퍼지화 영상데이타의 일치도연산에 의한 3차원물체의 식별

Three-Dimensional Object Discrimination by the Similarity Measures of the Fuzzified Image Data

조 동 욱*, 김 지 영*, 유 흥 균**
(Dong Uk Cho*, Ji Yeong Kim*, Heung Gyoon Ryu**)

ABSTRACT

Fuzzy theory is utilized in recognizing 3-D objects from input range data through feature extraction. Shape features are extracted from the Z-gradients and geometric features are extracted from the normal vectors of the surface patches. Then feature data are fuzzified to get similarity measure, which is used to perform matching operation between the prototype objects and the input scene object. Finally, the effectiveness of the method is demonstrated through various experiments.

요 약

본 논문에서는 입력으로 들어 온 레인지데이타에서 특징추출을 통하여 3차원물체를 식별하는 방법을 제안하고자 한다. Z축기울기를 이용하여 형상특징을 추출하고, 각 표면조각에서 법선벡터를 구해 기하학적 특징을 추출한다. 그 후 위에서 구한 특징들을 퍼지화데이타로 만들어 일치도 연산에 의해 표준 물체와 입력화상 물체 사이의 정합을 수행한다. 최종적으로 본 논문의 유용성을 실험에 의해 입증하고자 한다.

I. Introduction

As one of the grand human objectives, to make a machine to perceive and recognize the objects and their environments to the level of human being has been drawing much attention and research as the potential application areas of computer vision seem to be limitless. Automatic inspection of parts in factories, recognition of car number plate,, X-ray image processing, and target tracking, ALV, etc. are some of the areas in which computer vision is making remarkable progress[1]-[3]. Recent efforts to overcome the limitations of 2-D image recognition such as occlusion processing, distinction between curved surfaces and planar surfaces, lead to some noticeable results in 3-D image recognition[4]-[6]. In this paper a method is proposed to discriminate 3-D objects using the range data input.

The Z-gradient from the input range data is used to extract the shape feature of the object and the intersecting points of the normal vectors to the surface patches are used to extract the

* : 서원대학교 전자계산학과
** : 충북대학교 전자공학과
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geometric features, such as the axis equation. Also the features such as the intersection angles and distances are used to establish the relationship among the surface regions. In the discrimi nation process, the existing method determines the confidence level of the numerical data and performs matching operation with the prestored prototype objects. In this case, false recognition occurs when the confidence interval is inappropriately set. Hence the confidence value is decided roughly after some trial and-error processes.

However, humans discriminate objects by setting some conceptual confidence interval which is naturally fuzzy.

The recent trends in computer vision shows the frequent application of the fuzzy thory[7]~[9]. For example, through the use of the fuzzy theory, better results are shown in the recognition of two-dimensional human face images [7] and hanguel character recognition[8].

In the 3-dimensional computer vision, to over come the difficulty in finding the correspondance in the stereo images the fuzzy theory is also applied[9]. However, the application of the fuzzy theory in the previous works and limited to 2-dimensional image recognition or to get the range data. In this paper, the fuzzy theory is tried in the discrimination process for 3-dimensi onal image, which is considered to be vital for the realization of truly versatile computer vision sys tem.

The same human nature is utilized and fuzzy theory is adopted in the object discrimination. Similarity between the prototype object and the input scene object is measured by the min-max operation on the degree of match between them. Additionally the weight of each feature is included in computing the final confidence levels.

II. Feature Extraction[10]

In this paper according to the Z-gradient values the shape features of the objects are classified into the combinations of sphere, cylinder, cone, plane, then the intersection points by normal vectors are used to extract the geometric feature of each surface region and the features such as the intersection angles and distances are used to establish the relationship among the surface regions. The edge surface direction map, inner surface direction map and equi-magnitude contour of the Z-gradients furnish the necessary primitives.

Directional value in the direction map is direc tional change in the depth value taken from 2*2 mask as show in figure 1.

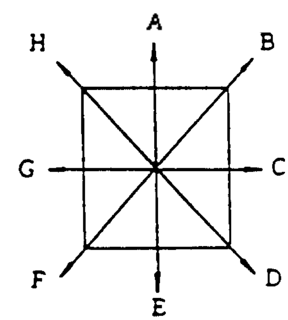


Fig 1. Direction of the Z-gradient

For example, since the image of a cylinder taken from the front has 4 directional measures, A, E, C and G,4 relations of 180-degree, 4 relations of 90-degree and no relations of 45 degree.. Therefore the flag value is 440. Fig. 2 shows the example of the various primitives. Also the kernel points are defined and the clustering operation is performed. The planar equation of Ax+By+Cz=D of the planar surface is obtained from surface patches. The geometric features of sphere, cylinder and cone are extracted from the surface patches through normal vectors Vp=(Xo+At, Yo+Bt, Zo+Ct). From the intersection points of the normal vectors, the center point for a sphere(point), the axis equation for a cylinder and cone (line) are computed and used to estab lish the relationships among the surface regions as shown in Table 1.

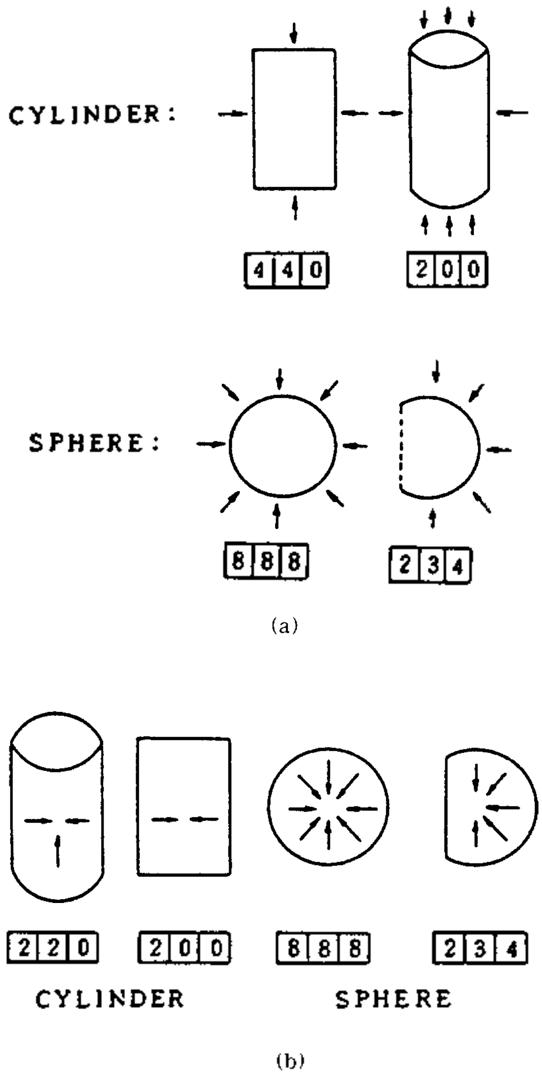


Fig 2. (a)Edge surface direction map
(b)Inner surface direction map

Table 1. Relations of the surface regions

Combinations of features		Extracted features
point	, point	distance
line	, line	intersection angle
point	, line	distance
point	, plane	distance
plane	, plane	intersection angle
plane	, line	intersection angle

Ⅲ. Discrimination Procedure

To discriminate the objects the existing method performs the matching operation by comparing the numerical feature values. In this process the determination of the error value is done by trial and error, which is one of the reasons leading to false recognition. In this paper we utilize the fuzzy theory in matching process to overcome the limitations of the existing method, i.e. the similarity measure is computed by the min-max operation and confidence interval is determined in consideration of the weight for each feature.

1. Formulation of Fuzzified Data

1) Scaling

To recognize the object regardless of its size and to get the fuzzified data, the scaling operation is performed using the following equations :

$$T = \sum_{i=1}^{n} P_i \tag{1}$$

$$SP_j = \frac{P_j}{T} \tag{2}$$

where T is the sum of the areas of all surfaces and SP_j is the normalized area of the surface region P_j.

2) Expression of Fuzzified Data

Among the various methods available to represent fuzzified data, we use triangular form which embodies human concepts very well and is computationally simple. Also one study shows that

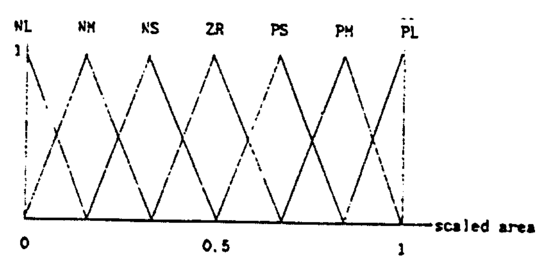


Fig 3. Magical Number

when we express our absolute feelings it is done in the levels of magical number seven[8]. We adopt seven levels in expressing the scaled area of each surface region as shown in Figure 3.

Where NL is a Negative Large, NM is a Negative Medium, NS is a Negative Small, ZR is a Approximately Zero, PS is a Positive Small, PM is a Positive Medium & PL is a Positive Large. For example, the membership degree of ZR of the scaled area is expressed as follows :

$$
A=(0.33,\ 0.5,\ 0.67)
$$

$$
\text{where } \mu_{A(x)} = \begin{cases} 0 & ,X<0.33 \\ \dfrac{X-0.33}{0.17} & ,0.33\le X\le 0.5 \\ \dfrac{0.67-X}{0.17} & ,0.5\le X\le 0.67 \\ 0 & ,X>0.67 \end{cases} \tag{3}
$$

Among the relationships between surface regions, the fuzzification of the intersection angles is done by coding process to the direction of 18, which the same angle of 10 degree. Here an 18-step fuzzy number is obtained by dividing 180 degree of maximum possible intersection angle with 10 degrees. Also to obtain the fuzzified data of the distance is done according to expression (4) and the triangular fuzzy number for the normalized distance value is formulated within the limits of ± 20 from its own value.

$$
\frac{\text{Less values of area sum between prototype \& input}}{\text{Greater values of area sum between prototype \& input}} \times (\text{greater distance value between prototype \& input}) \tag{4}
$$

2. Discrimination Process

1) Determination of Dominant Primitive and Ratio

We discriminate an object by taking the dominant shape out of it. We call the primitive formed by the dominant shape of an object, the dominant primitive (DP) and the ratio of the DP for each object the DP ratio (DPR), the expression of which are :

$$
DP = \max\ (P_j,\ S_j,\ CY_j,\ C_j) \tag{5}
$$

$$
DPR = \frac{\text{area of DP}}{\text{Area of Surface Region}} \times 100 \tag{6}
$$

Where P_j, S_j, CY_j and C_j represent the total areas of planar surface, sphere surface, cylinder surface and cone surface, respectively.

2) Discrimination Procedure

Figure 4 shows how the discrimination is done on an object.

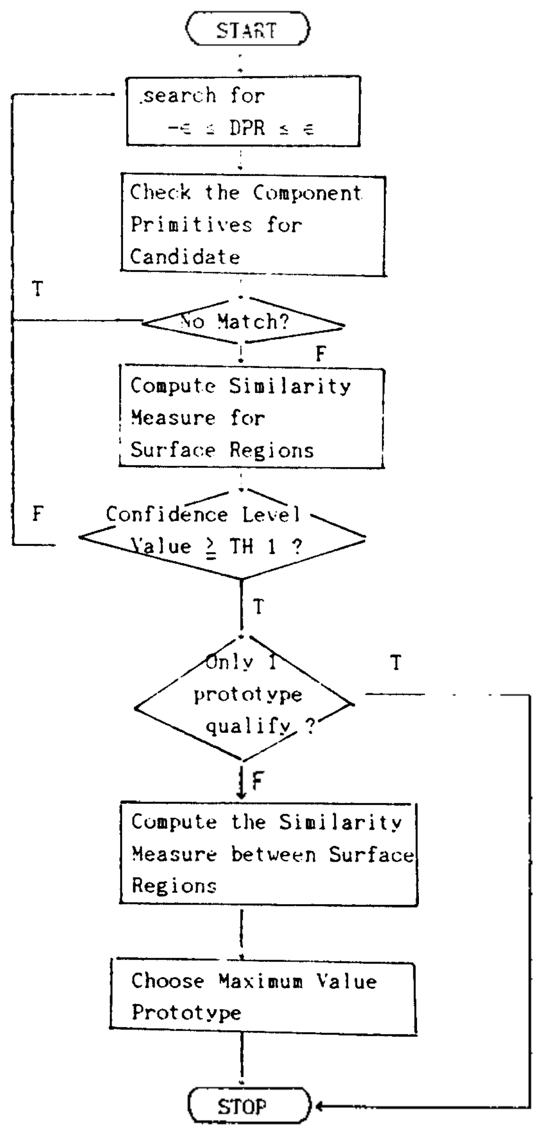


Fig 4. Flowchart of the Discrimination Process

3. Computations of the Similarity Measure & Confidence Level

Next step is to compute the similarity measure between the images of the prototype and the input scene objects. The similarity measure is the degree of match between prototype and input object. Existing method relies on the simple comparision of the corresponding numerical data, the results of which usually do not reflect true likeness correctly. To improve results we introduce the fuzzy theory, which best assimilate human mind in discriminating the objects as small, medium, big, etc. In this paper, first the numerical area data of the prototype and the input scene objects are scaled, then the triangular fuzzy numbers are computed to get the similarity measure between prototype and input.

Next, the min-max operation is performed as shown in Figure 5 to get the similarity measure between the surface region area values of the prototype object and the input scene object.

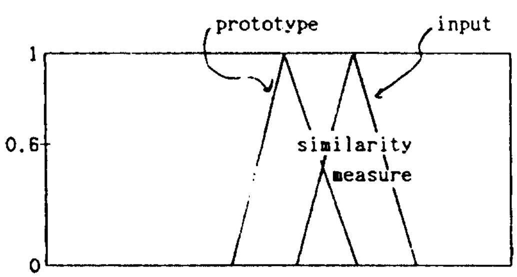


Fig 5. Example of Similarity Measure Computation

Also humans discriminate the objects by taking the dominant shape from the object into consideration. To emulate this human's object discrimination process, the computation of confidence level values according to the size of object area is performed such that the dominant shape feature is to influence toward the higher confidence level for the corresponding image area.

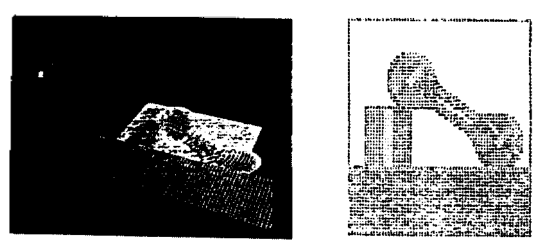
Hence, the confidence level value of object is computed as,

$$\text{Confidence Level value} = \sum \text{(Scaled value of each surface region)} \cdot \text{(similarity measure of } 0 \sim 1) \quad (7)$$

Even though several objects are formed by the same shapes of the same sizes, they must be distinguished if they have different intersection angles and distances between the surface regions of the shape features in them. To accomodate this difference the similarity measure is computed between every adjacent surface regions. This is done by the min-max computation if there are object which exceed TH1 value as shown in Figure 4. At this time since it is not necessary to consider the weights for the intersection angles and distances, only the mean value of similarity measures are computed and the final decision about the discrimination is made at the object which has the highest confidence level value.

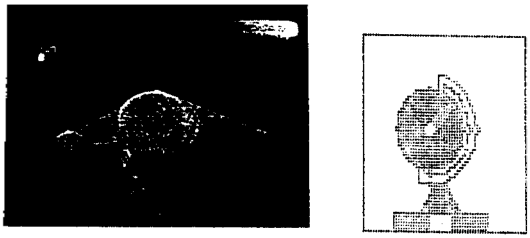
Ⅳ. Experimental Results

To test the effectiveness of the proposed method, experiments have been performed with the C language program run on an IBM-PC / AT computer. (a) of figures 6~9 show the synthetic range data for the prototype objects and (b) of figures 6~9 show their direction maps. Also (a) of figures 10 and 11 are the input synthetic range data and those of (b) are their direction maps.



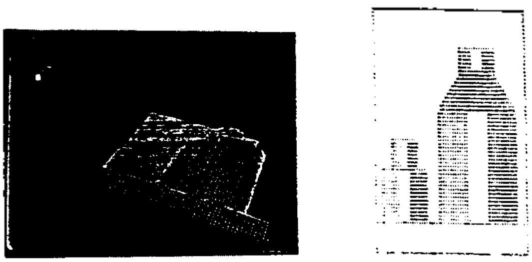
(a) (b)

Fig 6. (a)prototype range data of the plane, cup & dumbbell
(b)direction map of the plane, cup & dumbbell



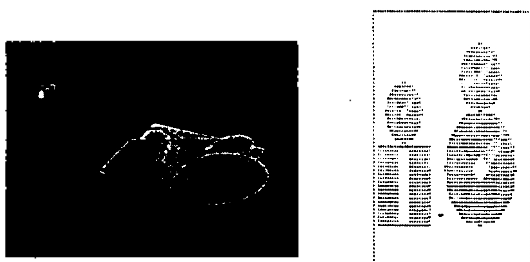
(a) (b)

Fig 7. (a)prototype range data of the globe
(b)direction map of the globe



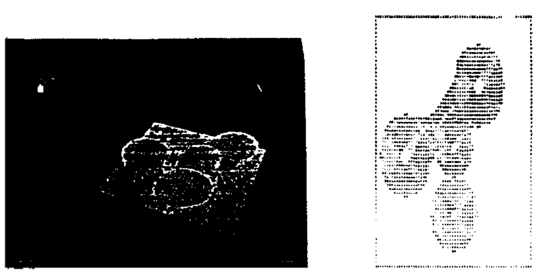
(a) (b)

Fig 8. (a)prototype range data of the liquid & thermobottle
(b)direction map of the liquid & thermobottle



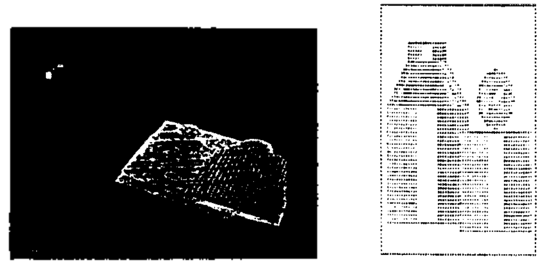
(a) (b)

Fig 9. (a)prototype range data of the toy & tumbling doll
(b)direction map of the toy & tumbling doll



(a) (b)

Fig 10. (a)input range data of the dumbbell & tumbling doll
(b)direction map of the dumbbell & tumbling doll



(a) (b)

Fig 11. (a)input range data of the toy & thermo-bottle
(b)direction map of the toy & thermo-bottle

Table 2 represents the feature values of the prototype objects which are the DP and DPR computed using expressions (5) and (6) after extracting the shape feature of the object by Z gradient. In the discrimination process to reduce the search time the largest area surface region is chosen as the kernel, the values of which are in "primitive" column. The area and the corresponding scaled area values are in the "area & its ratio" column.

Table 2. Feature values for the prototype objects

object name	DP, DPR & Kernel	Primitives	area & its ratio	features between surface regions
plane	plane	plane1	2317.112(100)	
	100			
	plane1			
cup	cylinder	cylinder1	5911.221(100)	
	100			
	cylinder1			
dumbbell	sphere	sphere1	9505.798(40)	30.327
	88	cylinder1	2979.361(12)	45.231
	sphere2	sphere2	11030.823(48)	171.754
globe	sphere	sphere1	25655.566(53)	45.263
	53	cone1	5917.859(12)	0.4374
	sphere1	cylinder1	15493.862(33)	62.311
liquid	cylinder	cylinder1	2726.902(23)	
	100			0.3012
	cylinder2	cylinder2	9148.317(67)	
thermo	cylinder	cylinder1	2741.039(6)	0.5082
bottle	83	cone1	7664.737(17)	0.4856
	cylinder2	cylinder2	35141.855(77)	0.1637
toy	cylinder	sphere1	7265.520(33)	19.393
	70			
	cylinder1	cylinder1	11534.580(67)	
tumbling	sphere	sphere1	10002.894(25)	
doll	100			113.605
	sphere2	sphere2	30899.707(75)	

Also shown are the relations of the surface regions(refer table 1) in the column of "feature between surface regions." The values of table 3 is computed for the input scene object in the same way as for table 2.

Table 4 shows the similarity measures and confidence level values between the images of the prototype and the input scene objects computed by "magic number 7" triangular fuzzy number from table 2 and 3 scaled area values.

The similarity values are obtained by the min-max operation and the confidence level values are computed by expression(7) to give different contribution by the area size. In the "similarity measure" column of table 5, the geometric feature values between surface regions are fuzzified and the results of min-max opeation on the prototype and input scene objects are shown. Meantime, the confidence level values are the arithmetic means of the similarity measures among the surface region.

Table 4 and 5 show that the objects (dmbbell, thermo-bottle) properly scaled to the sizes of prototype objects give higher similarity and confidence level values, while the objects, eventhough they are the same shapes as the prototype objects, display lower values. This is analogous to human perception, in which discrimination process becomes hesitant when there is disparity in the sizes for the same shape objects.

Table 3. Feature values for the input objects

object no	DP, DPR & kernel	Primitives	area & its ratio	features between surface regions
1	sphere	sphere1	15645.195(40)	38.857
(dumbbell)	80	cylinder1	7609.126(20)	44.352
	sphere1	sphere2	15582.550(40)	174.954
2	sphere	sphere1	7740.946(40)	
(tumbling	100			85.000
doll)	sphere2	sphere2	11725.932(60)	
3	cylinder	sphere1	7265.520(22)	
(toy)	78			47.427
	cylinder1	cylinder1	26363.870(78)	
4	cylinder	cylinder1	2033.489(5)	0.4723°
(thermo	84	cone1	6737.832(16)	0.5194°
bottle)	cylinder2	cylinder2	33150.091(79)	0.4368°

Table 4. Results of similarity measure & confidence level value for each surface regions

Object Name	Similarity Measure	Confidence Level Value
dumbbell	1.0 1.0 0.5	0.8
tumbling doll	0.5 0.5	0.5
toy	0.5 0.5	0.5
thermo bottle	1.0 1.0 1.0	1.0

Table 5. Results of similarity measure & confidence level value among surface regions

Object Name	Similarity Measure	Confidence Level Value
dumbell	0.95 0.975 1.0	0.975
tumbling doll	0.3	0.3
toy	0.95	0.95
thermo bottle	1.0 1.0 1.0	1.0

V. Conclusions

The similarity measure by the min-max operation of the fuzzy theory is introduced in the 3-D object discrimination process. To overcome the limitation of the existing method, the features are normalized and the weights are set in computing the confidence level values. In this work, only 4 major primitives and areas are considered, in which very good results are shown.

So, it is necessary to extend this study to other objects by increasing number of primitives and applying the methods other than area consideration to extract better geometric features.

Also it is well-known that for the complex shape objects, the shape feature extraction, geometric feature extraction and feature extraction among surface regions are the open areas for further research. Finally we are grateful for In-Ho Lee & No geon Kwak for their fine word processing job.

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▲**Dong-Uk Cho**(Regular Member)

He received the B.S. M.S and ph.D in Electronic Engineering all from the Hanyang University in 1983, 1985 and 1989 respectively. He is an assistant professor of computer science and engineering at Seowon University, Chongju since 1991.

Before joining Seowon University faculty, he was an assistant professor of telecommunication engineering at Dongyang Technical College for 2 years.

His research interests inclyde computer vision, fuzzy set theory and neural network . He is a member of the IEEE PAMI and KITE

▲**Heung-Gyoon Ryu**(Regular Member) vol.12.No. IE

▲**Ji-Yeong Kim**(Regular Member)

He is an associate professor of computer science and engineering at Seowon University, Chongju since 1989. His research interests include system performance evaluation, computer vision and tele-measuring and controlling system.

Before joining Seowon University faculty, he wae the Chief Research Scientist at the Central Research Center at Oriental Precision Company Ltd. for 2 1/4 years. Before then he was an assistant professor of computer science and engineering at Auburn University, Auburn, Alabama for a year.

He received M.B.A in MIS and M.S and ph. D in computer science all from the state University of New York at Binghamton NY. in 1977, 1979 and 1984 respectively. He is a member of the IEEE Computer and Communication Societies and the ACM