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Research Article

Noise Adaptation and Threshold Determination in Image Contour Recognition Method Based on Complex Network

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Abstract: In practice of image contour recognition, the precision of shape contour extraction is affected by lots of factors, such as noise, shelter and parameters. That will affect the shape contour quality and reduce the recognition effect. To solve these problems, a Shape Contour Recognition Method Based on Complex Network is discussed in this study. The main idea of the approach is to use complex network methodology to extract a feature vector for shape contour recognition under rotation, noise and shelter. An approximation method for Distance Threshold Determining (DTD) is presented to help modeling the complex networks. Experiments show that the proposed method and the DTD method have efficient power in shape recognition. It is also proved to be scale invariant, rotation invariant and partially overcome noise-sensitive and shelter.

Keywords: Complex network, distance threshold determining, image sequence, robustness, shape contour, shape recognition

INTRODUCTION

As important identity features, the contours and shape of images are widely used in the methods of recognition. Compared with other recognition methods based on K-L Transformation (Sirovich and Kirby, 1987; Turk and Pentland, 1991), Texture (Reed and Dubuf, 1993), Model (Pope, 1994; Brooks, 1983) and Geometric Feature (Roberto and Tomaso, 1993; Chin and Dyer, 1986), etc, the Methods based on Image Contour and Shape were successful applied in various areas (Torres *et al*., 2003; Wang *et al*., 2003; Sebastian *et al*., 2004; Gareth and Nick, 2004) with simple process and high identify efficiency.

There are mainly two approaches to shape representation (André *et al*., 2009; Pavlidis, 1978), namely the region-based approach and the boundary-based approach. The latter seems to be more efficient with object contours. The boundary-based approaches include Fourier descriptors (Mehtre *et al*., 1997; Osowski and Nghia, 2002), curvature scale space (Wu and Wang, 1993), wavelet descriptors (Chuang and Kuo, 1996; Quang and Boles, 1997) and multiscale fractal dimension (Torres *et al*., 2003; Plotze *et al*., 2005).

This study is related to the boundary-based approach. It is concerned that most of the shape recognition methods, which are boundary-based, consider the shape as a chain of continuous connected points. The adjacent and the sequence of boundary points, which perform important roles, are used to extract the measures for characterizing the shape boundary (Loncaric, 1998).

The proposed method approached to the image sequence contour recognition using the Complex Network theory. The physical aspects of the shape could be described by the topological features, which are derived from the dynamics of the network growth. These features are extracted from the networks and used in shape recognition.

Traditional shape boundary methods consider the contour as continuous closed curves. On the other hand, the proposed method only takes the topologic degree and distance between the boundary points into account. It considers the boundary of shape as a set of points and models them as a mathematic graph, without taking the adjacent and sequential of points into account (Wang *et al*., 2006).

An approximation method for Distance Threshold Determining is also present in this study. The method could help choosing the range of the threshold value, in order to achieve better recognition rate with higher possibility.

Experiments were done to evaluate the proposed method and the DTD method. In the experiments, the proposed method was applied in database of static image and image sequence. The shapes were also intentionally re-shaped to evaluate characteristics such as noise tolerance, robustness and rotate invariance.

As will be shown in this study, the proposed method presents better results in shape classification performances. It is proved to be scale invariant, rotation

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invariant and partially overcome noise-sensitive and shelter, due to the character of the Complex Network. Meanwhile, the DTD method is also proved to be effective in choosing the value of the distance threshold.

COMPLEX NETWORK

The current research interest is focused on applying the Complex Network theory to many real data and situations. The literature (Gonçalves *et al*., 2010) show that topics of computer vision can also be modeled into graphs, using the concepts of Complex Network. With the analysis of dynamics of the network growth and topological characteristics, the Complex Network theory can solve the problems such as image shape recognition.

Typical network is represented by mathematic graph that consists of a set of vertices connected by edges. Most social, biological and technological systems could be modeled into networks with substantial topological features. The patterns of connection between their elements are neither purely regular nor purely random.

A random graph generation model that produces graphs with small-world properties, including short average path lengths and high clustering, was proposed by Watts and Strogatz in their joint 1998 Nature paper, Collective Dynamics of 'Small-World' Networks. In 1999, Barabási and Albert introduced another concept of scale-free networks and proposed a model to explain it in their Science paper, Emergence of Scaling in Random Networks. Today, the complex network has become a field of investigation confers a truly multidisciplinary nature that is more and more popular.

Measurements on complex network: Each complex network presents specific topological features that characterize its connectivity and highly influence the dynamics and function of processes executed in the network. Therefore, the use of measurements is important in the analysis and discrimination of a complex network. The measurements used in this study are presented bellow.

The symbol $k_i \in K$ stands for the degree of a node i. It is defined as the number of edges directly connected to it. Degree is one of the most important measurements of a vertex. Based on the degree of the vertices, features can be extracted from the network. And k_i is defined in terms of the adjacency matrix A as follow:

$$k_i = \sum_{j=1}^{N} a_{ij}$$

The maximum degree $K\kappa$ and average degree $K\mu$ are other features used in this study. $K\kappa$ is defined as the maximum value of k_i. And $K\mu$ is defined as the average value of k_i:

$$K_\kappa = \max \mathrm{k}_i \in K$$

$$K_\mu = \frac{1}{N}\sum_{i=1}^{N} k_i$$

With these basic measurements, feature vector of the complex network can be extracted for shape recognition.

Parameters for analysis: Degree distribution, clustering coefficient and the average shortest path length are important parameters for network characteristics analysis.

The degree distribution of nodes in the network can be described by the distribution function $P(k_j=k)$. It stands for the probability that a randomly selected node j with degree k_j exactly equals to k.

Clustering coefficient is an important parameter for the complex network. In general, suppose a node i in the network has e_k edges, which connect it with the other e_k nodes. Between the e_k nodes may have at most $e_k(e_k-1)/2$ edges. Actually, there are e_i edges between these nodes. The clustering coefficient C_i for node i is defined as follow:

$$C_i = \frac{2e_i}{e_k(e_k-1)}$$

The clustering coefficient C_G for the network G is defined as the average value of C_i:

$$C_G = \frac{1}{N}\sum_{i=1}^{N} C_i$$

The average shortest path length is important characteristic for the small-world networks. The shortest path is a classic problem in graph theory research. It focuses on finding the shortest path of two nodes in the figure. Given the adjacent matrix of image shape, the value of the shortest path length can be provided by the Floyd algorithm. Traversing the graph for every node pair, the average shortest path length can be calculated for a certain network.

The network dynamic evolution: Dynamic evolution is an important characteristic in the Complex Networks. It affects various network properties. The measurements of the Complex Network, extracted with different thresholds, can be seen as an immediate consequence. They can be given by a function of time.

Monitored over time, the trajectories of measures can be used to analyze and classify networks. In this way, a more comprehensive characterization of the network is provided for further analysis.

Distance threshold and gray threshold are often used in the dynamic evolution analysis of image shape. Given by the function of time, the value of thresholds presents more details characterization of the network. That is important in image shape recognition.

SHAPE CONTOUR RECOGNITION BASED ON COMPLEX NETWORKS

The proposed method can be split into four steps:

- Shape contour presentation
- Complex network modeling
- Identification features generating
- Shape recognition

Shape contour presentation: Shape contour can be expressed as a set of coordinates.

All pixels of the shape image can be mapped to the set V_0. Any $v^i_0 \in V_0$ can be expressed as $v^i_0 = (p^i_0, w^i_0)$. The symbol p^i_0, which is defined as $p^i_0 = (x^i_0, y^i_0) \in P_0$, stands for the coordinates of v^i_0. The symbol $w^i_0 \in W_0$ stands for the gray value of v^i_0.

After processing shape contour extraction, set P is obtaining as a subset of the coordinates of P_0. And P is the set of contour points used for complex network modeling.

Consider P as the set of contour points for a image, where $P = [p^1, p^2, p^3, \ldots, p^N]$. The measures p^i are typical vectors in the form of $p^i = (x^i\ y^i,)$, whose components are discrete numerical values representing the coordinates of point i of the contour.

Complex network modeling: In order to apply the complex network theory to shape recognition, a representation of contour P should be built like graph G

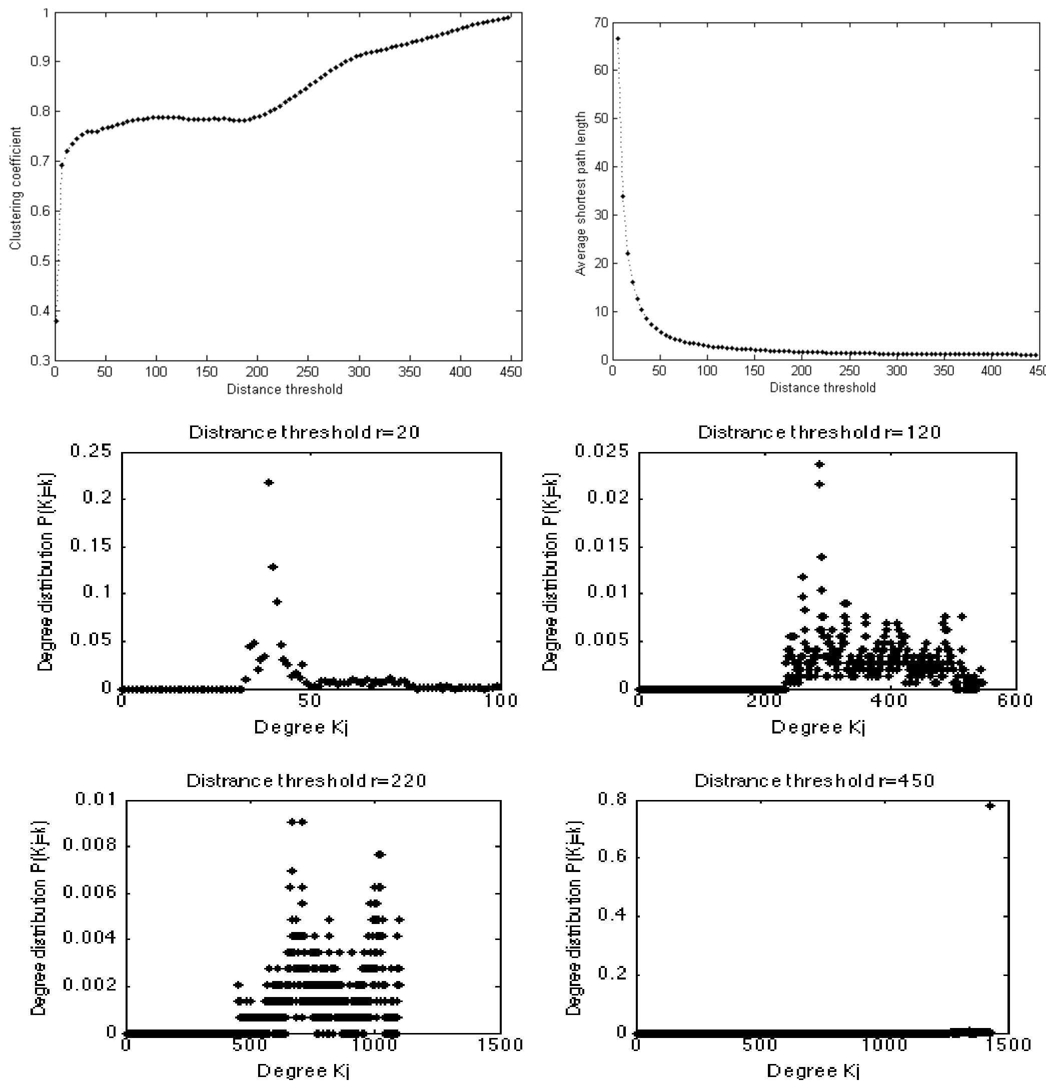

Fig. 1: Properties from a shape modeled as a small-world complex network: Clustering coefficient, average shortest path length and degree distributions

= (V, E). Each pixel of the contour is represented as a vertex in the network. So the set V is defined as V = P.

Each pair of vertices is bound by a set of non-directed edges E. The distance between point i and j of the set E is calculated in Euclidean Distance, which is represented as *dist* (p^i, p^j):

$$dist(p^i, p^j)=\sqrt{(x^i-x^j)^2+(y^i-y^j)^2}$$

The network will behave regularly if the set of edges connects all network vertices to each other. A possible way of transforming the network to a complex network is to apply a threshold r which produces a new set of edges for the network.

The transformation for selecting the group of edges from set E is performed as follow:

$$e_{ij}=\begin{cases} 0, & \text{if } dist(p^i,p^j)\ge r; \\ 1, & \text{otherwise.} \end{cases}$$

Figure 1 shows the clustering coefficient, average shortest path length and the degree distribution of the network model for the first shape contour from the PLANE Database. The modeled network presents both high clustering coefficient and small-world property, regardless of the threshold values used.

Identification features generating: Different values of distance threshold r could directly affect the structure and topology of network, which are important in identification.

For small values of r, the network provides more information of image details. Otherwise, the network provides better global information with some useful detail losing for large values of r.

The proposed method chooses several distance thresholds for complex networks modeling respectively. They are given by the function of time. Features for recognition are calculated for these networks.

User defines the initial and final thresholds of r, which are denoted by r0 and rm. The distance threshold is incremented at a regular interval rp. Therefore, given set R, elements r^j can be defined as follow function f:

$$Funtion\ f: R \to R,\ where$$

$$r^j=\begin{cases} r0\ , & if\ j=0; \\ f(r^{j-1}), & if\ j>0\ \&\ r^j \le rm. \end{cases}$$

$$f(x)=x+rp$$

A graph Gi composed of contour shape can be generated. Several complex networks are modeled by different distance thresholds r^j for Gi. Maximum degree $K\kappa(r^j)$ and average degree $K\mu(r^j)$ are separately calculated for each complex network. The feature θ for graph Gi is defined as follow.

$$\theta(Gi) = [K\kappa(r^0), K\mu(r^0), K\kappa(r^1), K\mu(r^1), \ldots, K\kappa(r^m), K\mu(r^m)].$$

And the feature vector θ(Gi) is used for shape recognition.

Shape recognition: The images are divided into sample group and test group. The feature vector $\theta(G_t)$ of each image from test group is calculated with $\theta(G_s)$ of images from sample group separately by function $F(\theta(G_t), \theta(G_s))$ using L2 norm. Classification result of the test image is determined by the subject of the sample image, with which $F(\theta(G_t), \theta(G_s))$ obtains the minimum value.

Threshold parameter determining: An approximation method for Distance Threshold Determining (DTD) is present in this part. Discrimination Degree δ is introduced to help determining the probable value range of distance threshold r.

The DTD method is applied in the sample group. The purpose of the method is to reach higher recognition rate in the sample group and test group recognition.

The sample group G_s is composed of n subject groups $G_1 \ldots G_n$. Each subject group i is composed of m shape graphs $G_{i1} \ldots G_{im}$.

For a given r, the Discrimination Degree δ is defined as follow:

$$\delta=\sum_{i=1}^{n}\sum_{j=1,j\neq i}^{n}\frac{F(\overline{\theta(G_i)},\overline{\theta(G_j)})}{\sum_{k=1}^{m}F(\overline{\theta(G_i)},\theta(G_{ik}))}$$

The feature vector stands for the average value of θ for graph $G_{i1} \ldots G_{im}$ from subject group i:

$$\overline{\theta(G_i)}=\frac{1}{\mathrm{m}}\sum_{j=1}^{m}\theta(G_{ij})$$

To a certain extent, the Discrimination Degree could represent the capabilities of r in classification.

Rotation and scale invariance: The proposed method has important properties of rotation and scale invariance by an additional process of normalization. The coordinates of the contour points and distance thresholds r^j are normalized at interval [0, 1].

The same image in different rotations is taken into account. The Euclidean distance between the same pair of nodes remains the same, regardless of the direction where points are found. In this way, the normalization ensures the same properties for the set of edge E.

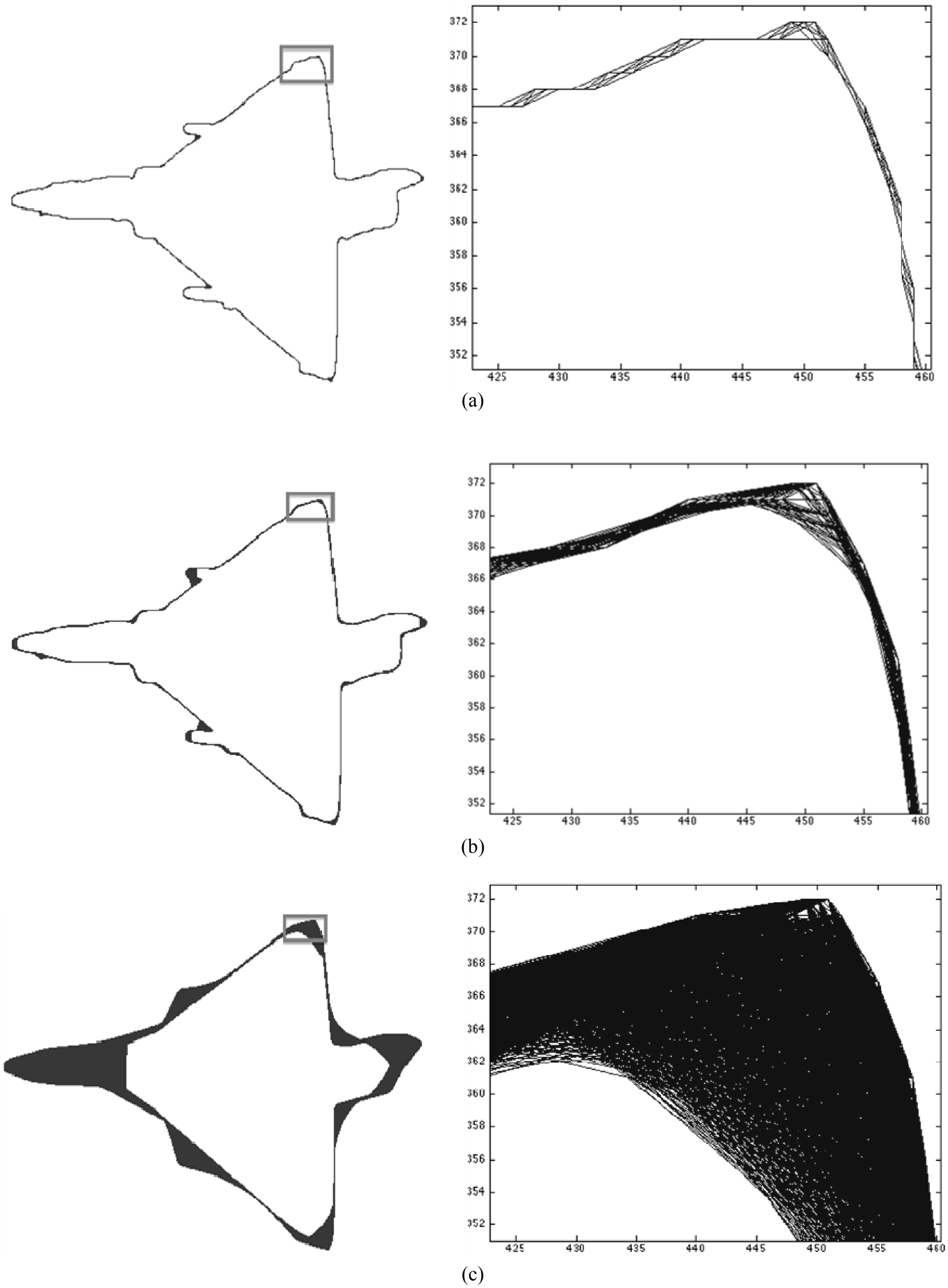

Fig. 2: Network dynamic evolution by a distance threshold and zoom area, (a) r = 4; (b) r = 10 and (c) r = 42

Images at different scales are also analyzed. In the process of normalization, the weight of the longest edge in the network is assigned to one. So the remaining edges are also normalized acquiring relative weights according to the size of the network.

Obviously, the proposed method is rotation and scale invariance with only a small addition of error deriving from the calculation of the Euclidean distance.

SHAPE RECOGNITION EXPERIMENTS

In order to validate the proposed method, experiments were carried out on different databases. The result was analyzed and compared with other methods.

The experimental environment: All of the experiments are executed in the same hardware and software environment, which are mainly shown as follow:

- Intel Core i5 CPU with the frequency of 2.5G Hz
- 4GB memory space
- Mac OS X operating system
- Matlab 7.12.0 (R2011a)

Introduction of the shape database: The following experiments use the MPEG-7 CE Shape-1 database

(MPEG Database) and the Fighter plane shapes database (PLANE Database), which are given by the literature (Thakoor *et al*., 2007).

The MPEG Database has 120 shape contours, which are divided into 6 subjects. All the shape contours from the same subject are different in details.

The PLANE Database has 210 fighter plane shape $\overline{\theta(G)_\iota}$contours, which are divided into 7 subjects. These shape contours are extracted from flying plane image sequences. They are different in visual angle, size and etc.

Experiment on static image: In this experiment, the proposed method was applied in the MPEG Database and compare with several methods.

The previous 2 image contours of each subject are chosen to build a 12 elements sample group. All of the 120 images contours are classified into the test group.

In this experiment, the distance thresholds r^j are defined by r0 = 1, rp = 14, rm = 57. After modeling the complex networks by these thresholds, θ can be calculated for shape recognition.

The results of the proposed method were compared to 7 other methods in Table 1. The proposed method

Table 1: Classification performances of various shape descriptors over the mpeg database

κ+ SVM	FD+ SVM	ZM+ SVM	HMM_E+ML	HMM_C+ML	HMM_{LR}+ML	HMM_E+WtL	The proposed method
83.57%	94.29%	92.14%	80.00%	92.14%	88.57%	97.62%	100.00%

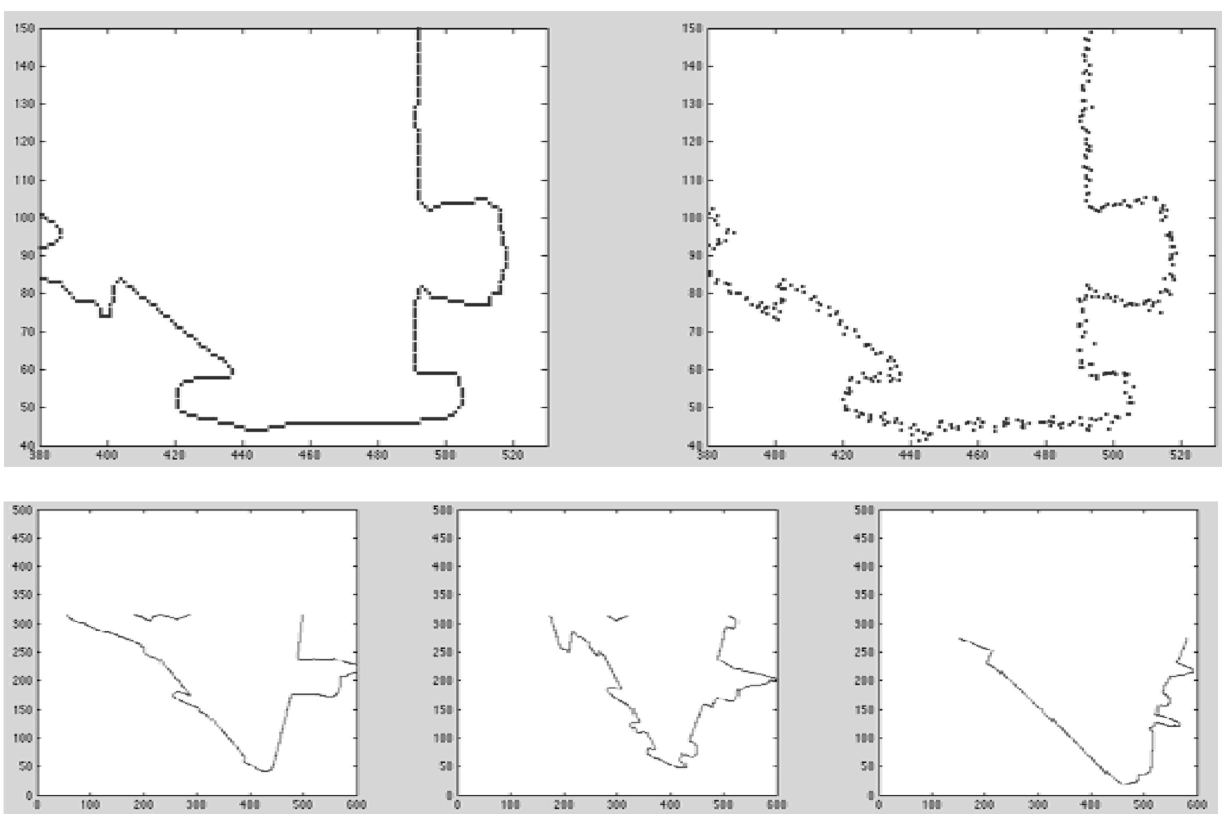

Fig. 3: Examples of applied noises (partial contour) and continuous degradation

was proved to be better in the classification rates over static image shapes.

Experiment on image sequence: Noise and shelter are considered to have great influence in methods of image sequence recognition and target tracking. In this experiment, the proposed method was applied in the PLANE Database. White Gaussian noise, rotation and shelter are taken into account.

Considering the shape contours are more complex in the PLANE Database, more samples are chosen for recognition. Totally 42 image contours are chosen to build the sample group. All of the 210 image contours are classified into the test group.

The visual angle, shape details, size and direction of the contours are changed gradually in this image sequence. In this experiment, the distance thresholds r^j are defined by r0 = 4, rp = 21, rm = 172.

Figure 2 shows the temporary characteristics of the network dynamic evolution.

Taking white-noise, rotation and shelter into account, the classification rates of most tradition methods dropped significantly. In order to test the robustness of the proposed method, the PLANE Database is extended as follow.

Certain range of White Gaussian noise had been added to the contours in Fig. 3. Each contour from the database had been rotated. Certain range of continuous degradation had been applied to the contours in Fig. 3. The average degradation level is 13%.

Table 2 shows that within a certain range, the proposed method could reach high correct percentage with the changes of visual angle, shape details, size, rotation, white Gaussian noise and shelter in shape contours recognition.

The experiment also shows the potential application with the proposed method in moving object tracking in image sequence.

Parameter analysis: The Distance Threshold r was determined by the DTD method in the last experiment. In order to provide more information of shape details, r0 was defined in the interval [1,5]. According to the scale of the shapes, rp and rm were defined in the interval [1,50] and [1,200].

For each distance threshold r, the Discrimination Degree δ was calculated with the DTD method on only 42 shapes from the sample group. After that, the values of δ were used to determine the capabilities of r in recognition. The recognition rate on 210 shapes from the sample group and test group could show the applicability of the DTD method.

Figure 4 shows the relation between the Discrimination Degree δ and the Recognition Rate. The higher value that δ reaches, the higher probability

Table 2: Classification performances of various shape descriptors over the increased plane database

Shape recognition method	Database	Correct Percentage
κ+ SVM	Original database	89.05%
FD+ SVM		99.52%
ZM+ SVM		89.05%
HMM_E+ ML		78.52%
HMM_C+ ML		99.05%
HMM_{LR}+ ML		94.76%
HMM_E+ WtL		99.05%
		99.52%
The proposed method	Database with white gaussian noise (1 dB)	98.57%
	Database with rotation	99.52%
	Database with continuous degradation	77.62%

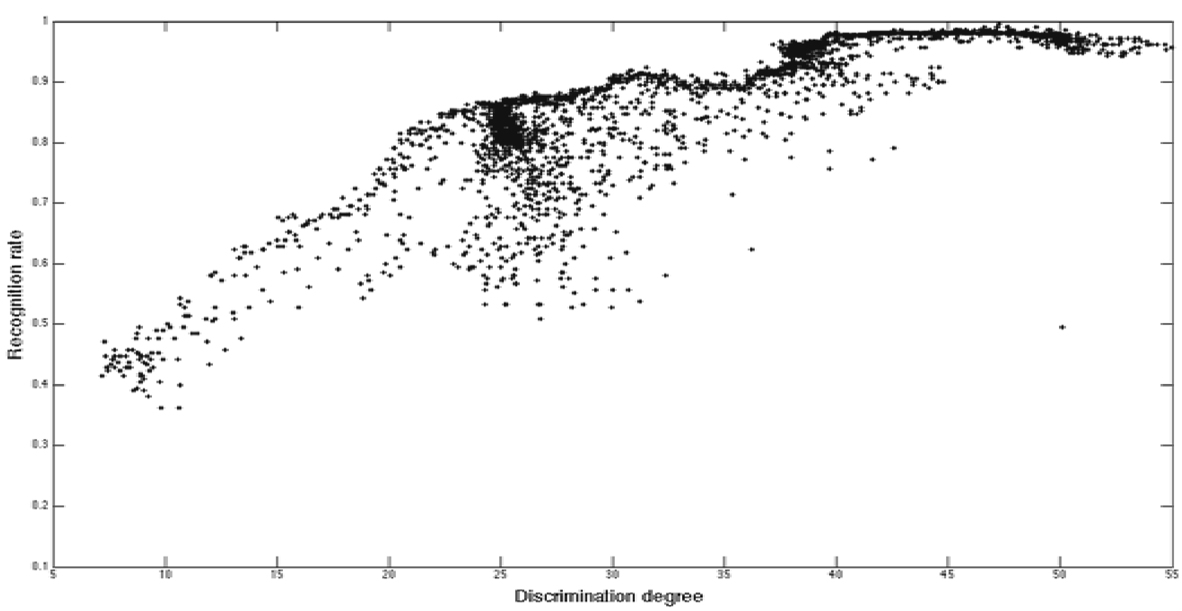

Fig. 4: Relation between discrimination degree and recognition rate

Table 3: Relation between discrimination degree and recognition rate

	δ>51	δ≤51
Probability of achieving Recognition rate over 94%	98.63%	27.49%
Probability of achieving Recognition rate lower than 90%	0%	63.45%
The minimum recognition rate	93.81%	36.19%

the maximum Recognition Rate might attain. Converse is also true.

When r0 = 4, rp = 38 and rm = 194, the Discrimination Degree δ reached the maximum value and the recognition rate was 95.71%. Take the set of r which satisfied δ>47 into account, minor adjustment was done in small interval and the recognition rate could finally improve to 99.52%.

Table 3 shows more details between the Discrimination Degree and the Recognition Rate.

CONCLUSION

This study presented a novel approach to shape contour recognition based on the complex network theory. In the proposed method, the shape contour is mapped onto a set of graphs with the thresholds of r. By using the complex network theory, various features are extracted, providing a feature vector that can be used in shape recognition. The proposed method could adapt to the changes in the boundary shape with efficient power of shape recognition. It is also proved to be scale invariant, rotation invariant and partially overcome noise-sensitive and shelter.

Some experiments are given to compare the method with other traditional methods. The proposed method is proved to be better in the classification rates. Moreover, according to the nature of the complex network theory, the method is also scale invariant, rotation invariant and partially overcome noise-sensitive.

This study demonstrates the potential of applying the proposed method to moving object tracking in image sequence. Further improvement is also required in order to apply the proposed method and the DTD method to larger datasets with higher efficiency.

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