Picture Processing by Computer

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Techniques for processing pictorial information by computer are surveyed. The topics covered include efficient encoding and approximation; position-invariant operations and applications; picture properties useful for pattern recognition; picture segmentation and geometrical properties of picture subsets; picture description and "picture languages."

Key words and phrases: picture processing, image processing, pattern recognition, bandwidth compression, efficient encoding, approximation, position-invariant operation, parallel computers, optical computers, matched filtering, template matching, spatial filtering, image restoration, image enhancement, picture properties, segmentation, geometrical pro perties, picture description, picture languages

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INTRODUCTION

Over the past 15 years, much effort has been devoted to developing methods of processing pictorial information by computer. This work has had a number of different goals, among them television bandwidth compression, image "enhancement" and "restoration," and pictorial pattern recognition Most of the studies in this field have been directed toward the solution of specific problems involving particular classes of pictures; but a body of "general purpose" picture processing techniques is gradually being built up. In this paper we review the picture-processing field from a technique-oriented standpoint.

We will deal here only with the processing of *given* pictures, not with pictures which have been synthesized by computer; this restriction rules out the areas of computer graphics, computer-generated movies, computer typography, and the like.

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As a further restriction, we will be concerned only with pictures as *two-dimensional* objects; this excludes pictorial representation of three spatial dimensions (stereopairs, contour maps, the hidden line problem, etc.), as well as time-varying pictorial information (e.g. on-line character recognition in real time). We will not discuss techniques for computer input or output of pictures; on this subject see, e g., A. Van Dam, "Computer driven displays and their use in man/machine interaction," *Advances in Computers, Vol. 7,* Academic Press, New York, 1967, pp. 239–290.

We will sometimes regard a *picture* as being a real-valued, nonnegative function of two real variables; the value of this function at a point will be called the *gray level* of the picture at the point. When necessary, we will assume that the function is analytically well-behaved (e.g. that it has an invertible Fourier transform). It will also often be convenient, in connection with picture processing by digital computer, to regard a picture as "discrete," being defined by specifying (say) an $n \times n$ *matrix* of gray levels; in this case the picture will be called a

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digital picture and the elements of the matrix will be referred to as *picture elements*. In either case, it is sometimes useful to assume that the picture is *quantized*, i.e. that it can take on only a finite set of values.

Although pictures (as just defined) are rather general mathematical objects, one would certainly not regard any mathematical operation performed on a picture function as "picture processing." For example, even though any square matrix with real, nonnegative elements defines a digital picture, it does not follow that inverting a matrix, or computing its eigenvalues, is picture processing. What makes picture processing a subject in its own right is that it deals with pictures which are not merely arbitrary functions or matrices, but which are pictures *of* something, which purport to represent a real scene (terrain, microscope slide, . . .) or an ideal symbol (such as an alphanumeric character). It is this representational aspect which gives rise to the basic picture-processing problems which are the subject of this paper.

Encoding and approximation. If pictures are not just arbitrary matrices, they do not all occur equally often. (This is certainly the case if the pictures being processed are all of some one type, e.g. printed matter, aerial photographs, etc.) In terms of information theory, this implies that the amount of information in an average picture is much less than if all possible pictures were equally probable. It is thus of interest to measure the information content of pictures and to devise encoding schemes for representing a picture as compactly as possible. One can also consider the possibility of approximating a picture acceptably—as defined by either objective or subjective standards—by another picture which has lower information content. The work done in these areas, most of which has been directed toward the goal of television bandwidth compression, is reviewed in the section on Picture Compression.

Filtering, restoration, and enhancement. There are many useful types of operations on pictures which are "position-invariant," that is, whose effect on a point does not depend on its position in the picture. Such operations have properties analogous to those of time-invariant operations in electronics. They can be implemented not only on conventional computers, but in a number of other useful ways as well (see the section on Position-Invariant Operations on Pictures), for example, optically. Operations of this type can be used (see the section on Spatial Filtering and Image Enhancement) to "filter" a picture so as to detect a given pattern in it ("template matching"); to "restore" a picture which has been degraded by other such operations ("image restoration"); and to "smooth" or "sharpen" a picture ("image enhancement") so as to improve its "quality."

Pattern recognition and picture description. In examining a picture, one is very often interested only in extracting from it a description of what it depicts; this is the problem of pictorial pattern recognition. The desired description may be merely a classification of the picture into one of a small set of prespecified classes; in this case it can often be accomplished by measuring various properties of the picture as a whole (see the section on Picture Properties and Pictorial Pattern Recognition). On the other hand, the description may involve properties of, and relationships among, "objects" which appear in the picture. To obtain such a description, it is usually necessary to explicitly locate the objects in the picture ("segmentation") and to measure their geometrical properties (topology, size, shape, etc.) and interrelationships. Picture descriptions in terms of objects, properties, and relationships can be represented using suitable "picture languages" (see the section on Picture Segmentation and Description).

PICTURE COMPRESSION [1–3]

Redundancy and Efficient Encoding

A quantized digital picture can be regarded as a discrete information source, with the gray levels as "messages." If there are m gray levels, the amount of information in an $n \times n$ digital picture is at most $n^2 \log m$ bits, with the actual information content depending on the probabilities with which the gray levels occur. Pictorial media can be used to store information at extremely high densities, and information can be transmitted optically at extremely high bandwidths. The maximum information capacities of various pictorial media (particularly, photographic materials) have been the subject of numerous papers (e.g. [4, 5]). There also exists literature on the information capacities of light beams, optical images, radiation detectors, and the eye.

Most of the classes of pictures encountered in practice are *redundant*, having information contents which fall considerably short of their potential capacities. Statistical estimates of the information content of television images have been made by various investigators (see the references cited at the end of the next paragraph). Statistical studies have also been made of various special classes of pictures, such as printed pages and line drawings [6, 7].

To take advantage of picture redundancy, one can use *efficient encoding* techniques in which the frequently occurring gray levels are represented by short codes and the infrequent ones by longer codes (rather than, e.g., representing each of the m levels by a ($\log_2 m$)-bit number). Even if the gray levels are equally probable, economical encoding is still possible if the levels of successive picture elements are interdependent, as described by specifying conditional probabilities. Under these circumstances, compression can be achieved by using the codes to represent blocks of elements ("block coding"), differences between successive elements ("predictive coding"), or the positions (or lengths) of "runs" of elements all having the same level ("run coding") [8–10; cf. 11].

If a picture contains only a few regions, each having a constant gray level and a simple shape, it can be very economically encoded by giving its *description*, i.e. by specifying the shape and gray level of each region. Line drawings can often be encoded very compactly in this way, particularly if they involve only curves and arcs made up of analytically simple pieces, such as straight lines and conic sections. (Run coding can be thought of as the case in which, if the usual raster scan is used, the pieces are horizontal line segments.) This type of "analytic encoding" is used in all computer graphics systems, since it not only compresses the pictures but also makes it especially easy to perform geometrical operations on them.

Approximation

The encoding techniques considered above provide means for compressing pictures without discarding any information. Except for very simple classes of pictures, the degree of compression which can be achieved using such techniques is limited. On the other hand, for many purposes there is no need for all the details which appear in a picture, and it is often possible to *approximate* a given picture by a simpler picture which looks like it but which has a lower information content.

One basic method of approximating a picture is to select a finite *sample* of its points and define a new picture by some type of *interpolation* between the gray levels at the selected points. *Digitization* can be thought of as a "zero-order" approximation scheme which uses constant functions for "interpolation." The *sampling theorem* states that if sinusoids are used for interpolation, the picture can be represented exactly if its Fourier transform is zero outside a bounded region, and the samples are taken sufficiently closely [12–14].

Another basic method of approximating a picture is to *quantize* it so that it takes on only a prespecified finite set of gray levels. The most straightforward approach is to use a set of evenly spaced levels (analogously, in sampling, it is usual to use evenly spaced sample points), but it may sometimes be desirable to use levels which are unequally spaced. For example, suppose that in the original picture, the gray levels in a certain range occur most frequently. In such a case one might use quantization levels which are finely spaced inside this range and coarsely spaced outside it; in this way one could reduce the average quantization error without increasing the number of levels. This method is sometimes called *tapered quantization*. The number of quantization levels required for acceptability can be reduced by appropriate pre- and post-"filtering," i.e. by suitably modifying the picture before and after quantizing it; for an interesting example of this approach see [15].

Sample points or quantization levels need not be selected in a predetermined manner; their choice can be allowed to depend on the nature of the picture. This can sometimes be done in such a way as to take advantage of the observer's visual limitations with respect to what he is willing to accept as an adequate approximation. For example, the eye is relatively poor at estimating the gray levels immediately adjacent to a sharp "edge" on a picture; but in a "smooth" region on the picture, if too few quantizing levels are used, the transitions from level to level will show up conspicuously as "false contours." Thus fine quantization is desirable in smooth areas, but coarse quantization is adequate near edges. Conversely, in sampling, closely spaced samples are required in the vicinity of a sharp edge in order to preserve its shape, whereas coarse sampling is adequate in a smooth region.

(In terms of television transmission, one can transmit the picture at low bandwidth, but also detect the edges in it and transmit their exact positions and approximate contrasts, so that "synthetic edges" can be added to the received picture. More generally, one can try to detect "essential elements" of a picture, and use crude approximation schemes for the inessential elements [16].)

Another approach to variable sampling (with or without quantization) is to pick as small as possible a set of sample points such that the given picture does not differ by more than a prespecified amount from the picture interpolated between the sample points [17, 18]. Note that ordinary quantization can be regarded as a "zero-order" method of this type.

A line drawing can be approximated by fitting pieces of analytically simple functions (e.g. line segments) to the actual curves and arcs. Here again, one has the choice of whether or not to use preselected sample points to construct the approximation. For example, one can use the points of a regular array such that the given curve passes through some prespecified neighborhood of them. In particular, one can imagine the points of the array as joined by lines, and each time the curve crosses one of the lines, use the point of the array which lies closest to this intersection point. (Here the "neighborhood" of each point is the portion of the grid closest to it.) This latter method is known as *chain encoding* [19].

Approximation of curves provides an interesting alternative approach to the approximation of surfaces (i.e. pictures): one can construct a contour map of the surface using a fixed quantization scheme and approximate the contour lines [20]. Another method of approximating a function is to expand it in a series, e.g. Taylor series, Fourier series (or, more generally, series expansion in terms of a given set of orthogonal functions), expansion of a matrix as a sum of dyads, etc., and use the sum of the first few terms of the series as an approximation. (In the case of television there are still other possibilities for bandwidth compression, which capitalize on the fact that the pictures vary with time.)

POSITION-INVARIANT OPERATIONS ON PICTURES

Basic Concepts

An operation which takes pictures into pictures will be called *position-invariant* if its effect on a point does not depend on the position of the point in the picture. Equivalently, the operation φ is position-invariant if it commutes with the translations, that is, if it makes no difference whether we first perform φ and then shift the picture by a given amount, or vice versa. Evidently the translations themselves ("shifting operations") are position-invariant, but other types of geometrical operations, such as rotations, scale changes, etc., are not.

An important class of position-invariant φ are the *point operations,* which change the gray level at each point in a manner which does not depend on the rest of the picture. For example, quantization is a point operation, and so is any transformation of the gray scale, e.g. linear ("gamma correction"), logarithmic, etc. More generally, if the effect of φ at a point depends only on the gray levels in a neighborhood of the point (where we use the same neighborhood at every point), φ is readily position-invariant; such a φ is called a *local operation.* Many examples of useful local operations are given in the next section.

It is well known that any position-invariant *linear* operation can be defined by an expression of the form

$$[\varphi(f)](x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x - u, y - v)f(u, v)\, du dv.$$

(Here the right member is called the *convolution* of f and g; it will be denoted by $f*g$. It is often useful to work with $f*\bar{g}$ rather than $f*g$, where $\bar{g}(x, y) = g(-x, -y)$; this is called the *cross-correlation* of f and g, and will be denoted by $f \otimes g$. Readily, $f \otimes g = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(u, v)f(u + x, v + y) du dv$. The cross-correlation $f \otimes f$ of f with itself is called the *autocorrelation* of f.) In the case of a digital picture we can replace the integration by summation. (A useful class of such operations can be defined, in the digital case, by pre- and post-multiplying the picture matrix by given matrices [21–22].)

If $\varphi(f) = f*g$, we call g the *point spread function* of φ. Intuitively, g is the result of applying φ to a "one-point" picture which is zero except at a single point; it is analogous to the *impulse response* in electronics, which is the output resulting from a "one-instant" input. When we write $\varphi = f{*}g$, we are treating f as the "sum" of a set of "one-point" pictures.

It is often convenient to describe φ in terms of its effect on other simple types of input pictures, e.g. pictures which are zero except at the points of a straight line. The result of applying φ to such a picture is called a *line spread function* of φ. Readily, the line spread function is obtained by integrating the point spread function in the direction parallel to the line.

Still another way of describing φ is by its effect on a sinusoidal input picture. The result of applying a linear position-invariant φ to such an input is still sinusoidal and with the same period, but with amplitude multiplied by (say) $M(\omega)$ and phase shifted by $P(\omega)$, where $M(\omega)$ and $P(\omega)$ are functions of the spatial frequency ω of the input sinusoid; they are called the *modulation transfer function* and *phase transfer function* of φ. Readily $M(\omega)$ and $P(\omega)$ are the modulus and phase of the Fourier transform of the line spread function of φ. They are analogous to the *frequency response* in electronics.

On the use of spread and transfer functions as measures of image "quality" see [23–26], and compare [27]. On other measures of image quality, relating to the sharpness of edges and the ability to "resolve" pairs of close objects, see [28–30]. On the suggestion that the information capacity of a picture can be regarded as a measure of quality see [4, 31]; for a general reference on image quality see [32].

It is well known that the convolution of two functions f and g is equal to the inverse Fourier transform of FG, the product of their Fourier transforms. (In particular, the Fourier transform of the autocorrelation $f \otimes f$ is equal to $|F|^2$, the *power spectrum* (or *Wiener spectrum*) of f.) This provides an alternative method of convolving functions, which can actually be faster than computing the convolution directly if a "fast Fourier transform" algorithm (e.g. [33]) is used.

Digital and Electronic Implementations

Conventional digital computers are basically sequential; they can perform at most a few arithmetic operations at a time. If one could perform many identical arithmetic operations "in parallel" (i.e. simultaneously), digital pictures could be convolved very rapidly. (Computers having a large number of processing units which can operate in parallel under central control are under development, but little work has been done on the application of such computers to picture processing.) Special purpose digital networks have been designed which can simultaneously shift an entire array of numbers (i.e. a digital picture) in any of the four principal directions, or simultaneously add or multiply two arrays elementwise [34–37]; see also [38–41].

Even on a conventional sequential digital computer, it is usually possible to perform simple logical and shifting operations simultaneously on each binary digit of a "word." This implies a potential saving in computation time by a factor equal to the word length, typically 32 or 36. Since arithmetic operations can be regarded as combinations of logical operations, much of this saving can be achieved for them as well, particularly if numbers having only a few binary digits (e.g. pictures having only a few gray levels) are involved [42–44; cf. 45].

If digital circuitry is used to perform operations in parallel on large arrays of numbers, a large network of individual components, or the equivalent, is required. There exist other electronic methods of performing certain types of operations—in particular, position-invariant linear operations—in parallel, with the picture represented by an electronic analogue (e.g. a pattern of voltages or charges) which is created directly from optical input. Two such methods involve the use of electroluminescent-photoconductive (EL-PC) arrays [46, 47] and of image storage tubes [48–51; cf. 52, 53], respectively.

Optical Implementations

Position-invariant linear operations on pictures can be implemented in especially simple ways by optical means. Although here we are primarily concerned with picture processing by digital computer, the growing interest in optical and hybrid optical/digital computation (see, e.g., [OPI, OEOIP, 54–56][1]) makes it desirable to briefly survey such methods as well.

In optical picture processing, the pictures are usually assumed to be in the form of transparencies; here the picture function $f(x,y)$ represents the fraction of the light incident on the point (x,y) which is transmitted through the transparency. Thus to multiply two pictures optically, one need only superimpose their transparencies; while pictures can be added by making successive exposures on photographic film. One could thus convolve two pictures by shifting one superimposed transparency relative to the other and cumulatively adding the resulting sequence of products; but this operation requires moving parts and is very time-consuming. A much simpler class of methods, which require no moving parts, involves the use of a diffuse light source to illuminate the two transparencies, which are not in contact with one another; here families of parallel light rays yield the required "shifts" [57–65]. On an optical method of computing the autocorrelation of a function which requires only a single transparency, see [66].

Optical processing devices can be interfaced with electronic processing at either their input or output ends. To convert an electronically stored picture into a transparency, one can "write" it on film, or on various other materials, using a cathode-ray tube [67, 68]. To convert a correlogram into an electrical signal for electronic processing, one can replace the diffuse light source (in an optical correlator) with a cathode-ray tube. If only one point of the tube face is illuminated at a time, only one point of the correlogram image is formed at a time; so that a photocell viewing the image plane will output a signal representing a scan of the correlogram [69–71].

Operations can be performed optically even on functions which are not necessarily nonnegative. The equivalent of "negative light" can be obtained by using photographic "reversal effects" in recording the image [72] or by using a "quenchable phosphor" as a light source [73]. If the light is coherent, orthogonally polarized rays can be made to subtract from one another [74]. Two images can be scanned synchronously and subtracted electronically; in fact, the two scans can be combined if color or polarization separation is used.

There are other methods of optical picture processing which require that the light source be *coherent*, so that the light rays passing through the system have definite phase relationships to each other, and interference can take place. It is well known that if a transparency f is illuminated by a parallel, coherent beam of light which then passes through a lens, the distribution of light in the focal plane of the lens is essentially the Fourier transform F of f. (In fact, f can be regarded as a linear combination of sinusoidal "diffraction gratings" of various line-spacings and directions; each grating contributes a single pair of points to F.) Similarly, one can compute the inverse Fourier transform optically, so that f can be convolved with g by placing a transparency of the Fourier transform G of g in the focal plane which contains F [75–83]. In general, both the transmittance and phase retardation of the transparency G must vary from point to point; this can be done by varying its thickness [84] or by designing it as a "diffraction grating" whose line widths and spacings are both variable [85, 86]. Alternatively, one can use a transparency in which G is mixed with a "reference signal" to yield an interference pattern such that the inverse Fourier transforming process separates out the desired convolution [87–99]. (Interference patterns from which a given picture can be "reconstructed" are the basis of *holography* [100–103].)

SPATIAL FILTERING AND IMAGE ENHANCEMENT

Matched Filtering ("Template Matching")

One often wants to determine how well

two pictures "match" one another, or to find a part of one picture which matches another picture. These questions are of obvious importance in pictorial pattern recognition, particularly in cases where the "patterns" are highly standardized (e.g. printed characters, or images of specific objects). Such questions also arise in map-matching navigation (e.g. star pattern recognition [104]), where one wants to find a region on an observed image which matches a reference "map"; and in automatic stereogrammetry [105], where the two images of the same point on a stereopair of pictures must be identified in order to measure the parallax at that point.

One can also consider the converse question of detecting *differences* between two pictures, e.g. the same scene at two different times. Even if the two pictures are in perfect registration, this problem of "change detection" can still be nontrivial if one wants to detect *significant* changes, as opposed to changes due to noise, differences in exposure, shadows, etc. On some interesting methods of detecting the *existence* of a difference between two pictures see [106, 107].

There are many ways of measuring the degree to which two functions differ. For example, one can simply compute their average (absolute or squared) difference, that is, $\iint |f - g|$ or $\iint (f - g)^2$ (divided by the area over which the integration is performed). A more commonly used method capitalizes on the fact (Schwarz's inequality) that the "normalized" cross-correlation

$$\frac{\iint f(u,v)g(u+x,v+y)\,dudv}{\left(\iint f^2 \cdot \iint g^2\right)^{1/2}}$$

is always less than or equal to 1, and it is 1 only for displacements (x,y) at which $g(u+x, v+y) = cf(u,v)$ for all u,v, where c is a constant. Thus cross-correlating f and g provides a method of determining whether they are identical except for translation and multiplication by a constant. This method can be very useful in certain simple types of pattern recognition tasks, for example, tasks involving the identification of stylized, noise-free characters of standard size and orientation, where only one character is examined at a time (so that a "picture" contains only a single character); here one can simply cross-correlate the given character with a "template" of each character. It can, in fact, be shown that under some circumstances, if one wants to "detect" the pattern f by cross-correlating a template with the (noisy) picture g, then the best template to use for this purpose is a copy of f itself—a "matched filter" (see [108–111]).

It should be pointed out that the value of the normalized cross-correlation at a point of perfect match is often not much greater than at other points; but the difference can be enhanced by nonlinear scaling [112]. "Sharp" matches are obtained if the patterns are line-drawing-like rather than "solid"; this suggests that template matching should be preceded, whenever possible, by some sort of edge detection operation. If the pictures and patterns under consideration are binary, i.e. they can take on only the values 1 and 0 ("transparent" and "opaque," or "white" and "black"), as is approximately the case in many character recognition tasks, one can detect a match using a difference, rather than a quotient, of two correlograms [113]. In the case of a digital binary picture, another way of testing for a match between the picture and a template is to multiply the picture pointwise by shifted copies of itself or of its negative; on this "window-card" method see [114].

Spatial Frequency Filtering and Image Restoration

As pointed out in the section on Position-Invariant Operations on Pictures, another way to convolve a template with a picture is to multiply their Fourier transforms and take the inverse Fourier transform of the product. One advantage of working with the Fourier transform ("in the spatial frequency domain") is that useful picture processing operations can be performed using very simple templates (the more usual term in this context is "filters"). For example, introducing an opaque disk (in optical terms: a "stop") centered on the optical axis has the effect of suppressing low spatial frequencies while transmitting high ones; typically, this will "wash out" smooth regions on the picture while preserving sharp edges and fine detail. Conversely, using an annulus as a stop will suppress high frequencies and transmit low ones, thus blurring the picture. A sector stop will tend to suppress edges which lie in the direction perpendicular to the sector. On the advantages of performing such filtering in conjunction with a logarithmic scale change see [115].

An important application of spatial frequency filtering is to the problem of "image restoration." Suppose that a picture has been obtained through some imaging or transmission process which has degraded it. If the degradation can be mathematically inverted, it is in principle possible to undo it and "restore" the picture to an undegraded condition. In particular, suppose that the degradation is a position-invariant linear operation, say that of convolving some g with the original picture f, so that the degraded picture is $f*g$. Then if we take the Fourier transform of $f*g$, we obtain FG, the product of the Fourier transforms of f and g; and if we now simply divide by G and take the inverse Fourier transform, we have restored the original f. (We can obtain G, at least approximately, by allowing the degradation to operate on a one-point picture and taking the Fourier transform of the result.) In practice, unfortunately, the degradation is rarely a position-invariant linear operation; we can think of it as also involving noise, and the restoration process is usually highly sensitive to this noise. Nevertheless, useful results can often be obtained by dividing by G in those spatial frequency ranges where the signal-to-noise ratio is high [116–124]. (On the use of such operations to change one picture into another see [125].)

Image Enhancement: "Smoothing"

In the following paragraphs we review operations which can be used to blur a picture, or to "smooth" it so as to suppress noise which may be present in it.

Averaging over a neighborhood. One can blur a picture by taking the average of the gray levels in a neighborhood of each point (Optically, one can image the picture out of focus, copy it out of contact, or vibrate it.) To smooth without blurring, one can average and then threshold; for example, one can clean up "pepper and salt" noise in a binary-valued picture (isolated black points in white regions and vice versa) by making a black point white if it has an above-threshold number of white neighbors, and vice versa [126]. An alternative approach is to average the picture isotropically only at points where "edges" are not present, but to average only along an edge when one is present [127] (on edge-detection criteria, see the next section). In some cases [128] it is advantageous to average over neighborhoods of different sizes at different points.

Averaging of multiple copies. Suppose that n copies of a noisy picture are available such that the samples of the noise in the copies are all independent. Since averaging independent samples preserves the mean while decreasing the variance, one can "attenuate" the noise without attenuating the picture itself by taking the average of the copies [129–132]. (On *multiplicative* superposition of multiple copies of a picture, or passing light repeatedly through a single copy, as a method of increasing its contrast, see [133, 134], and compare [135].) The image of a *symmetric* object can thus be enhanced by superposing copies of a single picture which have been, e.g., rotated in such a way as to take an object into itself [136, 137].

Bandpass spatial frequency filtering. As pointed out earlier, another way to smooth a picture is to suppress the high spatial frequencies from its Fourier transform and take the inverse transform of the result. If a picture contains periodic "noise" (television raster lines, halftone dots, etc.), or noise with a characteristic "grain size," it can be smoothed by suppressing a selected band of spatial frequencies [138–142; see also 143].

Introduction of noise. A picture can be "blurred" by introducing noise into it.

Particularly effective for this purpose is "random-walk" noise, in which points are interchanged with randomly selected nearby points [144].

Image Enhancement: "Sharpening"

Just as one can smooth or blur a picture in a variety of ways, so there are many ways to "sharpen" or "deblur" a picture. For example, this can be done by quantizing the picture ("clipping"), by reproducing it xerographically or on a high-contrast photographic medium, or by high-pass spatial filtering. Since integration (i.e. averaging) blurs a picture, a natural approach to "deblurring" is to perform some sort of differentiation or differencing operation [145]. A number of such operations are discussed in the following paragraphs.

The gradient. Edges in all directions can be sharpened by computing the *gradient* (the derivative along the direction in which the gray level is changing fastest). This can be done by taking the square root of the sum of the squares of the derivatives in two orthogonal directions, e.g.

$$\left(\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2\right)^{1/2},$$

or by approximating the derivatives by differences. For examples of digital "gradients" see [126, 146, 147]. On optical methods of computing various types of derivatives see [73].

The Laplacian. Another useful combination of derivatives is the *Laplacian*

$$\frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

(compare [38], [148–151]). If the derivatives are replaced by differences, this is proportional to the difference between the gray level at the point and the average gray level in an "annulus" centered at the point, which can be computed by convolving the picture with a template having a positive peak at the origin surrounded by a negative annular "valley"—or even more simply, by subtracting a blurred copy of the picture from the picture.

Neurons which appear to perform this type of operation on the retinal image, having "receptor fields" on the retina with "excitatory" centers surrounded by "inhibitory" annuli or vice versa, have been found in the visual systems of a number of animals [PR, 152].[1] On special-purpose devices which simulate information processing in animal visual systems see [B60, BPSS, B63, B66].[1]

The Laplacian can be computed optically by superposing a positive transparency and a blurred negative transparency of the picture ("unsharp masking"); or a single transparency can be used in conjunction with a quenchable phosphor screen [153, 154]. One can also compute the Laplacian by scanning the picture simultaneously with two light spots, one fine and one coarse, and subtracting the resulting signals electronically; or more simply, one can use a single focus-modulated spot, or a non-color-corrected spot in conjunction with color separation optics [155–157]. For a comparison of unsharp masking with other techniques in which the "blurred" image is produced by lateral shift or by "ring smear" rather than by defocus, see [158].

Directional derivatives and differences. Edges or lines in a given direction can be emphasized, while all others are attenuated or suppressed, by performing a suitable differentiation or differencing operation in the orthogonal direction. For example, one can convolve the picture with a template having a positive strip alongside a negative strip, both in the given direction.

Neurons having "receptor fields" of these types have been found in the visual cortexes of various mammals [PR, 152]. The required convolutions can be accomplished by adding shifted copies of the picture; on this concept of straight-line detection by self-congruence under shifting see [159, 160]. On other types of line detectors see [161].

Statistical differencing. Rather than differencing by comparing the average gray levels in two neighboring regions (point and annulus, adjacent strips, etc.),

[1] See References for explanation of code.

one can compare the *frequency distributions* of the gray levels in the regions [146, 162, 163]. Alternatively, given run length and noise statistics for the picture, one can compute the probability that a given gray level difference is due to an actual edge or to noise [164].

PICTURE PROPERTIES AND PICTORIAL PATTERN RECOGNITION

Pattern Recognition

As indicated in the introduction, one of the central problems in the field of picture processing by computer is that of describing given pictures. In general, a description of a picture might consist of a set of true statements about the picture in some appropriate language; we consider this general case below. Often, however, one needs only to classify the picture into one of a set of (usually prespecified) categories. It is usually convenient to do this in several steps:

1. Preprocessing. The given picture f is transformed ("preprocessed") into one or more new pictures $f_1, \cdots, f_k$ by performing a set of operations, or sequences of operations, on it.

2. Feature Extraction. A set of "property" (or "feature") functions $F_1, \cdots, F_m$, which take pictures into (real) numbers, are applied to the f_i. (It is sometimes useful to make this a two-step process in which pictures are first mapped into functions of a single variable, and these in turn into numbers.)

3. Classification. The result of steps 1 and 2 is an n-tuple ($n \leqslant mk$) of numbers each of which can be regarded as a property of the original picture f; we can think of such an n-tuple as a point in n-dimensional space. If the classes are specified as occupying given regions in this space, or as having given probability distributions over this space, one can now assign the given picture to the closest or most probable class.

There is extensive literature on step 3, classification on the basis of a given set of properties; since this is not a problem specific to picture processing, we will not discuss it further here. The basic idea in step 1 is to preprocess in such a way as to make it easier, at step 2, to extract good features—"good" in the sense that they in turn make classification easier, or make better classification possible. The techniques available for step 1 have been reviewed in the two preceding sections. In this section we deal with step 2, the problem of defining useful property functions which take pictures into numbers, or into functions of a single variable. (Binary-valued properties, which can be either "true" or "false" for a given picture, may be regarded as a special case of real-valued properties.)

In discussing picture properties, it is convenient to distinguish between properties which have natural definitions for an arbitrary picture and those which have such definitions only if a special subset of the picture (an "object") has been singled out. For example, it is pointless to speak about such properties as the size and shape of a picture, since we usually deal only with pictures which are nonzero on a standard-size square; however, one is very often interested in the sizes and shapes of various objects in a picture. Methods of singling out subsets from pictures ("segmentation"), and properties of picture subsets, are discussed in the section on Picture Segmentation and Description; in this section we are primarily concerned with properties which have natural definitions even if no subset is specified.

Most of the research in pattern recognition has involved alphanumeric characters; for general references on automatic character recognition see [OCR][1] and the first ten papers in [PR(2)],[1] as well as [165–172].

Much of the work on automatic handwriting recognition [173] has made use of real-time information (stroke sequences, velocities, accelerations, etc.), and so is not strictly "picture processing." In much of the work on reading devices for the blind [174, 175], the characters are not identified, but are only converted from pictorial to acoustic patterns.

Other major areas of activity in the pictorial pattern recognition field (see PPR)[1] include the automatic analysis of nuclear bubble and spark chamber pictures [176–179]; of terrain and military targets on aerial photographs [180, 181]; of various types of biomedical images (X-rays, photomicrographs, etc.) [182]; and of fingerprints [183]. For additional surveys and collections of papers in the field of pattern recognition see [184–188].

Property Selection

Given a set of properties, it is in principle possible to measure the contribution which each of them makes to the classification decision [189–194]. If this is impractical, one can still evaluate the properties empirically by implementing or simulating the recognition system [195–201; cf. 202]. Many pattern recognition systems are able to modify the properties which they use, in an attempt to find more effective ones (e.g. [203–206]; there are other systems which modify not the properties themselves, but the weights given to them in making the classification decision). Since these concepts are not specific to pictorial patterns, they will not be discussed further here.

Of greater relevance to *pictorial* pattern recognition is the problem of selecting a "good" set of properties to begin with. Unfortunately, there is no systematic procedure for defining properties when a classification task is specified; property selection is largely up to the designer of the pattern recognition system. In many cases, properties have been chosen because of their mathematical tractability or ease of implementation, or because they seem to play a role in visual information processing by animals or humans. (On this last approach see [B60, BPSS, B63, MPSVF, PR, B66],[1] as well as [207, 208].)

If models for the pattern classes can be formulated, they can serve as a guide for selecting useful properties. For example, suppose that all the patterns belonging to a given class can be obtained by adding noise to an ideal ("prototype") pattern. In this case, as indicated in the section on Spatial Filtering and Image Enhancement, the "template match" with the prototype is an optimum property. More generally, one can consider cases in which the patterns are combinations of a given set of "subpatterns" (plus noise) [209–211; cf. 212–214].

In many cases, two patterns must belong to the same class if they differ only in position, orientation, size, etc., or if they can be obtained from one another by a simple point-operation, such as a linear transformation of the gray scale. In other words, in many cases the classes are *invariant* under certain types of transformations (translation, rotation, magnification, gamma correction, etc.). This constitutes a partial description of the classes and suggests the use of properties which are invariant under the same transformations. The following are some of the methods of defining such properties:

(1) In some cases it is not impractical to actually apply all the transformations to each given pattern, either one after the other or "in parallel," and to compute property values for each of the transformed patterns. For example, when we cross-correlate a template with a picture, we are computing the "match" of the template with the picture in every possible position. This of course yields a very large set of property values, but one can obtain invariant properties from this set by taking its average, its maximum, etc.

(2) If the set of transformations has a simple mathematical description, one can usually define invariant properties mathematically. (In fact, the various branches of geometry are often regarded as being concerned with those properties of figures which are invariant under various groups of transformations.) For example, distances between points of a figure are invariant under translation and rotation of the figure, and their ratios are also invariant under magnification, so that these distances (ratios) can be used as properties by which to assign the figure to a class of congruent (similar) figures. For some less trivial examples see the references on "moment invariants" cited in the

subsection on Classes of Properties, as well as [215, 216].

(3) It is often possible to define a procedure for "normalizing" a pattern such that all patterns which differ only by a transformation in the given set will become identical when they are normalized. Thus any property of the normalized pattern is a transformation-invariant property of the original pattern. For example:

(a) a pattern can be translated so that its centroid is at the origin of the coordinate system, and rotated so that its principal axis of inertia lies along the x-axis. (Here we are regarding the gray level at a point as representing the "mass" of the point.) A figure (i.e. an "object" in a picture) can be normalized by finding its circumscribed rectangle of (say) smallest possible area and putting this rectangle into some standard position and orientation [217, 218]. The eye can be thought of as performing a certain degree of normalization when it "fixates" (i.e. centers) an object, or adapts to overall differences in brightness;

(b) the autocorrelation of a picture, and its power spectrum (the modulus of its Fourier transform), are invariant under translation of the picture. Thus template matching of autocorrelations, or of power spectra, provides a translation-invariant method of detecting a given pattern [219, 220] Similarly, particular values of the autocorrelation, corresponding to particular shifts of the given picture relative to itself, provide a class of translation-invariant properties [221] (On the converse problem of when does the autocorrelation determine the original function "up to translation," see [222, 223]; on analogous methods of obtaining rotation and scale invariance see [223–225].) There is evidence that certain insect eyes compute the autocorrelation of the visual field [226, 227];

(c) if the transformations in question are linear and form a group under composition of functions, a pattern can be converted into an invariant form by applying all the transformations to it and taking the sum, or average, of the resulting patterns. On the suggestion that the brain may construct invariants in this way, see [228, 229]; for some related work see [230–235].

Classes of Properties

Only a few of the many possible types of picture properties have been used for pattern recognition purposes. In this subsection we discuss some of the important classes of such properties.

Local properties and "textural properties." The value of a property $F(f)$ need not depend on the entire set of values of f, but only on a subset of these values, in other words, on the values of f restricted to a subset of the plane. We say that F is *local* if this set is small. For example, if φ is a local operation, the value of $\varphi(f)$ at any specified point is a local property of f. The extreme case of a local property is a "point property," i.e. a function of the gray level of the picture at a single specific point. (If there are just n possible patterns, they can be distinguished using at most $n - 1$ point-properties [236–238].)

The use of local properties is practical if the pictures in question can be normalized. For examples of local properties applied to the recognition of patterns which have been normalized in position, orientation, and scale, see [239–241]; on the use of local properties of the power spectrum of a picture see [242, 243]. To make a local property slightly insensitive to position, one can blur the picture before measuring the property [114].

Invariant properties of an unnormalized picture can be obtained by analyzing the frequency distribution of the values of any local property over the picture; for example, the statistics of the distribution, such as its average, or the fraction of the picture area over which it has a given range of values, are invariant. We will call statistics of local properties *textural properties*. For examples of the use of such properties see [244–252]; on the role of "visual texture" in perception, and on models for it, see [253–259].

Linear properties. Just as (see the section on Position-Invariant Operations on Pictures) any position-invariant linear operation is a convolution, so it can be shown that any "bounded" linear property F is a "template match." Specifically, if there exists an M such that $F(f) \leq M(\iint f^2)^{\frac{1}{2}}$ or all f, then there exists a function g such that $F(f) = \iint gf$ for all f.

Template match properties are particularly applicable in cases where the patterns can be normalized; they have been used extensively in character recognition systems. For highly standardized patterns, it becomes practical to use templates of complete patterns as properties; in this case one can simply classify an unknown pattern as being the same as the template which it best matches. Another important class of linear properties is that in which the templates are mathematically simple functions, polynomials, sinusoids, etc. For example, if the functions are the monomials $x^i y^j$, the properties are the *moments* of the picture [260–268]. On properties which are "linear with respect to" given sets of local properties see [269, 270].

Random properties. Many pattern recognition systems employ properties which are defined by random processes. For example, a random linear property can be defined by generating a random function and using it as a template. In the "simple Perceptron" [271], each "A-unit" computes a different property of this type, where the random functions can take on only the values 0, 1, and -1; for examples of other such systems see [272–274]. One need not use properties which are completely random; they can be designed to satisfy various types of constraints. For example, one can use random templates which tend to be "clustered" [275, 276] or line-like ("scribbles") [277, 278; cf. 279]. As another example, one can generate the properties "without replacement," so that they depend on disjoint subsets of the picture [280, 281].

Functions of pictures. As mentioned at the beginning of this section, it is sometimes useful to work with picture "properties" which are not numbers but functions (of a single variable). An example already considered is the frequency distribution of the values of a local property; in the following paragraphs we describe some other examples.

In many cases, sufficient information to perform a given pattern recognition task can be obtained from a (normalized) picture by analyzing only a few "slices" of it. For example, in character recognition one can take slices along the (printed or written) line at various heights; this yields functions of the form $f(x, y_0)$ [282–285]. Similarly, one can take "slices" of the autocorrelation $h = f \otimes f$, e.g. along circles centered at the origin, yielding functions of the form $h(r_0, \theta)$. Such slices give the values of $f \otimes f$ for a sequence of shifts in which f is "nutated"; in other words, f revolves around the origin, without rotating, in an orbit of radius r_0 [286, 287; cf. 288, 289].

Let $\mathcal{A}$ be a one-parameter family of subsets of the plane. If we compute the value of some given property for each subset, we can regard the result as a function of the parameter. E.g. we can compute the linear property $\iint gf$ by integrating over a subset rather than over the entire plane. In the following examples we take $g = 1$.

Example 1. If $\mathcal{A}$ is a family of parallel lines, say the lines parallel to the y-axis, the integration can be thought of as "collapsing" f onto the x-axis. A simple way of doing this is to move a thin vertical slit horizontally across the picture; the total amount of light which passes through the slit in a given position is approximately proportional to the integral of the picture function along the center line of the slit [290–292]. A process of "collapsing" onto the x and y axes is believed to play a major role in the discrimination of visual patterns by the octopus [293].

Example 2. Similarly, if $\mathcal{A}$ is a family of concurrent lines, the integration can be performed using a rotating slit [294], or equivalently, a "flying-line scanner" (that is, a flying-spot scanner in which the "spot" is a long, thin streak which can be rotated to any orientation) [295].

Example 3. Let $\mathcal{A}$ be a family of concentric circles [296, 297]. Here a simple way of performing the integration is to rotate an image of the picture (e.g. using rotating mirrors), and to integrate (over time) the light passing through a fixed radial slit in the image plane. (A similar result can be obtained by reflecting the picture in a concave conical mirror.) On this method applied to the autocorrelation rather than to the picture itself, see [224, 289, 298, 299].

PICTURE SEGMENTATION AND DESCRIPTION

Many pictorial pattern recognition problems involve more than just the assignment of a picture to one of a set of prespecified classes; they require a *description* of the picture, where the number of possible descriptions is so large as to make it impractical to regard each description as defining a class. Typically, a description refers to various "objects" in (i.e. subsets of) the picture and specifies geometrical properties of and relationships among these subsets.

Segmentation

The first step toward describing a picture is to single out the appropriate picture subsets ("segmentation"). There is no "universal" method of segmenting a given picture; many different types of subsets can be "objects," depending on the type of picture description which is required. However, only a few kinds of segmentation methods have been used in practice. The most commonly used class of methods involves *preprocessing and thresholding*. The preprocessing may be used to "clean up" the picture; to enhance "edges" in it, so that the extracted figures are line-like; to matched-filter it, so that thresholding selects points where a given pattern matches it closely; or it may involve combinations of such operations, or more complex ones (e.g. [300, 301]). On methods of automatically selecting a threshold see [224, 247]. An alternative approach to segmentation is to test points for membership in an "object" sequentially; this has the advantage that the threshold can be varied so as to depend on the nature of the already selected points (e.g. [163]).

Once subsets have been singled out from a picture, it becomes possible to perform operations on the picture in which the points of the subsets play special roles. In particular, such operations can be used to derive new subsets from the given ones. For example, one can single out the borders of a given subset, or its connected components, as new subsets. On methods of "following" the edge of a subset, see [302–311]; on methods of singling out (and counting) connected components, see [38, 267, 269, 309, 312–317]. One can also determine whether a given point is inside (i.e. in a hole surrounded by) or outside a given subset [318–320]. If a subset has many small connected components, one can simplify the picture by "shrinking" each component down to a single point [311, 321, 322]. Similarly, if a subset is everywhere very elongated, one can "thin" it into a line-drawing (e.g. [42, 323]).

Another way of defining new subsets is in terms of the distance to a given subset. This approach can be used to single out isolated parts of a subset, clusters of small parts, or elongated parts; and to "thin" a subset down to a "skeleton" [317, 324–332]. Similarly, one can define subsets in terms of the direction to a given subset, e.g. sets of points through which a line in a given direction intersects the given subset a given number of times [333–335].

The edge of a subset can be subdivided into pieces by picking "breakpoints" at position extrema (locally highest, lowest, rightmost, or leftmost points [310]), points of inflection [336], curvature maxima ("angles") [337; compare 338], etc. One can define criteria for detecting (straight) "strokes," "bays," "notches," "spurs," etc., in an edge, and use them as pieces of the edge, e.g. [35, 302, 339–342]. More generally, one can look for pieces of an edge which match given arcs, or given pieces of other edges [343]. A line-like subset can also be subdivided at "nodes" where arcs end or intersect [344, 345]

Another method of breaking a subset into pieces is to take successive cross-sections of it and look for "splits," "merges," or other abrupt changes in the "runs" of figure points [346–351]. More generally, one can "track" runs which form a specified shape. The detection of pieces of a subset having specified shapes can sometimes be facilitated by performing a change of coordinates [352, 353].

Geometrical Properties of Picture Subsets

As pointed out at the beginning of the section on Picture Properties and Pictorial Pattern Recognition, certain picture properties have natural definitions only if a subset is explicitly singled out from the picture. An important class of such properties relates to the geometry of the subset—connectivity, size, shape, etc. By a "property" we here again usually mean a real number, but we also briefly consider "properties" which are functions of a single variable.

Methods of counting the connected components of a subset have been referenced above; the "connectivity" of a subset is an example of a *topological* property. Important *metric* properties of a subset include its area, perimeter, "extent" (length, width, diameter), etc. (e.g. [354–358]).

Given any set $\mathfrak{A}$ of subsets of the plane, and any geometrical property F, new properties of a given subset S can be defined by taking statistics of the frequency distribution of the values of F for the intersections of S with the subsets in $\mathfrak{A}$. This is the concept which underlies the use of *integral geometry* to define subset properties [359–361].

The criteria mentioned in the subsection on Segmentation for breaking up a subset into pieces can also be used to define properties of the subset. For example, one can use the numbers and positions (in the picture or along the edge of the subset) of position extrema, concavities, etc., as properties (see the references cited in that subsection, as well as [362–365]). Another useful class of properties relates to the *complexity* of the subset—symmetry, "wiggliness" of its edge (as measured by number of "angles," perimeter^2/area, or variance of the radius vector), randomness (of a point or line pattern), etc. [366–371].

The curvature of the edge of a subset, as a function of arc length (measured from any starting point), determines the subset up to congruence. This description, which is called the *intrinsic equation*, is an example of a "function-valued property" [372–375]. Other useful properties of this type can be obtained as functions of distance from, rather than along, the boundary [376]. The distribution of values of any geometrical property (e.g. slope or curvature, distance) is a one-parameter function.

Given a one-parameter family of subsets of the plane, and a geometrical property F, the values of F for the intersections of the subsets with a given subset S constitute a function of the parameter [195, 377–381]. Similarly, given a two (or more)-parameter family of subsets, if we compute statistics with respect to (all but) one of the parameters, the result is a function of a single parameter [333–335, 382].

Picture Description and "Picture Languages"

Given a picture and a collection of its subsets ("objects"), one can formulate a description of the picture in terms of properties of the subsets and relationships among them ("above," "to the left of," "near," "between," "inside of," "part of," "larger than," "darker than," etc.). If one wants to be able to make effective use of such a description (e.g. for answering questions about the picture), the descriptive information should be stored in an appropriate data structure. Such structures have been implemented primarily in the area of *computer graphics;* most of them are relatively specialized, since most computer graphics systems permit only a limited number of types of subsets, properties, or relations [383–385].

In many cases, adequate descriptions of a picture can be formulated using a special formal "language" (a better term might be "notation") [386]. For example, a line drawing can be described as consisting of "vertices" (isolated points, arc ends, angles, points where two or more arcs meet), pairs of which may be joined by arcs, where the arcs can be described in terms of mean slope, straightness, length, etc. [387, 388]. If a picture contains simple geometric figures, or other easily "nameable" subsets, it can be concisely described in terms of the names of the subsets and the relationships among them [389–392]. Efforts are under way to develop "habitable" description languages for classes of complex pictures, in which any reasonable statement, question, or command concerning the pictures can be formulated [393].

If a picture description language is capable of expressing complete descriptions, from which pictures can be exactly reconstructed, it can be regarded as defining a "picture language," in which pictures are built up by combining a set of pieces (presumably corresponding to parts of the description) in various ways, just as phrases and sentences are built up by concatenating words. Here the pieces can range from single picture elements and unit line segments to complex geometrical figures which can be "attached" to one another in various ways [394–400].

Given a language for describing pictures, whether partially or completely, one can use it to formulate definitions for specific classes of pictures. (On definitions for alphabetic characters in terms of "strokes," see [43, 401–406]; for other examples see [316, 407, 408].) Even partial definitions can be very useful for pattern recognition purposes, since if a picture is known to be made up of pieces of certain types which are combined in certain ways, one can identify the picture by identifying the pieces and the way in which they are combined. This "syntax-directed" approach to pictorial pattern recognition is expected to become a major theme in picture processing research during the coming years.

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OPI *Optical Processing of Information,* D. K. Pollock, C. J. Koester, and J. T. Tippett (Eds.), Spartan Books, Baltimore, 1963.

OEOIP *Optical and Electro-Optical Information Processing,* J. T. Tippett, D. A. Berkowitz, L. C. Clapp, C. J. Koester, and A. Vanderburgh, Jr. (Eds.), MIT Press, Cambridge, Mass., 1965.

PR *Pattern Recognition,* L. Uhr (Ed.), Wiley, New York, 1966.

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