A PATTERN RECOGNITION PROGRAM THAT GENERATES, EVALUATES, AND ADJUSTS ITS OWN OPERATORS

by

Leonard Uhr
Mental Health Research Institute
University of Michigan
Ann Arbor, Michigan

Charles Vossler
System Development Corporation
Santa Monica, California

Summary

This paper describes an attempt to make use of machine learning or self-organizing processes in the design of a pattern-recognition program. The program starts not only without any knowledge of specific patterns to be input, but also without any operators for processing inputs. Operators are generated and refined by the program itself as a function of the problem space and of its own successes and failures in dealing with the problem space. Not only does the program learn information about different patterns, it also learns or constructs, in part at least, a secondary code appropriate for the analysis of the particular set of patterns input to it.

Background Review

The typical pattern recognition program is either elaborately preprogrammed to process specific arrays of input patterns, or else it has been designed as a tabula rasa, with certain abilities to adjust its values, or "learn." The first type often cannot identify large classes of patterns that appear only trivially different to the human eye, but that would completely escape the machine's logic.[2,7] The best examples of this type are probably capable of being extended to process new classes of patterns.[8,19] But each such extension would seem to be an ad hoc complication where it should be a simplification, and to represent an additional burden of time and energy on both programmer and computer.

The latter type of self-adjusting program does not, at least as yet, appear to possess methods for accumulating experience that are sufficiently powerful to succeed in interesting cases. The random machines show relatively poor identification ability.[15,16] (One exception to this statement appears to be Roberts' modification of Rosenblatt's Perceptron.[14] But this modification appears to make the Perceptron an essentially non-random computer.) The most successful of this type of computer, to date, simply accumulates information or probabilities about discrete cells in the input matrix.[3,10] But this is an unusually weak type of learning (if it should be characterized by that vague epithet at all), and this type of program is bound to fail as soon as, and to the extent that, patterns are allowed to vary.

Several programs compromise by making use of some of the self-adapting and separate operator processing features of the latter type of program, but with powerful built-in operations of the sort used by the first type.[6, 25] They appear to have gained in flexibility in writing and modifying programs; but they have not, as yet, given (published) results that indicate that they are any more powerful than the weaker sort of program (e.g. Baran and Estrin) that uses individual cells in the matrix in ways equivalent to their use of "demons" and "operators." A final example of this mixed type of program is the randomly coupled "n-tuple" operator used by Bledsoe and Browning.[4,5] In this program, random choice of pairs, quintuples and other tuples of cells in the input matrix is used to compose operators, in an attempt to get around the problems of pre-analyzing and pre-programming. This method appears to be guaranteed to have at least as great power as the single cell probability method.[23] But it has not as yet demonstrated this power. And it would, like most of the other programs discussed (or known to the authors) fall down when asked to process patterns which differed very greatly from those with which it had originally "gained experience" by extracting information.[22]

Summary of Program Operation

In summary, the presently running pattern recognition program works as follows: Unknown patterns are presented to the computer in discrete form, as a 20x20 matrix of zeros and ones. The program generates and composes operators by one of several random methods, and uses this set of operators to transform the unknown input matrix into a list of characteristics. Or, alternately, the programmer can specify a set of pre-generated operators in which he is interested.

These characteristics are then compared with lists of characteristics in memory, one for each type of pattern previously processed. As a result of similarity tests, the name of the list most similar to the list of characteristics just computed is chosen as the name of the input pattern. The characteristics are then examined by the program and, depending on whether they individually contributed to success or failure in identifying the input, amplifiers for each of these characteristics are then turned up or down. This adjustment of amplifiers leads eventually to discarding operators which produce poor characteristics, as indicated by low amplifier settings, and to their replacement by newly generated operators.

One mode of operation of the present program is to begin with no operators at all. In this case operators are initially generated by the program at a fixed rate until some maximum number of operators is reached. The continual replacement of poor operators by new ones then tends to produce an optimum set of operators for processing the given array of inputs.

Details of Program Operation

The program can be run in a number of ways, and we will present results for some of these. The details of the operation of the program follow.

1. An unknown pattern to be identified is digitized into a 20x20 0-1 input matrix.

2. A rectangular mask is drawn around the input (its sides defined by the leftmost, rightmost, bottommost, and topmost filled cells).

3. The input pattern is transformed into four 3-bit characteristics by each of a set of 5x5 matrix operators, each cell of which may be visualized as containing either a 0, 1, or blank. These small matrices which measure local characteristics of the pattern are translated, one at a time, across and then down that part of the matrix which lies within the mask. The operator is considered to match the input matrix whenever the 0's and 1's in the operator correspond to identical values in the pattern, and for each match the location of the center cell of the 5x5 matrix operator is temporarily recorded. This information is then summarized and scaled from 0 to 7 to form four 3-bit characteristics for the operator. These represent 1) the number of matches, 2) the average horizontal position of the matches within the rectangular mask, 3) the average vertical position of the matches, and 4) the average value of the square of the radial distance from the center of the mask.

A variable number of operators can be used in any machine run. This can mean either a number pre-set for that specific run, or a number that begins at zero and expands, under one of the rules described below, up to a maximum of 40. The string of 25 numbers which defines a 5x5 matrix operator can be generated in any of the following ways:

a. A pre-programmed string can be fed in by the experimenter.
b. A random string can be generated; this string can be restricted as to the number of "ones" it will contain, and as to whether these "ones" must be connected in the 5x5 matrix. (We have not actually tested this method as yet.)
c. A random string can be "extracted" from the present input matrix and modified by the following procedure (which in effect is imitating a certain part of the matrix). The process of inserting blanks in the extracted operator allows for minor distortions in the local characteristics which the operator matches.

(1) A 5x5 matrix is extracted from a random position in the input matrix.
(2) All "zero" cells connected to "one" cells are then replaced by blanks.
(3) Each of the remaining cells, both "zeros" and "ones," are then replaced by a blank with a probability of $\frac{1}{2}$.
(4) Tests are made to insure that the operator does not have "ones" in the same cells as any other currently used operator or any operator in a list of those recently rejected by the program. If the operator is similar to one of these in this respect a new operator is generated by starting over at step 1.

4. A second type of operator is also used. This is a combinatorial operator which specifies one of 16 possible logical or arithmetic operations and two previously calculated characteristics which are to be combined to produce a third characteristic. These operators are generated by the program by randomly choosing one of the possible operations and the two characteristics which are to be combined. This random generation process is improved by generating a set of ten operators, and then pre-testing these using the last two examples of each pattern which have been saved in memory for this purpose. This pre-testing is designed to choose an operator from the set which produces characteristics that tend to be invariant over examples of the same pattern yet vary between different patterns.

Since these operators may act upon characteristics produced by previous operators of the same type, functions of considerable complexity may be built up.

5. The two types of operators just described produce a list of characteristics by which the program attempts to recognize the unknown input pattern. At any time the program has stored in memory a similar list of characteristics for each type of pattern which the program has previously encountered. Corresponding to each list of characteristics in memory is a list of 3-bit amplifiers, which give the current weighting for each characteristic as a number from 0 to 7.

The recognition process proceeds by taking the difference between each of the characteristics for the input pattern and those in the recognition list of the first pattern. These differences are then weighted by the corresponding pattern amplifiers, and then by general amplifiers which represent the average of the pattern amplifiers across all patterns, producing a weighted average difference between the input list and the list in memory. This average difference is multiplied by a final "average difference" amplifier to obtain a "difference score" for the list in memory. When a difference score has been computed for each list in memory, the name of the list with the smallest score is printed as the name of the input pattern.

6. After each pattern is recognized the program modifies pattern amplifiers in those patterns which have difference scores less than or only slightly above the difference score for the correct pattern. This means that the program will tend to concentrate on the difficult discrimination problems, since amplifiers are adjusted only in those patterns which appear similar to the correct pattern in terms of the difference scores and therefore make identification of the input difficult. The correct pattern is compared with each of the similar patterns in turn. Each characteristic in the memory lists for a pair of patterns is examined individually, and a determination is made as to whether the correct pattern would have been chosen if the choice had been made on the basis of this characteristic alone. If this one characteristic would have identified the correct pattern, then the corresponding amplifier is turned up by one. If it would have identified the wrong pattern then the amplifier is turned down by one. If no information is given by the characteristic, for example, if it is the same for both patterns, then the amplifier is turned down with a probability of 1/8. If the pattern compared with the correct pattern had the higher difference score then the amplifiers are adjusted only in that pattern. Otherwise, amplifiers are adjusted in both patterns. This means that if several patterns obtained lower scores than the correct pattern then the amplifiers in the correct pattern will be drastically changed, since they will change when compared with each of these patterns.

The list of characteristics in memory for the pattern just processed is then modified. The first time a pattern is encountered its list of computed characteristics is simply stored in memory along with its name. On the second encounter of a pattern each of the characteristics in memory is replaced by the new characteristic with a probability of 1/2. For the third and following encounters each characteristic is replaced by the new value with a probability of 1/4. Since about 1/4 of the characteristics will be changing each time, after several examples of a pattern have been processed, the list of characteristics in memory will tend to be more similar to the characteristics of the last patterns processed than to those processed earlier. However, to the extent that the learning process is able to produce operators giving invariant characteristics for a single pattern, the list of characteristics will be representative of all the examples processed. The reason for not simply using the average value for each characteristic is that this would require saving in memory more than the 3 bits otherwise needed for each characteristic, as well as saving an indication of the number of times each characteristic had been calculated for each pattern.

An alternate scheme which we tried involved saving the highest and lowest values obtained by each characteristic, and averaging these to obtain a mean value with which to compare the input. This worked quite well in all our test runs, which used a few samples of each pattern. But there is the possibility that with large numbers of examples of a pattern, all the characteristics will eventually have very large ranges; that is, the lower bounds will tend to be 0 and the upper bounds will tend to be 7.

7. The average difference amplifiers which are used in the final step of the recognition process provide only coarse adjustments. These amplifiers are initially set to some fixed value, e.g. 60, and are then adjusted for the same pairs of patterns as the pattern amplifiers. The amplifier for the correct pattern is turned down by N if there are N incorrect patterns, and the amplifier for each of the similar patterns is turned up by one.

8. The general characteristic amplifiers are now computed by averaging the pattern amplifiers across all patterns. These indicate the general value of each characteristic in the recognition process and form the basis for the construction of success counts which control the replacement of operators. Since the combinatorial operators combine characteristics to produce other characteristics, the success count should reflect both the value of a characteristic in the recognition process and the importance of this characteristic in aiding the creation of other, possibly important characteristics.

9. This success count is formed by first storing the value of the general characteristic amplifier corresponding to each characteristic in a table for success counts. Then starting with the last combinatorial operator and working back through the list of these operators, 1/2 the value of the success count for the characteristic corresponding to the operator is added to the success counts of the two characteristics which the operator combines. Finally, two times the general characteristic amplifier setting is added to each success count.

10. Whenever a new operator is generated, the characteristics produced by the operator are computed for each of the possible patterns using the last example of each pattern, which has been saved in the computer memory. These newly calculated characteristics are then inserted into the list of characteristics for their respective patterns. At the same time the pattern amplifier settings for each of these new characteristics are set to 1 so that the characteristic will have very little weight in computing a difference score until it has been turned up as a function of proved ability at differentiation. Since the general amplifier for a characteristic is simply the average of the pattern amplifiers, it will also be 1 for the new characteristic. The success count of a new characteristic which is not combined to produce other characteristics is then 3 and this value will tend to increase if the operator proves to be valuable. On the other hand if a success count drops below 3 (or in the case of a matrix operator, if the average value of the success counts of its four characteristics drops below 3) the operator is rejected and a new operator is generated to take its place.

The pattern amplifiers play a crucial part both by aiding directly in the recognition process and by providing the information which ultimately

determines the generation of new operators to replace poor ones. Since the adjustment of these amplifiers is made selectively, based on their individual success or failure in distinguishing pairs of patterns where confusion is likely, the operators rejected by the program will tend to be those which are not useful in making the more difficult discrimination. Also, because amplifiers are usually changed more drastically when the computer makes an incorrect guess, the 5x5 matrix operators will have a higher probability of being extracted from unrecognized patterns. Although the rules governing the learning process seem rather arbitrary in many cases, and it is difficult to describe their effects quantitatively, qualitative effects, such as this ability to concentrate on difficult problems, are fairly easy to show. The description of the program's operation shows that the emphasis is not so much on the design of a specific problem solving code as it is on the design of a program which, at least in part, will construct such a problem solving code as a result of experience.

It is interesting to note that the memory of the program exists in at least three different places: 1) in the lists of characteristics in memory, 2) in the settings of the various amplifiers, and 3) in the set of operators in use by the program. While the lists of characteristics bear some direct relationship to the individual patterns processed by the program, the values of the amplifiers and the set of operators in use by the program depend in a more complex way on the whole set of patterns processed by the program, and on the program's success or failure in recognizing these patterns. The learning in the first case, which involves simply storing characteristics in memory, is merely "memorization" or "learning by rote." In the second case, the learning is more subtle for it involves the program's own analysis of its ability to deal with its environment, and its attempts to improve this ability.

Test Results

The program was written for the IBM 709 and required about 2000 machine instructions. The time required to process a single character was about 25 seconds when 5 different patterns were used and 40 seconds when each character had to be compared with ten possible patterns in memory. While such times are not excessive, they are large enough to make it impractical to run extremely large test cases.

In several early runs which we made, 48 preprogrammed matrix operators were used. These were designed to measure such things as straight and curved lines, the ends of vertical and horizontal strokes, and various other features. The program was tested using seven different sets of the five hand-printed characters A, B, C, D, and E. These involved a fair amount of distortion, and variation in size, but were not rotated to any great extent.

The program's performance on the last three or four sets in a run varied from about 70% to 80% depending on various changes which were made to the rules governing the learning process. Although the effects of the various rules were not extensively tested, the program's ability to recognize characters seemed quite dependent on the manner in which pattern amplifiers were adjusted. Originally, the amplifier for a characteristic had been turned up by 1 with a probability of 1/2 if the characteristic individually identified the correct pattern, and the amplifier had been turned down by 1 if it gave no information. Performance seemed to improve when this rule was changed so that the amplifier was always turned up for a correct response of the characteristic, and turned down only with a probability of 1/8 when no information was given by the characteristic. The first of these runs showed that few new matrix operators were being generated by the program, so changes were also made in the way the success counts were formed in order to increase the number of new operators generated.

One run was made which did not use the matrix operators. Instead, the individual cells of the 20x20 matrix were used as the first 400 characteristics and 500 combinatorial operators were used, to produce a total of 900 characteristics which the program used to recognize characters. With these changes the program recognized only a little more than 30% of the characters. The amplifier settings appeared to be generally somewhat higher for the characteristics produced by the combinatorial operators than for the input cells themselves. This indicated that the program might have done slightly, though probably not substantially, better if the recognition had been based only on these latter characteristics.

The last runs were made without pre-programmed operators, but with the program generating all operators from the start. A maximum of 40 matrix operators were used at any one time, and 160 of the combinatorial operators were used in addition to these. On a run with the same seven sets of five characters used in previous tests, the program recognized 86% of the characters correctly in sets 2 through 7. (The first set can never be correctly identified by the program, of course, since the program must always predict the name of some pattern whose characteristics it already has in memory.) In this run, the same sets of characters were then processed by the computer a second time, and in this case the program recognized 94% of them, missing only two of the 35 characters.

In another run three passes were made through three sets of the first ten alphabetic characters. In this case the program recognized 29 out of the 30 characters, or 97%, on the third encounter. With this rather limited training the program was then able to recognize 70% of the hand printed characters in a fourth set different from the three sets with which it was trained. In this case, the program's ability to recognize unknown characters was considerably less than its ability to recognize previously processed characters. This can be explained by the fact that three examples of each pattern contain only a few of the possible variations of a character. It can be expected that as

the number of examples with which the program is trained increases, its ability to recognize unknown characters will also increase.

We have not made any test runs of this program on the entire 26 letter alphabet, because of the computer time involved. We have, however, made some preliminary runs in debugging a modified program that was designed to increase the speed of processing by a factor of 10 or greater, along with a number of other changes. These runs gave preliminary processing abilities around 80%, using three sets of the alphabet, after only two passes. We anticipate that the completely debugged program, with improvements in such things as amplifier adjustments plus longer runs should raise this figure.

The program was also tested using line drawings representing a chair, a table, two different faces, and two types of particle decay similar to those shown in bubble chamber pictures. Two sets of these 6 drawings were used, with the second set drawn somewhat differently from the first set. After the first set was processed, 50% of the drawings in the second set were recognized correctly by the program. When the same two sets were then processed by the program a second time, all of the drawings were correctly recognized.

Discussion

When this program is given a neurophysiological interpretation, or a neural net analog, it can be seen to embody relatively weak, plausible, and "natural-looking" assumptions. The 5x5 matrix operator is equivalent to a 5x5 net of input retinal cones or photocells converging on a single output, with "ones" denoting excitatory and "zeros" denoting inhibitory connections, and the threshold for firing the output unit set at the sum of the "ones." Each translation step of the operator matrix over the larger matrix gives a sequential simulation of the parallel placement of many of these simple neural net operators throughout the matrix. Each different operator, then, is the equivalent of an additional connection pattern between input cones, firing onto a new output unit that computes the output for that operation. This is all quite plausible for the retina as known anatomically, with a single matrix of cones in parallel that feed into several layers of neurons. Evidence for excitatory and inhibitory connections is also strong.[9] And there is even beginning to be evidence of several types of simple net operators that exist in parallel iterated form throughout the retinal matrix (four of these as determined by Lettvin, Maturana, McCulloch and Pitts in the frog; and probably even more as determined by Hubel and Wiesel in the cat).[11, 12]

It would seem, however, that the known physiological constraints and the plausible geometric constraints on operators would suggest fewer than the 40-odd operators that we have used (or than the 30-odd used by Doyle or the 75 used by Bledsoe and Browning - ignoring the fact that they cannot be so easily interpreted neurophysiologically).[4, 6] For example, straight line and sharp curve operators would seem to be more plausible in terms of the ease of connection and the importance of the information to which they respond. A possible operator that might overcome this problem, with which we are now working, is a simple differencing operator that will, by means of several additional layers of operations, first delineate contour and then compute successively higher order differences, and hence straightness, slope and curvature, for the unknown pattern. This operator appears to be equivalent to a simple net of excitatory and inhibitory elements.[24]

This, then, suggests that the mapping part of the program would be effected by two layers of parallel basic units in a neuron net-like arrangement. The matching part might similarly be performed by storing the previously mapped lists in a parallel memory and sweeping the input list, now mapped into the same standard format, through these lists. Finally, the amplifiers can be interpreted as threshold values as to when the differences thus computed lead to an output. The specific pattern characteristic amplifier would be an additional single unit layer lying right behind the memory list; the interpretation of the general amplifiers might be made in terms of chemical gradients, but is more obscure.

Thus a suitable parallel computer would perform all of the operations of this program in from three to five serial steps. This is a somewhat greater depth than those programs, such as Selfridge's and Rosenblatt's, that attempt to remain true to this aspect of the visual nervous system.[15, 17] But it is well within the limits, and actually closer to the specifications, of that system. It also takes into consideration the very precise (and amazing) point-to-point and nearness relations that are seen in the visual system, both between several spots on the retina or any particular neural layer, and from retina to cortex.[20] It also is using operators that seem more plausible in terms of neural interconnections - again, in the living system, heavily biased toward nearness.

The size of the overall input matrix has also been chosen with the requirements of pattern perception in mind. Good psychophysical data show clearly that when patterns of the complexity of alphanumeric letters are presented to the human eye, recognition is just as sure and quick no matter how small the retinal cone mosaic, until the pattern subtends a mosaic of about the 20x20 size, at which time recognition begins to fall off, in both speed and accuracy, until a 10x10 mosaic is reached, at which point the pattern cannot be resolved at all. This further suggests something about the size of the basic operator, when we consider that most letters are composed of loops and strokes that are on the order of 1/2 or 1/4 of the whole. For our present purposes, the advantage of the 5x5 operator was not only its plausibility but also the fact that it cuts down to a workable size the space within which to generate random operators of the sort we are using when we permute through all possible combinations of the matrix. Again, with the constraint that these random operators be

connected, it becomes a more powerful geometry - and topology-sensitive operator, and also a simulation of a more plausible neural net.

Finally, psychophysical evidence also strongly suggests that the resolving power of the human perceptual mechanism is on the order of only two or three bits worth of differentiation as to dimensions of pattern characteristics - things such as length, slope, and curvature.[1, 13, 21] This, again, suggests a 5x5 matrix as a minimum matrix that is capable of making these resolutions.

The specifications for and methods used by living systems, and especially the human visual system, suggest certain design possibilities for a pattern recognition computer; but they certainly do not suggest the only possibilities. Nor should they be slavishly imitated. They should, however, be examined seriously, for the living pattern recognizers are the only successful systems that we know of today. Nor does it seem that the sort of use we have been making of these human specifications will impose any fundamental limitation on a program such as this, one that generates and adjusts its own operators. We have, in fact, already found the program making a different, and, apparently, more powerful, choice of operators than the choice suggested to us by the psychophysiological data and conjectures we have just described. The program's "learning" methods can now depend both on built-in connections (maturation) and on the inputs that need to be learned. The program will develop differently as a function of different input sets. It appears to be capable of extracting and successfully using information from these sets. This would seem to be as completely adaptive - being adaptive to inputs - as a computer or organism can be expected to be.

One of the most encouraging things about this program is that it still has a lot to learn. Its present level of success was achieved without any great sophistication in choice of operators or any great ability on the part of the program to generate and improve operators. More important, the program itself is in a position to improve on whatever choices it, or its programmers, make for it, and to make and to evaluate its own choices. This is so because it learns, and continues to learn, as it performs. There is good reason to feel that the present results reflect only the beginning to this process, since the program is still adjusting its set of operators and their values. The program, as it continues to run and be tested, should continue to improve. The program will be doing the improving - "learning," if you will - and not the programmers. It will be something of an experimenter on its own; and it should, in fact, present us with results, as it evolves toward "best" sets of operators, that will be the equivalent of parallel experiments between, and throw light on alternate, pattern recognition methods. For most pattern recognition schemes are close to being equivalents to one or another of the sets of operators that the present program can handle, except for those programs which make use of more complex analytic methods.

This sort of design would seem to have some applicability to a variety of more "intelligent" machines. The program replaces the programmer-analyst by a programmed operator that first generates operators that make effective enough use of the unknown input space, and then makes use of feedback as to the success of these new operators in mapping unknown inputs in order to increase their effectiveness. Thus neither programmer nor program needs to know anything specific about the problem ahead of time. The program performs, as part of its natural routine, the data collection, analysis, and inference that is typically left to the programmer. This would be a foolish waste of time for a problem that had already been analyzed. But pattern recognition, and many other problems of machine intelligence, have not been sufficiently analyzed. The different pattern recognition programs are, themselves, attempts to make this analysis. As long as pattern recognition remains in the experimental stage (as it must do until it is effectively solved), a program of this sort would seem to be the most convenient and flexible format for running what is, in effect, a continuing series of experiments upon whose results continuing modifications of theories are made. This becomes an extremely interesting process for the biologist or psychologist, especially to the extent that the program can be interpreted either physiologically or functionally, or at the least does not violate any known data. For the experimentation and concomitant theory building and modification being undertaken today is rapidly building what appears to us to be the first relatively firm and meaningful theoretical structure - for pattern, or form, perception - for the science of "higher mental processes."

Self-generation of operators, by the various methods employed in this program, may also suggest approaches toward solving a wide variety of pattern recognition and pattern extraction problems. Thus there is some hope that relatively powerful operators are being extracted and generated as a result of experience with and feedback from the program's quasi-experimental analysis on the body of data that is available to it - its inputs and the consequences of its actions. Further, the level of power of these operators, and the serial ordering of operators can also be placed under similar control. Thus operators need not be overly simple or random to be machine-chosen; nor pre-programmed to be powerful. Rather, they can arise from the problem, and thus be sensitive to the problem, and to changes in the problem.

References

1. Alluisi, E. A. "Conditions Affecting the Amount of Information in Absolute Judgements," Psychol. Rev., 1957, 64, 97-103.

2. Bailey, G. E. C. and Norrie, G. O. "Automatic Reading of Typed or Printed Characters," Brit. Inst. Radio Eng. Conv. on Electronics in Automation, 1957.

3. Baran, P. and Estrin, G. "An Adaptive Character Reader," Paper presented at IRE WESCON, Los Angeles, August, 1960.

4. Bledsoe, W. W. and Browning, I. "Pattern Recognition and Reading by Machine," Proc. Eastern Joint Comp. Conf., 1959, 225-232.

5. Bledsoe, W. W. "Further Results on the N-tuple Pattern Recognition Method," IRE Trans. Electronic Computers, in press.

6. Doyle, W. "Recognition of Sloppy, Hand-printed Characters," Proc. West. Joint Comp. Conf., 1960, 133-142.

7. Greanias, B. C., Hoppell, C. J., Kloomok, M., and Osborne, J. S. "The Design of the Logic for the Recognition of Printed Characters by Simulation," IBM J. Res. Development, 1957, 1, 8-18.

8. Grimsdale, R. L., Sumner, F. H., Tunis, C. J., and Kilburn, T. "A System for the Automatic Recognition of Patterns," Proc. IEE, Part B, 1959, 106, 210-221.

9. Hartline, H. K. "The Response of Single Optic Nerve Fibers of the Vertebrate Eye to Illumination of the Retina," Amer. J. Physiol., 1938, 121, 400-415.

10. Highleyman, W. H. and Kamentsky, L. A. "Comments on a Character Recognition Method of Bledsoe and Browning," IRE Trans. Electronic Computers, 1960, Vol. EC-9, 263.

11. Hubel, D. H. and Wiesel, T. N. "Receptive Fields of Single Neurons in the Cat's Striate Cortex," J. Physiol., 1959, 148, 574-591.

12. Lettvin, J. Y., Maturana, H. R., McCulloch, W. S., and Pitts, W. H. "What the Frog's Eye Tells the Frog's Brain," Proc. IRE, 1959, 47, 1940-1951.

13. Miller, G. A. "The Magical Number Seven, Plus or Minus Two: Some Limits on our Capacity for Processing Information," Psychol. Rev., 1956, 63, 81-96.

14. Roberts, L. G. "Pattern Recognition with Adaptive Network," IRE Conv. Rec. 1960, Vol. 8, Part 2, 1, 66-70.

15. Rosenblatt, F. The Perceptron. A Theory of Statistical Separability in Cognitive Systems. Buffalo: Cornell Aeronautical Laboratory, Inc., Report No. VG-1196-G-1, 1958.

16. Rosenblatt, F. "Perceptron Simulation Experiments," Proc. IRE, 1960, 48, 301-309.

17. Selfridge, O. G. "Pandemonium: A Paradigm for Learning," In: Mechanization of Thought Processes. London: HMSO, 1959, 511-535.

18. Selfridge, O. G. and Neisser, U. "Pattern Recognition by Machines and Men," Sci. Amer., 1960, 203, 60-68.

19. Sherman, H. "A Quasi-topological Method for the Recognition of Line Patterns," In: Information Processing. Paris: UNESCO, 1960, 232-238.

20. Sperry, R. W. "Mechanisms of Neural Maturation," In: (S. S. Stevens, Ed.) Handbook of Experimental Psychology. New York: John Wiley and Sons, Inc., 1951, 236-280.

21. Uhr, L. "Machine Perception of Printed and Hand-written Forms by Means of Procedures for Assessing and Recognizing Gestalts," Paper presented at ACM Meeting, Boston, 1959.

22. Uhr, L. "'Pattern Recognition' Computers as Models for Form Perception," (draft), Ditto, 1960.

23. Uhr, L. "A Possibly Misleading Conclusion as to the Inferiority of One Method for Pattern Recognition to a Second Method to Which it is Guaranteed to be Superior," IRE Trans. Electronic Computers, 1961, in press.

24. Uhr, L. and Vossler, C. "Suggestions for Self-adapting Computer Models of Brain Functions," Behav. Sci., 1961, in press.

25. Unger, S. H. "Pattern Recognition and Detection," Proc. IRE, 1959, 47, 1737-1752.

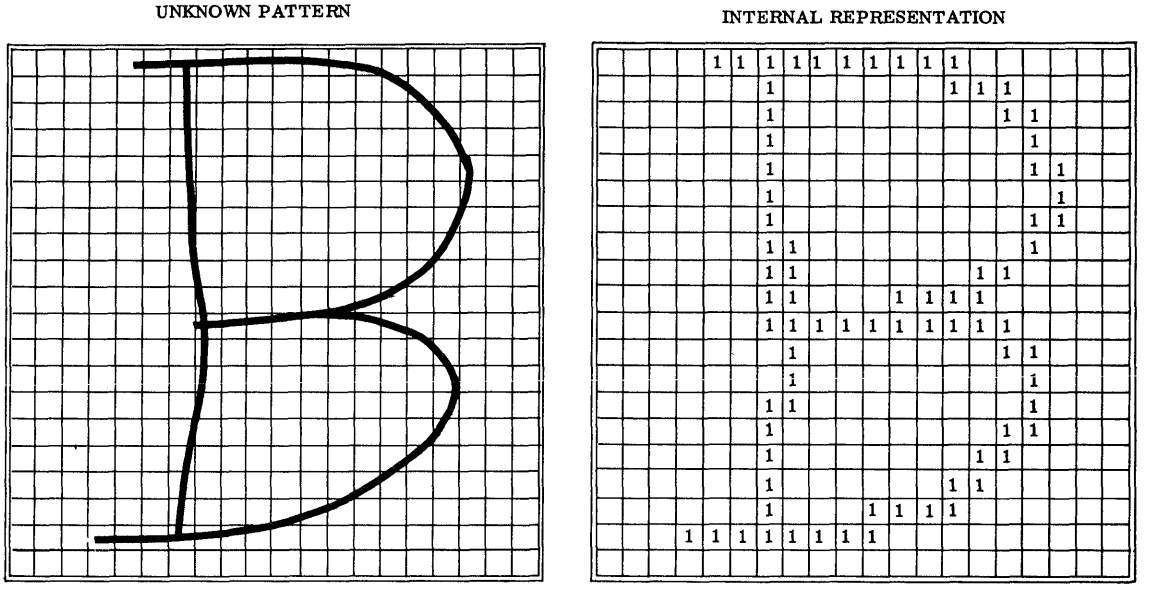


Figure 1 An unknown pattern is input as a 20 x 20 matrix with the cells covered by the pattern represented by '1's' and the other cells by '0's.'

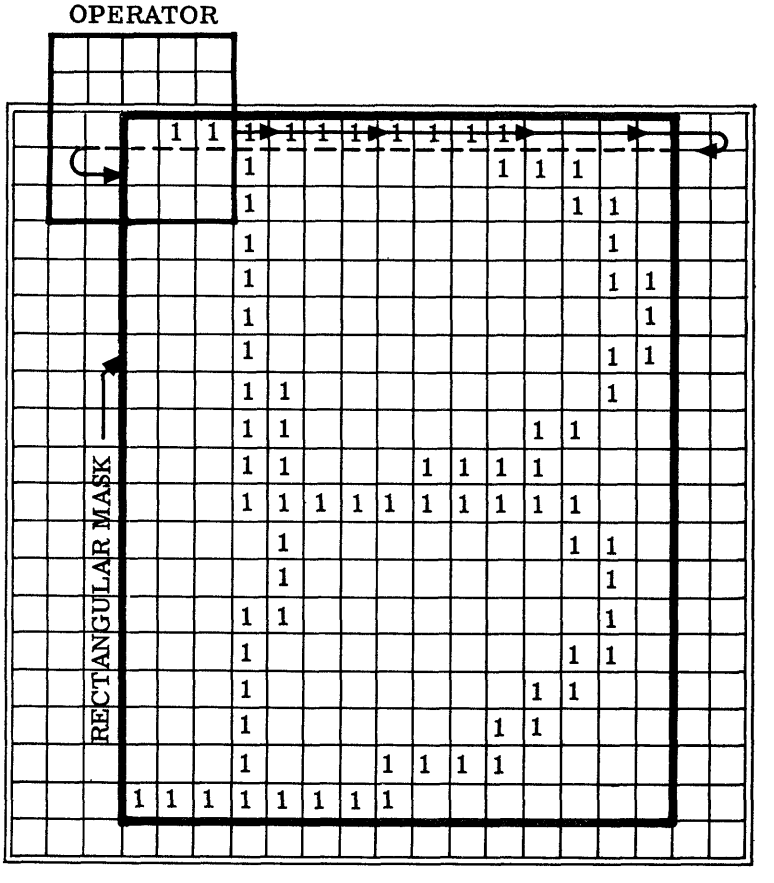
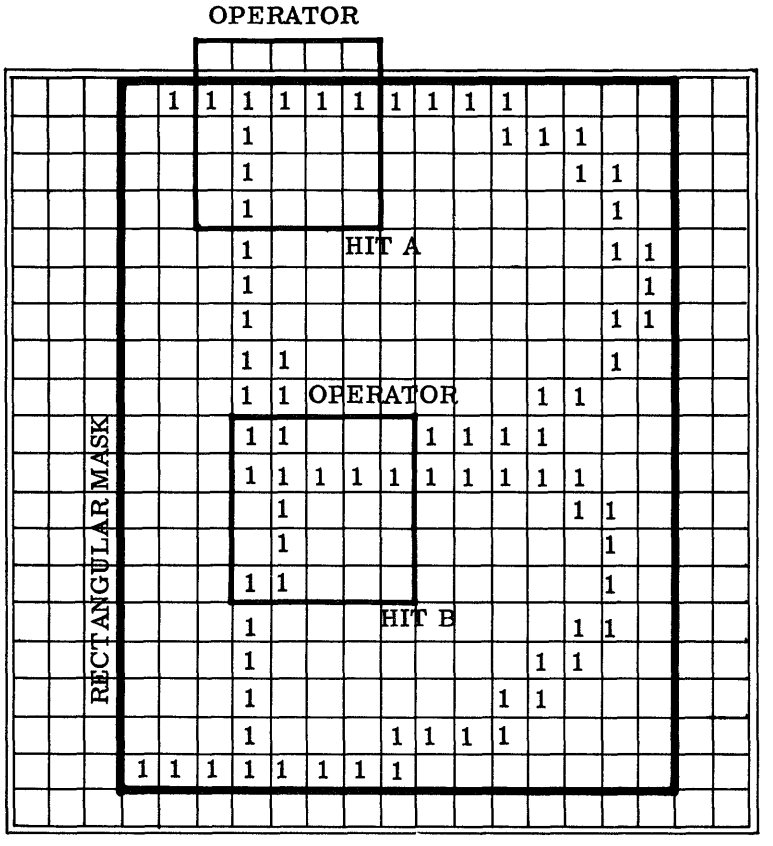
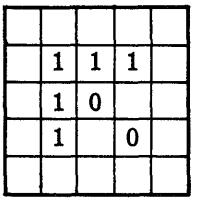


Figure 2 A rectangular mask is drawn around the unknown pattern. Each of the 5 x 5 matrix "operators" is then translated over the pattern.



OPERATOR

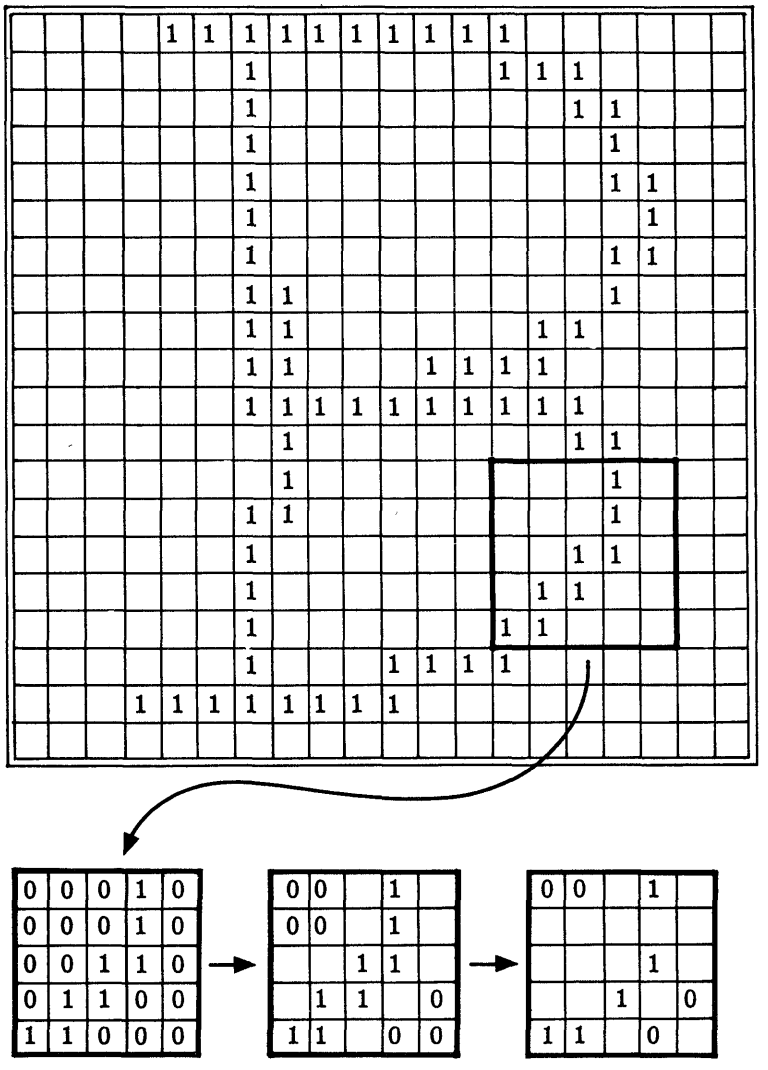


HIT	X	Y	R^2
A	1	0	4
B	2	4	0
N = 2	2	2	2

Figure 3 The operator at the lower left in the figure is shown in the two positions where it matches the input matrix. An operator gives a positive output each time its "1's" cover "1's" and its '0's' cover "0's" in the unknown pattern.

OPERATOR GENERATION

a) BY EXTRACTION



b) BY RANDOM CHOICE OF CELLS

1)

1		0	1	
	1		0	
		1		0
		1		0

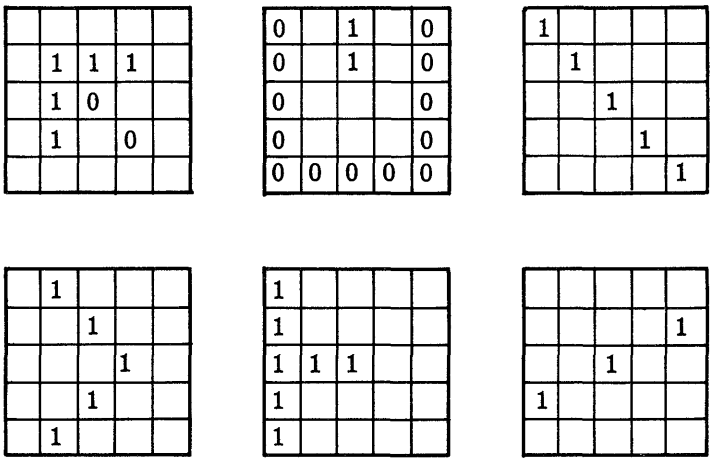
2)

		1		0
	1		0	
1	1	0	0	
	1		0	

Figure 4 Operators are generated within the 5 x 5 matrix by either: a) extraction from the input pattern (random placement of a 5 x 5 matrix, elimination of "0's" connected to "1's," and elimination of each of the remaining cells with a probability of $\frac{1}{2}$) or b) by random designation of cells as either "0" or "1" (choose a "1," then place a "0" two cells to its right). In 1) from 3 to 7 "1's" are chosen completely at random, while in 2) the choice is limited to connected cells.

OPERATORS USED

A. PRE-PROGRAMMED SET



B. SET GENERATED BY PROGRAM

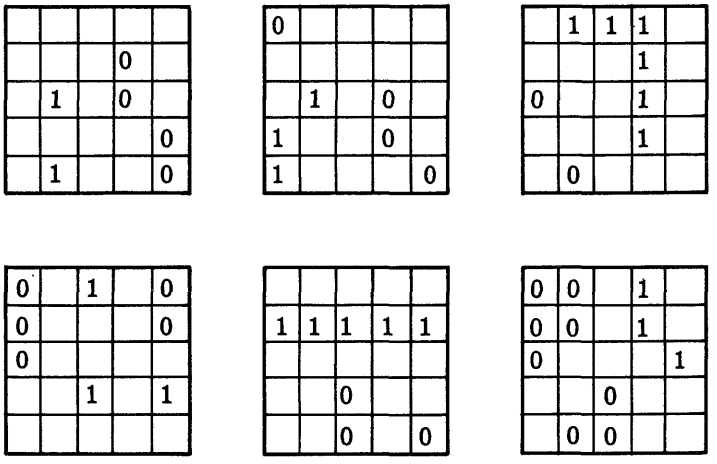


Figure 5 A) Some typical examples of pre-programmed operators are shown. B) Six of the operators generated by the program, during a run that reached 94% success on 7 sets of 5 patterns, are shown.

	← MATRIX OPERATORS →									COMBINATORIAL OPERATORS →		
PATTERN	OPERATOR 1				OPERATOR 2					CHARACTERISTIC		
NAME	N	X	Y	R^2	N	X	Y	R^2	...	m-2	m-1	m
?	2	2	2	2	2	3	1	6	...	6	7	4
A	3	3	4	1	4	0	1	1	...	1	2	3
B	2	2	3	2	3	3	2	5	...	4	7	5
C	4	5	6	5	1	0	0	4	...	2	1	7

Figure 6 Operator outputs are listed for the unknown pattern in the same format as in lists stored in memory.

PATTERN A

CHARACTERISTICS (A) :	3	3	4	1	4	. . .	3
INPUT (?) :	2	2	2	2	2	. . .	4
DIFFERENCE |A - ?| :	1	1	2	1	2	. . .	1
PATTERN AMPLIFIERS :	2	3	1	2	0	. . .	3
GENERAL AMPLIFIERS :	3	3	1	1	0	. . .	3
DIFF. X AMPLIFIERS :	6	9	2	2	0	. . .	9

WEIGHTED AVERAGE DIFF.	AVE. DIFF. AMPLIFIER	DIFFERENCE SCORE
$\frac{28}{27} = 1.04$	61	63

PATTERN B

CHARACTERISTICS (B) :	2	2	3	2	3	. . .	5
INPUT (?) :	2	2	2	2	2	. . .	4
DIFFERENCE |B - ?| :	0	0	1	0	1	. . .	1
PATTERN AMPLIFIERS :	4	3	2	3	2	. . .	2
GENERAL AMPLIFIERS :	3	3	1	1	0	. . .	3
DIFF. X AMPLIFIERS :	0	0	2	0	0	. . .	6

WEIGHTED AVERAGE DIFF.	AVE. DIFF. AMPLIFIER	DIFFERENCE SCORE
$\frac{8}{32} = .25$	60	15

Figure 7 Differences are obtained between the characteristics for the input pattern and each list of characteristics in memory. These differences are then weighted by the product of the "general amplifiers" and "pattern amplifiers," giving a weighted average difference for each list in memory. When multiplied by corresponding "average difference amplifiers," the weighted average differences give "difference scores" for each pattern in memory. The name of the pattern with the smallest "difference score" is chosen as the name of input.

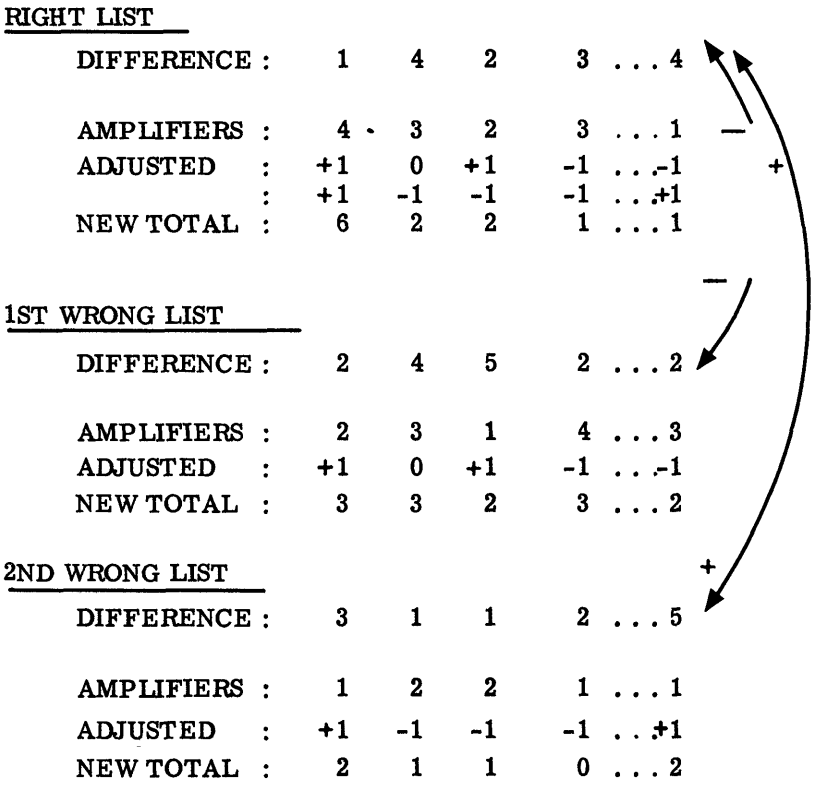


Figure 8 The pattern amplifiers for certain lists are adjusted to increase weightings of individual characteristics that gave differences in the right direction, and to decrease weightings that gave differences in the wrong direction

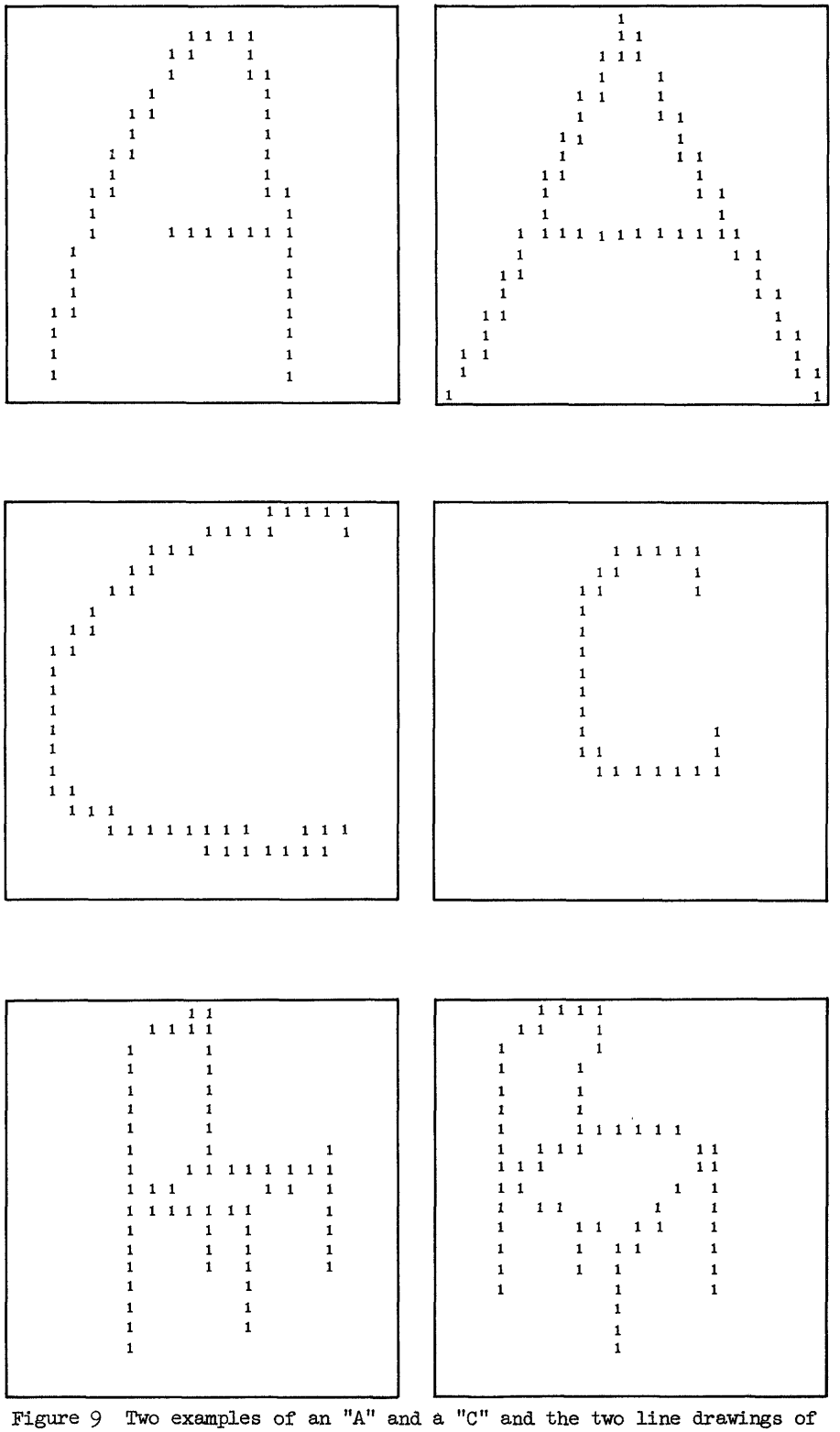


Figure 9 Two examples of an "A" and a "C" and the two line drawings of a chair are typical of unknown patterns processed.