

# Polar-Radius-Invariant-Moment Based on Key-Points for Hand Gesture Shape Recognition

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**Abstract**—For the whole matching cannot handle partial occlusion and lack of specificity, a new method using Polar-Radius-Invariant-Moment, which is based on Key-Points to extract features for target's shape recognition, is presented in this paper. Firstly, key-points of the hand shape are extracted through discrete curve evolution method. Secondly, Polar-Radius-Invariant-Moment based on Key-Points is used to describe the characteristics of the gesture shape. Finally, Euclidean distance is utilized in gesture recognition to verify the validity of this method. Hand objects are selected as the test case to testify the performance of the method. Simulation results prove that this method has a better classification character than that of obtained by the Polar-Radius-Invariant-Moment with recognizing the object shape rapidly and accurately, and that it also can keep highly stable even if the object contour was ill-segmented or noisy.

**Index Terms**—hand shape recognition, key-points, polar-radius-invariant-moment, DCE, euclidean distance

## I. INTRODUCTION

The ultimate goal of computer vision is to keep the machine have the perception and understanding ability of human vision system. Object identification and classification is a fundamental problem in computer vision. Many of the attribute of the target can be used for recognition and classification. For example, shape, color, texture, brightness, etc.

In the field of pattern recognition, the shape feature of the image is important for feature extraction. Among

them, the moment invariant method is a more classic feature extraction method. Moment function in the image analysis has extensive applications, such as pattern recognition, target classification, target recognition and estimate direction, image coding and reconstruction, etc [1-5]. In recent years, a variety of invariant moment description methods and improved methods are appeared for 2d target recognition. Those include: Hu moment invariant possess translation, scaling, rotating invariability, and has been widely used in image recognition domain [4, 5]. However, Hu moment's computation rapidly rises with increasing moment's number. The Zernike moment is orthogonal moment wildly used [6, 7], which can easily calculation high order moments arbitrarily. Pseudo Zernike moments [7] are similar with traditional Zernike moments. But they have better features expression ability and antinoise performance Polar-Radius-Invariant-Moment (PM) [8] can be used in not only area target recognition but also boundary shape identification. Common features usually are used to describe overall characteristics of the image shape. If parts of the object are sheltered by other objects, invariant moments cannot be calculated. On this occasion, we hope to find a better recognition method to describe local feature of object's boundary shape [9].

The local characteristics of the object [10] (such as: line, arc, hole and angular point) contain abundant information. Because the total of the characteristic for handling is less, the calculation speed has got greatly improved. Therefore, the processing method based on local characteristics was proved to be very effective, and has been used successfully to the camera calibration, object identification, object classification, 3D reconstruction, target detection and image retrieval [10]. Key points (angular point) detection is a key steps in

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image local feature extraction [10-12]. At present key point extraction methods can be divided into two classes: the methods based on image local grayscale value [10, 11] and the methods based on image edge information [13-15]. Harris detection method belongs to the former. In preference [16], C.Schmid proves that Harris detection is more stable and more reliable, but it does not have scale invariance [10, 11, 16]. For the latter we need to extract image edges at first, make the image as 2d curve, and choose the points which have biggest curvature as angular points.

Based on above articles, a method which uses Polar-Radius-Invariant-Moment based on Key-Points (PMKP) to recognize gestures shape is proposed. The method can resolve the problems of partial sheltering and lack of characteristics which targets overall matching cannot deal with. This paper can proceed to each gesture image as follows:

- (1) Obtains its edge messages after pretreatment;
- (2) Extract key points whose curvatures are larger from hand gesture contour using discrete curve evolution (DCE);
- (3) Use PMKP to describe gestures shape characteristics;
- (4) Recognize gestures by Euclidean Distance.

## II. STATE OF THE ART

### A. Polar-Radius-Invariant-Moment

Polar-Radius-Invariant-Moment has above characteristics. It can be used for not only the recognition of goal regional, but also the identification of boundary shape. For region recognition, it can be used for continuous area, and also be used to separate areas. For recognition of the border, it can be used in closed boundary, and also be used for the unclosed boundary.

For a binary image, given that  $f(x, y)$  is the gray value of the place  $(x, y)$ , and

$$f(x, y) = \begin{cases} 1, & \text{point in the territory} \\ 0, & \text{others} \end{cases}, (x_c, y_c) \text{ is}$$

the center of the region's shape;  $r$  is the distance from the point in the area to the center point;  $D$  and  $A$  separately stand area and region's area. Then, the  $P$  order radius area moment is defined:

$$m_p = \iint_D r^p ds \quad (1)$$

Among them,  $ds = r dr ds$  is the area unit of  $(r, \theta)$  under the polar coordinates,

$$r = [(x - x_c)^2 + (y - y_c)^2]^{\frac{1}{2}} \text{ is the polar radius, } x_c = \frac{1}{A} \iint_D x ds, \quad y_c = \frac{1}{A} \iint_D y ds,$$

$$\bar{r} = \frac{1}{A} \iint_D r ds.$$

The center moment is defined as:

$$m_{cp} = \iint_D (r - \bar{r})^p ds \quad (2)$$

The normalized moment is defined as:

$$m_{np} = \frac{1}{A} \iint_D \left(\frac{r}{\bar{r}}\right)^p ds = \frac{1}{A \bar{r}^p} \iint_D r^p ds \quad (3)$$

The normalized center moment is defined as:

$$m_{ncp} = \frac{1}{A} \iint_D \left(\frac{r - \bar{r}}{\bar{r}}\right)^p ds \quad (4)$$

For discrete form, integration is convertible into summation in the formula. Given the sampling unit is 1 pixel, the smallest increment of the area or the boundary is 1 pixel, then whether integrating formula is corresponding to the area, or corresponding to the line, the formula will be unified form:

$$m_{np} = \frac{1}{A} \sum_{i=1}^A \left(\frac{r_i}{\bar{r}}\right)^p \quad (5)$$

$$m_{ncp} = \frac{1}{A} \sum_{i=1}^A \left(\frac{r_i - \bar{r}}{\bar{r}}\right)^p \quad (6)$$

Here, if the region of object is tested,  $A$  stands for the area of this area; if the border of the object is tested,  $A$  stands for the perimeter of the border. In short,  $A$  is representative of the sum of pixels that object tested contains.

### B. Discrete Curve Evolution

Due to digitalization, the outline of shape themselves is a polygon. In digital image, digital noises and segmentation errors distort the contour of goals. We must cut down the distortions and keep perceptual appearance. The discrete curve evolution (DCE) method [15, 17] can achieve above objectives through simplifying shape. DCE can be very good at simplifying shape and meanwhile reserve basic information of shape. Recently, extensive researches and applications are carried out. And it is thought to have a bright future. During different evolutionary stages, DEC can get polygon simplified of shapes in different degrees. Please reference paper [17] to understand particular cases. The DEC's main idea is as follows:

1) In each iteration step, connective line segments  $s_1$  and  $s_2$  are instead of a single line segment connecting two endpoints of  $s_1 \cup s_2$ . The order of this evolution is decided by relevance measurement  $K$  given by:

$$K(s_1, s_2) = \frac{\beta(s_1, s_2)l(s_1)l(s_2)}{l(s_1) + l(s_2)} \quad (7)$$

Among them, the intersection of line segments  $s_1, s_2$  produces a vertex  $\nu$ ,  $\beta(s_1, s_2)$  is the turn angle of segment  $s_1$  and  $s_2$ , and  $l$  is the length function normalized by the total length of polygon curve  $C$ .

2) The value of  $K(s_1, s_2)$  is bigger, the contribution of the arc  $s_1 \cup s_2$  to describe shape outline is greater.

In fact, the relevance measurement  $K$  is equivalent to the curvature of points in shape. The key point of the outline is the vertex after the curve evolution. Key points are immune to panning, rotating and scaling, so it can be detected easily before and after transform.

### III. POLAR-RADIUS-INVARIANT-MOMENT BASED ON KEY-POINTS

#### A. The Extraction of Key Points

**Definition 1:** Contour Key point sets (CKPS): Given that the outline  $C$  consists of point set  $P = \{p_1, p_2, \dots, p_n\}$ , set  $Q = \{q_1, q_2, \dots, q_m\}$  consists of  $m$  points in set  $P$  and keep  $m$  to a minimum. The polygon  $S$  build up of Set  $Q$  can approach outline  $C$  best, and  $q_i \in P, i = 1, 2, \dots, m$ . Then  $q_i$  is the key point of outline  $C$ , and  $Q$  is the critical point set of outline  $C$ .

For binary gesture contour images, DCE is used to obtain key points of outline. Firstly, sample from contour curve, then delete the points whose  $K(s_1, s_2)$  is less than a certain threshold, and at last get shape points. In this paper threshold takes 0.9 [17]. The number of key points can be set. The following Fig.1 shows gestures P<sub>1</sub>'s simplified effect when point number respectively are set to 20, 50. The graph shows that gesture shape can be expressed when the number is 50 and that key points distribute uniform.

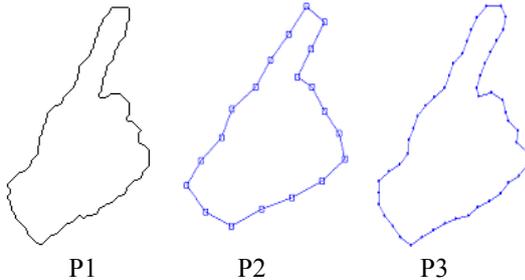


Figure 1. The extraction of key-points

#### B. Polar-Radius-Invariant-Moment Based on Key-Points

To shape classification, feature extraction of shapes is critical. The quality of feature extraction can directly affect identification accuracy. Feature vector should have translation, scaling, and rotating invariability, otherwise rotating correct will be done before image matching.

The definition of Polar-Radius-Invariant-Moment based on Key-Points is as follow:

For a binary image  $f(x, y)$ , the key-points sequence of the outline border is  $K = (k_1, k_2, \dots, k_n)$ , the coordinate of key point is  $k_i = (x_i, y_i)$ , and the number

of key point is  $N_k$ . For discrete form, normalized torque is defined as:

$$m_{knp} = \frac{1}{N_K} \sum_{i=1}^{N_K} \left( \frac{r_i}{\bar{r}} \right)^P \quad (8)$$

Normalized center moment is defined as:

$$m_{kncp} = \frac{1}{N_K} \sum_{i=1}^{N_K} \left( \frac{r_i - \bar{r}}{\bar{r}} \right)^P \quad (9)$$

$r_i = \left[ (x_i - x_c)^2 + (y_i - y_c)^2 \right]^{\frac{1}{2}}$  Is the pole radius,

$x_c = \frac{1}{N_k} \sum_{i=1}^{N_k} x_i$  and  $y_c = \frac{1}{N_k} \sum_{i=1}^{N_k} y_i$  are coordinate of

the center of the region's shape. Among them,

$$\bar{r} = \frac{1}{N_k} \sum_{i=1}^{N_k} r_i.$$

#### C. The Proof of Invariant

**Translation and Rotation Invariance:** Object's position translation or object rotation at an angle will produce new pixel sets and new shape heart coordinates, but the Euclidean Distance between pixels to shape heart remains unchanged. Because key points are one-to-one around transform, the Euclidean Distance between key points to shape heart remains unchanged. Therefore,  $m_{knp}$  and  $m_{kncp}$  based on key points have translation and rotation invariant.

**Scale Invariance:** Set  $\alpha$  for scale factor. Given that target object shape equally zooms at  $\alpha$  time,  $T(x, y)$  is the arbitrary point's coordinate in original image, and  $T'(x, y)$  is the coordinate of corresponding point in image after scale transformation, their relationship meet:

$$T'(x, y) = \alpha \cdot T(x, y) \quad . \quad \text{Therefore, } r'_i = \alpha r_i, \quad \bar{r}' = \alpha \bar{r}, N'_k = N_k \cdot N_k \text{ is the number of key points.}$$

$$\begin{aligned} m'_{knp} &= \frac{1}{N'_K} \sum_{i=1}^{N'_K} \left( \frac{r'_i}{\bar{r}'} \right)^P \\ &= \frac{1}{N'_K (\bar{r}')^P} \sum_{i=1}^{N'_K} (r'_i)^P \\ &= \frac{1}{N_K (\alpha \bar{r})^P} \sum_{i=1}^{N_K} (\alpha r_i)^P \\ &= \frac{\alpha^P}{N_K \alpha^P \bar{r}^P} \sum_{i=1}^{N_K} r_i^P \\ &= \frac{1}{N_K} \sum_{i=1}^{N_K} \left( \frac{r_i}{\bar{r}} \right)^P \\ &= m_{knp} \end{aligned} \quad (10)$$

$$\begin{aligned}
 m'_{kncp} &= \frac{1}{N_K'} \sum_{i=1}^{N_K'} \left( \frac{r'_i - \bar{r}'}{\bar{r}'} \right)^p \\
 &= \frac{1}{N_K' (\bar{r}')^p} \sum_{i=1}^{N_K'} (r'_i - \bar{r}')^p \\
 &= \frac{1}{N_K (\alpha \bar{r})^p} \sum_{i=1}^{N_K} \alpha^p (r_i - \bar{r})^p \quad (11) \\
 &= \frac{\alpha^p}{N_K (\alpha \bar{r})^p} \sum_{i=1}^{N_K} (r_i - \bar{r})^p \\
 &= \frac{1}{N_K} \sum_{i=1}^{N_K} \left( \frac{r_i - \bar{r}}{\bar{r}} \right)^p \\
 &= m_{kncp}
 \end{aligned}$$

**D. Selection PMKP**

From what has been discussed above, it can be seen that  $m_{knp}$  and  $m_{kncp}$  possess translation, rotation and scale invariance and can be used for identification as shape characteristics. But recognition rate is too low when only two features  $m_{knp}$  and  $m_{kncp}$  are applied to object recognition, so more variables are needed.

Because  $m_{knp}$  and  $m_{kncp}$  possess RTS invariabilities, its different combination will be invariant. The more Characteristics the higher object recognition rate. But at the same time, it needs great computational costs and computing speed gets slow. However, if the number of characteristics is too little, recognition rate is unreliability.

With the principle of high rate and low computation, this paper selects the following five moment invariants as the characteristics for object recognition through a lot of experiments.

$$V_1 = m_{kn2} = \frac{1}{N_K} \sum_{i=1}^{N_K} \left( \frac{r_i}{\bar{r}} \right)^2 \quad (12)$$

$$V_2 = m_{knc2} = \frac{1}{N_K} \sum_{i=1}^{N_K} \left( \frac{r_i - \bar{r}}{\bar{r}} \right)^2 \quad (13)$$

$$V_3 = m_{knc3} = \frac{1}{N_K} \sum_{i=1}^{N_K} \left( \frac{r_i - \bar{r}}{\bar{r}} \right)^3 \quad (14)$$

$$V_4 = m_{knc4} = \frac{1}{N_K} \sum_{i=1}^{N_K} \left( \frac{r_i - \bar{r}}{\bar{r}} \right)^4 \quad (15)$$

$$V_5 = \frac{m_{knc2}}{(m_{knc4})^{\frac{1}{2}}} = \frac{1}{\sqrt{N_K}} \frac{\sum_{i=1}^{N_K} (r_i - \bar{r})^2}{[\sum_{i=1}^{N_K} (r_i - \bar{r})^4]^{\frac{1}{2}}} \quad (16)$$

**E. The Method of Similarity Measurement**

In the field of pattern recognition, methods of target image identification can be roughly divided into two kinds: methods based on image matching and based on image characteristics matching [18]. Image matching refers to all information of target image, so this method achieves higher recognition rate, but it has relatively poor capacity of recognizing rotating and zooming target image. From the introduction of definition and calculation formula of PMKP feature above the article, it can be seen that they are statistical average description on the basis of analysis of boundary grey value. In target recognition, when image shape characteristics are extracted through a method, it is needed to determine that the two images are similar under some conditions. The method commonly used is the distance similarity measurement.

At present there are many distance similarity measurements. Euclidean distance, Mahalanobis distance and Minkowski distance were commonly used [19]. Euclidean distance is very convenient calculating on a computer, and the conversion in the high character space is not complex, therefore this paper chooses Euclidean distance to solve gestures shape recognition problem.

*Definition 2:* Euclidean distance between the sample vector I and the sample vector J is defined as:

$$D = \sqrt{\sum_{k=1}^N \|d_I(k) - d_J(k)\|^2} \quad (17)$$

The Euclidean Distance above is traditional recognition methods and  $N$  says characteristic dimension.

When different characteristics descriptions are used to calculate the differences of shapes, they are incomparable. All kinds of shape features need to be normalized to contrast. Therefore a calculating method of normalizing difference of different characteristic vector is put forward in this paper. It is aimed at making individual feature producing the same contribution on classification.

*Definition 3:* Normalized Euclidean distance between the sample vector I and the sample vector J is defined as:

$$D^* = \sqrt{\sum_{k=1}^M \left\| \frac{d_I(k) - d_J(k)}{d_I(k) + d_J(k)} \right\|^2} \quad (18)$$

**IV. EXPERIMENT RESULTS**

To validate the effectiveness of new method identifying object, we choose different gestures from literature [20] of 160×200 pixels. Matlab7.0 is chosen as experiment tool. Polar-Radius-Invariant-Moment [8] is used to compare with this new method. Because the dynamic range of the moment invariants is relatively large, the results take logarithm. For convenience,  $abs(\log_2(in\ variance))$  is used to process invariant moments, in which  $abs$  means absolute value.

A. Analysis Invariance of PMKP

Fig.2 shows different geometric changes of the same gesture. From left to right and from top to bottom arrangement is: original graph, rotating at 90°, 180°, and 270°, mirror image, zooming at 0.5 time. Form table I it can be seen that the feature values are very close, so the features have very good translation, rotation and scale invariance. According to calculation (18), Euclidean distances of the same shape description are calculated, and the average Euclidean distance is 0.0205. It also shows that the characteristic vector extracted by this algorithm basically unchanged in description of the same kind of shape.

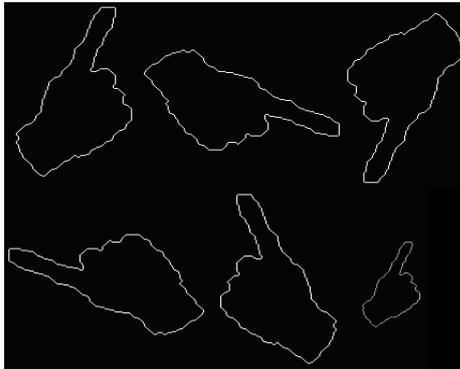


Figure 2. Hand gestures of the same shape. P<sub>1</sub>-P<sub>6</sub> from left to right and from top to bottom

TABLE I.  
PMKP OF THE SAME GESTURE

	V <sub>1</sub>	V <sub>2</sub>	V <sub>3</sub>	V <sub>4</sub>	V <sub>5</sub>
P <sub>1</sub>	0.1132	2.1210	4.5099	3.6231	0.3094
P <sub>2</sub>	0.1145	2.1085	4.6279	3.6139	0.3016
P <sub>3</sub>	0.1155	2.1129	4.5303	3.5914	0.3039
P <sub>4</sub>	0.1157	2.0977	4.5600	3.5903	0.3025
P <sub>5</sub>	0.1129	2.1234	4.4857	3.6211	0.3128
P <sub>6</sub>	0.1095	2.1562	4.5318	3.6936	0.3094

B. Comparative Analysis of Classification Effect

Fig.3 shows 10 different shape gestures used to test the classification effect of PMKP.

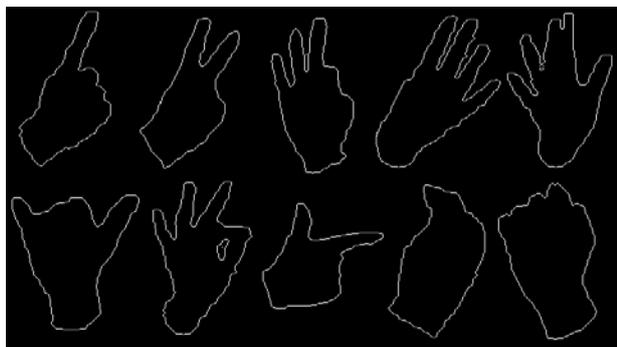


Figure 3. The 10 different hand gestures F<sub>1</sub>-F<sub>10</sub> from left to right and from top to bottom.

This experiment uses new method and PM to calculate respectively similarity between different shapes, and then compares the results. Experiment results show as Fig. 4. The parts of Fig.4 from left to right and from top to bottom show that: the Euclidean Distance between the F<sub>1</sub>-F<sub>10</sub> respectively with the 10 gestures. The points connected by blue dotted line stand the Euclidean Distance got by the new way and the dots connected by the red solid line mean PM's. The following conclusions can be received: PMKP has a better ability of distinguish different gestures shape. PMKP's classification ability is better than PM when gesture shape is relatively complex. Some examples are given. The dotted line in the first 4 part is higher. It shows that the new method is better in distinguishing hand F<sub>4</sub> with 10 different kinds of gestures. In addition, the average Euclidean Distance between gesture F<sub>5</sub> and other gestures is minimum and is 0.3015, indicating that F<sub>5</sub> is closer to other gestures. While the average Euclidean Distance 0.5321 between F<sub>4</sub> and others is the largest. The average Euclidean Distance used by PMKP is 0.3955 and by PM is 0.3739. This shows that the new characteristics have stronger ability of describing object shape and the size of the new similar distance between objects approximately reflects the changes of different shapes.

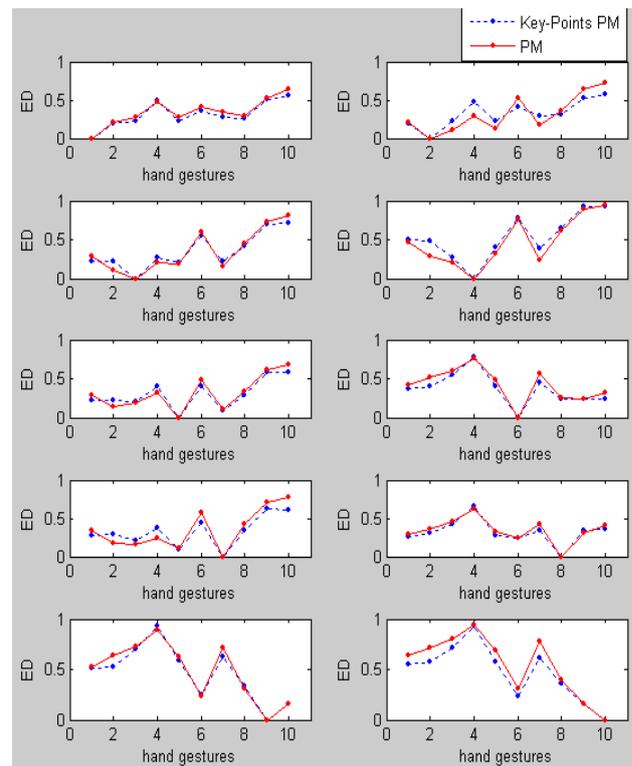


Figure 4. Comparison of classification effect

C. Contrast results of increasing pollution

Through increasing boundary pixels with different levels of noises we can test those classification features' robustness. The method in Reference [8] is adopted. Each pixel randomly moves to one of its eight adjacent domains with probability *p*. The value of *p* is larger, the

deformation is more serious. The Euclidean Distances under different values of  $p$  are shown in Table II and Table III. In Table II, there are only two bad numbers less than results used with Polar-Radius-Invariant-Moment. The Euclidean distance between  $A_1$  and  $A_2$  is 1.76, and the Euclidean distance between  $A_3$  and  $A_4$  is 2.05. But in Table III when  $p = 0.4$ , the data used by new method are bigger except one bad data with underline. The bad data is the Euclidean distance between  $A_2$  and  $A_4$ . It states that classify effect of PMKP is better than that of PM. (In order to make the comparison results obvious, the Computational Method of recognizing object shape utilizes (18) in this experiment, as well as in the experiment about contour defect).

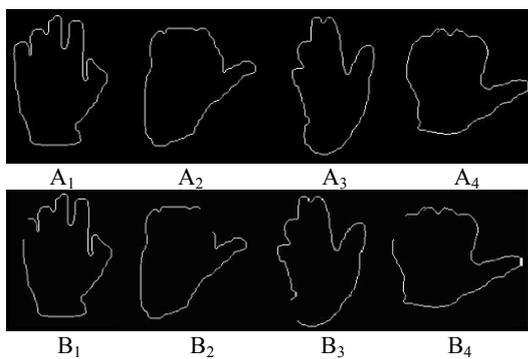


Figure 5. The hand gestures for pollution

TABLE II.  
THE SIMILARITY MEASURE WITH NOISY P=0.2

		P=0.2			
		A <sub>1</sub>	A <sub>2</sub>	A <sub>3</sub>	A <sub>4</sub>
PMKP	A <sub>1</sub>	0	<u>1.76</u>	2.27	1.55
	A <sub>2</sub>	<u>1.76</u>	0	1.84	1.91
	A <sub>3</sub>	2.27	1.84	0	<u>2.05</u>
	A <sub>4</sub>	1.55	1.91	<u>2.05</u>	0
PM	A <sub>1</sub>	0	<u>1.91</u>	2.19	0.41
	A <sub>2</sub>	<u>1.91</u>	0	1.77	1.91
	A <sub>3</sub>	2.19	1.77	0	<u>2.46</u>
	A <sub>4</sub>	0.41	1.91	<u>2.46</u>	0

TABLE III.  
THE SIMILARITY MEASURE WITH NOISY P=0.4

		P=0.4			
		A <sub>1</sub>	A <sub>2</sub>	A <sub>3</sub>	A <sub>4</sub>
PMKP	A <sub>1</sub>	0	2.14	1.11	1.85
	A <sub>2</sub>	2.14	0	3.25	<u>1.31</u>
	A <sub>3</sub>	1.11	3.25	0	2.96
	A <sub>4</sub>	1.85	<u>1.31</u>	2.96	0
PM	A <sub>1</sub>	0	2.08	0.65	0.52
	A <sub>2</sub>	2.08	0	2.35	<u>2.44</u>
	A <sub>3</sub>	0.65	2.35	0	1.02
	A <sub>4</sub>	0.52	<u>2.44</u>	1.02	0

In order to validate that the method can still effectively recognize objects which absent partial outlines, the related experiments are carried on. In Table IV, only the Euclidean Distance using new method between  $B_1$  and  $B_4$  is 1.44, and less than the Euclidean distance using PM. It can be seen that PMKP's classification effect excels extremely in the Table IV.

TABLE IV.  
THE SIMILARITY MEASURE WITH CONTOUR DEFECT

		B <sub>1</sub>	B <sub>2</sub>	B <sub>3</sub>	B <sub>4</sub>
PMKP	B <sub>1</sub>	0	1.74	1.32	<u>1.44</u>
	B <sub>2</sub>	1.74	0	3.05	2.10
	B <sub>3</sub>	1.32	3.05	0	1.16
	B <sub>4</sub>	<u>1.44</u>	2.10	1.16	0
PM	B <sub>1</sub>	0	1.43	0.85	<u>1.69</u>
	B <sub>2</sub>	1.43	0	1.30	1.84
	B <sub>3</sub>	0.85	1.30	0	0.87
	B <sub>4</sub>	<u>1.69</u>	1.85	0.87	0

For better inspecting the recognize ability of PMKP, figures  $A_1$ - $A_4$ , figures of  $p=0.2$  and  $p=0.4$  and figures  $B_1$ - $B_4$  are made transformation as follows:

1. Rotate 36° in turn clockwise;
2. Reduce to 0.5 time, and rotate 36° in turn clockwise;
3. Amplify to 2.0 time, and rotate 36° in turn clockwise.

Through transformations above, in all 360 pictures with different size and rotation direction are obtained. The results of identification samples using different characteristic extraction methods are given in Table V. The Euclidean Distance utilizes (18). From the experiment, the average identification accuracy of PMKP is 94.1%, respectively PM's is 81.1%. Therefore, the former have stronger ability of recognition object when objects are contaminated seriously.

TABLE V.  
THE COMPARISON RESULT ABOUT RECOGNIZING ABILITY OF DIFFERENT FEATURES

	p=0.2 (%)	p=0.4 (%)	Contour Defect(%)	Recognition Efficiency(%)	Average Time(s)
PMKP	0.975	0.966	0.883	0.941	0.082
PM	0.892	0.817	0.725	0.811	0.066

## V. CONCLUSION

This paper puts forward a feature extraction method of pole-radius-invariant-moment based on key-points. This method can be used for extracting boundary feature information of objects. Points of image contour took advantage of getting rid of irrelevant information and are suitable for feature extraction under circumstances of complicated background and partial shelter. Using gestures as target objects, simulation results show that the proposed method has an ability of describing characteristics of different targets, is stable to geometry transform, and has better robustness on the noise and fracture of digital contour. But this algorithm also exists deficiency: it will spend more time in extracting key points, so the time complexity of new algorithm is greater than pole radius invariant moment's.

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