Snake Model Based on Improved Genetic Algorithm in Fingerprint Image Segmentation

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Abstract: *Automatic fingerprint identification technology is a quite mature research field in biometric identification technology. As the preprocessing step in fingerprint identification, fingerprint segmentation can improve the accuracy of fingerprint feature extraction, and also reduce the time of fingerprint preprocessing, which has a great significance in improving the performance of the whole system. Based on the analysis of the commonly used methods of fingerprint segmentation, the existing segmentation algorithm is improved in this paper. The snake model is used to segment the fingerprint image. Additionally, it is improved by using the global optimization of the improved genetic algorithm. Experimental results show that the algorithm has obvious advantages both in the speed of image segmentation and in the segmentation effect.*

Keywords: *Fingerprint image, Snake model, Genetic algorithm.*

Introduction

Fingerprint identification technology is the most widely utilized among many biometric identification technologies. Currently, it has been widely used in house furnishing, electronic products and other fields. Fingerprint technology started to be used at the end of seventeenth Century [2]. Nehemiah Grew published the world's first fingerprint research paper in 1684, and systematically studied the fingerprint ridge and valley line and sweat gland pore structure [5]. Fingerprint preprocessing guarantees the correct identification of fingerprint in the late stage, while fingerprint image segmentation can remove the non-fingerprint area in fingerprint image and eliminate the low quality fingerprint area noise which cannot be recovered due to too much noise, so as to obtain the effective fingerprint area. This step can reduce processing time and improve the accuracy of feature extraction. As a mature technology, fingerprint identification technology has been widely used in fingerprint image segmentation to effectively obtain the fingerprint image [12].

Image segmentation is fundamental in the field of image processing, and it is a key technology from image processing to image analysis. There are a variety of image segmentation methods that can be divided into four categories: segmentation based on region, segmentation based on the boundary, segmentation based on the combination of the two methods and the segmentation method based on the specific theory [11]. The image segmentation method based on region is divided into the regional growth method [9], and the split merge method. The segmentation method based on the edge is divided into the differential operator method [3], and the boundary tracking method [7]. There is no general theory about image segmentation, and with the development of each subject, many new theories and methods have been proposed. The snake model [4] is first proposed by Kass in the first world computer vision conference in 1987. In order to solve the problem of Kass model's being sensitive to the initial value, the authors in [6] applied the multi-scale spatial algorithm in the model. The greedy algorithm was proposed by Williams and Shah [10] Mubarak in 1992, which directly improves the energy function of the snake model without constructing a new external force. In the B-snake model proposed by Menet et al. [8], the contour of the object is expressed by B-spline, and the expression of the contour is more effective. In the research [1], an approach based on the particle swarm optimization is utilized to control the snake behavior without the necessity of computing the additional information. The genetic algorithm was first proposed by Holland [13] of Michigan University in the United States in 1975.

On the basis of analyzing the research results of fingerprint image segmentation worldwide for many years, this paper has conducted in-depth research on the fingerprint image segmentation algorithm. Firstly, this paper outlines the fingerprint segmentation technology, and secondly, the snake model is introduced in this paper. Then, the operation process of the genetic algorithm is introduced. Finally, to overcome its defect of the local minimum, this paper improves the snake model by using a genetic algorithm. At the end of this paper, the experiments are designed to verify the performance of the proposed algorithm. Experiments show that the proposed algorithm has a high anti-fuzzy capability and an improved robustness when extracting the contour of the target, and therefore has a more accurate segmentation of the fingerprint image.

Materials and methods

Characteristics of fingerprint image and its segmentation features

Fingerprint images is related to personal privacy, so fingerprint identification systems generally preserves the characteristic information of the fingerprint images. By comparing the fingerprint characteristic, the system can identify a person's identity. The fingerprint image is made up of ridge and valley lines. Ridge lines refer to the convex part of fingers skin, and they are the gray thick lines the fingerprint images. Valley lines refer to the concave portion of the finger skin, sandwiched between two lines, and their lines are relatively bright when compared to the ridge lines. Fingerprint features can be classified into global features, local features and subtle features.

Fingerprint image segmentation is the first step in the preprocessing of fingerprint images, and it is also the beginning of the fingerprint identification system. The fingerprint ridges and valleys formed region is referred to as the foreground of the fingerprint image, while the non-fingerprint region is referred to as the background. In the automatic fingerprint identification system, the task of fingerprint image segmentation is to separate the fingerprint foreground area from the background area, which aims at eliminating the influence of the background area in the fingerprint feature extraction. Then the accuracy of fingerprint feature extraction can be improved and saves processing time. This will ultimately improve the performance and effects of the fingerprint identification system. Fig. 1 shows the definition of fingerprint image segmentation.

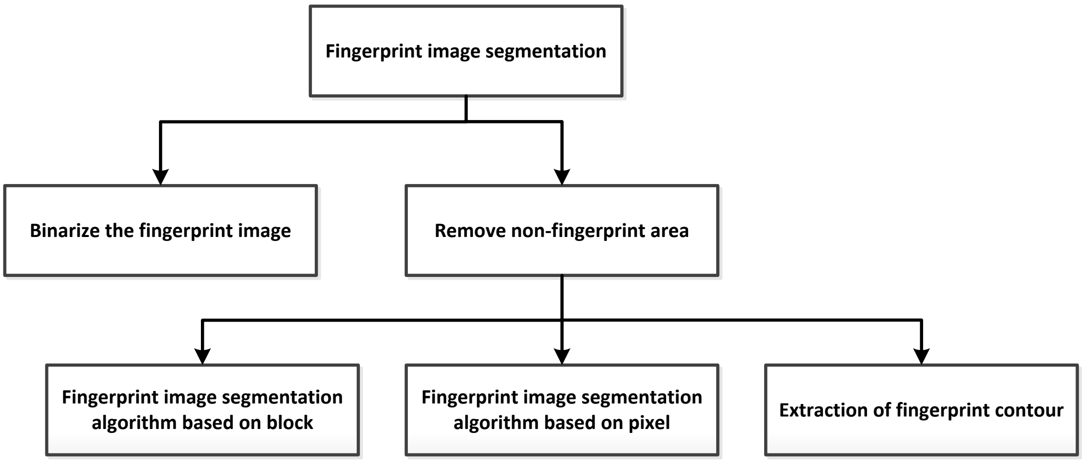

Fig. 1 Definition of fingerprint image segmentation

Overview of the Snake model

The active contour model is also known as the snake model. The snake model is based on the dynamic growth of two dimensional curves to realize the goal of edge detection. The idea of the snake model is derived from the physical deformation model; that is, the edge of the object is elastic, which can be deformed under the action of internal force and external force. The snake model uses many theories and methods such as differential geometry, dynamics, function approximation, numerical calculation theory. Its analysis of images is a dynamic process, and is widely used in many fields such as image segmentation, object recognition, contour extraction, moving object tracking, 3D reconstruction and stereo vision matching fields. Firstly, according to the need and the ability to identify the image, the snake model selects a number of control points near the target profile, and then links them to a continuous curve. Then it uses the information of the image itself, the external constraints and the curve's requirements of being continuous and smooth to form an energy function, which acts on each control point and allows the control point to move in the direction of decreasing energy function. Finally, when the energy function reaches the minimum, the edge profile of the target image is obtained.

The original snake curve is a contour parameter curve which is composed of a set of contour points $v(s) = v[x(s), y(s)],\ s \in (0, 1)$. Constructing the energy function is as follows:

$$E_{snake} = E_{internal} + E_{external} + E_{constraint}\,. \qquad (1)$$

When the total energy reaches the minimum, a good profile can be obtained. In this formula, E_{snake} is the total energy, $E_{internal}$ is the internal energy, which is usually determined by the internal properties of the curve. This energy requires the curve to be smooth and continuous to express the tensile and bending degree of the profile, and its value is independent of image itself. $E_{external}$ is the external energy, usually determined by the image, and refers to the fitting degree between the profile and the contour and intensity of the image. As constraint conditions, $E_{constraint}$ are usually determined by the user's needs or characteristics of the image, and the constraint information is provided by the user's interactive method, or by a more advanced computer vision processing process which is usually neglected. The continuum form of total energy is expressed as:

$$E_{snake} = \int_0^1 (E_{internal} + E_{external}) ds . \quad (2)$$

The internal energy is:

$$E_{internal}(v(s)) = \alpha(s) E_{continuity} + \beta(s) E_{smoothness} = \frac{1}{2}\left(\alpha(s) \left| \frac{dv}{ds} \right|^2 + \beta(s) \left| \frac{d^2 v}{d^2 s} \right|^2 \right). \quad (3)$$

The internal energy includes continuous energy $E_{continuity}$ and smooth energy $E_{smoothness}$, and the slope of the curve is expressed by the first order derivative, which guarantees the continuity of the snake curve. $\alpha(s)$ controls the continuity of the model; that is, the elasticity. When $\alpha(s) = 0$, it indicates that the first derivative of the snake curve is discontinuous. To ensure the smoothness of the snake curve, the second derivative expresses the curvature of the curve, $\beta(s)$ controls the smoothness of the model; that is, the rigidity. When $\beta(s) = 0$, it indicates the second order derivative is not continuous; that is, angular points appear in the snake curve.

The external energy $E_{external}$ is provided by the image information, and the snake curve is put to the image boundary by it. I represents the original image, the gradient change of the image is the fastest at the boundary. Therefore, the external energy is usually expressed as:

$$E_{external} = \gamma(s) E_{image} = -\gamma(s) \left| \nabla I \right|^2 . \quad (4)$$

In the external energy, with an increase or decrease of the parameters $\gamma(s)$, the contour of the snake model will be attracted by the bright or dark lines.
In summary, the total energy E_{snake} can be expressed as:

$$E_{snake} = \int_0^1 \left[\alpha(s) E_{continuity} + \beta(s) E_{smoothness} + \gamma(s) E_{image} \right] ds . \quad (5)$$

The parameters $\alpha(s)$, $\beta(s)$ and $\gamma(s)$ control the corresponding influence of energy.

For Eq. (2), if $V = \{v_1, v_2, ..., v_N\}$ is the N points on the initial contour of the snake. The discrete form of the snake model can be given, and the total energy expression is:

$$E_{snake} = \sum_{i=1}^{N} (\alpha(v_i) E_{continuity}(v_i) + \beta(v_i) E_{smoothness}(v_i) + \gamma(v_i) E_{image}(v_i)) , \quad (6)$$

$$\begin{cases} E_{continuity}(v_i) = \left| v_i - v_{i-1} \right|^2 \\ E_{smoothness}(v_i) = \left| v_{i+1} - 2v_i + v_{i-1} \right|^2 \\ E_{external}(v_i) = \gamma(v_i) E_{image}(v_i) \end{cases} . \quad (7)$$

Finally, after optimization the total energy is improved, and can be expressed as follows:

$$E_{snake}(V) = \sum_{i=1}^{N} E(v_i)\,. \tag{8}$$

Fig. 2 is the flow chart of the snake model.

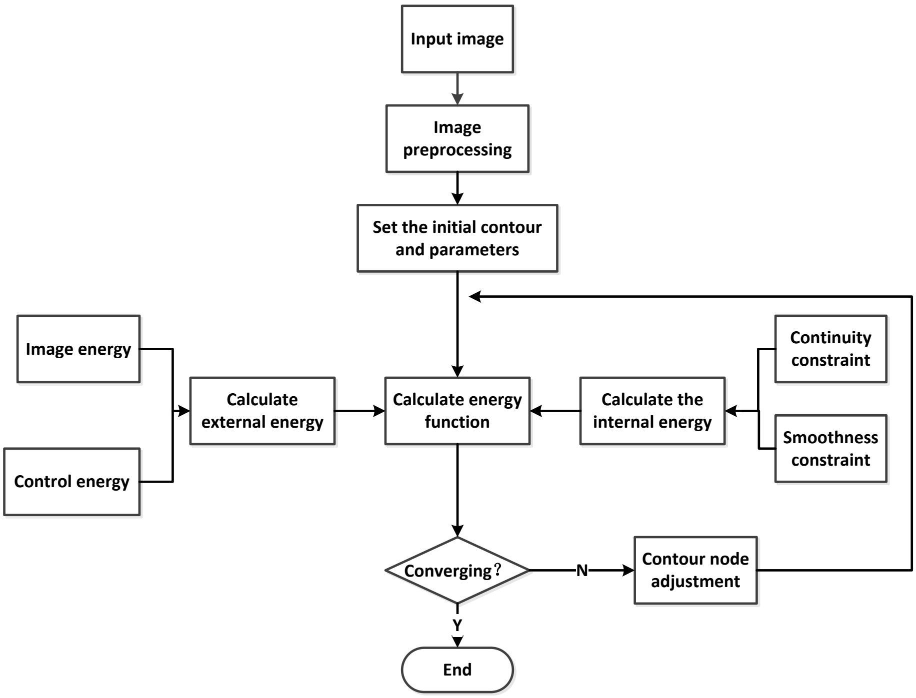

Fig. 2 Flow chart of snake model

Operation process of the genetic algorithm

The genetic algorithm is a highly parallel, random and adaptive search algorithm which is developed by natural selection and evolution mechanism. It uses group search technology, which makes a population as a set of problems to solve. Through a series of genetic operations such as selection, crossover and mutation, a new generation of population is produced, and gradually the population is evolved into the state of approximate optimal solution. Because the genetic algorithm is the product of the combination of natural genetics and computer science, it has borrowed many basic terms of natural evolution.

(1) Individual: the object of the genetic algorithm is the solution.

(2) Population: a collection of individuals, which represents the solution space of the problem.

(3) Population size: the number of individuals in the chromosome group is referred to as the size of the population or the size of the population.

(4) Fitness: the index value which is used to measure the quality in the population, usually expressed as a numerical form.

(5) Selection: screen chromosomes in a population, according to the fitness value of the chromosome and the requirements of problems. The higher the fitness of chromosome is, the more probable it will survive, and vice versa, or it will be eliminated.

(6) Crossover: one or a few genes of the two chromosomes exchange their position under certain conditions.

(7) Mutation: randomly change the value of one or more genes on a chromosome under certain conditions.

Application of snake model based on improved genetic algorithm in fingerprint segmentation

The snake model can be used to extract the contour of the image, which can utilize the local and global information of the image to realize the accurate localization of the boundary. It has a good capability to extract and track the contour of the target in a given area, and it can get the complete, continuous and smooth edge contour through crossing the discontinuous area in the object's contour. However, it is too sensitive to the initial location, and belongs to local optimization. In this paper, the genetic algorithm is improved, and the improved genetic algorithm is used to overcome the defects of the snake model.

Improvement of traditional genetic algorithm

In this paper, the genetic algorithm is used for its excellent global optimization capability, so this paper improves the convergence speed of genetic algorithm. The selection of operation parameters of the genetic algorithm is essential, and if the operation parameter is different, the performance of the genetic algorithm is also different. p_c is the crossover probability, which is used to control the frequency of crossover operation. p_m is the mutation probability, which controls the frequency of the mutation on the operation. We first adjust the method of obtaining the crossover probability and mutation probability, and then obtain the following equation:

$$p_c = \begin{cases} p_{c1} e^{-\frac{f' - f_{avg}}{f_{\max} - f_{avg}}} & f' \geq f_{avg} \\ p_{c1} & f' < f_{avg} \end{cases}, \tag{9}$$

$$p_m = \begin{cases} p_{m1} e^{-\frac{f - f_{avg}}{f_{\max} - f_{avg}}} & f \geq f_{avg} \\ p_{m1} & f < f_{avg} \end{cases}, \tag{10}$$

where $f_{\max}$ is the maximum fitness value in a population, f_{avg} is the average fitness value for each generation, f' is the larger fitness value of the two cross individuals, f is the fitness value of variation individual, p_{m1} is the maximum mutation probability, p_{c1} is the maximum crossover probability. The improved calculation method can increase the crossover probability and mutation probability of excellent individuals in a population, so they stay in a stagnant state, and finally the algorithm can obtain the global optimal solution.

In order to speed up the operation efficiency of the genetic algorithm, some improvements on the convergence criterion is proposed in this paper. When setting the convergence criterion of the genetic algorithm, the total number of evolution I is generally used as the convergence basis. Once the number of evolution reaches I, the operation of the program will end. However, such a situation is not excluded; that is, in the process of algorithm implementation, if the initial population and other parameters can select the ideal case, then the genetic algorithm can quickly search the optimal solution. In this case, even if the optimal solution has been found, the operation cannot be completed until the total evolution number I runs over, which obviously increases unnecessary computation time. Accordingly, the double criteria are used to determine whether to meet the convergence condition. One is the total number of evolution I, the other is that the optimal results of the continuous evolution are the same, or the difference of the results is less than a decimal fixed in advance. In the process of genetic evolution, meeting either of the above two conditions satisfies the convergence condition. This double convergence constraint can reduce the unnecessary computation time.

Fusion algorithm in this paper

This paper combines the improved genetic algorithm and snake model, and then proposes a new algorithm with high efficiency and accurate segmentation. In this paper, the energy function of the snake model is used as the objective function of the genetic algorithm, and the snake model solves the objective function of the improved genetic algorithm.

(1) First of all, the initial contour of the snake model after discretization is obtained, which is expressed as $V = \{v_1, v_2, ..., v_N\}$, and these are some discrete points with approximately the same distance. In the place v_i belonging to the normal snake curve, points are taken at a certain distance.

(2) A point in each v_i neighborhood is randomly selected, and these N points constitute a chromosome.

(3) Steps (2) are repeated M times to get M chromosomes. In such a population, each chromosome contains nodes of the same number.

(4) The snake energy function is adopted as the objective function, and it is minimized. That is, the convergence contour line is infinitely close to the real edge of the image.

$$\begin{aligned}E_{snake} = &\sum_{i=0}^{N-2} (\lambda E_{internal}(v_{i-1}, v_i, v_{i+1}) + (1-\lambda) E_{external}(v_i)) \\ &+ \lambda E_{internal}(v_{N-2}, v_{N-1}, v_0) + (1-\lambda) E_{external}(v_{N-1})\end{aligned} \quad . \tag{11}$$

Among them, λ is the weight coefficient, $\lambda \in [0, 1]$, and it is generally determined by the smoothness of the target edge and the size of the gradient. The fitness function is $f = \frac{1}{E_{snake}}$.

(5) Select the roulette method and keep the best 5% of the individuals to the next generation.

(6) Each chromosome is coded by using the real number, and the corresponding discrete points in the curve are coded according to the horizontal and vertical coordinates.

(7) The crossover probability is adjusted according to the crossover probability calculation Eq. (9) of the improved genetic algorithm.

(8) The mutation probability is adjusted according to the mutation probability calculation Eq. (10) of the improved genetic algorithm.

(9) The improved convergence criterion is used as the method to judge the termination of the algorithm

Results and discussion

In order to verify the effectiveness of the algorithm, the snake model based on the improved genetic algorithm is used to segment the fingerprint image. Experimental results show that compared with the traditional snake algorithm, the proposed algorithm in this paper can quickly and accurately segment the required fingerprint image. The experimental platform used is the hardware Intel(R) Core(TM) i5-4300M @2.60GHz, 4G memory, and Windows 7 software, with MATLAB as the design language.

In Fig. 3, the fingerprint images are selected and tested in the FVC2004 standard database, comparing the algorithm in this paper with the snake model and the traditional genetic algorithm. Fingerprint images can be divided into the following areas. Foreground area is the fingerprint region which must be retained, where the fingerprint texture is clear, and there is almost no noise interference. The background area is the fingerprint area that should be removed. The fuzzy area is divided into two categories. One area is seriously affected by noise, and in this area ridge and valley structures are severely damaged or the fingerprint is not clear, so that it cannot be repaired. The other can be repaired as its interference is not too serious. The repairable fingerprint area should be restored, and the non-recoverable area should be removed. According to the characteristics of the algorithm and the features of the fingerprint image, experiments are first conducted to compare the running time of several algorithms and the effect of segmentation. Then, a typical fingerprint image is first labeled to give the ideal fingerprint image segmentation interface, and the specific index of measuring segmentation effect is manually defined. False foreground rate (FFR), is the rate of the background area which is wrongly defined as the effective fingerprint area. False background rate (FBR), is the rate of the effective fingerprint area which is wrongly defined as the background area. Right segmentation rate (RSR), is the rate of the corresponding image which has completely correct segmentation.

Fig. 3 Fingerprint images in the FVC2004 standard database

Table 1 shows the time cost and segmentation results of different algorithms in the segmentation of fingerprint images, and shows that the algorithm proposed in this paper is superior to other algorithms both in time and segmentation results.

Table 1. Time cost and segmentation results of different algorithms

	Run time (ms)	Segmentation effect
Genetic algorithm	864	Good
Snake	1312	Good
Proposed method	407	excellent

Table 2 shows the index of the image obtained by the different segmentation algorithms compared with the standard image.

Table 2. The index of the image obtained by the different segmentation algorithms compared with the standard image

	FFR (%)	FBR (%)	RSR (%)
Genetic algorithm	5.34	0.62	94.04
Snake	6.23	0.59	93.18
Proposed method	1.11	0.18	98.71

The presented in Table 2 results show that the algorithm has obvious advantages, which can achieve more accurate fingerprint image segmentation.

Conclusion

In this paper, the segmentation of fingerprint image is studied, and the improved method of the genetic algorithm is proposed. Combined with the snake model, a new algorithm with less running time and high segmentation accuracy is finally put forward. This paper firstly introduces the characteristics of the fingerprint image. Secondly, the snake model and genetic algorithm are introduced. Lastly, this paper uses the improved algorithm to segment the fingerprint database. Experimental results show that compared with the traditional algorithm, the proposed algorithm has obvious advantages, which can achieve good segmentation results, and reduce the running time.

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