Mansoura Engineering Journal (MEJ). Vol.18.No.3,September,1993.


# طريقة عامة للتعرف على الأشكال المسطحة

# A GENERAL TECHNIQUE FOR RECOGNITION OF PLANAR SHAPES

M. M. Hamed, A. S. Tolba and H. M. El-Hendy
Dept. of Elect. Eng., Suez Canal Uni, Egypt

ملخص البحث:

يقدم البحث طريقة عامة للتعرف على الأشكال المسطحة وتعتمد هذه الطريقة على حساب متجة المساحة للشكل المطلوب التعرف عليه. كما يقدم البحث طريقة محسنه لحساب كود السلسلة للاطار الخارجى للشكل المطلوب التعرف عليه رغم وجود ازلحه أو دوران أو تغير فى الحجم . تم تدريب النظام لاستخلاص السمات من مجموعة تدريب تشتمل على عدد ٢٠ شكل مختلف وتم اختبار أداء الطريقة المقترحة على مجموعة اختبار تتضمن عدد ٢٤ شكل آخر وأمكن التعرف على جميع أشكال مجموعتى التدريب والاختبار ومقارنة النتائج مع طريقة رقم الشكل والتى تعتمد على حساب مشتقة كود السلسلة. وتقدم الطريقة المقترحة مزايا تتعلق بدقة التعرف ومتطلبات التخزين وسرعة عملية التعرف بالمقارنة مع طريقة رقم الشكل

ABSTRACT:

Shape recognition is an essential component in any computer vision system. A general technique based on the normalized area vector concept is presented for sloving the problems of distortion and invariance against translation, rotation and zoom. A new algorithm is described for extraction of contours of complex nonoverlapping objects which may contain any number of holes of any shape and in any configuration. Experimental results show the robustness of the proposed technique in comparison with other well known techniques such as the shape number. A training set of twenty patterns is used for generation of reference patterns. A test set of tenty four patterns is used to show the performance of the proposed technique and resulted in a hundred percentage of correct classification for both the training and test set patterns.

## 1. INTRODUCTION

An important topic in computer vision is the classification of shapes in a scene. It has been noted [1] that features based on the boundaries or edges of shapes are closely related to the salient features used by the human visual system for scene analysis. Shape analysis based on boundary information has found wide applications in military target identification [2-4], character recognition [5], measurement of biological shapes [7], x-ray diagnosis, idustrial part identification and many other areas. Many approaches to description of shape have been proposed and used in a wide variety of engineering and computer vision applications. Pavlidis [6] suggested a taxonomy of shape descriptors based on: (1) whether just the boundary, or the entire interior of the object was examined (external and internal); (2) whether the characterization was made on the basis of a scalar transform or a space transform; and (3) whether the procedure is or is not information preserving in the sense that the originl image can be rconstructed from the shape descriptors. Existing methods include shape numbers [9] based on chain-coding of the boundary, and the medial-axis transform [9], which transforms the original object to a stick figure that approximates the skeleton of the figure.

We present here a new internal, scalar non-information preserving shape measure that allows fast shape recognition and is immune against noise.

A general technique is presented here for recognition of planar shapes. Invariance against translation, rotation and zoom is considered . The normalized shape is divided into area strips each having one pixel width and the whole image length. The resulting area vector is used together with the chain code of the planar shape to form a robust set of features for reliable shape description. Experimental results of the proposed technique are compared to those of the well known shape number technique and are shown to be superior concerning the noise immunity, memory requirements, recognition speed and percentage of correct classification.

2. SHAPE RECOGNITION SYSTEM:

A 30 MHz frame grabber (CYCLOPE) with 512 x 512 pixels resolution and 256 gray levels is used for real time image acquistion from a Panasonic Vidicon tube camera. The acquired gray level image array is then thresholded with a dynamic threshold technique [7] to generate a corresponding binary image.

3. GRAPHICAL USER INTERFACE (GUI):

A hardware independent interactive graphical user interface is designed and implemented for the following purposes:

1. Editing and manipulation of synthetic images by using the keyboard, mouse or the fractal image generator
2. Interfacing the shape classifier with real images acquired from the video camera.
3. As an educational environment for implementation and testing of various algorithms for digital image processing and shape recognition. Considerable work can then be done with simple means.

The GUI has been proved to be a useful tool for quickly testing or explanation of pattern recognition or computer vision techniques, providing a simple and cheap alternative to the often very costly commercial image processing systems. An optional "DEMO" mode helps following up every processing step in chain code generation and pattern classification. The different possible resolution levels available in the editor demonstrate in a systematic manner what is actually meant by image quantization

4.1 CHAIN-CODED IMAGES:

Any two-dimensional shape could be represented by the chain code of its boundary. The chain code is a compact representatio. for a digital image. For a survey of algorithms that operat directly on the chain code, see Freeman [8]. The chain form of representation has been shown to be well suited for most of the processing tasks likely to be encountered. Features such as chain length, width, height , area, first moment about x-axis, second moment about x-axis, distance between two points, rotation of a chain, expansion and contraction of a chain, minor and major axes are exreacted from the chain code as follows:

1. Length of a chain

$$L = T * ( N_e + N_o \sqrt{2} )$$

where $N_e$ and $N_o$ are the numbers of even and odd valued links, respectively and T is the image size [11].

2. Width and Height of a chain:
Let

$$X_i = \sum_{j=1}^{i} a_{jx} + X_o$$

$$Y_i = \sum_{j=1}^{i} a_{jy} + Y_o$$

where $a_{jx}$ and $a_{jy}$ are respectively the x and y components of the links a .Then for J = 0.1,....,n, we have

$$Width = \max_j X_j - \min_j X_j$$

$$Height = \max_j Y_j - \min_j Y_j$$

where $X_o$ and $Y_o$ are the coordinates of initium which may be arbitrarily selected.

3. Freemans area enclosed by the contour path:

$$S = \sum_{i=1}^{n} a_{ix} ( Y_{i-1} + 0.5 * a_{iy} )$$

The Pascal code for this process is as follows:

```
Scale_Factor    := N / Main_Axis_Length;
Vertical_Shift := -Y[Lower_Axis,1];
Horizontal_Shift := - X[Main_Axis_First_Point];
Vertical_Width    := Minor_Axis_Length * Scale_Factor;
For I := 1 to chain_Length do
Begin
  Y[I] := Scale_Factor * ( Y[I] + Vertical_Shift);
  X[I] := Scale_Factor * ( X[I] + Horizontal_Shift);
End;
```

5. THE SCAN-PATH ALGORITHM FOR CHAIN-CODE GENERATION:

A new algorithm is developed for contour following of complex shapes (narrow arcs and line drawing images). The idea behind this algorithm is to view the contour as your hand can touch it in a complete cycle to overcome the problem of cutting the contour by the scan path. The scan path is the path consisting of all the lower-value points that have at least one side in common with a contour point. Thus instead of following up the contour itself we follow up the scan path and concurrently collect the contour points till we come back to the starting point. The scan path algorithm can be summarized as follows:

1. Find a first point on the scan path
2. Initialize variables
3. Get the corresponding contour points if any
4. Get another scan point
5. If this point is not the starting scan point then back to step number three.
6. Adjust the chain code so that the left-top point of the contour be the first point in the chain;
7. Compute the features.

A generalization of the previous algorithm for the case of multi-nonoverlapped non-simple contours is found in [11]. The scan path algorithm is a completely sequential process for obtaining region contours in images. Efficient extraction is attained by manipulating pointers in a dynamic data structure. The only image buffer required is that for a signle line so that increasingly high resolution sensors could be used.

6. THE SHAPE SIMILARITY MEASURE:

The shape number [9] is generated for arbitrary grid sizes.

To measure the similarity between two shapes we use the following algorithm:

1. Let the highest possible resolution be M x N where M=N
2. Divide the two images to N x N equal sqaures and generate the corresponding shape numbers for both.
3. Compare the two shape numbers of the two images
4. Compute the degree of similarity by $\log_2 (M/N) + 1$

Shapes could be classified on the basis of the degree of similarity by sorting the degrees of similarities at different resolutions in descending order for all the training set patterns having a degree of similarity more than 50 % with the unkown pattern. If there are more than one pattern of the training set with a high degree of similarity to the unkonwn pattern, we compare the original sizes as a distinguishing factor.

## 7. THE NORMALIZED AREA VECTOR TECHNIQUE:

In the shape number method [9]. the classification process depends mainly on the external contour of the normalized image. The shape number is obtained from the dereivative of Freeman's chain code [8]. This is not a very safe process because any small distortion in the image or any noise affects the shape number. A simpler approach to overcome this problem uses the shape area vector instead of the external contour. A similarity measure is used instead of the shape factor. The normalized shape is divided into area slides with one pixel width. The number of pixels in a strip is used to construct an area vector. This area vector is used to compare different images. The algorithm for computing the normalized area vector is given as follows:

1. Acquire an image
2. Normalize the acquired image
3. Divide the image into area strips with one pixel width
4. Count the number of pixels in each strip and construct the area vector.
5. Compare a new area vector with the training vectors
6. Assign the area vector to the corresponding class with the highest similarity degree with at least a value of 50%.
7. Goto step 1 and repeat until all tested patterns are classified.

A similarity degree based on two area vectors VI and VS is computed according to the following equation:

$$S = 100 * (Area - \sum_{i=1}^{n} (VI[i]-VS[i]) ) / Area$$

8. NOISE AND DISTORTION IMMUNITY:

The performance of both the shape number and area vector methods depend on the accuracy of the normalization operation. The normalization depends mainly on the major axis of the object. Any noise or distortion which preserves the major axis as the longest axis in the object could result in a successful recognition. On the other hand, any noise or distortion which results in another major axis results in failure of both methods to corerectly identify the object. In the first case, the main axis remains the longest axis inside the object, and the area vector method shows better behaviour than the shape number method, because the shape number depends on the external contour only. If just one pixel is distorted, the whole contour is distorted also and the processing must proceed to lower resolution. In the area vector method, the process depends on the total area enclosed inside the normalized contour. The distortion in one or even ten pixels may lead only to a total distortion of the area of about 5 or 10 percent. So the area vector method is less sensitive to noise and distortion than the shape number method. As an example, we process a square of 20x20 pixels as and its normalized shape shown in Fig. 2-a. The system is trained to recognize the square by both methods, which succeeded in the classification process. The same shape is then distorted by removing 2 pixels as shown in Fig. 2-b and then classified by both methods. The similarity degree in the case of the shape number method is found to be of the fifth order so that we must reduce the resolution to 1/16 of the original resolution such that the shape be similar to the original square. The area vector method gives a similarity degree of 99 percent for the same shape. The same test is repeated for the case of a distortion of 25 pixels. The shape number method

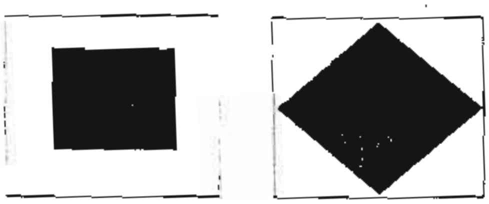

Fig. 2-a A simple square with its normalized form

could not recognize the shape while the area vector method gives a similarity degree of 88 percent. Fig.2-c shows the relation between the similarity degree and the distortion level for both methods.

Fig. 2-b A square with a notch and its normalized form

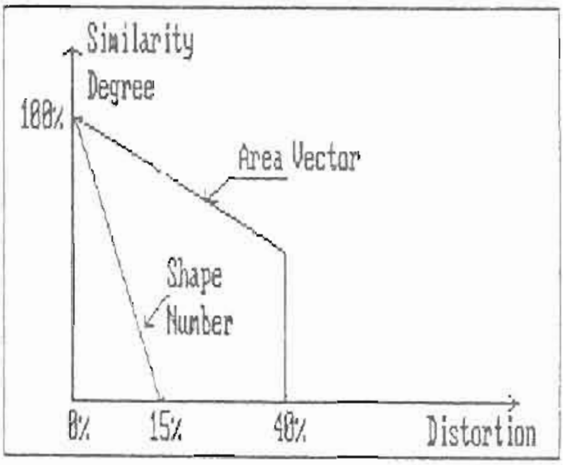


Fig. 2-c The similarity degree as a function of distortion for both methods.

9. RESULTS AND DISCUSSION:

Experiments are performed on a real time system for classification of both synthetic and real images. A training set including twenty patterns and their corresponding normalized patterns is shown in Fig. 3 and is used for generation of the reference pattern vectors. In selecting these patterns we tried to generate different shaped patterns such as squares, rectangles. and fractal images. The features of the training patterns are summarized in table 1. The test patterns are differently selected to test the performance of each method in the following cases:

1- The unknown pattern is very typical to a known one
2- The unkonwn pattern is similar to a known pattern but is displaced, rotated or magnified.
3- The unknown pattern is similar to a known pattern but with some distortion at different levels.

4- The unknown pattern is similar to a known pattern but with a distortion on either the major or the minor axes or both.
5- The unknown pattern has some similarity to more than one trained pattern.

In the classification phase, a test set of twenty four patterns as shown in Fig. 4 is used for testing the performance of the proposed technique. The corresponding features are shown in table 2. Every entry of the similarity table 3 shows the results of classification of each test pattern for the two cases of the shape number method and normalized area vector method. An entry in the table is empty for the case of failure of the recognition process. The leftmost column of the similarity table shows the number of the test pattern. Every test pattern has two rows for the resulting classification. The first row gives the first five probable patterns as suggested by the shape number method. Each pattern number is followed by its similarity degree to the current test pattern. The second row gives the similarity degrees for the case of the area vector method. The overhead of preprocessing, classification time, storage requirements and noise and distortion immunities are the basic factors for comparing the proposed technique with the shape number technique. The same preprocessing steps including the chain-code generation, feature extraction, normalization are used in both techniques. The time required for the shape number method is proportional to 8*N*N. where N is the resolution of the square image. On the other hand. the time required for the area vector technique is only the time required for computation of the normalized area vector, which is equal to the time required for scanning the whole image array and is proportional to N*N. It is clear that the proposed technique is much faster than the shape number technique. Concerning the storage requirements, the shape number method needs 8*N*N bytes in addition to the shape number length, which is given by 4*N for resolution N, since it is computed at different resolutions which needs 8*N-16 bytes. The area vector method needs only N bytes for the case of an image resolution of value N.

## 10. CONCLUSIONS:

Fast shape recognition, less memory requirements and more reliability are the basic advantages of the proposed technique over the well known technique of shape number. Experimental results on both training and test set patterns showed the recognition capability of the system with different degrees of similarity with stored matching patterns. The system could be used for many real time applications such as character regonition. recognition

Table 1 Features For The Trained Patterns

| Pattern No. | Chain Length | Chain Perimeter | Area | Major Axis | Minor Axis |
|---|---|---|---|---|---|
| 1 | 80 | 80.0 | 441 | 28.3 | 28.3 |
| 2 | 150 | 150.0 | 1326 | 55.9 | 44.7 |
| 3 | 120 | 144.9 | 961 | 67.1 | 26.8 |
| 4 | 80 | 96.6 | 741 | 31.6 | 31.6 |
| 5 | 160 | 193.1 | 2281 | 60.0 | 60.0 |
| 6 | 156 | 190.8 | 881 | 44.7 | 44.7 |
| 7 | 320 | 402.8 | 2311 | 130.4 | 60.6 |
| 8 | 212 | 284.1 | 1303 | 98.5 | 51.7 |
| 9 | 130 | 166.5 | 827 | 51.4 | 29.0 |
| 10 | 60 | 72.4 | 256 | 30.0 | 15.0 |
| 11 | 68 | 89.5 | 461 | 30.0 | 30.0 |
| 12 | 73 | 92.5 | 446 | 30.0 | 30.0 |
| 13 | 78 | 95.4 | 431 | 30.0 | 30.0 |
| 14 | 80 | 104.9 | 541 | 40.0 | 25.0 |
| 15 | 228 | 282.7 | 2421 | 64.0 | 64.0 |
| 16 | 200 | 241.4 | 2976 | 66.7 | 66.7 |
| 17 | 312 | 381.6 | 6461 | 100.0 | 100.0 |
| 18 | 160 | 201.4 | 956 | 45.3 | 45.3 |
| 19 | 246 | 305.6 | 1526 | 68.0 | 51.1 |
| 20 | 220 | 278.0 | 1336 | 75.2 | 45.2 |

Table 2 Features Table For The Testing Patterns

| Pattern No. | Chain Length | Chain Perimeter | Area | Major Axis | Minor Axis |
|---|---|---|---|---|---|
| 1 | 80 | 80.0 | 441 | 28.3 | 28.3 |
| 2 | 280 | 280.0 | 5041 | 99.0 | 99.0 |
| 3 | 120 | 169.7 | 1861 | 60.0 | 60.0 |
| 4 | 310 | 310.8 | 5740 | 106.1 | 106.1 |
| 5 | 320 | 320.8 | 5600 | 106.1 | 106.1 |
| 6 | 330 | 330.8 | 5366 | 106.1 | 106.1 |
| 7 | 340 | 340.8 | 5020 | 106.1 | 106.1 |
| 8 | 350 | 350.8 | 4580 | 106.1 | 106.1 |
| 9 | 360 | 360.8 | 4040 | 106.1 | 106.1 |
| 10 | 212 | 284.1 | 1303 | 98.5 | 51.7 |
| 11 | 130 | 166.5 | 827 | 51.4 | 29.0 |
| 12 | 130 | 138.3 | 793 | 51.4 | 28.3 |
| 13 | 130 | 139.9 | 859 | 51.4 | 29.0 |
| 14 | 130 | 165.6 | 826 | 51.4 | 29.0 |
| 15 | 130 | 165.6 | 828 | 51.4 | 29.0 |
| 16 | 160 | 193.1 | 2281 | 60.0 | 60.0 |
| 17 | 180 | 221.4 | 2291 | 70.7 | 56.6 |
| 18 | 80 | 104.9 | 541 | 40.0 | 25.0 |
| 19 | 90 | 114.9 | 546 | 40.0 | 30.0 |
| 20 | 92 | 116.9 | 547 | 40.0 | 28.0 |
| 21 | 162 | 203.4 | 994 | 46.3 | 45.3 |
| 22 | 180 | 204.9 | 1616 | 75.2 | 45.2 |
| 23 | 368 | 469.1 | 1963 | 90.2 | 59.9 |
| 24 | 264 | 328.6 | 1843 | 90.2 | 43.3 |

Table 3 The similarity table for the test patterns

| Pattern No. | First Probable | Second Probable | Third Probable | Fourth Probable | Fifth Probable |
|---|---|---|---|---|---|
| 1 | 1 /First | — | — | — | — |
| | 1 / 100% | 11/ 94 % | 12/ 90 % | 13/ 87 % | 6 / 82 % |
| 2 | 1 /First | — | — | — | — |
| | 1 / 100% | 11/ 94 % | 12/ 90 % | 13/ 87 % | 6 / 82 % |
| 3 | 1 /First | — | — | — | — |
| | 1 / 100% | 11/ 94 % | 12/ 90 % | 13/ 87 % | 6 / 82 % |
| 4 | 1 /Fifth | — | — | — | — |
| | 1 / 99 % | 11/ 95 % | 12/ 91 % | 13/ 87 % | 6 / 82 % |
| 5 | 1 /Sixth | — | — | — | — |
| | 1 / 96 % | 11/ 96 % | 12/ 93 % | 13/ 89 % | 6 / 81 % |
| 6 | 1 /Sixth | — | — | — | — |
| | 11/ 96 % | 12/ 92 % | 1 / 91 % | 13/ 88 % | 6 / 80 % |
| 7 | — | — | — | — | — |
| | 11/ 90 % | 12/ 88 % | 1 / 84 % | 13/ 83 % | 6 / 78 % |
| 8 | — | — | — | — | — |
| | 11/ 80 % | 13/ 78 % | 1 / 73 % | 13/ 73 % | 6 / 71 % |
| 9 | — | — | — | — | — |
| | — | — | — | — | — |
| 10 | 8 /First | — | — | — | — |
| | 8 / 100% | — | — | — | — |
| 11 | 9 /First | — | — | — | — |
| | 9 / 100% | — | — | — | — |
| 12 | 9 /Sixth | — | — | — | — |
| | 9 / 94 % | — | — | — | — |

Table 3 (Conc.) The similarity table for the test patterns

| Pattern No | First Probable | Second Probable | Third Probable | Fourth Probable | Fifth Probable |
|---|---|---|---|---|---|
| 13 | 9 /Sixth | — | — | — | — |
| | 9 / 96 % | — | — | — | — |
| 14 | 9 /Third | — | — | — | — |
| | 9 / 99 % | — | — | — | — |
| 15 | 9 /Third | — | — | — | — |
| | 9 / 99 % | — | — | — | — |
| 16 | 5 /First | 4 /Sixth | 15/Sixth | 16/Sixth | 17/Sixth |
| | 5 / 100% | 16/ 93 % | 15/ 92 % | 17/ 91 % | 4 / 66 % |
| 17 | — | — | — | — | — |
| | 2 / 76 % | 19/ 69 % | — | — | — |
| 18 | 14/First | — | — | — | — |
| | 14/ 100% | 9 / 81 % | 10/ 73 % | — | — |
| 19 | 14/Third | 13/Sixth | — | — | — |
| | — | — | — | — | — |
| 20 | 14/Third | — | — | — | — |
| | 14/ 99 % | 9 / 81 % | 10/ 74 % | — | — |
| 21 | — | — | — | — | — |
| | 18/ 92 % | 13/ 85 % | 12/ 28 % | 11/ 79 % | 1 / 73 % |
| 22 | 20/Sixth | — | — | — | — |
| | 20/ 80 % | 9 / 75 % | — | — | — |
| 23 | 20/Sixth | — | — | — | — |
| | 20/ 71 % | — | — | — | — |
| 24 | 20/Fifth | — | — | — | — |
| | 20/ 96 % | — | — | — | — |

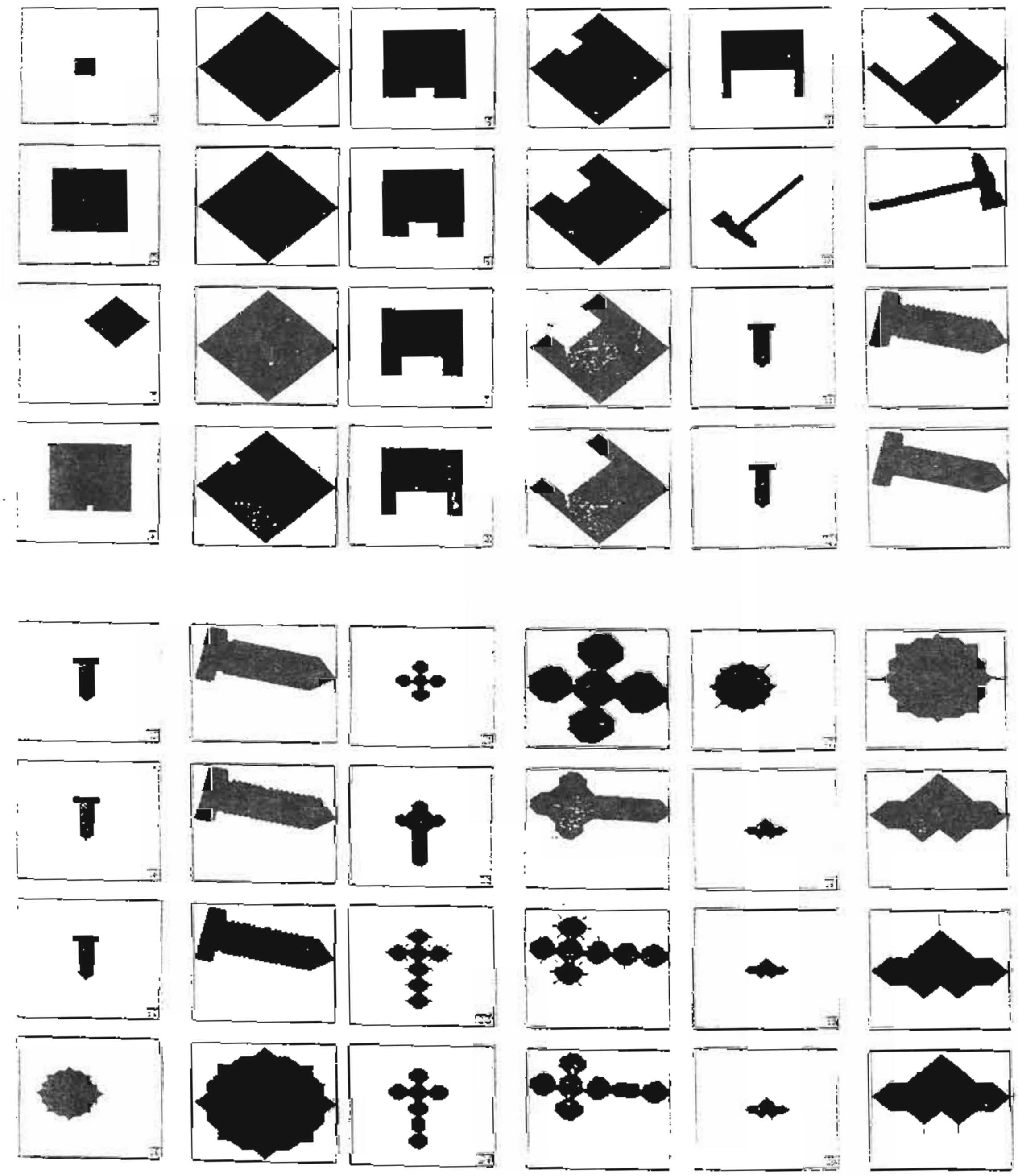

FIG. 4 Patterns of the testing set

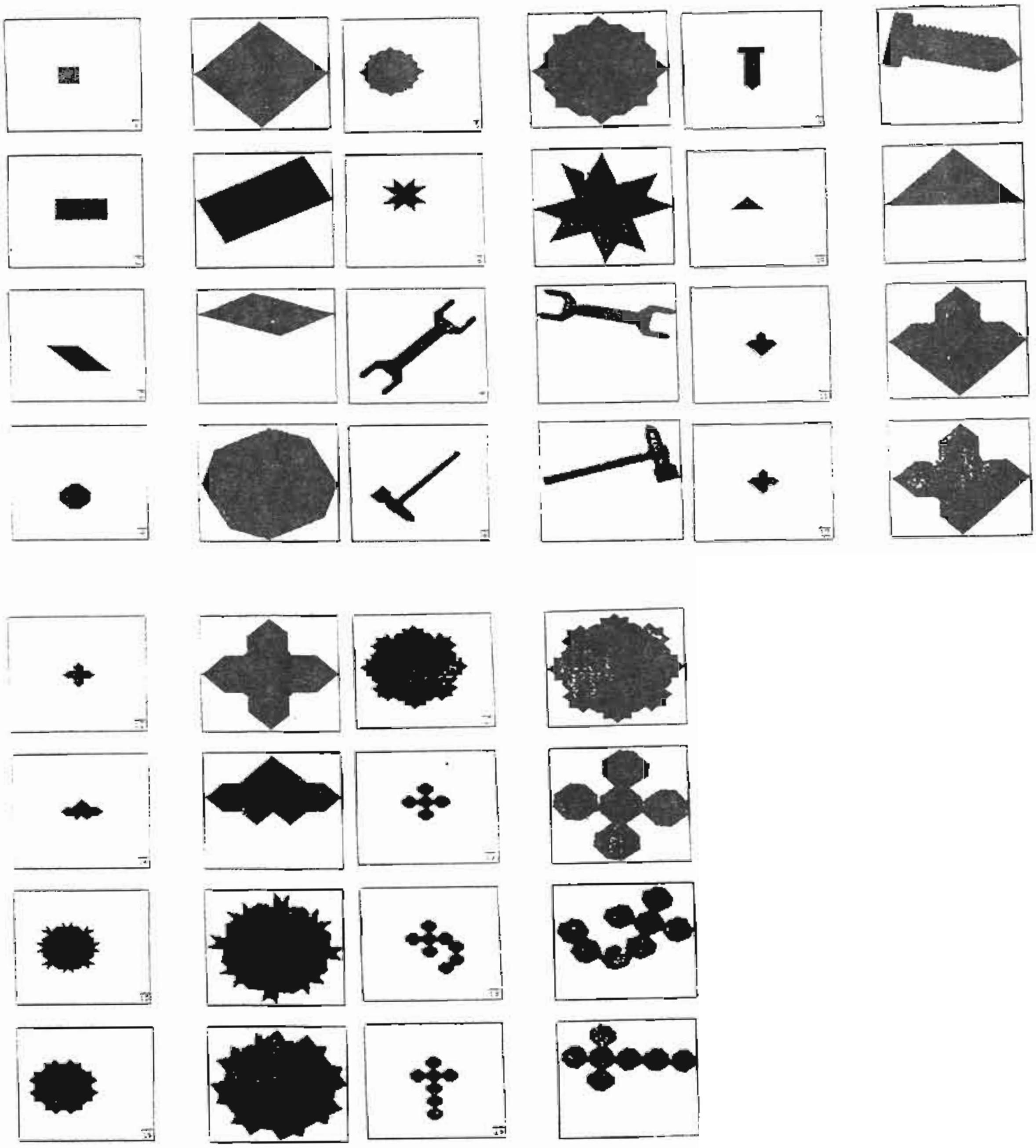

FIG. 3 Patterns of the training set

of machine parts for robot manipulation and defect detection in machined parts.

11. REFERENCES:

[1] C.T. Zahn and R.Z. Roskies,"Fourier descriptors for plane closed curves," IEEE Traans. Comput.,vol. C-21,no. 3,pp. 269-281. Mar 1972.

[2] S.A. Dudani, et al.,"Aircraft identification by moment invariants", IEEE Trans. comput.,vol. C-26,pp. 39-46, Jan 1977.

[3] C.C. Lin and R. Chellappa, "Classification of partial 2-D shapes using Fourier descriptors," IEEE Trans. Pattern Anal. Machine Intell.. vol. PAMI-9,no.5.pp. 686690,Sept. 1987.

[4] L. Gupta and M.D. Srinath,"Contour sequence moments for the classification of closed plahar shapes," Pattern Recognition vol. 20.no. 3,pp. 267-272, 1987.

[5] E. Peterson and K.S. Fu, " Shape discrimination using Fourier descriptors," IEEETrans. Syst., Man, Cybern., vol. SMC-7,no 3, Mar. 1977.

[6] T. Pavlidis,"Algorithms for Graphics and Image Processing", Rockville, MD: Computer Science Press. 1987.

[7] A. T. Alam Eldin, et al,"A Machine Vision System For Measurement of biological Shapes", Proc. of the International Society for Photogrammetry and Remote Sensing Symposium, Zurich, Sept. 3-7, 1990..

[8] H. Freeman , "On the quantization of line-drawing data", IEEE Trans. Syst.. Sci., Zybern. ,vol. SCS-5,no.1,pp. 70-79, Jan. 1969.

[9] Bribiesca, Ernesto and Gutyman, Adolfo "How to describe pure form and how to measure differences in shape using shape numbers", Pattern Recognition, Vol 12, 1980.

[10] M. G. Thomson, "Synthetic/Semantic Techniques in Pattern Recognition: A Survery", Int. Journal of computer and Inforation Science, Vol.11, No. 2, 1982.

[11] H. M. El-Hendy "A General Method For Recognition Of Plane Objects", M.Sc Thesis, Suez-Canal University. Dept. of Electrical Eng. 1991.