Recognizing Partially Occluded Object from a Line Drawing

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Abstract—**Most existing methods for partially occluded object recognition are only suit for Euclid and similarity transformation. As a result, the performance would be degraded in the affine and perspective transformation. This paper focuses on partially occluded shape recognition under affine transformation. The recognition algorithms are as follows ： First, a new local invariant under affine transformation is given based on the invariants in affine geometry. Second, a new similarity function is established to measure the similarity between models and object to be recognized on the basis of the local invariant. And then, a transform function is designed to normalize the similarity value between 0 and 1, so it is convenient to select similarity threshold. Finally, a loss feature judged function is constructed to judge whether each local feature is lost, and similarity is calculated only use the local features which are not lost. By comparing similarity with pre-threshold, we can recognize object from a partially occluded line drawing. The similarity function and the loss feature judge function consider the noises and occlusion. As a result, the reliability of recognition is improved greatly. The experiment results show that the proposed algorithms are quite robust to shape variations, including noise and occlusion. Moreover, they establish one-to-one correspondence between model features and object features in a scene, and can recognize multiple objects.**

Index Terms—**partially occluded, polygon, line drawing, recognition**

I. INTRODUCTION

A line drawing is the two-dimensional representation of a three-dimensional object. It is an important problem in computer vision and computer aided design that machine recognizes line drawing automatically. Most existing methods for object recognition are only suit for Euclid and similarity transformation. Or they assume that the objects to be matched are non-occluded. As a result, the performance would be degraded in the cluttered circumstances, including occlusion and noise, as well as affine and perspective transformation. However, in most real situations, all the features of the object are not visible in the scene, due to occluding, noise, and inaccurate, low-level feature extracting process, and so forth. Recognition of geometrical shapes, which are partially

occluded, is important in many applications. This is especially true in situations where ideal-imaging conditions cannot be maintained. For example, in robot assembly line, occlusion occurs where two or more objects in a given image touch or overlap one another. In remote sensing image recognition, it is more difficult to recognize and locate target due to target occluded by shadow of tree, house or vehicle.

Recently, some scholars presented methods for recognizing partially occluded objects. Krolupper[1] proposed an approach of object representation for partially occluded object recognition. Objects are represented by their boundaries, which are deformed by the occlusion. The boundary representation was made by approximation with circle arcs. The representation was designed to be local and robust to occlusion. In this method, it is assumed that the occluded object undergo just three basic transformations: translation, rotation, scaling. Shan[2] proposed a method to present model object using histogram, then matched the histogram between model and object to be recognized. Their method can match partial occluded object. Gorman[3] presented a partial shape recognition technique using local features described by Fourier descriptors. However, his method is only suit for similarity transform. Orrite[4] presented a method to recognize partial shape under projective transform. He estimated projective transform using alignment approach and extracted the invariant points-bitangents. However they require a full search for matching, the computation complexity is very high. Park [5] represented an object using the attributed relational graph (ARG) model with nodes (features) of a set of the binary relation vectors. By defining relation vector space which can describe the structural information of an object centered at specific feature, the labels of objects are only affected by the binary relation vectors of features. Cho [6] reconstructed the partial shapes based on symmetry. His method is only suit for the objects which are symmetry and whose section is ellipse or approximately circle. The two methods are also suit for similarity case.

This paper aims for recognizing partially occluded object under affine transformation. We assume that object

contours are approximately polygon, because many objects can be represented approximately by polygon.

II. EXTRACT LOCAL INVARIANT FEATURE

The traditional object recognition methods are all take objects as a whole, extracted their global feature, such as areas, perimeter, moment invariant and Fourier descriptors and so on. When one object occlude the other, the distortion of an isolated region of the shape will result in changes to every feature. This property is undesirable
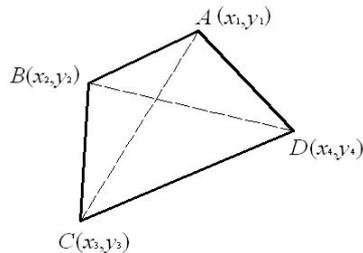

Figure 1. Two quadrangles corresponding to under affine transformation

If the two quadrangles as shown in Fig.1（can be extend to random polygon）, correspond to each other, then:

$$\frac{S_{\Delta acd}}{S_{\Delta bcd}} = \frac{S_{\Delta ACD}}{S_{\Delta BCD}} \quad ; \quad \frac{S_{\Delta ACD}}{S_{\Delta ABC}} = \frac{S_{\Delta acd}}{S_{\Delta abc}} \quad ;$$

$$\frac{S_{\Delta ACD}}{S_{\Delta ABD}} = \frac{S_{\Delta acd}}{S_{\Delta abd}} \quad ; \quad \frac{S_{\Delta BCD}}{S_{\Delta ABC}} = \frac{S_{\Delta bcd}}{S_{\Delta abc}} \quad ; \quad \frac{S_{\Delta BCD}}{S_{\Delta ABD}} = \frac{S_{\Delta bcd}}{S_{\Delta abd}} \quad ;$$

$$\frac{S_{\Delta ABC}}{S_{\Delta ABD}} = \frac{S_{\Delta abc}}{S_{\Delta abd}} \quad , \text{ where } S \text{ is the area of the}$$

corresponding triangle.

Theorem 2: If the ratios of the triangles areas which shared the same hemline in a polygon are equal, the two polygons correspond to each other under affine transform.

As shown in Fig.1, if $\frac{S_{\Delta acd}}{S_{\Delta bcd}} = \frac{S_{\Delta ACD}}{S_{\Delta BCD}}$, $\frac{S_{\Delta ACD}}{S_{\Delta ABC}} = \frac{S_{\Delta acd}}{S_{\Delta abc}}$,

$\frac{S_{\Delta ACD}}{S_{\Delta ABD}} = \frac{S_{\Delta acd}}{S_{\Delta abd}}$, $\frac{S_{\Delta BCD}}{S_{\Delta ABC}} = \frac{S_{\Delta bcd}}{S_{\Delta abc}}$, $\frac{S_{\Delta BCD}}{S_{\Delta ABD}} = \frac{S_{\Delta bcd}}{S_{\Delta abd}}$,

$\frac{S_{\Delta ABC}}{S_{\Delta ABD}} = \frac{S_{\Delta abc}}{S_{\Delta abd}}$, the two polygons correspond to each other under affine transform.

The proof of the Theorem 1 and Theorem 2 can be seen in [7, 8]. It is observed that the ratios of areas sharing the same hemline as an affine invariant can be introduced to recognize polygon, which is sufficiency and necessary.

The polygon's each edge is viewed as hemline, the former point, the hind point of the edge and the edge are constitute two triangles, as shown in Fig.1, i.e., edge 23, the former point 1 and the hinder point 4, constitute two triangles $\Delta 123$ and $\Delta 234$, the ratios of the two triangles areas sharing the same hemline 23 is viewed as local invariant feature $I = \frac{s_{\Delta 123}}{s_{\Delta 234}}$, The distortion of another points except for the considered four points 1,2,3,4 would not affect the local feature.

when partially shapes are under consideration. So far, some scholars proposed the matching methods based on local feature. When occlusion occurs, there are only partial local features vary, and the rest local features keep invariant, this is ideal for partial shape recognition.

A. The Choice of Local Feature

Theorem 1: If the two polygons correspond to each other under affine transform, the ratios of the triangles areas that shared the same hemline in a polygon are equal.
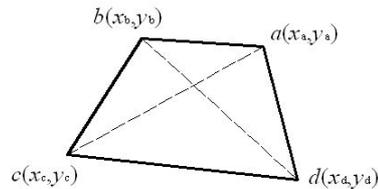

Figure 2. The choice of local feature

B. The improved local invariant

The local feature above is local invariant, which describe local shape, and it is unaffected by other regions of the object. This is ideal for partial shape recognition. However, the problem will occur if we describe object use the local feature in section 2.1 directionally, when there are three points are approximately co-linear, the area of the triangle become close to zero. And when this area is taken as denominator, the local invariant becomes infinity. And then this invariant I is much sensitive to the errors of image data or the errors of feature points extracting, which affect the difference of local invariant greatly.

In order to overcome this problem, we employ the function $I' = \frac{e^I - 1}{e^I + 1}$.

I is an affine invariant, so I' is also an affine invariant.

Noted that I' increased as I increased monotony. When I is approximately to infinity, I' become close to parameter 1, when I is close to negative infinity, I' become close to parameter -1, i.e., $I \in (-\infty, +\infty)$, $I' \in (-1, +1)$.

So we introduced the new invariant to describe partial shape.

C. Match local feature

If we know the correspondence relation of object's each local feature and that of model, we can calculate the absolute distance of these local invariant, then compare

the distance with pre-threshold. We can also match polygon's vertex or edge according to calculated invariant in section 2.2. Assume v_j is feature edge of object to be recognized and v_i is feature edge of model, I_i and I_j are their corresponding local invariants respectively, TI_i^m is the threshold which I_i corresponds to. If the local invariant of edge v_i corresponding to satisfies the following inequality, we consider v_i and v_j match. The match rule is as follow

$$|I_i^m - I_j| < TI_i^m$$

where I_i^m is the local invariant of model m corresponding to.

We begin with the matched edges, record the number of matched edges of object and model sequentially traversed in clockwise and counter-clockwise directions.

III. SIMILARITY FUNCTION

It is much difficult to determine the correspondence relation of feature points due to projective distortion, especially some vertex lost, which result in the start point is always not consistent while extracting feature.

Assume the number of local feature vector of two objects g_1, g_2 is N_1 and N_2, the similarity between these two objects can be defined by

$$S(g_1, g_2) = \sum D(I_i, I_j)\omega_{ij} \qquad 1 \le i \le N_1, \quad 1 \le j \le N_2$$

(1)

where $D(I_i, I_j)$ is a function to measure the difference between local feature I_i^{g1} and I_j^{g2}, and w_{ij} is the weighting for feature I_i^{g1} and I_j^{g2} respectively.

It is noted that although the similarity between two objects can be measured directly by comparing the absolute distance between the corresponding local features in two objects, due to noise, inaccurate low-level feature extraction process and partially occluded, which usually affect the local feature. Thus, in this paper, we introduce a probabilistic interpretation of the difference between the corresponding features, by defining $D(I_i, I_j)$ as the weighted probability of all matched local feature, given by

$$D(I_i, I_j) = C(v_i^{g_1}, v_j^{g_2}) = p(I_i^{g_2} - I_j^{g_1})$$
$$1 \le i \le N_1, \quad 1 \le j \le N_2 \qquad (2)$$

where $C(v_i^{g_1}, v_j^{g_2})$ is the compatibility measure between two corresponding local feature, which is defined by the probability of error in local feature.

Assume that the scene local feature vector is an independent Gaussian random vector. Then, we can obtain the probability density of the error of the local feature, given by

$$p(I_i - \bar{I}_j) = \frac{1}{\sqrt{2\pi} \cdot \sigma} \cdot \exp(-\frac{(I_i - \bar{I}_j)^2}{2 \cdot \sigma^2}) \qquad (3)$$

Note that by assigning appropriate values to weighing ϖ_{ijj} in equation (1), which determines how each individual feature influences the recognition efficiency, the similarity measure in equation (1) can be used for an effective criterion for general matching, including partial matching. Actually, since the weights depend on the type of the graph and the mutual relations between features, it is very difficult to adjust the weighing factors optimally in any scene. Thus, in this work, we assume that all features in the object and model have the same importance impartially. Based on this assumption, if the p feature is not lost in the scene, we set the corresponding weighs $\omega_{ip} = 1$, where $1 \le j \le N_2, j \ne p$. While, in the case that the q feature is found to be lost in a scene, by setting the $\omega_{ip} = 0$, where $1 \le j \le N_2, j \ne q$, we can eliminate undesired effects due to the lost feature in matching. Fortunately, we have observed empirically that the weighing is not so sensitive that substantial variations of the weighs have little effect on the overall matching performance.

According to equations (1), (2) and (3) and experiments we note that the similarity measure decrease as the noise and lost rate increase, which result in assigning threshold difficultly, thus it is necessary to normalize the similarity measure. It is required that when s is higher, s' become close to 1, when s varies from a low range (ie. from 0 to 0.2), s' varies from a larger range (ie.from 0 to 0.5). It is noted that the function

$$s' = \frac{2}{\pi}\arctan(b \cdot s) \qquad (4)$$

has the property. As shown in Fig. 3, where horizontal axis denoted similarity measure s before transform, while vertical axis denoted similarity measure s' after transform.

From Fig.3 we know that s' increases monotony as s increases, moreover, when s ($s \ge 0$) vary in more large rang, s' would vary from 0 to 1, this is our expected.

It is noted by much experiments that assigning 5 to parameter b can obtain better experiment result. So substitute parameter b with 5, we can obtain the normalized transform function, give by

$$s' = \frac{2}{\pi}\arctan(5s) \qquad (5)$$

IV. DETECT LOSS FEATURE

Due to occluded, it may occur that the dimension of local feature between model and object are not equal. So it is necessary to construct a function to detect loss feature, using this function the partial feature can be detected. And we calculate the similarity only use the features which are not lost.

In order to detect loss feature, we first derive the error detection inequality. Then, the feature loss vector is constructed through a voting scheme, and finally the loss features are identified by analyzing it. Let us denote an error region as
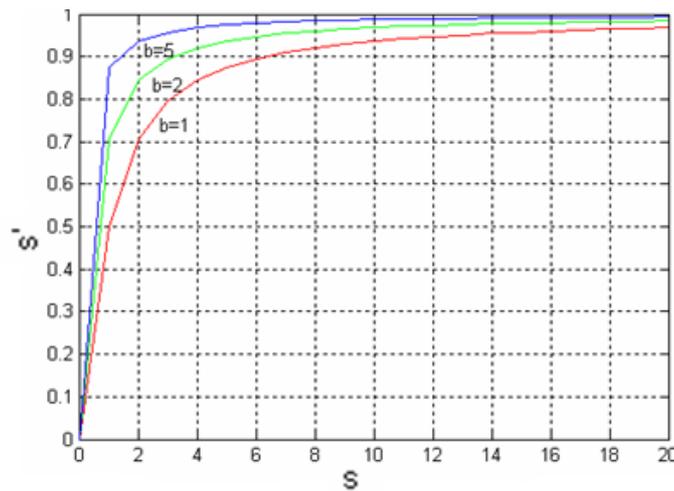
Figure 3. The transform function curves at different parameter value b

$$D_E(I_i) = \{I \mid ||I_i - I| \le \Delta_k \quad\}, \text{ for small } \Delta k \tag{6}$$

Then, if the observed feature vector I is in $D_E(I_i)$, it is considered to correspond to I_i. For local feature of some object image, if $I_i^{g_c} \notin D_E(I)$ can be interpreted as

$$p(I_i^{g_c} - I_i^{g_M}) < p_{thres} \tag{7}$$

where p_{thres} is a pre-threshold value. By substituting (3) into (7), we obtain a novel error detection inequality

$$\exp(-\frac{e_i^2}{2\sigma^2}) < f \tag{8}$$

where e_i is the error vector, $e_i = I_i^{g_c} - I_i^{g_M}$, f is a pre-threshold fraction parameter. Using (8), we can construct a feature loss vector, given by

$$L = \begin{bmatrix} l(1) & l(2) & ... & l(i) \end{bmatrix}^T \qquad i = 1,2,...N \tag{9}$$

where the component $l(i)$ is the result based on (8), if $l(i)$ satisfy the inequality (8), $l(i) = k$, k is a pre-threshold large parameter, else $l(i) = 0$. Note that if the two images to be matched are almost identical, then all the components in L become close to zero. However, when there exist occlusions or some missing features, then the corresponding components in L become large, while the others remain close to zero. By analyzing the components in L, we can detect the loss features.

Eliminating the detected loss features from both model and object to be recognition, this process is repeated until no more features is found to be lost. Note that by using this iterative voting scheme, we can not only detect the loss features but also determine the weight factor in equation (1), thus we can match object and model using equation (1).

V. EXPERIMENT RESULTS AND DISCUSSION

A. Experiments

Experiment 1

We select two polygons which have the same number of vertex, Fig.4 (a) and Fig.4 (b) are two model contours selected randomly from database respectively, take three pictures for either model, and assume the either polygon is occluded one vertex when taking pictures , as shown in Fig. 5, their contours are shown as Fig.6.

Calculate the invariants of two models in Fig.4 and six objects to be recognized in Fig.6 respectively, and then calculate their similarity. Experiment datum is shown as table 1 and table 2. It is clear from the experiment results that Fig. 6(a), (b), (c) is the projections of Fig. 4(a), and the correspondence relation of each vertex is as follow: 1-1, 2-2, 3-3, 4-4, 5-5, 6-6, 7-7, Fig. 6(d), (e), (f) is the projections of Fig. 4(b), and the correspondence relation of each vertex is as follow: 1-1, 2-2, 3-3, 4-4, 5-5, 6-6, 7-7.
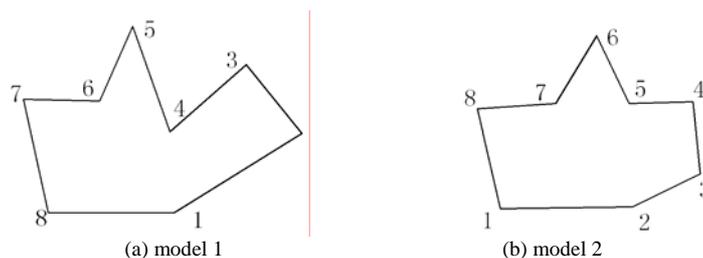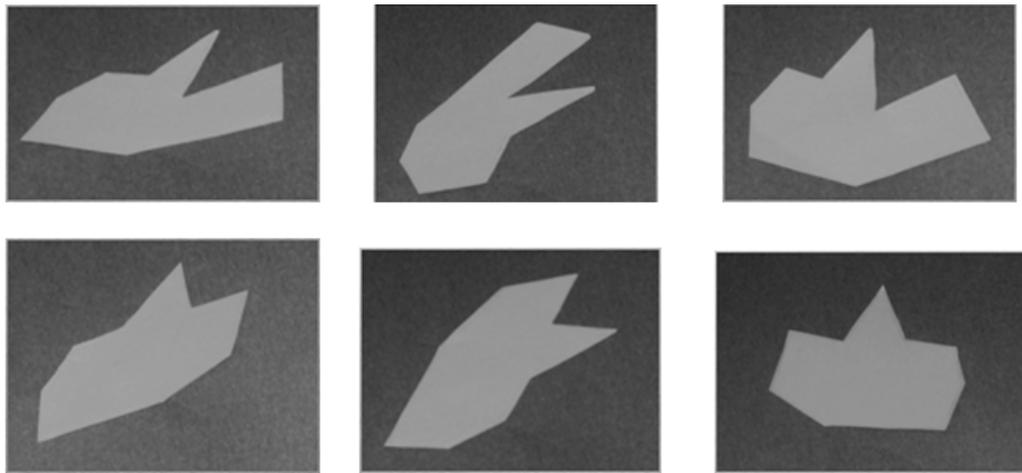

(a) model 1   (b) model 2

Figure 4. Model

Figure 5.   Images of object to be recognized

(a)   (b)   (c)

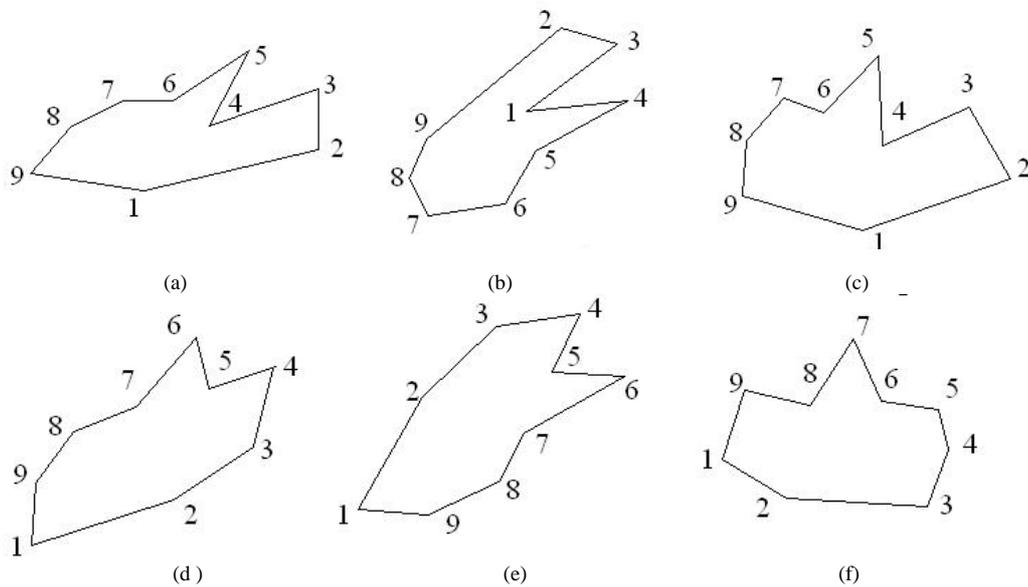(d)   (e)   (f)

Figure 6.   Object contour to be recognized

TABLE 1   Calculated Invariants

Invariant	Fig.4(a)	Fig.6(a)	Fig.6 (b)	Fig.6 (c)	Fig.6 (d)	Fig.6 (e)	Fig. 6(f)	Fig.4 (b)
I'_1	1.6124	1.6162	1.6109	1.6039	2.4529	2.4993	2.4789	2.4785
I'_2	2.5303	2.5201	2.5156	2.5248	1.8910	1.8905	1.8900	1.8891
I'_3	1.3858	1.3995	1.3969	1.4076	2.2281	2.2324	2.2415	2.2441
I'_4	2.1787	2.1609	2.1762	2.1764	2.2742	2.2684	2.2685	2.2719
I'_5	3.1224	1.9325	1.9308	1.7743	1.6319	1.6340	1.6338	3.6466
I'_6	3.0710	1.5962	1.6567	1.5330	1.6471	1.6385	1.6491	3. 5046
I'_7	1.6489	1.8092	1.7566	7.2390	1.4613	1.4942	1.4969	2.4138
I'_8	2.8863	3.5561	4.2054	3.5613	9.7110	9. 7906	9.6920	8.9165
I'_9		5.3436	5.5846	3.7879	1.5409	1.5318		1.4286

TABLE 2   Match result (The values shown in table 2 are similarity measure)

	Fig.6（a）	Fig.6（b）	Fig.6（c）	Fig.6（d）	Fig.6（e）	Fig.6（f）
Fig.4（a）	0.9654	0.9703	0.9521	0.0904	0.125	0.0890
Fig.4（b）	0.108	0.0983	0.109	0.9201	0.9547	0.9464

Experiment 2

Fig.7 is model simplified contour. We selected four types plane model image; the images are always partially occluded due to occluded by cloud when taking pictures.

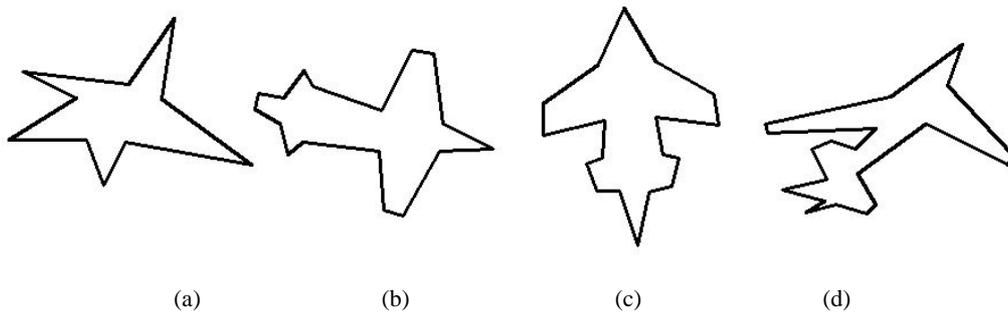Extract their profile and simplify using line, their contours are shown as Fig.8.

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

Figure 7.   Model contours

(a)   (b)   (c)   (d)
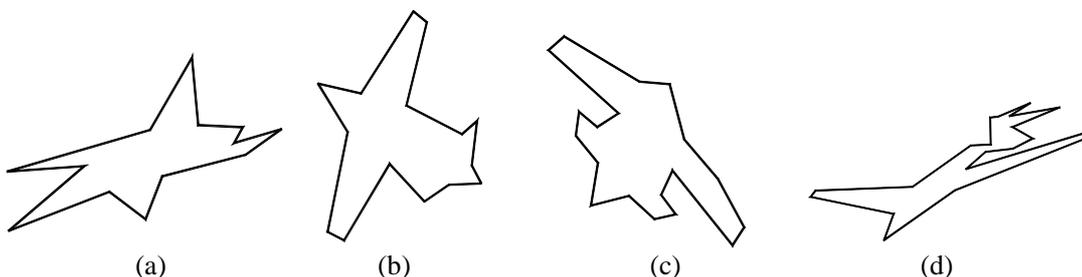
Figure 8.   Airplanes contours to be recognized

Based on the proposed algorithms we calculate local invariants of model and object to be recognized, detect the loss features, and calculate similarity measures between model and objects, the experiment result are shown as table.3, match results are shown as Fig.9.

It is observed from experiment results that Fig.8 (a) corresponds to Fig.7 (a), Fig.8 (b) corresponds to Fig.7 (b), Fig.8 (c) corresponds to Fig.7 (c), and Fig.8 (d) corresponds to Fig.7 (d).
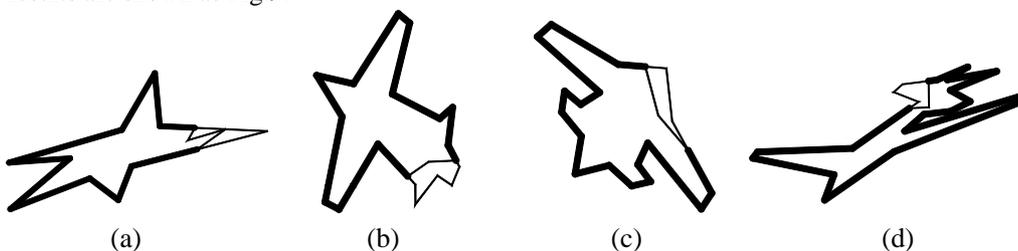

(a)   (b)   (c)   (d)

Figure 9.   The match result

TABLE 3 Match result (The values shown in table 3 are similarity measure)

	Fig.8(a)	Fig.8(b)	Fig.8(c)	Fig.8(d)
Fig.7(a)	0.8524	0	0.1832	0.04216
Fig.7(b)	0	0.9131	0.09615	0.08351
Fig.7(c)	0.07859	0.0217	0.8947	0
Fig.7(d)	0.04321	0.05263	0	0.8863

B.   Experiment results analysis

We take the experiment 1 as example to analysis the relation between recognition rate and noise or the relation between recognition rate occlusion rates.

We disturbed the contour by adding Gaussian noise to their vertexes. The standard deviation σ^2 of the Gaussian noise varies from 0.5，1，1.5，2.5 to 3. Repeat

experiments, we use the approved local features and two recognition methods to take experiments. For recognition method, one is directly comparing the absolute distance of feature vector (the method 1), the other is probability interpreted (the method 2), experiments results are shown as Fig.10. In Fig.10 curve marked with 'o' denote the experiment result using the recognition method 1, and curve marked with '*' denote the experiment result using

the recognition method 2. It is noted that the recognition rate decreases as the noise variance increases, however, using the recognition method 2 is more robust to noise variance than using the recognition method 1.

Then we analyzed the relation between recognition rate and occluded rate.

We overlap images by adding occlusion. The occluded rate varies from 10%, 20%, 30%, 40%, 50% , 60% to 70%, repeat experiments, we can obtain the relation between the recognition rate and occluded rate(where $\sigma^2 = 0.5$), as shown in Fig. 11. The curve marked with 'o' is the relation curves between the

recognition rate and occluded rate, using the recognition method 1, and curve marked with '*' is the relation curve between the recognition rate and occluded rate, using the recognition method 2.

From the results it is observed that recognition rate decreases as the occluded rate increases, however, using the recognition method 2, the recognition rate is improved greatly, moreover, it is noted that using the recognition method 1, object can be correctly recognized if 66% contour survived in, and using the recognition method 2, object can be correctly recognized if only 40% contour survived in.
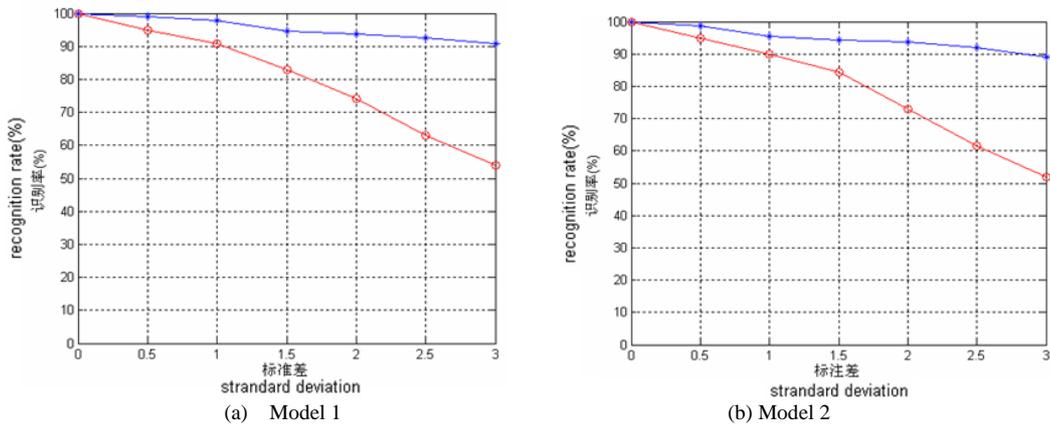

(a)   Model 1   (b) Model 2

Figure10. The relation between recognition rate and noise
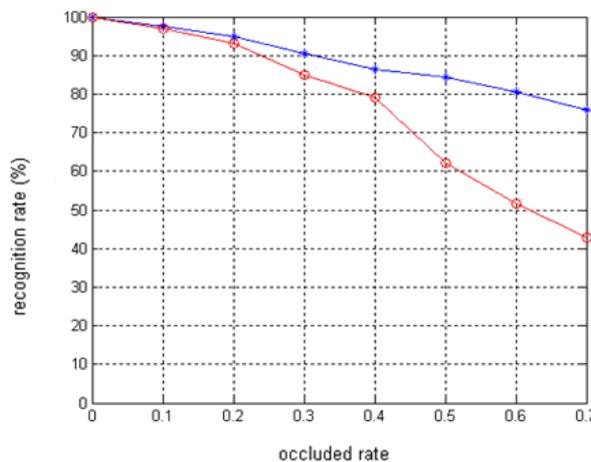

Figure 11.   The relation between recognition rate and occluded rate

VI.   CONCLUSION

In this paper, we proposed a new algorithm for recognizing partially occluded polygon object, employing a local invariant to describe model and polygon object. The new local features are invariant under affine transform, so our algorithm can solve the problem that many existed method are only suit for Euclid transform or similarity transform. We considered the influences of noises and occlusion simultaneity when constructing new similarity function and loss feature judged function. Thus, the recognition algorithm is insensitive to occlusion and noise. Experiment results show our recognition algorithm is robust and effective. The proposed algorithm for recognizing partially occluded objects is quite robust to shape variations, including noise and occlusion.

Moreover, they establish one-to-one correspondence between model features and object features in a scene, and can recognize multiple objects.

Our algorithm can be extended to perspective transform through being improved. However, our algorithm is not always acceptable as the number of polygon vertex conserved under transform is less than four or the conserved four vertexes constitute a parallelogram.

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