RBF neural network and active circles based algorithm for contours extraction*

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Abstract For the contours extraction from the images, active contour model and self-organizing map based approach are popular nowadays. But they are still confronted with the problems that the optimization of energy function will trap in local minimums and the contour evolutions greatly depend on the initial contour selection. Addressing to these problems, a contours extraction algorithm based on RBF neural network is proposed here. A series of circles with adaptive radius and center is firstly used to search image feature points that are scattered enough. After the feature points are clustered, a group of radial basis functions are constructed. Using the pixels' intensities and gradients as the input vector, the final object contour can be obtained by the predicting ability of the neural network. The RBF neural network based algorithm is tested on three kinds of images, such as changing topology, complicated background, and blurring or noisy boundary. Simulation results show that the proposed algorithm performs contours extraction greatly.

Keywords: **contours extraction, RBF neural network, dynamic clustering.**

Contours extraction is a very important issue in computer vision. Active contour model was firstly introduced by Kass[1] in 1998. The model takes an initial contour defined for an object contour and makes it evolve until the contour satisfactorily approximates the actual object contour. The initial contour is a rough approximation and the final contour is an accurate representation of the object boundary. The active contour model can be achieved by introducing an energy function and then minimizing it. This work is the foundation of the research issue[2,3]. But the minimization may trap in local minimum, especially in the case of the contour with long concavities. Then Chop[4], Caselles et al.[5] and Malladi et al.[6] used level set theory to deal with topological changing of the evolving contour. The disadvantages of these methods are that the initial contour must fully be inside or outside the object contour, and the direction of contour evolution must be given to the algorithm in advance.

Recently, some authors[7—9] proposed an important alternative approach based on self-organizing map to extract the object contours. In this method, initial contour is composed of a series of image feature points. Then the network is created to be isomorphic to initial contour with neurons in a closed chain topology. At the end of the training, the network converges to the actual contour. However, this approach has two main limitations. One is the contour evolution greatly depending on the initial contour. If the initial contour is outside the object, contours inside an object cannot be extracted. The other is that feature points must be obtained by edge detection based on the whole image. If the edge detection results are given, the primary contour has been obtained. This seems illogical.

Addressing to the problems of active contour model and self-organizing map based approach, a RBF neural network based algorithm is proposed in this paper. In order to search the representative feature points that are scattered enough and save more computations, a circular searching algorithm is proposed. After creating and training the RBF neural network, the property of the unsearched pixels can be predicted. Circular searching algorithm does not need to process every pixel on the whole image. Furthermore, contours extraction does not depend on initial contour, because feature points locate dispersedly enough.

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1 Circular searching algorithm for feature points

The algorithm arbitrarily chooses a circle in the observed image, and then searches the feature points within all pixels on the circle. After creating a new circle with changing radius and centers, searching continues on this new circle as before. The above procedure repeats till the radius tends to zero. This series of circles are called as "Searching Circles".

Firstly, a pixel in the middle (as possible) of the image is arbitrarily chosen as the initial center $O_0=(x_0, y_0)$, and initial radius r_0 is large enough. Because feature points' searching is the first step of the contour extraction algorithm, we can roughly define feature points as the pixels whose norm of gradient are bigger than a given threshold.

1.1 Radius changing

Generally, in order to stop the searching process, the radius is supposed to become smaller and smaller. So the key problem is the way to reduce the radius, that is, the reduction of radius can neither be too big nor be too small. If it is too big, some important parts of the contour will possibly be missed, and if it is too small, the computational costs will be enhanced. So, we can choose a bigger reduction when the curve is far away from the actual contour, and vice versa. Denote $I(x, y)$ as the intensity of pixel (x, y), and r_n as the radius of the current searching circle C_n. Then compute the reduction of radius by

$$\begin{aligned}\Delta r_n &= r_n - r_{n+1}\\ &= f_{\Delta r}(\text{median}\{\| \nabla I(x,y) \| \mid (x,y) \in C_n\})\end{aligned} \tag{1}$$

where median$(\cdot)$ represents the median function, $\| \nabla I(x,y)\|$ is the norm of gradient at pixel (x, y), and

$$f_{\Delta r}(x)=\frac{\log(255/2)}{\log(2+x)} \tag{2}$$

So, with respect to x, $f_{\Delta r}(x)$ is a decreasing function. It makes Δr become smaller as the searching circle is closed to object contour and the norm of gradient becomes bigger, and vice versa.

In Eq. (2), avoiding the denominator being 0, we use "$2+x$". If the gradient is bigger than 255/2, there is a strong enough edge passing this pixel. So, "$2+x$" is comparable to 255/2. And logarithm is used to make the value of $f_{\Delta r}(x)$ within the range of radius changing.

1.2 Center changing

Suppose the feature points obtained from the current searching circle C_n mainly concentrate on one side of the circle. It means that the object probably leans to one side of the circle. If the next searching circle still shares the same center, it may miss some parts of the object contour. Denoting $P_n=(x_{pn}, y_{pn})$ as the representative point of all feature points obtained from C_n, we can compute its coordinate by the median value of all feature points' coordinates. As shown in Fig. 1, when the radius is reduced, the center of next searching circle C_{n+1} will be closed to P_n to make the object in the middle of C_{n+1} as possible.

Denote the center of C_n and C_{n+1} by $O_n=(x_n, y_n)$ and $O_{n+1}=(x_{n+1}, y_{n+1})$ respectively. Then the coordinate of O_{n+1} can be computed by

$$\begin{aligned}x_{n+1} &= x_n - (x_n - x_{pn}) \circ \frac{\Delta r_n}{r_n}\\ y_{n+1} &= y_n - (y_n - y_{pn}) \circ \frac{\Delta r_n}{r_n}\end{aligned} \tag{3}$$

If there are no feature points obtained from the he current searching circle C_n, the representative point P_n does not exist. In this case, the center does not need changing, either.

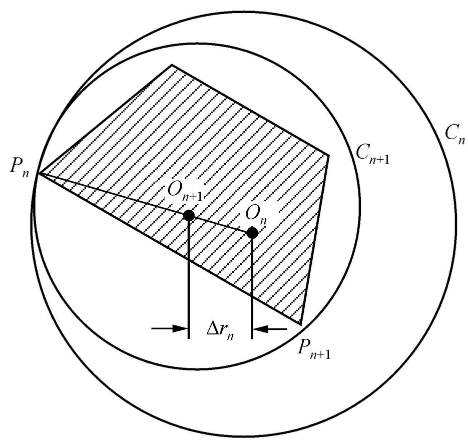

Fig. 1. Center changing.

2 Contours extraction based on RBF neural network

If the object contour can be looked on as a curve on the two dimensional plane, and feature points can be looked on as the sample points on this curve, then

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the final contour will be obtained by approaching this curve. It can be found that the contour points in different locations have different intensities and gradients. But in total, they will cluster into several classes. RBF neural network uses a group of radial basis functions to realize function approaching. Denote the curve function by $f(s)$, and then it can be expressed by

$$f(s)=\sum_k \alpha_k \varphi_k(s, c_k, \sigma_k) \tag{4}$$

where $\{\varphi_i(s, c_i)\}$ is a group of radial basis functions. The most traditional form of them is Guassian function

$$\varphi_k(s, c_k, \sigma_k)=\exp\left(-\frac{\| s-c_k \|^2}{2\sigma_k^2}\right) \tag{5}$$

where c_k and σ_k are the key parameters of a radial basis function. In this paper, after all feature points being clustered into several classes, the center of each class is considered as c_k and the variance of each class is considered as σ_k. The final contour will be extracted by curve function approaching based on the RBF neural network.

2.1 Input vectors

It can be found that gradient and intensity of each pixel are the main factors affecting its classification. If the classification merely depends on gradient, it may be misled by image noise. So, for the pixel at the coordinate (x, y), we can create a three-dimensional vector as the input vector of the neural network

$$s=(I(x, y), I_x(x, y), I_y(x, y)) \tag{6}$$

where $I(x, y)$ is the intensity, $I_x(x, y)$ and $I_y(x, y)$ are the gradients in x and y directions, respectively.

2.2 Feature points clustering

Because the number of classes is unknown before clustering, we must use dynamic clustering method. Denoting the feature points set by $\{s_i | i=1, \cdots, N\}$, and the total number of feature points by N, the steps for clustering are as the following:

(i) Given a positive constant ε, create a sphere with each feature point s_i as its center and ε as its radius. Define density μ_i as the number of feature points falling into the sphere of s_i.

(ii) Sort the densities in descending order. Select the feature point with maximal density as the first clustering center c_1. Classify all feature points in the sphere of this feature point into the first class. Denote the number of the first class by N_1.

(iii) Having obtained $k-1$ clustering centers, remove all feature points belonging to former $k-1$ classes. Select the feature point s with maximal density in the remaining feature points. If it satisfies

$$\| s-c_t \| > 2\varepsilon \tag{7}$$

where

$$t=\underset{1\leqslant j\leqslant k-1}{\arg\min} \| s-c_j \| \tag{8}$$

it will be the kth clustering center c_k. All unclassified feature points in its sphere will be classified into the kth class, and the number of feature points in this class is denoted by N_k. If it does not satisfy Eq. (7), all unclassified feature points in its sphere will be classified into the tth class, the number N_t of feature points in the tth class will be modified, and the clustering center c_t will be replaced with the mean value of the tth class.

(iv) The remaining clustering centers can be obtained by a similar processing. The clustering will be continued, until all feature points are classified.

Supposing we obtain K clustering centers, such as $c_1, \cdots, c_K$, and compute the variance of each class, and then we get K radial basis functions whose form are given by Eq. (5).

2.3 Network training

For all feature points obtained from circular searching algorithm, use distance between each feature point s_i and the nearest clustering center is used to define the output of the neural network,

$$f(s_i)=\frac{1}{\min\limits_{1\leqslant k\leqslant K} \| s_i-c_k \|+1}, \quad i=1, \cdots, N \tag{9}$$

Then the network predicting error is

$$\begin{aligned} E&=\sum_{i=1}^{N}[f(s_i)-f(s_i)]^2 \\ &=\sum_{i=1}^{N}\left[\sum_{k=1}^{K}\alpha_k\varphi_k(s_i, c_k, \sigma_k)-f(s_i)\right]^2 \\ &=\sum_{i=1}^{N}\left[\sum_{k=1}^{K}\alpha_k\exp\left(\frac{-\| s_i-c_k \|^2}{2\sigma_k^2}\right)-f(s_i)\right]^2 \end{aligned} \tag{10}$$

Compute the partial derivative with respect to weight α_k. Then we have

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$$\frac{\partial E}{\partial \alpha_k}=2\sum_{i=1}^{N}\left\{\left[\sum_{k=1}^{K}\alpha_k\exp\left(\frac{-\|s_i-c_k\|^2}{2\sigma_k^2}\right)-f(s_i)\right]\circ\exp\left(\frac{-\|s_i-c_k\|^2}{2\sigma_k^2}\right)\right\} \tag{11}$$

So, the iterative training of weights can be obtained by the following equation

$$\alpha_k^{n+1}=\alpha_k^n-\eta_k^{n+1}\frac{\partial E}{\partial \alpha_k^n} \tag{12}$$

where η_k^{n+1} denotes the step size of the $(n+1)$th iteration. Its value will become smaller during iterations,

$$\eta_k^{n+1}=0.5\eta_k^n \tag{13}$$

Given a threshold d_0, if the output of the network $f\leqslant d_0$, then the corresponding pixel will be classified into the contour points set. In the simulation of this paper, $d_0=0.01$.

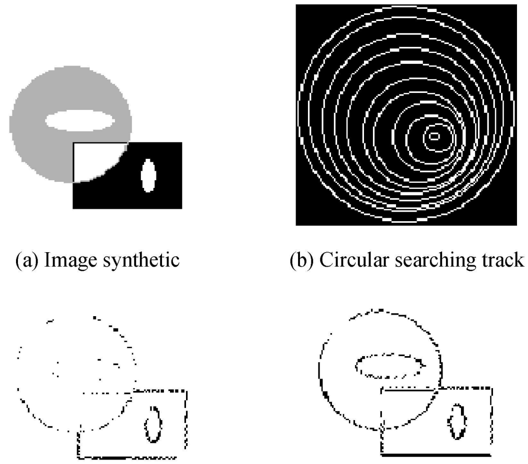
3 Simulation results and analysis

In order to verify the performance of the proposed algorithm, simulations are implemented in three kinds of images, such as changing topology, complicated background, and blurring or noisy boundary. Supposing the resolution of the observed image is $M\times N$, we choose initial center $O_0=([M/2],[N/2])$ and initial radius $r_0=[\min(M,N)/2]$. In general, such initial circle C_0 can cover almost the whole image.

3.1 Changing topology

In this kind of image, object contour may be multiple geometries. It means that the object contains several independent geometries or one geometry includes another geometry. In this case, active contour model[1-3] must use the level set method with large computational costs, and self-organizing map based algorithm[7-9] is invalid because it greatly depends on initial contour.

The proposed circular searching algorithm can solve this problem by obtaining feature points scattered enough. We use an image "Synthesis" with changing topology and 128×128 in size to do the simulation. In Fig. 2 (b), the track of circular searching reveals that the centers of searching change in the direction of big gradient variation in the image. In Fig. 2 (d), the final contour can approximate the actual object contour of image "Synthesis".



(a) Image synthetic (b) Circular searching track

(c) Feature points (d) Final contour

Fig. 2. RBF based contour extraction algorithm for image "Synthesis".

3.2 Complicated background

If the image contains complicated background, the contour of an object may be composed of different parts of boundaries, or objects' contours are very different from each other. The traditional contour extraction algorithm mainly depends on the variation of gradients to do the judgments. Simple judging mode cannot discriminate different parts of contour. Active contour model[1-3] depends on a gradient-directed function to control curve evolution. If gradients change on the contour, and the gradient-directed function still use the same mode to stop evolution, the optimization of the energy function will fall into local minimum.

The proposed contour extraction algorithm is based on feature points clustering. After obtaining the statistical properties of the contours in different parts or different objects, it will be more efficient than using simple gradient method. We use image "Highway" with complicated background and 128×128 in size to do the simulation. In Fig. 3 (b), the track of circular searching reveals that the centers of searching change towards the middle of left part in the image, and far from the right down corner with fewer parts of object contour. So, the feature points can be much scattering in Fig. 3 (c). After clustering, we obtain 4 clustering centers, which help neural network training. In Fig. 3 (d), the final contour can approximate the actual object contour of image "Highway".

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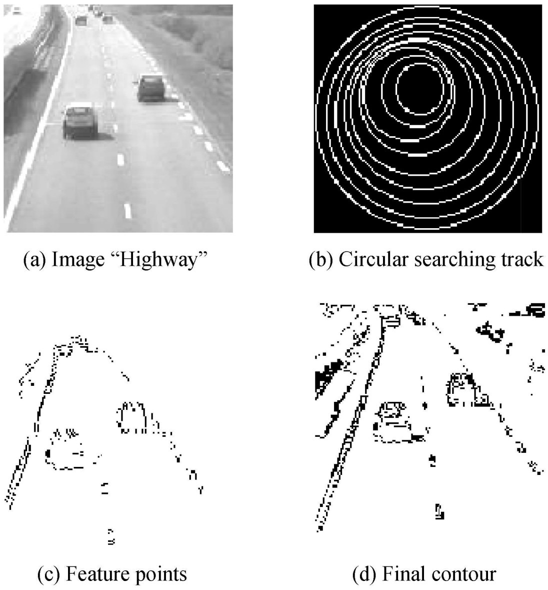

Fig. 3. RBF based contour extraction algorithm for image "Highway".

3.3 Blurring or noisy boundary

In active contour model[1−3], if the evolving curve reaches the object contour, the gradient-directed function will tend to zero. In fact, this function has some limitations. On one hand, image gradients are bounded. On the other hand, if the object boundary is blurring, the gradients does not change obviously. In these cases, the function does not tend to zero even if the evolving curve reaches the object contour. It will cause the evolving curve pass through the actual contour. For image noise, neither active contour model nor self-organizing based algorithm[7−9] gives solutions. But the proposed statistical method can solve the problem efficiently.

We use image "Cells" with size of 83×65 to do the simulation. It can be found that the object boundary is blurring and there are lots of noisy points. The centers of searching circles move towards the left cell, because its boundary is relatively clear. We obtain 3 clustering centers fewer than those in last simulation, because the background is simple relative to image "Highway". In Fig. 4 (d), it can be found that the final contour obtained by the proposed algorithm is quite accurate.

In the simulations, we also observe the training of neural network. Table 1 contains the important factors for creating and training the RBF neural network. For the images with a complicated background, the number of neurons is bigger. The iterative times and computational costs are mainly affected by the number of feature points.

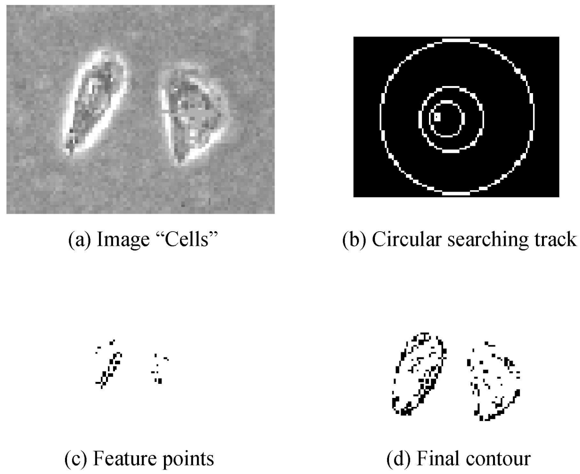

Fig. 4. RBF based contour extraction algorithm for image "Cells".

Table 1. RBF neural network factors comparisons between different images

Image	Feature points	Neurons	Iterative times	Computational time (s)
Synthesis	453	3	25	30.78
Highway	395	4	18	23.88
Cells	40	3	14	4.98

4 Conclusions

Recently, the active contour model and self-organizing map based algorithm are the popular issue of image object contour extraction. The active contour model can be achieved by introducing an energy function, and minimizing that function. But the minimization may trap in local minimum, especially in the case of the contour with long concavities. And the self-organizing map based algorithm greatly depends on initial contour and is lack of efficient feature points selection methods.

In this paper, a RBF neural network based contour extraction algorithm is proposed. A series of circles with adaptive radius and center is firstly used to search image feature points, which are scattered enough. After the feature points are clustered, a group of radial basis functions are constructed. Using the pixels' intensity and gradients as the input vector, the final object contour can be obtained by the predicting ability of the neural network.

The proposed algorithm is tested on three kinds of images, such as changing topology, complicated background, and blurring or noisy boundary. Simula-

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tion results show that the proposed algorithm has a great performance in contours extraction.

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