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Pattern Recognition

M.Shalini
MCA, M.Phil, Ph.D, Sr.Lecturer,
Kasturba Gandhi Degree & PG College For Women.

Dr.Indira Reddy, Ph.D
Associate Professor,
Kasturba Gandhi Degree & PG College For Women.

Abstract:

Extensive research and development has taken place over the last 20 years in the areas of pattern recognition and image processing. These areas have applications 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.

Keywords: Image processing, pattern recognition, decision trees, segmentation.

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. 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 pattern 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.

PATTERN RECOGNITION:

Pattern Recognition

• Pattern recognition in remote sensing has been based on the intuitive notion that pixels belonging to the same class should have similar gray values in a given band. Given two spectral bands, pixels from the same class plotted in a two-dimensional histogram should appear as a localized cluster. o If n images, each in a different spectral band, are available, pixels from the same class should form a localized cluster in n-space.

What is a pattern?

For the purpose of standard classification methods, a pattern is a cluster of data points in an n-dimensional feature space, and classification is the procedure for discriminating that cluster from other data sources in the feature space.

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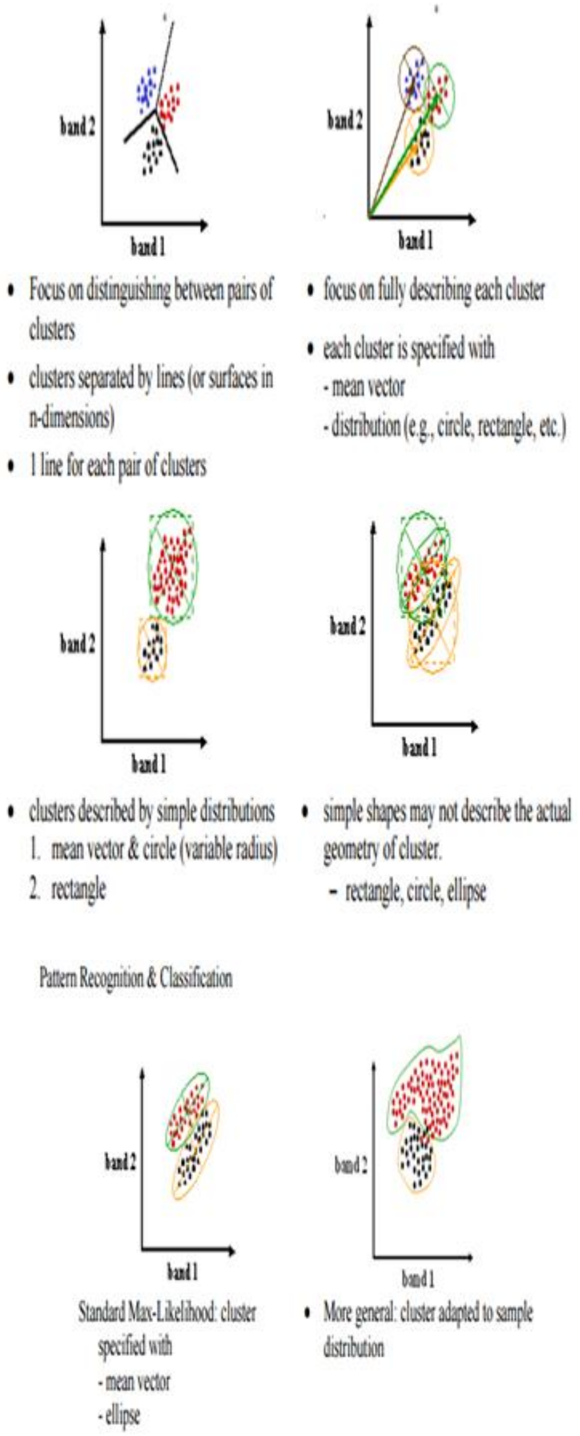
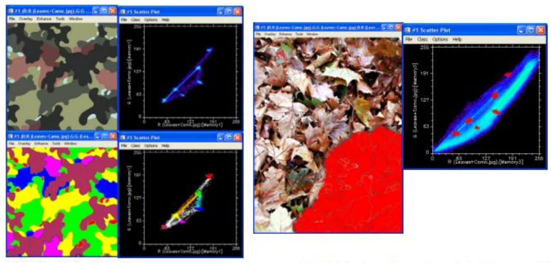


Pattern recognition in remote sensing has been based on the intuitive notion that pixels belonging to the same class should have similar gray values in a given band.

• Variations in a cluster will occur even if the pattern is very well defined (e.g., quantization noise, atmospheric variability, illumination differences, or any number of other 'natural" and instrumental sources of variability (e.g., mixed pixels).

• If several patterns (classes) appear as distinct clusters then the classes are discriminable.



Camouflage uses dyes with a very narrow color range, and the colors plot in narrowly defined regions in color space. The connecting lines in the scatterplot are due to mixed pixels on the boundary between two colors.

The distribution of natural materials (e.g., leaves) in color is much broader and may not exhibit distinct cluster

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. 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.

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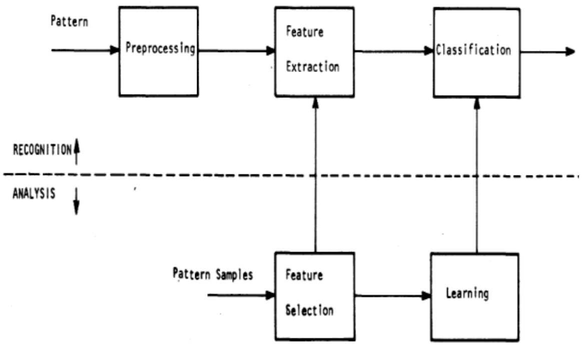

Fig. 1. Block diagram of a decision-theoretical pattern recognition system.

Syntactic (or Structural) Methods:

A block diagram of a syntactic pattern recognition systemis shown in Fig. 2. Again, we divide the block diagraminto the recognition part and the analysis part, where therecognition part consists of preprocessing, primitive extraction(including relations among primitives and subpatterns),and syntax (or structural) analysis, and theanalysis part includes primitive selection and grammatical,(or structural) inference.In syntactic methods, a pattern is represented by asentence in a language which is specified by a grammar.The language which provides the structural descriptionof patterns, in terms of a set of pattern primitives and theircomposition relations, is sometimes called the "patterndescription language." The rules governing the compositionof primitives into patterns are specified by the socalled"pattern grammar." An alternative representationof 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 betweensubpatterns.

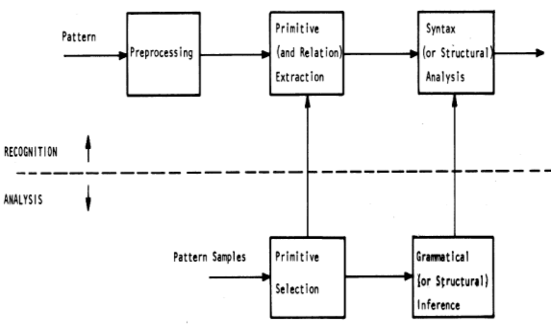

Fig. 2. Block diagram of a syntactic pattern recognition system.

A. Image Processing:

Coding: In order to acceptably approximate a standardtelevision image digitally, one normally needs an array ofabout 500 X 500 samples, each quantized to about 50 discrete gray levels-i.e., a total of about 6 bits for each of the250 000 samples, or 1.5 million bits in all. The goal of imagecompression (or, as it is more commonly called, imagecoding) is to represent the image acceptably using a muchsmaller number of bits. One basic approach to image coding is to apply an invertibletransform to the given image, approximate thetransform and then construct the approximated image byinverting the transform. The transform can be designedso that it can be approximated more economically than theoriginal image, and so that errors in this approximationbecome less noticeable when an image is reconstructedfrom its transform. For example, if we use the Fouriertransform, we can achieve economical approximationsbecause many of the Fourier coefficients have negligible magnitudes, and so canbe ignored or at least quantized very coarsely.

Moreover, errors in approximating the Fourier coefficients are generally hard to notice when the image is reconstructed, becausetheir effects are distributed over the entire image.Image compressions of as much as 10:1 can be achievedusing this "transform coding" approach. Many other approaches to image coding have been extensivelyinvestigated, but only a few of these can bementioned here. One class of approaches takes differencesbetween successive image samples; since these have a verynon-uniform probability density (peaked at zero), they canbe quantized acceptably using relatively few quantization levels. Note, however, that when the image is reconstructedfrom such difference images by summing them, errors in thedifferences will tend to propagate, so that care is neededin using this type of approach. The differences used canbe either spatial (intra-frame) or temporal (inter-frame).The expected accuracy of an image coding system canbe predicted theoretically if we assume a model for theclass of images being encoded and a specific error criterion (usually, meansquared error).

Both of these assumptions are questionable.Images usually consist of distinct parts, so that a homogeneous random field model isinappropriate. On the other hand, the human visual system'ssensitivity to errors is highly context-dependent, sothat an integrated squared error criterion is inadequate.Work is needed on image coding techniques which segmentthe image into significant parts before attempting to approximateit; some image segmentation methods will bediscussed here under Segmentation. At the same time,increased understanding of human visual capabilities isneeded so that better error criteria for image coding systemscan be developed.Enhancement and restoration: There has been increasinginterest in recent years in techniques for designingtwo-dimensional digital filters. At the same time,much work is being done on digital methods of enhancingor restoring degraded images. Some enhancement techniquesare conceptually very simple, and involve onlypointwise modification of the image's grayscale. For example,one can analyze the gray levels in a neighborhoodof each image point, determine a grayscale transformationthat stretches these levels over the full displayable range,and apply this transformation to the given point (and thepoints in its immediate vicinity); this and similar techniquestend to give very good enhancement results.

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 orintegral operation applied to the ideal image, and the noiseis uncorrelated with the ideal image. A variety of methodshave been developed for inverting the effects of the blurringoperator; for example, pseudoinverse techniques canbe used to define a de-blurring operator which yields thebest approximation to the ideal image in the expected leastsquares sense. Other classes of methods, e.g., basedon Kalman filtering, have been devised to yield leastsquaresestimates of an ideal image corrupted by additive noise. As in the case of image coding, these approacheshave usually been based on homogeneous randomfield models for the images (and noise), and on leastsquareserror criteria, both of which are questionable assumptions.Here too, image models based on segmentationof the image, and success criteria more closely related tohuman perceptual abilities, would be highly desirable.A problem closely related to image restoration is that ofreconstructing images; or three-dimensional objects, from sets of projections, e.g., from X-ray views taken from manyangles. (The gray levels on a projection are linear combinationsof the ideal gray levels, just like the gray levels on a blurred image.) Much work has been done in this area inthe past few years, especially in connection with medical radiographic applications.

B. Image Recognition:

The goal of image recognition is the classification orstructural description of images. Image classification involvesfeature detection and property measurement; imagedescription involves, in addition, segmentation and relationalstructure extraction. Some significant ideas in eachof these areas are reviewed in the following paragraphs.Historically, the techniques used have usually been developedon heuristic grounds, but there is increasing interestin deriving optimum techniques based on models forthe classes of images to be analyzed.Matching and feature detection: Detecting the presenceof a specified pattern (such as an edge, a line, a particularshape, etc.) in an image requires matching the image witha "template," or standardized version of the pattern.

Thisis a computationally costly process, but techniques havebeen developed for reducing its expected cost. For example,one can match a sub-template (or a reduced-resolution"coarse template") with the image at every point,and use the remainder of the template (or the full-resolutiontemplate) only at points where the initial match valueis above some threshold. The sub-template size, or the degreeof coarseness, can be chosen to minimize the expectedcost of this process. In computing these matches, oneshould first check parts of the template that have largeexpected mismatch values (with a randomly chosen partof the picture), in

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order to minimize the expected amountof comparison that must be done before the possibility ofa match at the given point is rejected. Of course, thesavings in computational cost must be weighed against thepossible increased costs of false alarms or dismissals.Template matching is often implemented as a linearoperation in which the degree of match at a point is measuredby a linear combination of image gray levels in aneighborhood of the point. However, the result of such alinear operation is generally ambiguous; for example, itmay have the same value for a high-contrast partial matchas it does for a lower contrast, but more complete match.Such ambiguities can often be eliminated by breaking thetemplate up into parts and requiring that specified matchconditions be satisfied for each part, or for the most of theparts.

This approach has been used to detect curves innoise; it needs to be extended to other types of imagematching problems.The use of template parts can also help overcome thesensitivity of template matching to geometrical distortion.Rather than matching the entire template with the image,one can match the parts, and then look for combinationsof positions. Optimal combinations can be determined bymathematical programming techniques, or by simultaneousiterated reinforcement of the partial matchesbased on the presence of the other needed matches.Research on these approaches is still at an exploratorystage.

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. Detection of the peaks can be facilitated by histograms of only a selected set of image points, e.g. Points where the local property value is a local maximum, or points that lie on or near region boundaries (which can be identified by the presence of high values of a derivative operator).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 informationabout the types of regions or objects that are supposed to be present in the image. Such information can beused to control merging and splitting processes with theaim of creating an acceptable partition of the image intoregions. An important special case of sequential region growingis tracking, which extracts regions (or region boundaries)in the form of thin curves. This technique can be regardedas a type of piecewise template matching, where the piecesare short line or curve segments, and a curve is any combinationof these that smoothly continue one another; thus,here again, curves can be extracted by mathematical programmingor iterated reinforcement techniques. The sameis true for a wide variety of problems involving the selectionof image parts that satisfy given sets of constraints.

Properties:

Once regions have been extracted from animage, it becomes possible-to describe the image in termsof properties of these regions. Much work has been doneof regions in a digitized image, such as connectedness,convexity, compactness, etc. Describing the shape of aregion involves not only global properties such as those justlisted, but also a hierarchically structured description interms of "angles" and "sides" (i.e., polygonal approximation,of varying degrees of coarseness), symmetries, and soon.Two "dual" methods of describing a region involve itsboundary and its "skeleton." A region is determined byspecifying the equations of its boundary curves; and it isalso determined by specifying the centers and radii of themaximal disks that it contains [14]. These disks define asort 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

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out of"generalized cylinders," each of which is specified by alocus of centers and an associated radius function. Grayscale, as well as geometrical, properties of regionsare of importance in image description. Of particular importanceare textural properties (e.g., coarseness and directionality),which can be measured in terms of certainstatistics of the second-order probability density of graylevels in the region -or equivalently, statistics of thefirst-order probability density of gray level differences (orother local property values). Textures can be modeledas distorted periodic patterns, as two-dimensional"seasonal time series", or in terms of random geometry;such models can be used to predict the values of theproperty measures for real-world textures.Image and scene analysis: Image descriptions canusually be expressed in the form of relational structureswhich represent relationships among, and properties of,image parts. A major area of artificial intelligence researchhas been the study of how knowledge about the given classof scenes can be used to control the process of extractingsuch descriptions from an image.

In addition to the studyof control structures for image analysis, there has also beenrecent interest in special data structures for image processingand description, e.g., "cone" or "pyramid" structuresfor variable-resolution image analysisand"fuzzy" structures for representing incompletely specifiedimage parts.The term "scene analysis" is generally used in connectionwith the description of images of three-dimensionalobjects seen from nearby, so that perspective and occlusionplay major roles in the description. (Note that theimages being analyzed in applications such as documentprocessing, photomicrography, radiology, and remotesensing are all basically two-dimensional.) Much work hasbeen done on the extraction of three-dimensional depthinformation about scenes, using range sensors, stereo pairsof images, or single-image depth cues such as shading andtexture gradients. These techniques are beginning to beapplied to the analysis of various types of real-world indoorand outdoor scenes.

Another approach to image analysis involves the use offormal models derived from the theory of multidimensionalformal languages.

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 lookingfor 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 thesyntactic approach, the problem of primitive extractionand selection certainly needs further attention.

An appropriateselection of the pattern grammar directly affectsthe computational complexity or analysis efficiency of theresulting recognition system. Grammatical inference algorithmswhich are computationally feasible are still highlyin demand.In image processing, better image models are needed for user (the human visual system).Image models should also be used more extensively in thedesign of optimal image segmentation and feature extractionprocedures. Thus image and visual models needfurther development in both image processing and recognition.

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