [128]. Cover [25] has given a comprehensive review of the five books published in 1972–1973 [5], [35], [47], [79], [89]. A specialized journal has existed for nearly ten years [73], and some special pattern recognition machines have been designed and built for practical use. Applications of pattern recognition and image processing include character recognition [37], [71], [123], target detection, medical diagnosis, analysis of biomedical signals and images [45], [57], [97], remote sensing [44], [57], identification of human faces and fingerprints [83], reliability [90], socio-economics [13], archaeology [12], speech recognition and understanding [43], [45], [98], and machine part recognition [3].

Many of the books and paper collections on pattern recognition contain material on image processing and recognition. In addition, there are four textbooks [4], [35], [99], [108] and several hardcover paper collections [21], [51], [60], [67], [74], [106], [132], [138] devoted especially to the subject, as of the end of 1976. There is a specialized journal in the field [107], and there have also been special issues of several other journals on the topic [1], [6], [7], [53]. For further references, the reader may consult a series of annual survey papers [100]–[105] which cover a significant fraction of the English language literature.

Although pattern recognition and image processing have developed as two separate disciplines, they are very closely related. The area of image processing consists not only of coding, filtering, enhancement, and restoration, but also analysis and recognition of images. On the other hand, the area of pattern recognition includes not only feature extraction and classification, but also preprocessing and description of patterns. It is true that image processing appears to consider only two-dimensional pictorial patterns and pattern recognition deals with one-dimensional, two-dimensional, and three-dimensional patterns in general. However, in many cases, information about one-dimensional and three-dimensional patterns is easily expressed as two-dimensional pictures, so that they are actually treated as pictorial patterns. Furthermore, many of the basic techniques used for pattern recognition and image processing are very similar in nature. Differences between the two disciplines do exist, but we also see an increasing overlap in interest and a sharing of methodologies between them in the future.

Within the length limitations of this paper, we provide a very brief survey of recent developments in pattern recognition and image processing.

II. PATTERN RECOGNITION

Pattern recognition is concerned primarily with the description and classification of measurements taken from physical or mental processes. Many definitions of pattern recognition have been proposed [112], [125], [127]. Our discussion is based on the above loose definition. In order to provide an effective and efficient description of patterns, preprocessing is often required to remove noise and redundancy in the measurements. Then a set of characteristic measurements, which could be numerical and/or nonnumerical, and relations among these measurements, are extracted for the representation of patterns. Classification and/or description of the patterns with respect to a specific goal is performed on the basis of the representation.

In order to determine a good set of characteristic measurements and their relations for the representation of patterns so good recognition performance can be expected, a careful analysis of the patterns under study is necessary. Knowledge about the statistical and structural charac-

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teristics of patterns should be fully utilized. From this point of view, the study of pattern recognition includes both the analysis of pattern characteristics and the design of recognition systems.

The many different mathematical techniques used to solve pattern recognition problems may be grouped into two general approaches. They are the decision-theoretic (or discriminant) approach and the syntactic (or structural) approach. In the decision-theoretic approach, a set of characteristic measurements, called features, are extracted from the patterns. Each pattern is represented by a feature vector, and the recognition of each pattern is usually made by partitioning the feature space. On the other hand, in the syntactic approach, each pattern is expressed as a composition of its components, called subpatterns or pattern primitives. This approach draws an analogy between the structure of patterns and the syntax of a language. The recognition of each pattern is usually made by parsing the pattern structure according to a given set of syntax rules. In some applications, both of these approaches may be used. For example, in a problem dealing with complex patterns, the decision-theoretic approach is usually effective in the recognition of pattern primitives, and the syntactic approach is then used for the recognition of subpatterns and of the pattern itself.

A. Decision-Theoretic Methods

A block diagram of a decision-theoretic pattern recognition system is shown in Fig. 1. The upper half of the diagram represents the recognition part, and the lower half the analysis part. The process of preprocessing is usually treated in the area of signal and image processing. Our discussions are limited to the feature extraction and selection, and the classification and learning. Several more extensive surveys on this subject have also appeared recently [18], [26], [32], [66], [120].

Feature extraction and selection: Recent developments in feature extraction and selection fall into the following two major approaches.

Feature space transformation: The purpose of this approach is to transform the original feature space into lower dimensional spaces for pattern representation and/or class discrimination. For pattern representation, least mean-square error and entropy criteria are often used as optimization criteria in determining the best transformation. For class discrimination, the maximization of interclass distances and/or the minimization of intraclass distances is often suggested as an optimization criterion. Both linear and nonlinear transformations have been suggested. Fourier, Walsh–Hadamard, and Haar transforms have been suggested for generating pattern features [5]. The Karhunen–Loeve expansion and the method of principal components [5], [39], [47] have been used quite often in practical applications for reducing the dimensionality of feature space.

In terms of the enhancement of class separability, nonlinear transformations are in general superior to linear transformations. A good class separation in feature space will certainly result in a simple classifier structure (e.g., a linear classifier). However, the implementation of nonlinear transformations usually requires complex computations compared with that of linear transformations. Results of transformations need to be updated when new pattern samples are taken into consideration. Iterative algorithms and/or interactive procedures are often suggested for implementing nonlinear transformations [45], [57].

In some cases, the results of transformations based on pattern representation and class discrimination respectively are in conflict. An optimization criterion for feature space transformation should be able to reflect the true performance of the recognition system. Some recent work appears to move in this direction [31].

Information and distance measures: The main goal of feature selection is to select a subset of l features from a given set of N features ($l < N$) without significantly degrading the performance of the recognition system, that is, the probability of misrecognition, or more generally, the risk of decision. Unfortunately, a direct calculation of the probability of misrecognition is often impossible or impractical partially due to the lack of general analytic expressions which are simple enough to be treated. One approach is to find indirect criteria to serve as a guide for feature selection.

The most common approach is to define an information or (statistical) distance measure, which is related to the upper and/or lower bounds on the probability of misrecognition, for feature selection [17], [19], [54], [66]. That is, the best feature subset is selected in the sense of maximizing a prespecified information or distance measure. Recently, Kanal [66] provided a fairly complete list of distance measures and their corresponding error bounds. Assuming that the most important characteristic of the distance measure is the resultant upper bound on the probability of misrecognition, the various measures can be arranged in increasing order of importance. For a two-class recognition problem, denoting the upper bound on the probability of misrecognition by P_e, for Bhattacharyya's distance by U_B, for Matusita distance by U_M, for equivocation by U_E, for Vajda's entropy by U_V, for Devijver's Bayesian distance by U_D, for Ito's measure (for $n = 0$) by U_I, for Kolmogorov's variational distance by U_K, and for the M_0-distance of Toussaint by U_T, the following point-wise relations hold [75]:

$$P_e = U_K \leq U_V = U_D = U_I = U_T \leq U_E \leq U_B = U_M.$$

The divergence and Kullback–Leibler numbers, which are simply related to each other, are excluded from the ordering because of the lack of a known upper bound except for the case of a normal distribution where its bound is larger than U_B. In terms of computational difficulty, however, the divergences and Bhattacharyya distance are easier to compute than the other distance measures.

It is interesting that the best bound on the probability of misrecognition (except U_K which is nothing but P_e itself) derived from the distance measures is equal to the

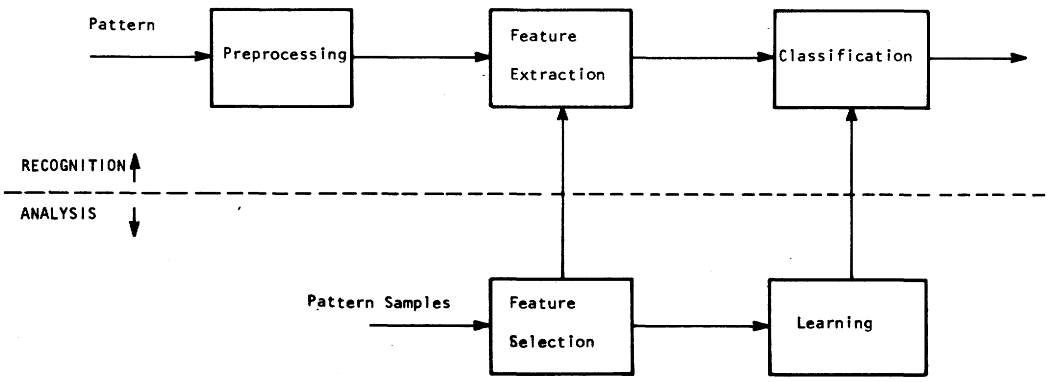

Fig. 1. Block diagram of a decision-theoretical pattern recognition system.

asymptotic error of the single nearest neighbor classifier. In addition to the information and distance measures mentioned above, a generalized Kolmogorov distance, called the J_α separability measure, was recently proposed as a feature selection criterion, and its upper and lower bounds on the probability of misrecognition derived [75]. When $\alpha = 1$, J_α is equivalent to the Kolmogorov distance. For $\alpha = 2$, the upper bound of the probability of misrecognition is equal to the asymptotic probability of error of the single nearest neighbor classifier.

Classification and learning: Most developments in pattern recognition involve classification and learning. When the conditional probability density functions of the feature vectors for each class (which we may call the class density functions) are known or can be accurately estimated, the Bayes classification rule that minimizes the average risk or the probability of misrecognition can be derived. When the class density functions are unknown, nonparametric classification schemes need to be used. In practice, when a large number of pattern samples is available, class density functions can be estimated or learned from the samples [24], [28], [126], and then an optimal classification rule can be obtained. If the parametric form of each class density function is known, only parameters need to be learned from the pattern samples. When the number of available pattern samples is small, the performance of density and parameter estimations is poor. Nonparametric classification schemes usually suggest a direct learning of the classification rule from pattern samples, for example, the learning of parameters of a decision boundary.

Depending upon whether or not the correct classification of the available pattern samples is known, the process of learning can be classified into supervised learning (or learning with a teacher) and nonsupervised learning (or learning without a teacher). Bayesian estimation and stochastic approximation and the potential function method have been suggested for the learning of class density functions or a decision boundary. When the learning is nonsupervised, a mixture density function can be formed from all the individual class density functions and *a priori* class probabilities. Nonsupervised learning of the parameters of each class density function can be treated as a supervised learning of parameters of the mixture density function from the unclassified pattern samples followed by a decomposition procedure. Under certain conditions, the decomposition can be accomplished and the estimates of the parameters of each class recovered. A related topic which has received an increasing amount of attention recently is learning with finite memory [26].

When the *a priori* information is sufficient, the classifier may be able to make decisions with good performance. In this case, the learning process could be carried out using the classifier's own decisions; that is, the unclassified pattern samples are now classified by the classifier itself. This type of nonsupervised learning is called decision-directed learning. When the classification of the pattern samples is incompletely known, learning with an imperfect teacher and learning with a probabilistic teacher have recently been proposed [27], [64]. An appropriate combination of supervised and nonsupervised modes of learning could result in a system of lower cost than those using a single learning mode [18], [23].

Classification based on clustering analysis has been regarded as a practically attractive approach, particularly in a nonsupervised situation with the number of classes not precisely known. Various similarity and (deterministic) distance measures have been suggested as criteria for clustering pattern samples in the feature space [33], [34]. Both hierarchical and nonhierarchical strategies are proposed for the clustering process. Often, some of the clustering parameters, such as the similarity measure and threshold, criteria for merging and/or splitting clusters, etc., need to be selected heuristically or through an interactive technique. It should be interesting to relate directly the distance measures for feature selection to those for clustering analysis [19], [135]. Recently, clustering algorithms using adaptive distance were proposed [34]. The similarity measure used in the clustering process varies according to the structure of the clusters already observed. Mode estimation, least mean-square optimization, graph theory and combinatorial optimization have been used as a possible theoretical basis for clustering analysis [5], [20],

[70], [80], [133]. Nevertheless, clustering analysis, at its present state-of-the-art, still appears to be an experiment-oriented "art."

Remarks: Most results obtained in feature selection and learning are based on the assumption that a large number of pattern samples is available, and, consequently, the required statistical information can be accurately estimated. The relationship between the dimensionality of feature space and the number of pattern samples required for learning has been an important subject of study. In many practical problems, a large number of pattern samples may not be available, and the results of small sample analysis could be quite misleading. The recognition system so designed will usually result in an unreliable performance. In such cases, the study of finite sample behavior of feature selection and learning is very important. The degradation of performance in feature selection, learning and error estimation [48], [119] due to the availability of only a small number of samples needs to be investigated.

In some practical applications, the number of features N and the number of pattern classes m are both very large. In such cases, it would be advantageous to use a multilevel recognition system based on a decision tree scheme. At the first level, m classes are classified into i groups using only N_1 features. Here, $i \ll m$ and $N_1 \ll N$, and the N_1 features selected are the best features to classify these i groups. In an extreme case, $i = 2$ so a two-class classifier can be used, or $N_1 = 1$ so a one-dimensional (thresholding) classifier can be used. The same procedure is then repeated at the second and third levels, etc., until each of the original m classes can be separately identified. Now, following each path in the decision tree, we should be able to recognize each of the m classes.

The idea of adaptively selecting a smaller number of features at different levels of classification appears to be very attractive in applications. An optimal design of such a tree scheme may be computationally quite complex. However, several heuristic design techniques have recently been suggested [44], [58], [72], [134].

B. Syntactic (or Structural) Methods

A block diagram of a syntactic pattern recognition system is shown in Fig. 2. Again, we divide the block diagram into the recognition part and the analysis part, where the recognition part consists of preprocessing, primitive extraction (including relations among primitives and subpatterns), and syntax (or structural) analysis, and the analysis part includes primitive selection and grammatical (or structural) inference.

In syntactic methods, a pattern is represented by a sentence in a language which is specified by a grammar. The language which provides the structural description of patterns, in terms of a set of pattern primitives and their composition relations, is sometimes called the "pattern description language." The rules governing the composition of primitives into patterns are specified by the so-called "pattern grammar." An alternative representation of the structural information of a pattern is to use a "relational graph," of which the nodes represent the subpatterns and the branches represent the relations between subpatterns.

Primitive extraction and selection: Since pattern primitives are the basic components of a pattern, presumably they are easy to recognize. Unfortunately, this is not necessarily the case in some practical applications. For example, strokes are considered good primitives for script handwriting, and so are phonemes for continuous speech; however, neither strokes nor phonemes can easily be extracted by machine. The segmentation problems for script handwriting and continuous speech, respectively, are still subjects of research. An approach to waveform segmentation through functional approximation has recently been reported [92]. Segmentation of pictorial patterns is discussed in Section III under Segmentation.

There is no general solution for the primitive selection problem at this time. For line patterns or patterns described by boundaries or skeletons, line segments are often suggested as primitives. A straight line segment could be characterized by the locations of its beginning (tail) and end (head), its length, and/or slope. Similarly, a curve segment might be described in terms of its head and tail and its curvature. The information characterizing the primitives can be considered as their associated semantic information or as features used for primitive recognition. Through the structural description and the semantic specification of a pattern, the semantic information associated with its subpatterns or the pattern itself can then be determined. For pattern description in terms of regions, half-planes have been proposed as primitives [91]. Shape and texture measurements are often used for the description of regions; see Section III under Properties.

Pattern grammars: After pattern primitives are selected, the next step is the construction of a grammar (or grammars) which will generate a language (or languages) to describe the patterns under study. It is known that increased descriptive power of a language is paid for in terms of increased complexity of the syntax analysis system (recognizer or acceptor). Finite-state automata are capable of recognizing finite-state languages although the descriptive power of finite-state languages is also known to be weaker than that of context-free and context-sensitive languages. On the other hand, nonfinite, nondeterministic procedures are required, in general, to recognize languages generated by context-free and context-sensitive grammars. The selection of a particular grammar for pattern description is affected by the primitives selected, and by the tradeoff between the grammar's descriptive power and analysis efficiency. Context-free programmed grammars, which maintain the simplicity of context-free grammars but can generate context-sensitive languages, have recently been suggested for pattern description [41].

A number of special languages have been proposed for the description of patterns such as English and Chinese characters, chromosome images, spark chamber pictures,

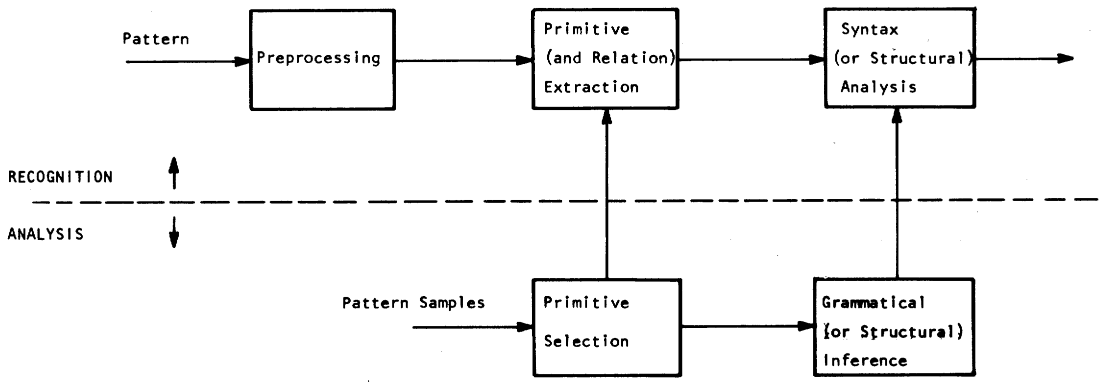

Fig. 2. Block diagram of a syntactic pattern recognition system.

two-dimensional mathematics, chemical structures, spoken words, and fingerprint patterns [41], [46]. For the purpose of effectively describing high dimensional patterns, high dimensional grammars such as web grammars, graph grammars, tree grammars, and shape grammars have been used for syntactic pattern recognition [41], [50], [88], [131]. Initial applications include fingerprint pattern recognition and the interpretation of Earth Resources Technology Satellite data [44], [46], [83].

Ideally speaking, it would be nice to have a grammatical (or structural) inference machine which would infer a grammar or structural description from a given set of patterns. Unfortunately, such a machine has not been available except for some very special cases [42]. In most cases so far, the designer constructs the grammar based on the *a priori* knowledge available and his experience.

In some practical applications, a certain amount of uncertainty exists in the process under study. For example, due to the presence of noise and variation in the pattern measurements, segmentation error and primitive extraction error may occur, causing ambiguities in the pattern description languages. In order to describe noisy and distorted patterns under ambiguous situations, the use of stochastic languages has been suggested [41], [52]. With probabilities associated with grammar rules, a stochastic grammar generates sentences with a probability distribution. The probability distribution of the sentences can be used to model the noisy situations. Other approaches for the description of noisy and distorted patterns using syntactic methods include the use of approximation and transformational grammars [43], [93]. The effectiveness of these approaches remains to be developed and tested.

Syntactic recognition: Conceptually, the simplest form of recognition is probably "template-matching." The sentence describing an input pattern is matched against sentences representing each prototype or reference pattern. Based on a selected "matching" or "similarity" criterion, the input pattern is classified in the same class as the prototype pattern which is the "best" to match the input. The structural information is not recovered. If a complete pattern description is required for recognition, a parsing or syntax analysis is necessary. In between the two extreme situations, there are a number of intermediate approaches. For example, a series of tests can be designed to test the occurrence or nonoccurrence of certain subpatterns (or primitives) or certain combinations of them. The result of the tests, through a table lookup, a decision tree, or a logical operation, is used for a classification decision.

A parsing procedure for recognition is, in general, nondeterministic and, hence, is regarded as computationally inefficient. Efficient parsing could be achieved by using special classes of languages such as finite-state and deterministic languages for pattern description. The tradeoff here between the descriptive power of the pattern grammar and its parsing efficiency is very much like that between the feature space selected and the classifier's discrimination power in a decision-theoretic recognition system. Special parsers using sequential procedures or other heuristic means for efficiency improvement in syntactic pattern recognition have recently been constructed [76], [94], [114].

Error-correcting parsers have been proposed for the recognition of noisy and distorted patterns [49], [117]. Different types of segmentation and primitive extraction errors (substitution, deletion and addition) are introduced into the pattern grammar. The recognition process is then based on the parsers designed according to the expanded pattern grammar. The error-correcting capability is achieved by using a minimum-distance criterion. Since the original grammar is expanded to include all possible error situations, the parser so designed is less efficient than that designed according to the original grammar. This tradeoff between error-correcting capability and parsing efficiency seems to be expected. Nevertheless, it could be a very serious drawback in practical applications.

When stochastic grammars are used for pattern description, the probability information is useful in resolving ambiguous situations. For example, if a sentence is found to be generated by two different pattern grammars, the ambiguity can be resolved by comparing the generation probabilities of the sentence in the two grammars. A maximum-likelihood or Bayes decision rule based on the two generation probabilities will yield the final recognition. Besides, the probability information can also be utilized to speed up the parsing process [41]. The use of a sequential decision procedure could result in further reducing the parsing time by slightly increasing the probability of misrecognition [76]. Of course, when a sequential procedure is used, the parsing procedure stops most of the time before a sentence is completely scanned, and, consequently, in these cases the complete structural information on the pattern cannot be recovered.

Remarks: Compared with decision-theoretic pattern recognition, syntactic pattern recognition is a newer area of research. When the patterns are complex and the number of pattern class is very large, it would be advantageous to describe each pattern in terms of its components and to consider description and classification of patterns rather than classification only. Of course, the practical utility of the syntactic approach depends upon our ability to recognize the simple pattern primitives and their relationships represented by the composition operations.

As research in both decision-theoretic and syntactic approaches is still in progress, heuristic methods are also being developed for specific purposes. New approaches proposed recently for pattern recognition include variable-value logic [81] and relation theory [55]. The effectiveness of these approaches still has to be tested.

III. Image Processing and Recognition

From its earliest beginnings, pattern recognition has dealt to a substantial extent with pictorial patterns. Section 3.2 of this paper reviews a few of the major themes in "image recognition." At the same time, extensive work has been done on aspects of image processing that are not directly related to pattern recognition—in particular, on image coding (for reduced-bandwidth transmission) and on image enhancement (for improving the appearance of images). Some aspects of this work are briefly discussed in Section 3.1.

For the purposes of this review, image processing refers to operations that transform images into other images, while *image recognition* is the mapping of images into (nonimage) descriptions. Different from both of these is *computer graphics,* which deals primarily with the computer synthesis and manipulation of images that are specified by descriptions; this subject is not reviewed here. We also do not cover optical (or other analog) methods of image processing, which has a large literature of its own.

A. Image Processing

Coding: In order to acceptably approximate a standard television image digitally, one normally needs an array of about 500 × 500 samples, each quantized to about 50 discrete gray levels—i.e., a total of about 6 bits for each of the 250 000 samples, or 1.5 million bits in all. The goal of image compression (or, as it is more commonly called, *image coding*) is to represent the image acceptably using a much smaller number of bits [61].

One basic approach to image coding is to apply an invertible transform to the given image, approximate the transform, and then construct the approximated image by inverting the transform. The transform can be designed so that it can be approximated more economically than the original image, and so that errors in this approximation become less noticeable when an image is reconstructed from its transform. For example, if we use the Fourier transform, we can achieve economical approximations because many of the Fourier coefficients (in the transform of a normal image) have negligible magnitudes, and so can be ignored or at least quantized very coarsely. Moreover, errors in approximating the Fourier coefficients are generally hard to notice when the image is reconstructed, because their effects are distributed over the entire image. Image compressions of as much as 10:1 can be achieved using this "transform coding" approach [7].

Many other approaches to image coding have been extensively investigated, but only a few of these can be mentioned here. One class of approaches takes differences between successive image samples; since these have a very nonuniform probability density (peaked at zero), they can be quantized acceptably using relatively few quantization levels. Note, however, that when the image is reconstructed from such differences by summing them, errors in the differences will tend to propagate, so that care is needed in using this type of approach. The differences used can be either spatial (intraframe) or temporal (interframe) [7].

The expected accuracy of an image coding system can be predicted theoretically if we assume a model for the class of images being encoded (usually, a homogeneous random field) and a specific error criterion (usually, mean squared error). Both of these assumptions are questionable. Images usually consist of distinct parts (objects or regions), so that a homogeneous random field model is inappropriate. On the other hand, the human visual system's sensitivity to errors is highly context-dependent, so that an integrated squared error criterion is inadequate. Work is needed on image coding techniques which segment the image into significant parts before attempting to approximate it; some image segmentation methods will be discussed here under Segmentation. At the same time, increased understanding of human visual capabilities is needed so that better error criteria for image coding systems can be developed.

Enhancement and restoration: There has been increasing interest in recent years in techniques for designing two-dimensional digital filters [60]. At the same time, much work is being done on digital methods of enhancing or restoring degraded images. Some enhancement techniques are conceptually very simple, and involve only pointwise modification of the image's grayscale. For example, one can analyze the gray levels in a neighborhood of each image point, determine a grayscale transformation that stretches these levels over the full displayable range, and apply this transformation to the given point (and the points in its immediate vicinity); this and similar techniques tend to give very good enhancement results [62].

A more sophisticated class of image enhancement techniques are designed to undo the effects of degradations on the image. It is customary to model these degradations as additive combinations of blurring and noise operations, where the blurring takes the form of a weighted sum or integral operation applied to the ideal image, and the noise is uncorrelated with the ideal image. A variety of methods have been developed for inverting the effects of the blurring operator; for example, pseudoinverse techniques can be used to define a deblurring operator which yields the best approximation to the ideal image in the expected least squares sense [7], [60]. Other classes of methods, e.g., based on Kalman filtering, have been devised to yield least-squares estimates of an ideal image corrupted by additive noise [7], [60]. As in the case of image coding, these approaches have usually been based on homogeneous random field models for the images (and noise), and on least-squares error criteria, both of which are questionable assumptions. Here too, image models based on segmentation of the image, and success criteria more closely related to human perceptual abilities, would be highly desirable.

A problem closely related to image restoration is that of reconstructing images; or three-dimensional objects, from sets of projections, e.g., from X-ray views taken from many angles. (The gray levels on a projection are linear combinations of the ideal gray levels, just like the gray levels on a blurred image.) Much work has been done in this area in the past few years, especially in connection with medical radiographic applications [22].

B. Image Recognition

The goal of image recognition is the classification or structural description of images. Image classification involves feature detection sr property measurement; image description involves, in addition, segmentation and relational structure extraction. Some significant ideas in each of these areas are reviewed in the following paragraphs. Historically, the techniques used have usually been developed on heuristic grounds, but there is increasing interest in deriving optimum techniques based on models for the classes of images to be analyzed.

Matching and feature detection: Detecting the presence of a specified pattern (such as an edge, a line, a particular shape, etc.) in an image requires matching the image with a "template," or standardized version of the pattern. This is a computationally costly process, but techniques have been developed for reducing its expected cost [9]. For example, one can match a subtemplate (or a reduced-resolution "coarse template") with the image at every point, and use the remainder of the template (or the full-resolution template) only at points where the initial match value is above some threshold. The subtemplate size, or the degree of coarseness, can be chosen to minimize the expected cost of this process [124]. In computing these matches, one should first check parts of the template that have large expected mismatch values (with a randomly chosen part of the picture), in order to minimize the expected amount of comparison that must be done before the possibility of a match at the given point is rejected [84]. Of course, the savings in computational cost must be weighed against the possible increased costs of false alarms or dismissals.

Template matching is often implemented as a linear operation in which the degree of match at a point is measured by a linear combination of image gray levels in a neighborhood of the point. However, the result of such a linear operation is generally ambiguous; for example, it may have the same value for a high-contrast partial match as it does for a lower contrast, but more complete, match. Such ambiguities can often be eliminated by breaking the template up into parts and requiring that specified match conditions be satisfied for each part, or for the most of the parts. This approach has been used to detect curves in noise [109], it needs to be extended to other types of image matching problems.

The use of template parts can also help overcome the sensitivity of template matching to geometrical distortion. Rather than matching the entire template with the image, one can match the parts, and then look for combinations of positions. Optimal combinations can be determined by mathematical programming techniques [38], or by simultaneous iterated reinforcement of the partial matches based on the presence of the other needed matches [63]. Research on these approaches is still at an exploratory stage.

Segmentation: Images are often composed of regions that have different ranges of gray levels, or of the values of some other local property. Such an image can be segmented by examining its gray level (or local property) histogram for the presence of peaks corresponding to the ranges, and using thresholds to single out individual peaks [30], [87], [116]. Detection of the peaks can be facilitated by hitogramming only a selected set of image points, e.g., points where the local property value is a local maximum [140], or points that lie on or near region boundaries (which can be identified by the presence of high values of a derivative operator) [130].

Parallel methods of region extraction based on thresholding are potentially less flexible than sequential methods, which can "learn as they go" about the geometrical, textural, and gray level properties of the region being extracted, and can compare them with any available information about the types of regions or objects that are supposed to be present in the image. Such information can be used to control merging and splitting processes with the aim of creating an acceptable partition of the image into regions [36], [59], [116].

An important special case of sequential region growing is tracking, which extracts regions (or region boundaries) in the form of thin curves. This technique can be regarded as a type of piecewise template matching, where the pieces are short line or curve segments, and a curve is any combination of these that smoothly continue one another; thus, here again, curves can be extracted by mathematical programming or iterated reinforcement techniques. The same is true for a wide variety of problems involving the selection of image parts that satisfy given sets of constraints [63].

Properties: Once regions have been extracted from an image, it becomes possible to describe the image in terms of properties of these regions. Much work has been done on defining and measuring basic geometrical properties of regions in a digitized image, such as connectedness, convexity, compactness, etc. Describing the shape of a region involves not only global properties such as those just listed, but also a hierarchically structured description in terms of "angles" and "sides" (i.e., polygonal approximation, of varying degrees of coarseness), symmetries, and so on [29].

Two "dual" methods of describing a region involve its boundary and its "skeleton." A region is determined by specifying the equations of its boundary curves; and it is also determined by specifying the centers and radii of the maximal disks that it contains [14]. (These disks define a sort of minimal piecewise approximation to the shape; such approximations can also be defined for grayscale images composed of regions that are approximately piecewise constant.) Skeleton descriptions can also be used in three dimensions, where a shape can be constructed out of "generalized cylinders," each of which is specified by a locus of centers and an associated radius function [2], [85].

Grayscale, as well as geometrical, properties of regions are of importance in image description. Of particular importance are textural properties (e.g., coarseness and directionality), which can be measured in terms of certain statistics of the second-order probability density of gray levels in the region [56]—or equivalently, statistics of the first-order probability density of gray level differences (or other local property values) [129]. Textures can be modeled as distorted periodic patterns [139], as two-dimensional "seasonal time series" [78], or in terms of random geometry; such models can be used to predict the values of the property measures for real-world textures.

Image and scene analysis: Image descriptions can usually be expressed in the form of relational structures which represent relationships among, and properties of, image parts. A major area of artificial intelligence research has been the study of how knowledge about the given class of scenes can be used to control the process of extracting such descriptions from an image. (See also the article on artificial intelligence in this issue.) In addition to the study of control structures for image analysis, there has also been recent interest in special data structures for image processing and description, e.g., "cone" or "pyramid" structures for variable-resolution image analysis [68], [115] and "fuzzy" structures for representing incompletely specified image parts.

The term "scene analysis" is generally used in connection with the description of images of three-dimensional objects seen from nearby, so that perspective and occlusion play major roles in the description [116]. (Note that the images being analyzed in applications such as document processing, photomicrography, radiology, and remote sensing are all basically two-dimensional.) Much work has been done on the extraction of three-dimensional depth information about scenes, using range sensors, stereo pairs of images, or single-image depth cues such as shading and texture gradients. These techniques are beginning to be applied to the analysis of various types of real-world indoor and outdoor scenes.

Another approach to image analysis involves the use of formal models derived from the theory of multidimensional formal languages. On this topic see the discussion of syntactic pattern analysis in Section II-B of this paper.

IV. Conclusions

It has been felt that in the past there was an unbalanced development between theory and practice in pattern recognition. Many theoretical results, especially in connection with the decision-theoretic approach, have been published. Practical applications have been gradually emphasized during the last five years, particularly in medical and remote sensing areas. Most of the practical results are considered inconclusive and require further refinement. Implementation of a practical system is often on a general purpose computer facility rather than on special purpose hardware. There is no doubt that, though heavily motivated by practical applications, pattern recognition is still very much an active research area.

In the decision-theoretic approach, we are still looking for effective and efficient feature extraction and selection techniques, particularly in nonparametric and small sample situations. The computational complexity of pattern recognition systems, in terms of time and memory, should be an interesting subject for investigation. In the syntactic approach, the problem of primitive extraction and selection certainly needs further attention. An appropriate selection of the pattern grammar directly affects the computational complexity or analysis efficiency of the resulting recognition system. Grammatical inference algorithms which are computationally feasible are still highly in demand.

In image processing, better models are needed for both the images and their user (the human visual system). Image models should also be used more extensively in the design of optimal image segmentation and feature extraction procedures. When the goal is not objectively specifiable, but rather involves general-purpose man-machine dialog about images, the computer will be also need to understand the visual capabilities and limitations of its human partner. Thus image and visual models need further development in both image processing and recognition.

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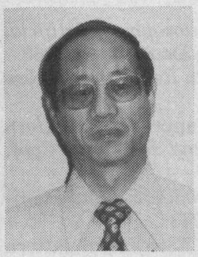

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Artificial Intelligence: Cooperative Computation and Man–Machine Symbiosis

MICHAEL A. ARBIB

Abstract—**Artificial intelligence (AI) joins forces with brain research, cognitive psychology, and linguistics to probe the nature of intelligence. It is asserted that the current AI emphasis on representation of knowledge will be augmented by increasing attention to *cooperative computation* and learning. AI also contributes to a *man-machine symbiosis:* providing specialized packets of intelligence to augment our own. As we augment our intelligence with our machines, building on current success with robotics, scene analysis, language understanding, and expert systems, we must better understand our own intelligence to enable the construction of high-bandwidth man–machine interfaces. This, too, is a form of cooperative computation.**

Index Terms—**Artificial intelligence, brain theory, cognitive psychology, cooperative computation, data-base management, expert systems, man–machine symbiosis, personal computers, representation of knowledge, robots.**

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I. INTRODUCTION

A TYPICAL definition of artificial intelligence (AI) is as a field of computer science whose goal is "to