Proceeding of the IEEE
International Conference on Automation and Logistics
Zhengzhou, China, August 2012

Application of Improved HU Moments in Object Recognition

Lei Zhang, Fei Xiang , Jiexin Pu and Zhiyong Zhang

Electronic Information Engineering College
Henan University of Science&Technology
Luoyang, Henan Province, China

why219@163.com

Abstract **- HU moments aren't invariant for scaling in the discrete state, so they are improved in the paper. The improved moments are consistent with region, boundary and discrete situation. Therefore, they are applied to three-dimensional object recognition. Firstly the improved moments are calculated. Then the similarity measure is computed between objects to be recognized and the standard one. Finally experiments are simulated by MATLAB, and experimental results demonstrate that the improved moments are invariant to the translation, rotating and scaling of objects, the recognition rate is relatively high and the proposed algorithm has some practical value. So the feasibility of the proposed method is proved in the paper.**

Index Terms – object recognition, HU moments, improve, similarity measure.

I. INTRODUCTION

There is a wide range of application for 3D object recognition, such as industry, agriculture, military, medical and so on. Therefore, object recognition is one of the focuses of computer vision and pattern recognition. Object in the actual environment affected by illumination, noise, partial occlusion, geometric transformation and position in the field of view may cause some difficulty for object recognition. At present, there are many ways to object recognition, such as SVM, neural network, invariant moments, Markov model Etc. Three eigenvectors, Colour moments, texture features, and the affine-invariant Fourier descriptors were extracted from 2D images of 3D objects, and then were inputted to SVM in order to train and recognize in [1]. For objects perspective changed, the proposed method in [1] was very limited. The feature, shape of the object was described by chain code, and then was inputted to back propagation neural network, the output was the membership of object in [2]. The proposed method in [2] had some limitations of the integrity of chain code, so the recognition rate was not very high. In [3], the local feature of object was represented by densely sampled grids, and a Markov random field model was used to model, then the highest confidence first method was used to match images in order to recognize objects. The method had large amount of calculation. In [4], exponents of two second order moments and five moment invariants were as features, and then recognition of planes and cars was performed by the range of eigenvalues. The method could only recognize objects of orthophoto. Therefore, different methods should be designed for different classes of objects and for different groups of assumed deformations. Then recognizing translated, rotated or scaled objects is of priority concern issue.

Invariant moments were firstly proposed by HU in 1962, and the theory is used to extract the features of grayscale images. At that time the moments were mainly used to recognize shapes of objects. The moments are invariant to the translation, rotating and scaling of objects in a continuous state. But they are not invariant to the scaling in a discrete state. Therefore, the moments are mainly used to recognize objects of closed shape. The invariant moments were improved based on [6] in the paper. Then the improved moments were used to recognize regions, boundaries and objects of closed and not closed shape. Therefore, the proposed algorithm can be applied to Columbia Object Image Library (COIL-100). The performance of the method is demonstrated by experiments. The experimental results show that the improved HU moments are invariant to the translation, rotation and scaling and the recognition rate is rather high. So the proposed algorithm is effective and valuable.

II. THE IMPROVED HU MOMENTS

A. The HU Moments

The two-dimensional invariant moments of $(p+q)$ order of a digital image $f(x,y)$ are defined in (1).

$$m_{pq} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} x^p y^q f(x,y)dxdy \qquad p,q=0,1,2,\cdots \tag{1}$$

and the central moments are defined in (2).

$$\mu_{pq} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} (x-\bar{x})^p (y-\bar{y})^q f(x,y)dxdy \qquad p,q=0,1,2,\cdots \tag{2}$$

Here, $(\bar{x},\bar{y})$ the centroid of grayscale image $f(x,y)$ may be defined as

$$\bar{x} = m_{10}/m_{00} \qquad \bar{y} = m_{01}/m_{00} \tag{3}$$

The central moments are used to normalize the moments. η_{pq}, the normalized central moments of $(p+q)$ order are given in (4).

$$\eta_{pq} = \mu_{pq}/\mu_{00}^{r} \qquad r=(p+q+2)/2 \qquad p+q=2,3,\cdots \tag{4}$$

HU proposed seven invariant moments by using the normalized central moments of second-order and third-order. The first six moments are given in (5).

The theory of invariant moments is more and more widely used in object recognition and classification. Then

978-1-4673-0364-4/12/$31.00 ©2012 IEEE

Chen proposed a fast algorithm to calculate the regional invariant moments with regional boundaries. The origin moments of $(p+q)$ order he used are given in (6).

$$\begin{cases} \phi_1 = \eta_{20} + \eta_{02} \\ \phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}{}^2 \\ \phi_3 = (\eta_{30} - 3\eta_{12})^2 + (\eta_{03} - 3\eta_{21})^2 \\ \phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\ \phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12}) \cdot [(\eta_{30} + \eta_{12})^2 \\ \quad - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \\ \quad \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\ \phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\ \quad + 4\eta_{11}[(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})] \end{cases} \tag{5}$$

$$m'_{pq} = \int_C x^p y^q f(x,y) ds \tag{6}$$

The central moments of $(p+q)$ order he used are given in (7).

$$\mu'_{pq} = \int_C (x-\bar{x})^p (y-\bar{y})^q f(x,y) ds \tag{7}$$

Here, C represents a smooth curve, and $(\bar{x}, \bar{y})$ is defined in (3).

To calculate the boundary moments, we can not directly make use of the formula of regional moment, and we must improve the formula of the regional moment. For any region $f(x,y)$, the scaling transformation can be described as $x' = tx, y' = ty$, and the corresponding moments multiply t^2, t^p, t^q accordingly, here t^2 is changed by the object area which is caused by scaling. If the curve, the scaling transformation will the change of the object perimeter, so the change factor is t. The central moments can be simplified as $\mu' = \mu_{pq} \cdot t^{p+q+1}$. According to the scaling invariance, we can obtain $\eta'_{pq} = \eta_{pq}$, the detailed description is given in (8).

$$(\mu_{pq} \cdot t^{p+q+1}) / (\mu_{00} \cdot t)' = \mu_{pq} / (\mu_{00})' \tag{8}$$

Thus we can describe as (9).

$$\eta'_{pq} = \mu_{pq} / \mu_{00}^r \qquad r = p+q+1, p+q = 2,3,4,\cdots \tag{9}$$

B. The Improved HU Moments

In the discrete case, the origin moment and central moments of $(p+q)$ order with the two-dimensional functions $f(x,y)$ are defined in (10) and (11).

$$m'_{pq} = \sum_{x=1}^{M} \sum_{y=1}^{N} x^p y^q f(x,y) \tag{10}$$

$$\mu'_{pq} = \sum_{x=1}^{M} \sum_{y=1}^{N} (x-\bar{x})^p (y-\bar{y})^q f(x,y) \tag{11}$$

In the discrete case, assuming that the scaling transformation factor is n, the changed coordinates are (x', y'), the relationships between the changed and unchanged coordinates are given in (12).

$$x' = nx \qquad y' = ny \tag{12}$$

When we Substitute (12) for (11), the changed central moments μ''_{pq} can be given in (13).

$$\mu''_{pq} = n^{p+q} \mu_{pq} \tag{13}$$

When we Substitute (13) for (4), the new central moments η''_{pq} can be given in (14).

$$\eta''_{pq} = \mu''_{pq} / \mu_{00}^r = n^{p+q} \eta_{pq} = (n^{p+q} \mu_{pq}) / \mu_{00}^{(p+q+2)/2} \tag{14}$$

From the previous, we see that the scale factor n has a certain impact on the moments η_{pq}. Further we can conclude that the seven HU invariant moments do not have the proportion of invariance in the discrete case.

For regional and boundary invariant moments, the formulas of normalized central moments to calculate are different. In the discrete case, the scaling transformation also has an impact on the normalized central moments, therefore, we must improve the invariant moments, not only in order to apply to calculate the regional and boundary invariant moments, but also in order to meet a proportion of invariance in the discrete case.

According to (4), (9) and (14), we carry out the moments which are given in (15) after a series of transformations.

$$\begin{cases} \eta_{pq} = \mu_{pq} / \mu_{00}^{(p+q+2)/2} \\ \eta'_{pq} = \mu_{pq} / \mu_{00}^{p+q+1} \\ \eta''_{pq} = n^{p+q} \eta_{pq} = n^{p+q} \mu_{pq} / \mu_{00}^{(p+q+2)/2} \end{cases} \tag{15}$$

From (15), we can conclude that these three formulas have the same factor μ_{pq}, the coefficient of the front forms by μ_{00} and the scale factor n. Therefore the impacts by the two on these three formulas are equivalent. If these three formulas remove μ_{00} and the scale factor n at the same time, the invariant moments have nothing to do with the area of objects, the scaling transformation of structure, and then the invariant moments with only μ_{pq} can be obtained. The invariant moments not only simplify the calculation process, but also facilitate the identification and classification of objects. According to this idea, for the purpose of generality and university, a set of invariant moments is derived as following by using (5) and (15).

$$\begin{gathered} \beta_1 = \sqrt{\phi_2} / \phi_1, \quad \beta_2 = \phi_2 / (\phi_1^2 + \phi_2), \quad \beta_3 = \sqrt{\phi_4} / \sqrt{\phi_3}, \\ \beta_4 = \phi_3 / \phi_1^3, \quad \beta_5 = \phi_5 / \phi_3^2, \quad \beta_6 = \phi_6 / (\phi_1 \bullet \phi_3) \end{gathered} \tag{16}$$

Here, to reduce the computational complexity of the formulas, we only make use of the first six HU invariant moments ϕ_1, ϕ_2, ϕ_3, ϕ_4, ϕ_5, ϕ_6. $\phi_1 \sim \phi_6$ can meet the region's translation, rotation and scale invariance.

In order to prove that the improved HU moments are consistent with the boundary moments, regional moments and the discrete state, we take β_1 as example to illustrate. The other moments can also be proved using the same method.

According to (17), (18) and (19), we can obtain $\beta_1 = \beta'_1 = \beta''_1$. Using the same method, we can also obtain,

$\beta_2 = \beta_2' = \beta_2''$, $\beta_3 = \beta_3' = \beta_3''$, $\beta_4 = \beta_4' = \beta_4''$, $\beta_5 = \beta_5' = \beta_5''$, $\beta_5 = \beta_5' = \beta_5''$, $\beta_6 = \beta_6' = \beta_6''$. This proves the improved HU moments are the same to regions, boundaries and discrete case.

$$\beta_1 = \sqrt{\phi_2}\Big/\phi_1 = \sqrt{(\eta_{20}-\eta_{02})^2 + 4\eta_{11}{}^2}\Big/(\eta_{20}+\eta_{02})$$
$$= \sqrt{(\mu_{20}-\mu_{02})^2/\mu_{00}^4 + 4\mu_{11}{}^2/\mu_{00}^4}\Big/(\mu_{20}/\mu_{00}^2 + \mu_{02}/\mu_{00}^2) \quad (17)$$
$$= \sqrt{(\mu_{20}-\mu_{02})^2 + 4\mu_{11}{}^2}\Big/(\mu_{20}+\mu_{02})$$

$$\beta_1' = \sqrt{\phi_2'}\Big/\phi_1' = \sqrt{(\eta_{20}'-\eta_{02}')^2 + 4\eta_{11}'^2}\Big/(\eta_{20}'+\eta_{02}') =$$
$$\sqrt{(\mu_{20}-\mu_{02})^2/\mu_{00}^4 + 4\mu_{11}{}^2/\mu_{00}^4}\Big/(\mu_{20}/\mu_{00}^2 + \mu_{02}/\mu_{00}^2) \quad (18)$$
$$= \sqrt{(\mu_{20}-\mu_{02})^2 + 4\mu_{11}{}^2}\Big/(\mu_{20}+\mu_{02})$$

$$\beta_1'' = \sqrt{\phi_2''}\Big/\phi'' = \sqrt{(\eta_{20}''-\eta_{02}'')^2 + 4\eta_{11}''^2}\Big/(\eta_{20}''+\eta_{02}'') =$$
$$\sqrt{n^4[(\mu_{20}-\mu_{02})^2/\mu_{00}^4 + 4\mu_{11}{}^2/\mu_{00}^4]}\Big/[n^2(\mu_{20}+\mu_{02})/\mu_{00}^2] \quad (19)$$
$$= \sqrt{(\mu_{20}-\mu_{02})^2 + 4\mu_{11}{}^2}\Big/(\mu_{20}+\mu_{02})$$

Because the invariant moments change with a wide range, in order to compare, we take use of the logarithm for data compression. Therefore, the invariant moments actually used in this paper is defined in (20).

$$\beta_i = \left|\lg|\beta_i|\right| \quad (20)$$

HU invariant moments are applicable to the closed shape of objects recognition, while the improved invariant moments are applicable to the area, unclosed and closed shape of objects recognition and classification. We can calculate the feature vector $(\beta_1', \beta_2', \beta_3', \beta_4', \beta_5', \beta_6')$, to be identified samples using the mentioned method, and match the feature vectors and standard ones (β_1, β_2, β_3, β_4, β_5, β_6'), calculated in advance. Then objects recognition and classification are performed with a similarity measuring function.

To calculate the similarity measuring function, the normalized function is defined as bellow

$$f(\theta) = \begin{cases} \theta & \theta < 1 \\ 1/\theta & \theta \ge 1 \end{cases} \quad (21)$$

Accordingly, the similarity measuring function is defined as bellow

$$s = \sum_{i=1}^{6} f(\beta_i'/\beta_i)\Big/6 \quad (22)$$

The more the similarity measuring function s is close to 1, the higher the similarity is. Accordingly the higher matching degree is, the higher objects recognition rate is. On the contrary, the more the similarity measuring function s is close to zero, the lower the similarity is. Accordingly the lower matching degree is, the lower objects recognition rate is.

III. APPLICATION OF IMPROVED HU MOMENTS IN OBJECT RECOGNITION

A. Simulation Experiments for Objects Recognition

To confirm the effectiveness of our proposed method, we performed experiments using MATLAB 7.0 on a personal computer with a Pentium IV-2.8G CPU, RAM DDR 512M. The experimental objects were acquired from COIL-100. COIL-100 is a large image database used to test object recognition by many researchers currently. The database consists of 100 colour images of the appearance of very different 3D objects. The objects were placed on a motorized turntable against a black background. The turntable was rotated through 360 degrees to vary object pose with respect to a fixed colour camera. Images of the objects were taken at pose intervals of 5 degrees. This corresponds to 72 poses per object. The images were size normalized. COIL-100 is available online. The image resolution is 128X128 pixels.

To test the effectiveness of the improved HU moments to recognize objects, we choose four different cups of COIL-100 which are too similar in appearance for experiments. Each object has 24 sample images with translation, rotation and scaling. Therefore, a total of 96 samples of the four categories of objects are used for system training. We digitize these colour image samples, and convert it to a 256 grayscale image before formally training and testing so as to fulfil feature extraction, and save them with PNG, image size 128x128 pixels. Grayscale images of the experimental samples are showed in Fig.1. (a) is a standard image, (b)、(c)、(d)are different from (a), those are three different image of other cups. The corresponding invariant moments and similarity measures between the last three cups image and the standard one are illustrated in Table I.

From Table I we can see that there are obvious differences between invariant moments of the standard image and those of other images. The maximum similarity measure s, between the images of other three cups and the standard ones is 0.5513. Because the more the similarity measuring function is close to 1, the higher matching degree is, the standard image can be identified from the other cups, if the threshold of the similarity measuring function is set appropriately, such as 0.5600.

B. Experimental results and analysis

To test the performance of the proposed method better, we do some experiments with the same objects in different states for objects recognition further. Some cup samples with translation, rotation and scaling are showed in Fig. 2. (a) is a standard image, (b) is the translated, (c) is the enlarged image

TABLE I
The improved HU moments of the four different cups

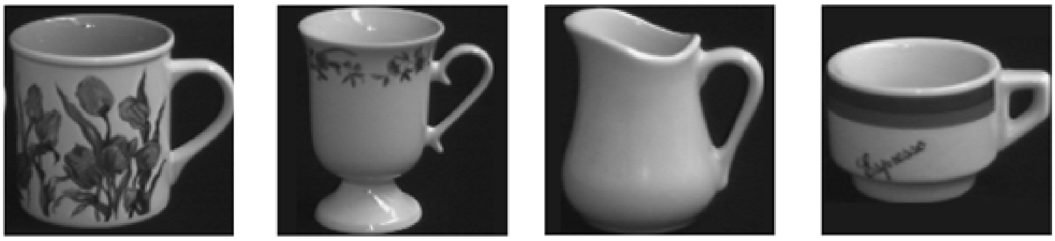
	(a)	(b)	(c)	(d)
β_1	0.5736	0.3141	0.4057	0.0612
β_2	0.6302	1.2250	1.0621	0.4852
β_3	0.1095	0.7896	0.0032	0.3025
β_4	0.0529	0.0329	0.0045	0.0139
β_5	0.0216	0.0343	0.0048	0.0158
β_6	0.4971	0.5810	0.3217	0.0587
s		0.5513	0.3807	0.4818

after 1.2 times, (d) is the reduced image after 0.8 times, (e) is the image rotated 30°, (f) is the image rotated 90°. The tested results are showed in Table II.

The part of similarity measure between different posed images of the same cup and the standard one is listed in Table II. Translation includes moving up, down, left, right, as illustrated in Table II. For rotation, because the case of 180°-360°and 0°-180°is completely symmetrical, the similarity measure between the different posed images of 0°-180°and the standard is only listed. For scaling, some enlarged or reduced case is listed, and other cases can also be obtained by experiments.

From Table II we can see that the similarity measure between the translated image and the standard one is 1, when the cup translates in any direction, which indicates the improved invariant moments with translation is the same as that with the standard image. Therefore, we can conclude that the improved invariant moments are translational invariance. When the rotation with angle of 90°and 180°, the similarity measure between the rotated image and the standard one is also 1, which shows that the improved invariant moments are also the same. When the other angles of rotation, the minimum similarity measure between the rotated image and the standard one is 0.9838. Its small changes indicate that the improved invariant moments have better rotation invariance. Zoom in or out, the minimum similarity measure is 0.9436. That the change is also small indicates the improved invariant moments have better scaling invariance. Therefore, the improved HU moments have the translation, rotation and scaling invariance.

It can be seen from Table II, the similarity measures are relatively close to 1, and to be able to recognize cups more



(a) (b) (c) (d)

Fig. 1 Grayscale of four different cups

(a) (b) (c)

(d) (e) (f)

Fig. 2 Different poses for the same cup

TABLE II
The similarity measure between different posed images and the standard one

translation	location	up	down	left	right		
	s	1.0000	1.0000	1.0000	1.0000		
rotation	degree	30°	60°	90°	130°	160°	180°
	s	09963	0.9941	1.0000	0.9838	0.9869	1.0000
scaling	times	1.3	1.2	1.1	0.9	0.8	0.7
	s	0.9885	0.9733	0.9874	0.9742	0.9551	0.9436

accurately, the most critical thing is the choice of threshold. So the best we can do is to choose a suitable threshold to perform object recognition. In these experiments, when the threshold is set at 0.9830, the recognition rate is 75%. When the threshold is set at 0.9600, the recognition rate is 87.5%. The Euclidean distance of objects to be recognized and the sample ones is calculated and compared in [7], the closest sample is the final recognition result. Corresponds to the algorithm in this paper, the recognition rates are respectively 72.5% and 85%. This shows the recognition rate in this paper is higher than that in [7] for objects similar in appearance recognition. Simulation experiments demonstrate the superiority of the proposed algorithm.

IV. CONCLUSION

With the development of computer vision, object recognition with invariant moments becomes an important issue. This study presents a method of object recognition based on improved HU invariant moments. We do some experiments on the COIL-100. Firstly we compute the improved moments of objects. Then compute the similarity measure between objects to be recognized and the standard one. Finally we recognize and classify objects by comparing the similarity measure. After applying the improved moments for three-dimensional object recognition with the similarity measure, we conclude that the improved moments are translation, rotation and scaling invariance whether in a continuous state or in a discrete state. Simulation experiments show the improved method is feasible, effective and superior, and we obtain satisfactory recognition results.

ACKNOWLEDGMENT

This research is fully supported by Research Program of Foundation and Advanced Technology of Henan Provience (102300410113) and Key Scientific and Technological Project of Henan Provience (092102210293).

REFERENCES

[1] Xu Sheng, Peng Qizong and Guan Qing. “A method for 3-d object recognition based on support vector machine,” Journal of Electronic Measurement and Instrument, vol.23, no.2, pp.43-48, April 2009.

[2] Sun Yigang, Sun Chengqi and Du Yanhong. “Study on Approach of 3-D Object’s Visual Recogniton,” Journal of Civil Aviation University of China, vol.22, no.6, pp.5-10, December 2004.

[3] Huang Ying, Ding Xiaoqing and Wang Shengjing. “Recognition of multiple 3-D objects based on Markov random field models,” Journal of Tsinghua University, vol.45, no.1, pp.28-32, January 2005.

[4] Xiao Jiaoqing, Lu Ling and Li Cheng. “Image Target Recognition Based on Moment Invariant,” Journal of Wuhan University of Technology, vol.30, no.4, pp.696-699, April 2006.

[5] Hu M K. “Visual pattern recognition by moment invariants,” IRE Transactions on Information Theory, vol.8, pp.179-187, 1962.

[6] Chen C C. “Improved moment invariants for shape discrimination,” Pattern Recognition, vol.26, no.5, pp.683-686, 1993.

[7] Hu Wei, Zhang Guilin and Ren Xianyi. “Eigenspace-based approach for object recognition and pose estimation,” Infrared and Laser Engineering, vol.33, no.6, pp.592-596. December 2004.