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TARGET RECOGNITION ALGORITHM BASED ON SALIENT CONTOUR FEATURE SEGMENTS

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A target recognition algorithm based on salient contour feature segments is presented. The algorithm segments the contour according to the contour division scheme and evaluates the value of the contour segment from three aspects: curvature difference, fluctuation amplitude, and bending ratio. The segments of unreasonable division are merged. The importance of the segment is evaluated from the aspect of the length of the contour segment relative to the overall contour length. On this basis, the reasonable segmentation result of the contour segments is obtained. The similarity measures are performed between the reasonably divided contour segment and the contour segment database to obtain the best matching result of the target. Experimental results show that the proposed algorithm determines the parameters of significance evaluation of contour segmentation, which ensures that the segmented contour segment has significant features and improves the target recognition rate.

Keywords: Contour division, Contour feature segments, Significant features, Object Recognition

1. Introduction

Contour feature is a kind of advanced visual information. Even when an image object loses its color or texture features, the object's category can still be identified according to the target contour. The contour segment description method is one of the most widely used target recognition methods in natural image target recognition in recent years [1-3]. Ma and Latecki et al. [4] proposed a shape descriptor, which is particularly suitable for the shape matching of image edge fragments to simulate the outline of the target object. However, this method is greatly affected by noise. Filip Krolupper et al. [5] achieved the purpose of dividing the contour by performing polygon approximation of the contour through the inflection point on the contour. Eli Saber et al. [6] selected points with local maximum curvature along contours as feature points and computed distance matrices for each candidate object

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region and example template. Xiang Bai et al. [7] divided the contour into several parts by using the DCE (discrete curve evolution) algorithm on the complete contour of a known object. Chunjing Xu et al. [8] proposed the contour flexibility based on the topological relationship of contour shape and convexity. This method can accurately obtain the global and local features of the target contour. The target has strong robustness but high computational complexity. Shi Siqi et al. [9] proposed to select the concave points with the largest absolute curvature in continuous non-characteristic points to segment the contour. The segmentation of nonsense contour is processed. And the locality of the contour segment is evaluated by the ratio of feature points and non-feature points in the contour segment. Huang Weiguo et al. [10] proposed to segment the contour according to the corner point. The feature point and the non-characteristic point are judged using parameters which are different from the ones proposed by Shi et al. [9] to evaluate the value of the contour fragment.

Aiming at the problem of unreasonable contour segmentation or lack of evaluation of contour segments, this paper proposes a target recognition algorithm based on salient contour feature segments and determines the significance evaluation parameters of contour segment.

2. Target recognition algorithm based on the salient contour feature segments

The target recognition algorithm based on salient contour feature segments proposed in this paper firstly obtains the target contour, calculates the curvature and segments the target contour. Secondly, the evaluation value of the divided contour fragments is carried out. The fragments which don’t satisfy with the value are merged according to the segmentation rules. The importance of the contour fragment is calculated, and the contour fragment with significant features is selected according to the importance of the outline segment. Finally, the similarity measure is performed on the contour segment to obtain the target matching result. Compared with the existing technology, the algorithm proposed in this paper determines the evaluation parameters of the contour segmentation and evaluates the contour segment by value and importance to ensure that the contour segment has significant features. The overall flow chart of the algorithm is shown in Fig. 1.

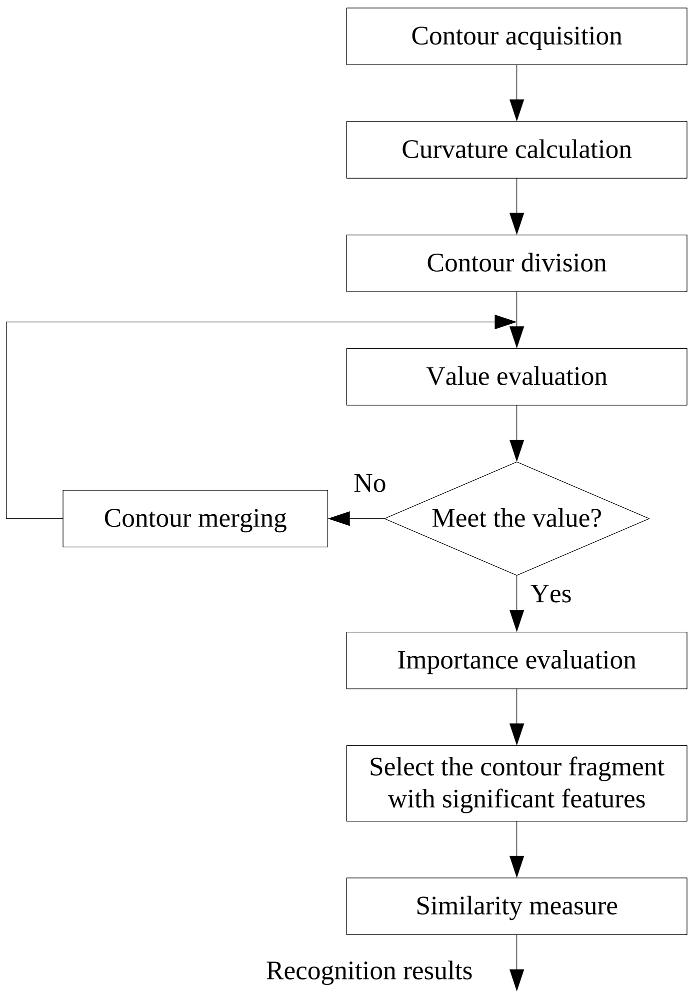


Fig. 1. Target recognition flow chart

2.1 Contour acquisition

According to the visual psychology, when the human vision observes an image, it firstly perceives a significant area of the image, that is, a prominent edge part, and then the details in the image. Therefore, it can be seen that the edge feature of the image has more important significance for the target recognition. Contour acquisition is an important step in the contour-based target detection method. The quality of the contour detection method directly affects the target detection result.

The Canny edge detection method is one of the most used methods at present. The Gaussian filtering part in the Canny operator has a poor suppression effect on the impact noise, so that part of the impact noise is easily detected as an edge. Median filtering can suppress the random noise without blurring the edge. Therefore, the median filtering is selected to smooth the impact noise, and then the Canny operator edge detection is performed on the smoothed image to extract the contour. The contour of the smoothed motorcycle graph extracted by the Canny operator is shown in Fig. 2. It can be seen from Fig. 2 that the contour extracted by the Canny operator has many small segments that we do not care about or have no influence on the recognition. In order to eliminate the small segments in the contour, the contours extracted by the Canny operator are processed by expansion, erosion, region filling, opening operation and closing operation to obtain the target shape map. The target shape map is shown in Fig.3. Finally, the edge pixels are connected into boundary edge segments. The final motorcycle profile is shown in Fig. 4.

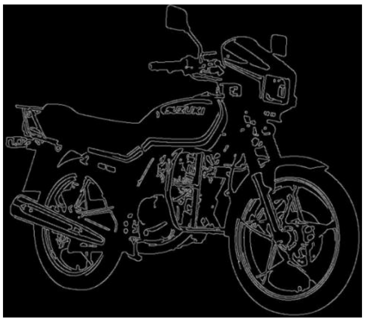


Fig. 2. Motorcycle contour extracted by Canny operator

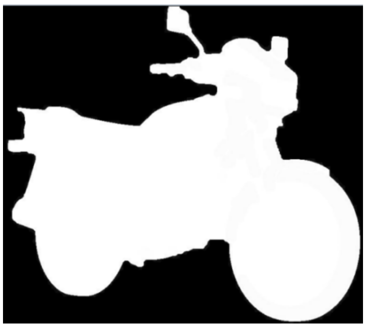


Fig.3. The target shape map

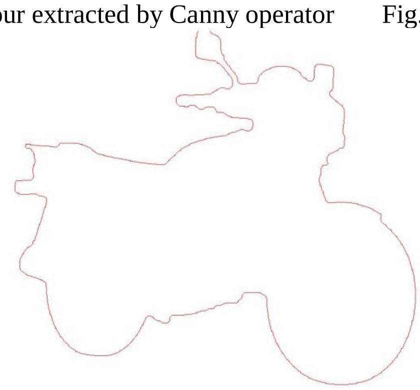


Fig. 4. Final motorcycle contour

2.2 Curvature calculation of the contour

When the overall contour of the target is extracted, how to divide the contour into pieces with obvious local features becomes a key point. Different contour segments have different effects on the accuracy of target recognition. A reasonable contour segmentation can describe the characteristics of the target efficiently and completely. When the segment is too short, the characteristics are not obvious, and the mismatch rate is increased. When the contour segment is too long, it is not conducive to describing similar objects. Therefore, the segmented contour segments must not only be able to describe the object itself, but also be able to distinguish it from other objects. In this paper, the curvature of the target contour is calculated, and the contour is divided according to the curvature calculation result.

The curvature of a curve is defined as the rotation rate of the tangent direction angle to the arc length at a point on the curve, which is defined by differential, indicating the degree of deviation of the curve from the straight line. The curvature has the invariance of rotation, scaling and translation. The contour curve is set to be $C(t)=(x(t),y(t))$, the curvature of the contour curve can be expressed as formula (1):

$$k=\frac{x'(t)y''(t)-x''(t)y'(t)}{((x'(t))^2+(y'(t))^2)^{3/2}} \tag{1}$$

In formula (1), $x'(t)$ and $y'(t)$ represent the first derivative of $x(t)$ and $y(t)$ to the arc length; $x''(t)$ and $y''(t)$ represent the second derivative of $x(t)$ and $y(t)$ to the arc length.

The curvature of the curve reflects the degree of bending of the curve, and the degree of angle change in the arc length between the two adjacent tangent vectors on the curve. The calculation results of the contour curvature of the motorcycle are shown in Fig. 5. It can be seen from Fig. 5, the curvature value of the contour has a sharp change region, where the corresponding target contour segment has a significant feature, while the region with a smaller curvature change corresponds to the meaningless contour segment.

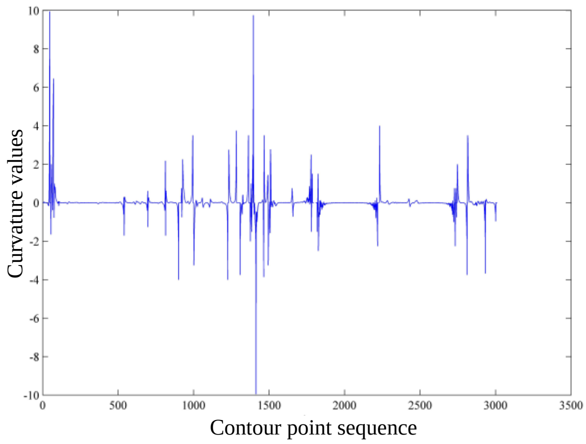


Fig. 5. Motorcycle contour curvature

2.3 Contour division

After obtaining the curvature calculation results of the target contour, the part with the steepest contour change or the largest curvature is the place where the information is most concentrated, and the place where the contour direction is consistent is the place where the information is most redundant. Therefore, the contour division scheme based on the curvature data is shown in Fig. 6.

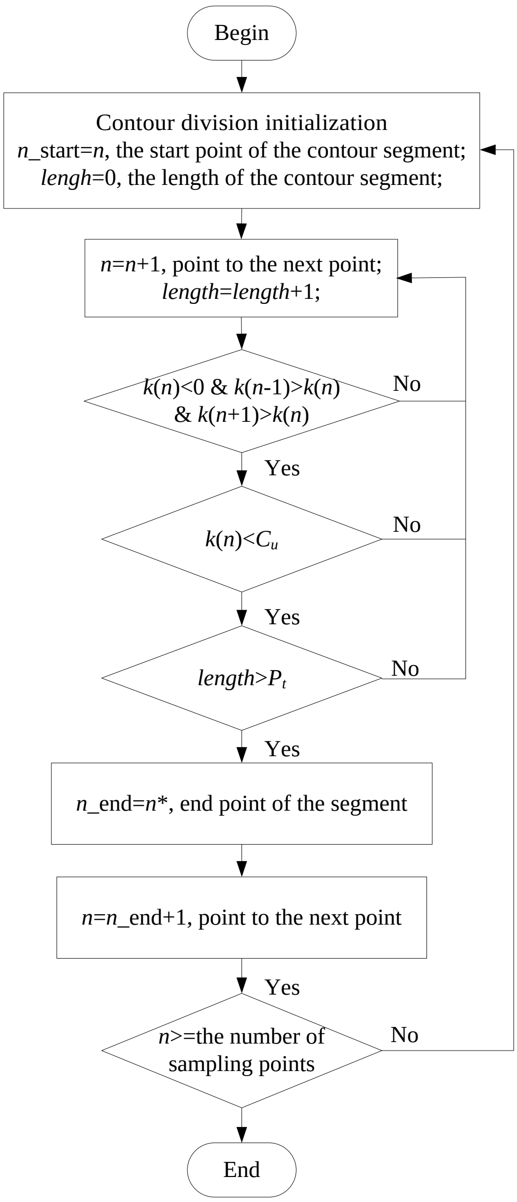


Fig.6. The contour division scheme based on the curvature data

The leftmost point of the contour is selected as the starting point of the current segment, and the contour point adjacent to it is merged in a clockwise direction. When the segmentation cutoff conditions are met, the next point is selected as the starting point for the new segment. The above processes are repeated until the end of the contour curve. In Fig.6, $k(n)$ represents the curvature of point n; Pt is the threshold for the length of the segment; Cu is the threshold for the curvature of the concave point. The segmentation cutoff conditions are as below:

(1) The length of the segment is greater than Pt;

(2) There is at least one local extreme point of concave point in the segment;

(3) The curvature of the concave point must be less than Cu.

The above three conditions must be met at the same time. The condition for Pt ensures that the segment is not too short. The condition for Cu ensures that the segment has more significant features.

The motorcycle profile segmentation is shown in Fig.7, where $Cu = -1$ and $Pt = 450$. Different line types represent the results of each fragment of the profile.

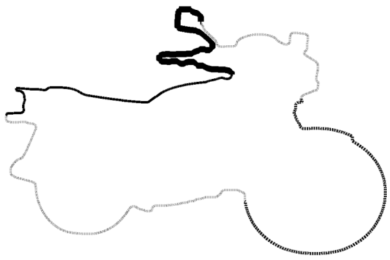


Fig. 7. The motorcycle profile segmentation

2.4 Evaluation and merging of contour fragments

After obtaining the result of contour segmentation, the value of contour segments must be evaluated. In this paper, the curvature difference, fluctuation amplitude and bending ratio of contour fragments are presented to evaluate the value of segment.

(1) Curvature difference. The more prominent parts of the contour segment the greater the contribution to the target recognition. The maximum curvature $\max(cur)$ and the minimum curvature $\min(cur)$ on the contour segment are calculated. The curvature difference is calculated as formula (2):

$$\text{Curvature difference} = \max(cur) - \min(cur) \tag{2}$$

The greater the curvature difference is, the greater the fluctuation of

the curvature of the segment will be, the more prominent parts of the contour segment may be, and the more obvious the characteristics will be.
(2) Fluctuation amplitude. The fluctuation amplitude of the contour segment is the distance from each point on the contour segment to the straight line SE, as shown in Fig. 8.

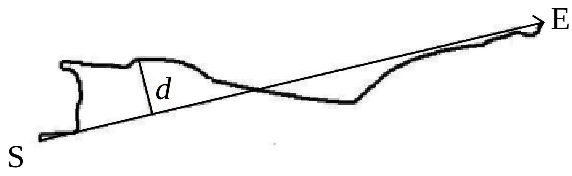


Fig. 8. Fluctuation amplitude of contour segment

The start point of the contour segment is set to be $S(x_s, y_s)$ and the end point to be $E(x_e, y_e)$. The distance formula from point (x, y) to straight line SE on the contour segment is deduced as below:

The slope of straight-line SE is:

$$k = \frac{y_e - y_s}{x_e - x_s} \tag{3}$$

The formula of straight-line SE is:

$$y - y_s = k(x - x_s) \tag{4}$$

The distance formula from point (x, y) to straight line SE is calculated as formula (5):

$$d = \frac{kx - y + (y_s - kx_s)}{\sqrt{k^2 + 1}} \tag{5}$$

When the point on the segment is on the upper side of straight line SE, d is positive; when the point on the segment is on the lower side of straight line SE, d is negative. The maximum fluctuation amplitude of the contour segment is max(d)-min(d). The larger the fluctuation amplitude of the contour segment, the more obvious the change of the contour segment, and the more representative for the contour.
(3) Bending ratio. The total number of points of the contour segment is calculated as L. The length $l(SE)$ of the line SE is calculated as formula (6).

$$l(SE) = \sqrt{(x_e - x_s)^2 + (y_e - y_s)^2} \tag{6}$$

The bending ratio is calculated as formula (7).

$$\gamma = \frac{l(SE)}{L} \tag{7}$$

The smaller the bending ratio is, the greater the degree of curvature of the contour segment is, and the more obvious the feature is. When the bending ratio is close to 1, the contour segment is close to a straight line, and the contour segment feature is not obvious.

The value of the contour segment is evaluated by the evaluation criteria: (1) the curvature difference is greater than the threshold value Tc; (2) the fluctuation amplitude is greater than the threshold value Tf; (3) the bending ratio is greater than the threshold value Tr. The above three principles must be met at the same time. In order to obtain the contour segments that can effectively describe the target characteristics, the contour segments that do not meet the evaluation criteria are processed as below:

(1) For the target contour, the contour section obtained by initial contour division is represented as $S=\{s_i, i=1,2,3\cdots\}$.The minimum number of contour segments is set to be *N*.

(2) If the number of contour segments is less than or equal to *N*, the merge process is ended. Otherwise, the next step is carried on.

(3) The first segment S_i that does not meet the criteria to merge is found out by clockwise.

(4) The contour segments around S_i are represented as S_i^L and S_i^R, respectively. The curvature difference, fluctuation amplitude and bending ratio between S_i^L and S_i^R are compared. Then, S_i is merged with the more obvious features of the two. If S_i is merged to S_i^L, the new contour segment is marked as $S_{new}=S_i^L \cup S_i$. If S_i is merged to S_i^R, the new contour segment is marked as $S_{new}=S_i \cup S_i^R$.

(5) The new contour segment S_{new} is added to the contour segment set S while the contour segment S_i is removed from the set S.

(6) The curvature difference, fluctuating amplitude, and bending ratio of the new contour segment S_{new} are calculated. If the evaluation criteria are satisfied, the new segment S_{new} can be used as a feature segment. Otherwise, the second step is carried on.

In the contour segment merging process, the low-value contour segments are selected to be merged to obtain a new contour segment, which ensures that the contour segment has obvious local features and can make the original feature change more obvious. The segmentation and merge results of a horse contour are shown in Fig. 9. The contour of the horse is initially divided into 5 segments and merged to 4 segments.

(a) Initial contour division results. (b) Contour segment merge results

Fig. 9. The segmentation and merge results of a horse contour

After the contour segments are merged, how to measure the importance of contour segments becomes a key issue. When the contour segment is longer, the contour segment has more significant features, which is more conducive to the target's recognition. Therefore, the importance of the contour fragment is calculated using the ratio of the relative length of the contour segment to the overall length of the contour. The contour fragment with significant features is selected according to the importance of the contour segment. Finally, the similarity measure is performed on the contour segment to obtain the target matching result.

2.5 Similarity measure

The shape context feature is a very popular shape descriptor that is mostly used for shape matching and target recognition [11,12]. The shape context is described based on the object contour sample points. By performing edge extraction and uniform sampling on the target contour, a set of points in the shape of an object is obtained as $P=\{p_i, i=1,2,\cdots n\}$. The shape information of a single point is described by the relative vector formed with all other points. In a log polar coordinate system, a single point and its neighboring points fall into different bins, which represent different relative vectors. These relative vectors become the shape context of this point. The matching cost of a certain point p_i of contour segment P and a point q_j of contour segment Q is shown as formula (8):

$$C_{ij} = C(p_i, q_j) = \frac{1}{2}\sum_{k=1}^{K}\frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)} \tag{8}$$

Where $k = \{1, 2, ..., K\}$; K is the number of bins; $h_i(k)$ and $h_j(k)$ are the shape histogram values corresponding to p_i and q_j, respectively.

After obtaining the matching cost of each point, a cost matrix can be formed. Then an optimal matching algorithm (Hungarian algorithm) [13] is run to find the optimal match. The result is a permutation $\pi(i)$ such that the sum $\sum_i C(p_i, q_{\pi(i)})$ is minimized. Finally, the overall shape cost is obtained based on this optimal matching. The minimized shape cost can be measured as the difference between two shapes. The smaller the cost, the more similar the shape. The shape cost is shown as formula (9):

$$H(\pi) = \sum_i C(p_i, q_{\pi(i)}) \tag{9}$$

Where π is a permutation.

The contour shape distance can be expressed by formula (10):

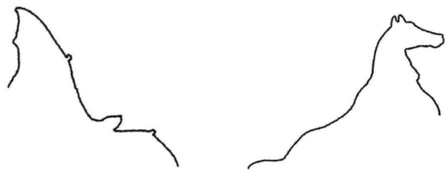
$$D_{sc}(P,Q) = \frac{1}{n}\sum_{p\in P}\arg\min_{q\in Q} C(p,T(q)) + \frac{1}{m}\sum_{q\in Q}\arg\min_{p\in P} C(p,T(q)) \tag{10}$$

Where $D_{SC}(P,Q)$ is the contour segment distance of the contour segment P and Q; n is the number of points of the contour segment P; m is the number of points of the contour segment Q; $\arg\min_{q\in Q} C(p,T(q))$ indicates the value of p and $T(q)$ at the moment when $q \in Q$ and $C(p,T(q))$ get the minimum value; $\arg\min_{p\in P} C(p,T(q))$ indicates the value of p and $T(q)$ at the moment when $p \in P$ and $C(p,T(q))$ get the minimum value; $T(\cdot)$ denotes the estimated TPS (thin plate spline) shape transformation[14].

The difference between the two object shapes can be basically measured based on the contour shape distance, and further work on object recognition can be performed.

3. Experimental results and analysis

In order to test the accuracy of the target recognition algorithm based on salient contour feature segments proposed by this paper, many experiments were carried out, the matching results were given, and the experimental data were analyzed. Firstly, five types of targets in the MPEG-7 Shape-1 Part-B database were selected as the test targets. The outer contours were extracted from the 5 types of targets. 10 types of each class are selected to set up a segmented database according to the contour division scheme proposed in this paper. The rest is used as the test object to establish the segmented database of the test object contour. In the simulation experiment, the salient contour feature segment of bats, horses, elephants, cars, and dogs were selected and tested. The parameters used in the simulation were $Tc=2$, $Tf=120$, $Tr \in [0.6,0.7]$, $N=2$. The bat and horse test contour segments are shown in Fig. 10.



(a) bat (b) horse

Fig. 10. Test contour segments

The first 10 groups of contour shape distance calculated from the similarity of the fragments in the bat, horse, elephant, dog, and car sample libraries are shown in Table 1 and Table 2 respectively. If the shape distance between fragments is less than 0.2, the sample library segment corresponding to the minimum distance is selected as the successful result. If the distance between fragments is not less than 0.2, the matching fails. As can be seen from Table 1 and Table 2, this method successfully achieves the correct target match

Table 1.

The contour shape distance of bat test segment

	bat									
Bat database	0.504	0.350	0.429	0.639	0.158	0.659	0.539	0.500	0.468	0.465
Horse database	0.569	0.442	0.417	0.422	0.267	0.613	0.477	0.522	0.410	0.257
Elephant database	0.382	0.444	0.290	0.394	0.422	0.382	0.413	0.392	0.410	0.449
Dag database	0.431	0.469	0.389	0.394	0.421	0.451	0.387	0.398	0.553	0.505
Car database	0.494	0.551	0.513	0.542	0.517	0.571	0.469	0.482	0.502	0.594

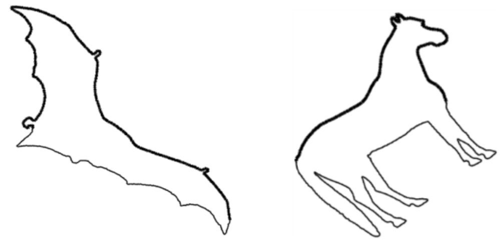
Table 2.

The contour shape distance of horse test segment

	horse									
Bat database	0.402	0.449	0.531	0.415	0.515	0.334	0.413	0.442	0.489	0.477
Horse database	0.443	0.431	0.439	0.375	0.548	0.427	0.391	0.401	0.557	0.106

Elephant database	0.459	0.372	0.540	0.441	0.362	0.433	0.457	0.332	0.435	0.503
Dag database	0.526	0.505	0.611	0.476	0.482	0.497	0.566	0.483	0.347	0.436
Car database	0.440	0.534	0.378	0.522	0.415	0.560	0.604	0.527	0.517	0.400

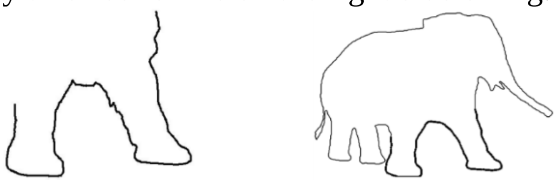
The matching result of the contour fragment is shown by the thick line in Fig. 11.



(a) bat (b) horse

Fig. 11. The matching result of the contour fragment

The test contour segments of the elephant, car, and dog are shown in (a), (c) and (e) on the left side of Fig. 12 and the matching results are shown in (b), (d) and (f) by thick solid line on the right side of Fig. 12.



(a) elephant contour segment (b) elephant matching result

(c) car contour segment (d) car matching result (e) dog contour segment (f) dog matching result

Fig. 12. The contour segment test result of elephant, car and dog

The comparison results of the target retrieval rate of this algorithm in the database and other representative methods in recent years are shown in Table 3.

Table 3.

Comparison of recognition rate of each method in MPEG-7 database

method	Target retrieval rate
Visual part [15]	76.45%
Skeletal context [16]	79.92%
SSC [17]	82.39%
Polygonal Multiresolution [18]	84.33%
Inner Distance Shape context [19]	85.4%
Shape tree [20]	87.7%
Paper [10]	91.05%
Method of this article	92.5%

It can be seen from the experimental data that the contour segmentation criterion and the fragment value scale evaluation criterion proposed in this paper ensure that the contour has obvious characteristics, which is favorable for object recognition and has a significant effect on improving the target recognition rate.

4. Conclusions

This paper proposes a target recognition algorithm based on salient contour feature segments. Firstly, the curvature of the acquired target contour is calculated, and the target contour is segmented by the contour segmentation algorithm. The curvature difference, fluctuation amplitude, and bending ratio are used to evaluate the value of the contour segment, and the contour segments that do not meet the conditions are merged. Then, the importance of the segment is evaluated from the length of the contour segment relative to the overall contour length to obtain the segmentation result of the contour segment. Finally, the contour segment matching is performed using the shape context similarity between contour segments. Compared with the existing technology, this algorithm determines the evaluation parameters of the contour segmentation. Through the value and importance of the overall evaluation of the contour segment, it ensures that the contour segment has significant features and is effectively applied to the contour segment target. Experimental results show that the algorithm improves the target recognition rate.

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