1992

3-D object modelling and recognition using absorption in a colour liquid

Hao Shi
Victoria University of Technology

Fazel Naghdy
University of Wollongong, fazel@uow.edu.au

Christopher D. Cook
University of Wollongong, chris_cook@uow.edu.au

3-D object modelling and recognition using absorption in a colour liquid

Hao Shi

Department of Electrical & Electronic Engineering
Victoria University of Technology, PO Box 64
Melbourne, VIC, Australia 3011

Fazel Naghdy and Chris D. Cook

Department of Electrical & Computer Engineering
The University of Wollongong, Locked Bag 8844
Wollongong, NSW, Australia 2521

ABSTRACT

The application of computer vision in industry has been increasing as greater use is made of flexible automation and robotics. Quality control and sorting can also be heavily dependent on artificial vision interfaced to an intelligent decision making system. Traditionally industrial tasks requiring computer vision are simplified to a 2-D problem in a plane. This permits the use of a single camera and hence reduces the complexity of the procedures of frame grabbing, image processing and decision making. Such a solution is however not suitable when 3-D information is vital in the control or decision making processes. Generation and processing of 3-D images are required for such applications.

The work presented in this paper provides a simple method of deriving a 3-D computer model for a special class of industrial objects and then using this model for machine recognition. The object is immersed in a colour liquid and the intensity of the pixels of the captured image is modulated by the depth of the object along the camera axis. The depth maps generated from the image are represented by parallel layers located in planes normal to the camera axis. The 2-D features of the layers are derived and a 3-D model is constructed for the object based on these features.

The object is distinguished by contour groups which are classified into three types according to their features. These 3-D features include object features and contour group features. Three steps are adopted for object recognition. The object features are first used in a basic test in order to reduce the number of possible models which an unknown object can match. Secondly, the contour features are used to test each of the contour group models. The models with a higher match rate are then selected for verification using chi-squared (χ^2) statistical methods. Finally the χ^2 test is employed to verify the above test results. The object match is governed by both the χ^2 test and the contour group test. From these tests, a model which best matches the object can be obtained.

1. INTRODUCTION

Computer vision has great potential for a number of industrial applications including object recognition, inspection, locating, counting, measurement and control. Present applications are typically limited to sorting and quality control. A small but rapidly growing number of robot applications require computer vision for object recognition and inspection. In these applications, robots are used in conjunction with sensors, such as television cameras, laser, or ultrasonic detectors, to check part locations, identify defects, or recognize parts for sorting. Object recognition means part identification and part sorting. Inspection usually implies measurement for quality control of certain part properties such as geometric dimensions, surface finish, position accuracy and assembly integrity.

3-D object recognition consists of matching an object in a scene with a model. In this process a correspondence between the object and the model will be established. Achieving such a correspondence between scene features and the object model is referred to as the matching process.

In this paper a summary of the previous work in object recognition is presented. A method for matching processing will then be discussed and a method developed in this study for object matching will be described. This method is based on contour groups reported earlier in the paper[1] for object description. The 3-D features used include object features and contour group features.

2. PREVIOUS WORK

Among the early applications is the work of Zeller and Doemens[2] who introduced a pattern recognition system to assist a shaker conveyor in sorting bulk materials. The part-specific dimensioning and preparation of this production equipment required a great deal of experience. Satisfactory functioning was often not attained until very many time-consuming trials had been made. The outlay in development and production was significantly reduced by detecting and sorting out those parts using the pattern recognition system.

An approach to automatic recognition of 3-D objects is presented by Tou and Huang[3]. It is based on the concept of spatial understanding which determines the orthographic projections from the knowledge obtained from the camera system geometry and pictorial drawings derived from 2-D images of the object. The orthographic projections are used as 2-D features of the object which consist of the top, front and side views of the 3-D object. These views are generated via spatial understanding of pictorial drawings and are projections of the pictorial drawing on the orthographic planes.

Industrial parts have been studied extensively by Han *et al.*[4]. In their work only a small set of surface shapes such as planes, cylinders and spheres are considered as such shapes make up the most common industrial parts. An approach to the recognition of stacked objects with planar and curved surfaces has been developed by Oshima and Shirai[5]. The system works in two phases. In the learning phase, a scene description is produced. This description is stored as an object model. In the recognition phase, an unknown scene is described in the same way as in the object models so that the stacked objects are recognized sequentially. Efficient matching is achieved by a combination of data-driven and model-driven search processes.

Yang and Luo[6] have introduced a 3-D curved object recognition scheme using view-point independent features. By applying a three-dimensional generalized Hough transformation to general 3-D curved object recognition, both the computation time and storage requirements are reduced. A new approach for explicitly relating the shape of the image contours to models of curved three-dimensional objects is proposed by Kriegman and Ponce[7]. Object models consist of collections of parametric surface patches and their intersection curves. The image contours considered are the projections of surface discontinuities and occluding contours.

A model-based method for detection and recognition has been developed by Shariat[8]. Object recognition is achieved by identifying features and patterns at various levels of complexity. The shape descriptions of the parts are first used to extract a set of candidates for each part. A model-based prediction and verification scheme is then used to verify the existence of the object candidates with low certainty. A single model could be used for various purposes such as recognition, prediction, verification, and merging of different parts of an object.

There are many other approaches to object recognition which are reported in the literature. Brooks[9,10] forms a 2-D parameterized model from a 3-D object model, which is then used for detection of that object in the scene. Silberberg *et al.*[11] model an object by defining a Hough space of possible transformations of a set of 3-D line segments, which are observable on the given object from a given viewpoint. A generalized Hough transform is used to match a set of observed line segments with model lines from each viewpoint. A similar approach[12] is presented which uses vertices of a 3-D object to determine the position of a known object.

Chakravarty and Freeman[13] define a model using characteristic views for recognizing curved and polyhedral objects. Fan *et al.*[14] match two sets of range image from the same object. The edges are classified into several categories and used, along with surface patches, to build adjacency graphs. Several constraints are used to limit the best-first tree search. In the case of partial occlusion, it is necessary to partition the graphs and merge as needed. A match is accepted when a certain percentage of the graph nodes are matched. Comprehensive reviews on this subject can be found in the papers written by Besl and Jain[15] and Chin and Dyer[16].

Although the actual and potential applications are quite varied, the underlying principles are the same. They are well on their way to simulating the human faculty of visual perception in numerous production applications in industry. Many current industrial inspection systems are limited to 2-D shape processing which is not able to examine depth information.

3. OVERVIEW OF THE TECHNIQUE

3-D objects are represented by a sequence of parallel layers consisting of a number of contours[17,18]. It is not necessary to keep all the contours in memory as some layers and contours may be identical or reproduced by few parameters. A technique based on the centroid of the contours is adopted to classify all the contours into different groups/subgroups, and reduce the amount of information required to represent the object.

3.1. Contour processing

To study 3-D contours, the basic objects shown in Fig. 1 are considered. All these objects can be represented by 2-D contours of the parallel cross-sections of the objects. Examination of the contours of the objects shown in Fig. 1 reveals that the x-y coordinates of the centroids of the contours belonging to one object are identical. The relationship between the parameters of the various contours can be established and hence each object can be represented by its individual contours.

Considering such observations, a set of rules may be defined for the contours of the objects shown in Fig. 1 from which the classification algorithm can be derived:

- The object in Fig. 1a is a cylinder whose contours are a series of circles having the same centroid, radius and perimeter/area (Fig. 2a).
- The object in Fig. 1b is a cone whose contours are circles having the same centroid and ever increasing radius and perimeter (Fig. 2b).
- The object in Fig. 1c consists of contours whose centroids and perimeters/areas are the same (Fig. 2c).

It is reasonable therefore to conclude that the objects shown in Fig. 2 can be easily defined using the three parameters of centroid, radius and perimeter. Fortunately the majority of industrial parts are a combination of these basic objects[4].

A contour group is defined as a group of contours having centroids with the same (x,y) coordinates and evenly increasing/decreasing perimeter/radius. This contour group cannot be further divided into subgroups. Based on Fig. 2 a total of three contour groups may be specified:

- type 0—cylinder as shown in Fig. 2a;
- type 1—arbitrary contours as shown in Fig. 2c;
- type 2—cone as shown in Fig. 2b.

3.2 Feature extraction

In practice, the feature selection process usually involves testing a set of intuitively reasonable features and reducing this set to an acceptable number of the best ones. In our case, the 3-D features consist of not only object features but also contour features since an object is represented by parallel layers. Contour features depend on the group type which in turn produce different contour features[19].

The following are the contour features corresponding to each of the three contour group types as described above:

- type 0, specifying a cylinder
  1) centroid;
  2) radius;
  3) height;
  4) hole_ID.

- type 1, specifying an arbitrary contour
  1) centroid;
  2) area;
  3) perimeter;
  4) minimum radius;
  5) maximum radius;
  6) height;
  7) hole_ID.

- type 2, specifying a cone
  1) centroid;
  2) radius;
  3) radius difference;
  4) height;
  5) hole_ID.

- Object features, including
  1) number of contour groups;
  2) number of holes;
  3) number of type 0 groups;
  4) number of type 1 groups;
  5) number of type 2 groups.

4. MATCHING PROCESS

It is possible in an industrial environment to set up the workspace in a way that the scene contains only one object at a time. In the paper reported here, the object is processed and described using a method presented previously[1]. Each scene object O is represented by its contour groups o.

Models M_1, M_2, ..., M_N are stored in a database in the memory. Each model M_i consists of several contour groups m_i, and each contour group has its contour group features.

The objective of the matching process is to find the model which best matches an object. The matching process used in this study consists of three tests: the Basic Test, the Contour Group Test, and the χ^2 Test.

- Basic Test:
  This module is used to find the most likely model candidates which the object can be matched to. It implements a fast search involving the computation of coarse similarity. Object features are used in this test. The details are given in Section 5.

- Contour Group Test:
  Once the set of candidates has been formed, an extensive comparison between the contour groups of the object and that of the models are carried out. The contour group features are used in this test. After this test, the best matched contour group for each contour group of the object will be found. The detail of this process is given in Section 6.

- χ^2 Test:
  The chi-squared test is employed to verify the results of the Contour Group Test from a statistical viewpoint. The definition of χ^2 and the chi-squared significant test are introduced in Section 7.

5. BASIC TEST

To measure the similarity between the object in the scene and a model, the normalized measure between 0 and 1 is introduced. For two variables x and y the normalized measure can be defined as:

$$s(x,y) = 1 - \frac{|x-y|}{\max(x,y)} \tag{1}$$

This equation can be also written as:

$$s(x,y) = \frac{\min(x,y)}{\max(x,y)} \tag{2}$$

If $\max(x,y)$ equals to 0, $s(x,y)$ is defined as 1.

Object features are selected to perform the basic test. The features described in Section 3.2 include the number of contour groups, number of holes, number of contour group type 0, type 1 and type 2. The similarity between the object O and the model M is measured by:

$$B(M,O)=\frac{\sum_{i=1}^{5} w_i s(x_i,\mu_i)}{\sum_{i=1}^{5} w_i} \tag{3}$$

where:

w is the weighting factor of feature i ;

x_i is the value of feature i of the object O;

μ_i is the mean of feature i of the model M;

$s(x_i,\mu_i)$ is the normalized measure of the object features.

It is obvious that the number of the contour group for the object and that for the models is not always the same as there may be more than one model in the memory or defect in the object. There are three cases:

1. The number of contour groups for the object is smaller than that of the model;
2. The number of contour groups for the object is larger than that of the model;
3. The number of contour groups for the object is equal to that of the model.

Similarly, there are also three cases for other features like the number of holes, number of contour groups of type 0, type 1 and type 2. A model M_1 is said to be more similar to scene object O than model M_2 if $B(M_1,O)$ is larger than $B(M_2,O)$.

6. CONTOUR GROUP TEST

Since an object normally contains more than one contour group, it is necessary to match each contour group of the object with that of the model. The group numbering between the object and the model may be different. For example, consider an object which has three contour groups as shown in Fig. 3. Contour group number 1 may match contour group number 1 in the model shown in Fig. 4. However, contour group number 2 of the object matches contour group number 3 of the model. This is because the contour group number is generated by the position of the object in the viewing area of the camera and so is position-dependent. A necessary condition for a contour group of the object to match that of the model is that the group type for both the object and the model is the same.

To measure the similarity between each pair $<m,o>$ where m and o are respectively contour groups of the model and the object, the normalized measure (see Eq. 1) of the similarity of the features for each contour group is computed. The similarity measure of two contours m and o is defined by

$$C_j(m,o)=\frac{\sum_{i=1}^{n} w_i s(x_i,\mu_i)}{\sum_{i=1}^{n} w_i} \tag{4}$$

where:

n is the number of features; (group type 0: n=4; type 1: n=7; type 2: n=5);

j is the number of contour groups;

$s(x_i,\mu_i)$ is the normalized measure of the contour group features.

The contour group *1* is said to be more similar to the contour group of object than the contour group *2* if $C_1(m,o)$ is larger than $C_2(m,o)$.

7. χ^2 TEST

7.1. The definition of χ^2

The chi-squared (χ^2) is the method proposed by Karl Pearson[20] as a measure of discrepancy between observed and expected values in a multinomial distribution. The formal definition of chi-squared is as below[21,22]:

$$\chi^2 = \frac{\sum (observed - expected)^2}{expected}$$

$$= \sum_i^k \frac{d_i^2}{e_i} \tag{5}$$

where:

e_i is the expected value;

d_i is the deviation of the observed value from its expected value;

k is the number of features.

It is convenient to let $\vartheta = k - 1$, where ϑ is called "degrees of freedom". A table of such probabilities is listed in Table 1. The calculated χ^2 is compared with the value of χ^2 in Table 1 to determine how good the observed value is. If the computed χ^2 is less than the one in the table then the observed value is close enough to the expected value.

As an example, assume that the calculated value of χ^2 for $\vartheta = 2$ equals 1.02. From Table 1, for ".05 significance point", $\chi^2[2; .05] = 5.99$. Since the calculated value is much smaller than 5.99 then the agreement between the observed value and expected value is here arbitrarily defined as "good". In object recognition terms, this is taken to mean that a good match has been obtained.

7.2 Chi-squared statistical significant test

A chi-squared (χ^2) statistical significant test is defined based on the χ^2 test and is used to measure how closely the unknown object matches each of the models. The value is calculated using the following formula as below:

$$\chi^2 = \frac{\sum_{i=1}^{k} (x_i - \mu_i)^2}{\mu_i} \tag{6}$$

where:

χ^2 is the chi-squared value;

k is the number of features;

x_i is the value of feature i of the object O;

μ_i is the mean of feature i of the model M.

The value of k varies with the number of the contour group type. The features considered for the chi-squared test are contour group features.

For each feature, Eq. 6 is used to calculate the standard deviations between the object and the model. These deviations are squared and added to give an indication of the total deviation of the object from the model. It is necessary to compare the unknown object with each of the models in turn in order to find which model is the best fit. A smaller value of chi-squared indicates a better match between the unknown object and model.

Assume that an object to be tested has 5 contour groups (2 for type 0; 2 for type 1; 1 for type 2). Then its number of

features for the chi-squared test is 27 ($2\times4+2\times7+1\times5$). Therefore the degree of freedom is 26. From Table 1, $\chi^2[26\ .05] = 38.885$. If and only if the value of χ^2 calculated from Eq. 6 is smaller than 38.885, will the object tested match the model in the memory.

8. OBJECT RECOGNITION PROCESS

The recognition process aims to identify an object in a scene and assign a model to it by establishing correspondence between the object and the model.

A necessary condition for an object to match a model is that the number of contour groups of the object equals that of the model. Thus Eq. 3 can be simplified as:

$$B(M,O) = \frac{\sum_{i=1}^{5} w_i s(x_i, \mu_i)}{\sum_{i=1}^{5} w_i} = 1.0 \tag{7}$$

The models which satisfy Eq. 7 can therefore pass the basic test. The objective of the basic test is to reduce the number of models and select certain models for the subsequent tests.

Since the basic test still produces a multiple number of models, it is necessary to carry out the contour group test. Each contour group of the object is compared with the contour groups of the model, and corresponding $C_j(m,o)$ values are obtained. The contour group number of the model is recorded when $C_j(m,o)$ reaches the maximum. In a similar way, all the contour groups of the object are tested and the corresponding contour groups of the model are found. The match rate of the object to the model is defined by

$$R(M,O) = \frac{\sum_{j=1}^{N} w_j \max(C_j(m,o))}{\sum_{j=1}^{N} w_j} \tag{8}$$

where:

$\max(C_j(m,o))$ is maximum match rate of contour group j and
N is the number of contour groups.

Each model which passes the basic and contour group test has an $R(M,O)$ value. The higher the value, the closer the object is to the model. Logically, the model with highest $R(M,O)$ value is the best match for the object. To determine the best model matching the object, the models with $R(M,O)$ values higher than a certain threshold, will be checked by χ^2 (chi-squared).

The two parameters $R(M,O)$ and χ^2 determine whether an object is a match for a model. If the χ^2 values for all or some of the pre-determined models calculated according to Eq. 5 are smaller than the .05 significant value from Table 1, then the model with a highest $R(M,O)$ value will be the best match for the object. If χ^2 values for all pre-determined models are higher than the .05 significant value, then the object does not match any model.

9. EXPERIMENTAL RESULTS

The four objects used for object recognition are shown in Fig. 5. After various processes as described above, the 3-D features of these objects are listed in Table 2. According to Eq. 3, the results of the basic test for each model are recorded

and are listed in the second column in Table 3. The match rate of the object is obtained and listed in the third column in Table 3 using Eq. 8. Finally, from Eq. 8, the results of the χ^2 test against the models are listed in the fourth column of Table 3. The best match results of each object against the models are produced and shown in Table 3. The relevant results of the object recognition are summarised and listed in Table 4.

10. CONCLUSIONS

In this paper, a simple technique used for deriving a 3-D model of an object was introduced and the object recognition process was described. The object features are firstly used in a basic test in order to reduce the number of possible models for object recognition. Secondly, the contour features are used to test each contour group of the models. The models with a higher match rate are selected for a verification test. Finally, the chi-squared test is employed to find the best match. The object match is governed by both the chi-squared test and the contour group test. From these tests, a model which best matches the object can be obtained. Four objects are selected for object recognition in order to demonstrate how the system works. The experimental results verifies the theoretical work.

11. REFERENCES

1. H. Shi, F. Naghdy and C. D. Cook, "Three-dimensional modelling by parallel layers of an object using coloured liquid," *Proc. of DICTA-91, Digital Image Computing: Techniques and Applications*, pp. 97–103, Melbourne, December 1991
2. H. Zeller and G. Doemens, "Industrial applications for pattern recognition," *IEEE Proc. of Robotics*, pp. 202-213, 1982
3. J. T. Tou and C. L. Huang, "Recognition of 3-D objects via spatial understanding of 2-D images," *IEEE Conf. on Artificial Intelligence Applications*, pp. 641–646, Miami Beach, 1985.
4. J. Han , R. A. Volz and T. N. Mudge, "Range image segmentation and surface parameter extraction for 3-D object recognition of industrial parts," *IEEE 1987 Int. Conf. on Robotics and Automation*, pp. 380–386, 1987.
5. M. Oshima and Y. Shirai, "Object recognition using three-dimensional information," *IEEE Transactions on Pattern Analysis and Machine Intelligences*, Vol. 5, No. 4, pp. 353–361, 1987.
6. W. S. Yang and R. C. Luo, "View-point independent 3D curve object recognition using range data," *IEEE Int. Conf. on Robotics and Automation*, pp 2032-2037, Cincinnati, 1990.
7. D. J. Kriegman and J. Ponce, "On recognition and positioning curved 3-D objects from image contours," *IEEE Transactions on Pattern Analysis and Machine Intelligences*, Vol. 12, 12, pp. 1127–1137 '990.
8. H. Shariat, "A model-based method for object recognition," *IEEE Int. Conf. on Robotics and Automation*, pp. 1847--1851, Cincinnati, 1990
9. R. A. Brook, "Symbolic reasoning among 3-D models and 2-D images," *Artificial Intelligence*, Vol. 17, pp. 285–384, 1981.
10. R. A. Brook, "Model-based three-dimensional interpretations of two-dimensional images," *IEEE Transactions on Pattern Analysis and Machine Intelligences*, Vol. 5, No. 2, pp. 140–149, 1983.
11. T. M. Silberberg, D. Harwood and L. S. Davis, "Three-dimensional object recognition using oriented model points," *Techniques for 3-D Machine Perception* (Ed. by A. Rosenfeld), Elsvier Science Publishers B.V., North Holland, pp. 271–320, 1986.
12. M. Brady, J. Ponce, A. Yuille and H. Asada, "Describing surfaces". *Computer Vision, Graphics, and Image Processing*, Vol. 32, No. 1, pp. 1–28, 1985.
13. I. Chakravarty and H. Freeman, "Characteristic views as a basis for three-dimensional object recognition," *Proc. of the SPIE Conference on Robot Vision*, Vol. 336, pp. 37–45, Bellingham, May, 1982.
14. T. J. Fan, *Describing and Recognition 3-D Object Using Surface Properties*. Spring-Verlag, New York, 1990.
15. P. J. Besl and R. C. Jain, "Three-dimensional object recognition," *ACM Computer Surveys*, Vol. 17, No. 1, pp. 75–145, 1985.
16. R. T. Chin and C. R. Dyer, "Model-based recognition in robot vision," *Computing Surveys*, Vol. 18, No. 1, pp. 77–108, 1986.
17 Y. F. Wang and J. K. Aggarwal, "Surface Reconstruction and Representation of 3-D Scenes," *Pattern Recognition*, Vol. 19, No. 3, pp. 197–207, 1986.
18. P. Srinivasan, P. Liang and S. Hackwood, "Computational Geometric Methods in Volumetric Intersection for 3D

Reconstruction," *Proc. of IEEE Int. Conf. on Robotics and Automation*, pp. 190–195, Scottsdale, 1989.
19. H. Shi, "Automatic depth maps generation through absorption in a colour liquid", *PhD Thesis*, Department of Electrical and Computer Engineering, The University of Wollongong, Wollongong, NSW, Australia, February, 1992.
20. E. S. Pearson, *Karl Pearson*, Cambridge University Press, London, 1938.
21. C. A. B. Smith, *Biomathematics*, Charles Griffin & Company Limited, London, 1969.
22. K. A. Brownlee, *Statistical Theory and Methodology in Science and Engineering*. Second Edition, John Wiley & Sons, Inc., New York, 1965.

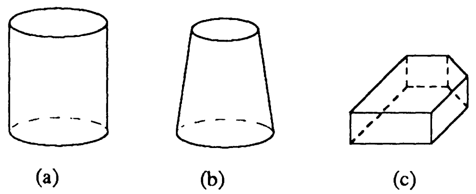

Fig. 1 Some 3-D objects

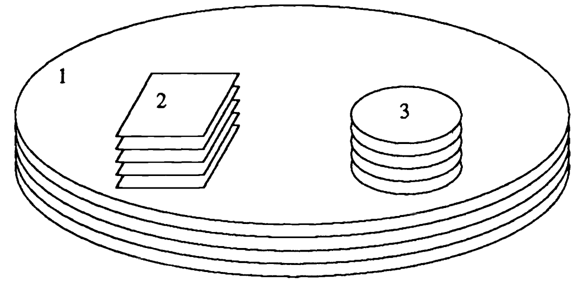

Fig. 3 An object with three contour groups

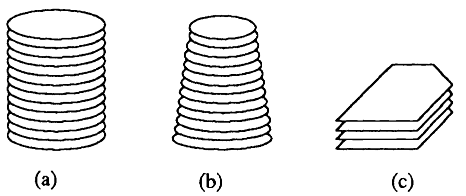

Fig. 2 3-D representations of the objects

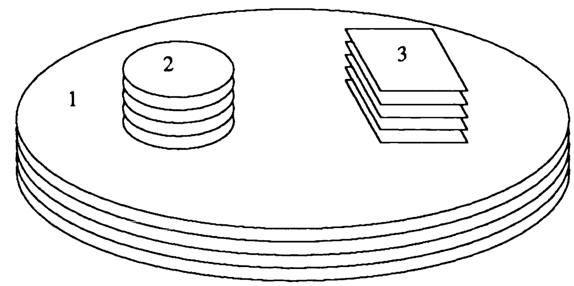

Fig. 4 A model with three contour groups

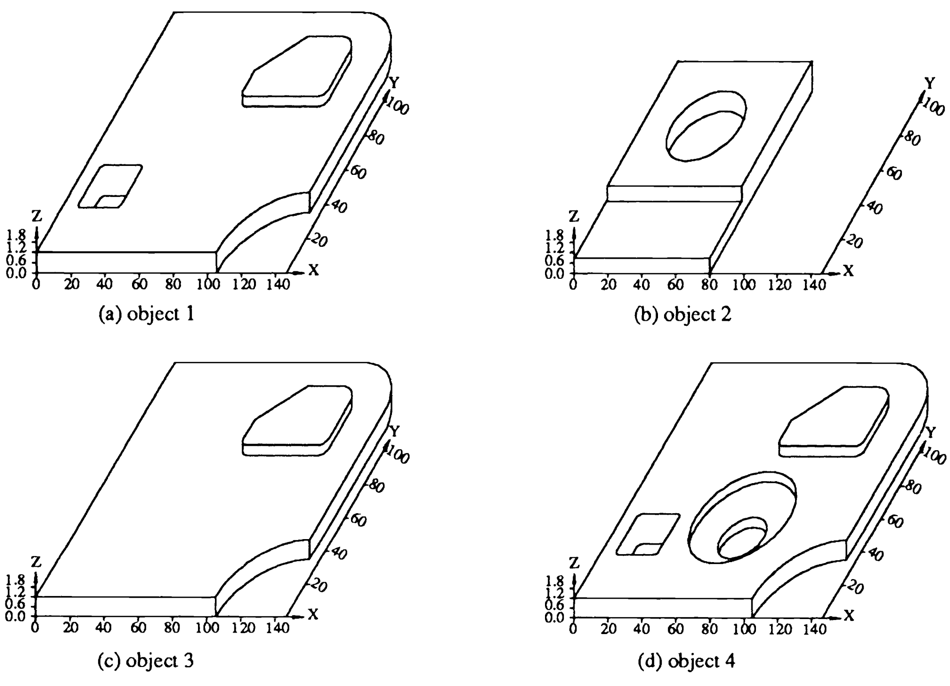

Fig. 5 The objects used for recognition

Table 1 Significant points for χ^2

ϑ	χ^2	ϑ	χ^2	ϑ	χ^2
1	3.84	11	19.67	21	32.67
2	5.99	12	21.02	22	33.92
3	7.81	13	22.36	23	35.17
4	9.48	14	23.68	24	36.41
5	11.07	15	24.99	25	37.65
6	12.59	16	26.29	26	38.88
7	14.06	17	27.58	27	40.11
8	15.50	18	28.86	28	41.33
9	16.91	19	30.14	29	42.55
10	18.30	20	31.41	30	43.77

Table 2 3-D features of objects

(a) object 1

N	N_h	N_o	N_1	N_2
3	1	0	3	0

C_n	I	ΔL_c	A	P	R/R_{min}	$\Delta R/R_{max}$	H	h
1	1	0.00	18444.6	538.4	66.4	98.1	6	0
2	1	58.5	595.2	92.2	12.4	15.6	6	1
3	1	41.9	1494.3	152.0	15.6	29.8	3	0

(b) object 2

N	N_h	N_o	N_1	N_2
3	1	1	2	0

C_n	I	ΔL_c	A	P	R/R_{min}	$\Delta R/R_{max}$	H	h
1	1	0.00	9555.5	399.0	39.8	72.0	3	0
2	1	20.0	6243.8	316.9	39.0	56.0	6	0
3		20.1	—	—	20.0	—	6	1

(c) object 3

N	N_h	N_o	N_1	N_2
2	0	0	2	0

C_n	I	ΔL_c	A	P	R/R_{min}	$\Delta R/R_{max}$	H	h
1	1	0.00	18447.7	538.3	66.4	98.1	6	0
2	1	42.1	1483.1	152.2	15.5	30.0	3	0

(d) object 4

N	N_h	N_o	N_1	N_2
5	3	2	2	0

C_n	I	ΔL_c	A	P	R/R_{min}	$\Delta R/R_{max}$	H	h
1	1	0.00	18454.0	537.8	66.4	98.1	6	0
2	1	58.5	600.5	92.9	12.4	15.6	6	1
3	0	33.2	—	—	12.8	—	3	1
4	0	33.2	—	—	27.4	—	3	1
5	1	41.9	1507.6	152.4	15.9	29.5	3	0

Table 3 The results of the three tests

(a) object 1

M	B(M,O)	R(M,O)	χ^2	Decision
1	38.6%	—	—	—
2	100.0%	95.5%	2.8	GOOD
3	66.6%	—	—	—
4	73.3%	—	—	—

(b) object 2

M	B(M,O)	R(M,O)	χ^2	Decision
1	62.0%	—	—	—
2	73.3%	—	—	—
3	53.3%	—	—	—
4	100.0%	94.4%	4.0	GOOD

(c) object 3

M	B(M,O)	R(M,O)	χ^2	Decision
1	41.3%	—	—	—
2	66.6%	—	—	—
3	100.0%	96.2%	4.2	GOOD
4	62.0%	—	—	—

(d) object 4

M	B(M,O)	R(M,O)	χ^2	Decision
1	100.0%	93.7%	4.0	GOOD
2	38.6%	—	—	—
3	41.3%	—	—	—
4	62.0%	—	—	—

Table 4 The results of object recognition

Model Number	Object Number			
	1	2	3	4
1	—	—	—	GOOD
2	GOOD	—	—	—
3	—	—	GOOD	—
4	—	GOOD	—	—