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Iris recognition based on improved particle swarm optimization

Yining Du

Philippine Christian University, Manila, Philippine

Abstract

In this intelligent era, technology and information have been fully integrated into People's Daily life, the public is paying more and more attention to the protection of personal information. Iris recognition through the biological iris for identity authentication, accurate and secure, now has been applied to a number of fields. However, in the face of medium-scale iris recognition scenarios, the deep learning method cannot obtain the required large number of samples, and the distance method can only achieve high accuracy in small-scale situations. In order to meet the needs of medium-sized iris recognition, this paper proposes a new iris recognition method based on GAHPSO algorithm. The algorithm combines genetic algorithm and particle swarm optimization algorithm, and sets the crossover method and mutation method for the identification problem, and selects the suitable particle for genetic operation. In this method, Harr wavelet is used to process the image, and then BP neural network optimized by the above algorithm is used to classify the image. The training efficiency of the optimized neural network is improved, thus improving the accuracy of iris recognition. The experimental results show that the proposed method can recognize iris quickly and accurately.

Keywords

Biometric recognition; Iris recognition; Particle swarm optimization; Genetic algorithm; BP neural network.

1. Introduction

People are in an era of data "explosion", there are a lot of information in circulation and dissemination every day, and the frequency of use of personal information is getting higher and higher, and personal identity authentication has been widely concerned. We usually use keys and electronic passwords to verify our identity, but objects can be lost, forged, passwords are easy to forget and confuse, they even give criminals the opportunity, it is difficult to accurately protect people's own interests. The advent of biometrics has greatly alleviated this phenomenon.

Biometrics is a kind of technology for identification through the physiological characteristics or behavioral characteristics of the organism itself, which makes full use of the principles of biology, optics, acoustics and so on, and with the help of advanced intelligent products. The recognition gets rid of the trouble of easy loss and theft, and the selected features have high uniqueness, so it can achieve high recognition accuracy. Biometrics includes palm vein recognition, finger vein recognition, face recognition, iris recognition and so on[1]. Both palmaric vein recognition and digital vein recognition belong to vein recognition that extracts characteristic values from vein maps. The former saves and compares more vein images, the recognition speed is relatively slow, and the safety index is higher. The latter has large capacity and faster recognition speed. The recognition overcomes the shortcomings of traditional fingerprint recognition that can not be used when the finger is stained or damaged. However, the veins are located under the skin, which is difficult to see with the naked eye, and a certain degree of user cooperation is required when identifying them. Face recognition is based on the feature information of the face, including the size, shape and distribution of the organ. The recognition is non-contact, and the acquisition cooperation requirement is low, but the facial features may change greatly with age. In addition, heavy makeup may also affect the recognition results. Iris recognition is recognized through the texture features of the iris, which is difficult to change once it is developed and has extremely high stability. Moreover, there are great differences between different irises, and the iris features of the left and right eyes of the same person are also difficult to be the same, so the recognition accuracy is very high, and the recognition stands out in a series of biometrics.

Iris recognition has been widely used in enterprise attendance[2], public security, airport management and other fields, and the scale of recognition is becoming more and more rich. However, in the face of medium-scale iris recognition, the accuracy of using distance method is not high enough, and the neural network method needs a large number of samples. In this paper, a new iris recognition method based on GAHPSO algorithm is proposed. In the algorithm, the frame structure of embedded hybrid algorithm is used for reference, and the appropriate operator is selected, the particle suitable for genetic operation is selected, and the two vectors of the parent are involved in the cross operation. Make full use of population information exchange during mutation operation. The convergence efficiency of the algorithm is improved. By optimizing the BP neural network with this algorithm, the performance of iris classification is greatly improved.

2. GAHPSO algorithm

Particle swarm optimization (PSO) is a kind of bionic intelligent optimization algorithm, and its idea comes from the process of bird searching for food. There is communication between the birds, and each bird is able to determine how to fly based on its own situation and the situation of its population. First, we initialize a population of particles, each with its own velocity and position. In each iteration process, individuals adjust their speed according to the optimal position of individuals and the optimal position of the whole group, and update their position[3], which is "flying". The algorithm is simple, versatile and convergent fast. Moreover, multiple particles make the algorithm have a certain parallelism and improve the optimization efficiency. However, the algorithm is prone to fall into local optimal values. The algorithm formula is,

$$v_i^{t+1} = \omega \times v_i^t + c_1 r_1 (p_i^t - x_i^t) + c_2 r_2 (p_g^t - x_i^t) \tag{1}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{2}$$

Where, c_1 and c_2 are learning factors, r_1 and r_2 are random numbers between (0,1), p_i is the individual optimal position, and p_g is the group optimal position.

Genetic algorithm (GA) is a kind of algorithm to find the optimal value through iteration, which is inspired by the laws of heredity and evolution in nature, and well interprets the idea of "natural selection, survival of the fittest". The algorithm mainly includes three parts: gene coding, computational fitness and evolutionary operation. The gene coding is to map the solution of the sought problem into the genetic algorithm, and each particle has its own gene coding, that is, each particle can be regarded as the solution of the problem. Computational fitness is the evaluation process of particles. Suitable fitness function can express the particle condition well and improve the optimization performance of the algorithm. Evolutionary operations usually include selection operations, crossover operations and mutation operations. The selection operation is to select particles according to their merits. Cross operation is the exchange of part of genetic information between parent individuals, which makes genetic algorithm different from random variation algorithm. Mutation manipulation is the alteration of individual genetic information, which is of great help to improve particle diversity. The algorithm has good global optimization performance and universality, but its convergence speed is relatively slow.

Particle swarm optimization is easy to fall into the local optimal value, and the genetic operation of genetic algorithm can help particles jump out of the local optimal value. This paper draws on the embedded hybrid algorithm framework and introduces genetic operation into particle swarm optimization to improve the optimization ability of the algorithm. The algorithm adopts a suitable operator. In crossover operation, both the velocity and position of parent particles are involved. In mutation operation, the information of the optimal position is introduced.

$$\begin{cases} v_i^{t\,\prime} = \alpha v_i^t + (1-\alpha) v_j^t \\ v_j^{t\,\prime} = (1-\alpha) v_i^t + \alpha v_j^t \end{cases} \tag{3}$$

$$\begin{cases} x_i^{t\,\prime} = \beta x_i^t + (1-\beta) x_j^t \\ x_j^{t\,\prime} = (1-\beta) x_i^t + \beta x_j^t \end{cases} \tag{4}$$

Where, α and β are random numbers between (0,1).

$$x_i^{t*} = k x_i^t + \gamma_1 (p_i^t - x_i^t) + \gamma_2 (p_g^t - x_i^t) \tag{5}$$

Where, k is the adjustment coefficient, γ_1 and γ_2 are random numbers between (0,1).

The algorithm steps are as follows:

1) Initialize particle population and set relevant parameters.

2) Update the velocity and position of particles according to formula (1-5).

3) The fitness of particles is obtained according to the fitness function.

9) The values of the fitness of the particles are ranked in decreasing order of the degree of adaptation.

5) The corresponding particles in the previous sequence remain unchanged; The corresponding particles after the middle in the sequence are crossed according to equations (3) and (4) (at this time, if there is a single particle that cannot be paired, it is directly retained). If the new particle has a higher degree of adaptation, the original particle is replaced; otherwise, the original particle remains unchanged; The corresponding particles later in the sequence are mutated according to equation (5). If the new particle has a higher degree of adaptation, the original particle will be replaced; otherwise, the original particle will remain unchanged.

6) Update the optimal positions p_i and p_j.

7) Update number of iterations.

8) Determine whether the conditions for termination are met. If yes, the iteration ends. Otherwise, skip to step 2).

3. BP neural network optimization

BP neural network is a multi-layer pre-feedback neural network, which adopts the learning method of error backpropagation. It has the input layer, hidden layer and output layer, layer contained within neurons, the whole connection between adjacent two layers of neurons, and no connections between neurons within the layer. The commonly used BP neural network has three layers, two hidden layers and so on. It reduces errors by adjusting the connection weights in the network, which is the process of learning. Network is convenient and intelligent, but it also has a certain degree of uncertainty. In addition to the structure of the network affects the performance of the network, the initial value of the network also has a great impact on the training efficiency of the network. If an initial value is arbitrarily given, the training times may increase and the convergence speed may be slowed down. In this paper, the GAHPSO algorithm in Chapter 2 is used to optimize the parameters of BP neural network, thereby enhancing its generalization ability and achieving better iris classification effect.

In this paper, a four-layer network consisting of two hidden layers is selected. Each hidden layer contains 12 nodes, the input layer contains 32 nodes, and the output layer contains 1 node. The hyperbolic tangent function $\tanh(x)$ is selected as the transfer function. The parameter optimization process of BP neural network is as follows:

1) Initialize a population of 20 particles and set parameters.

2) Update particle velocities and positions according to equations (1-5).

3) Calculate the adaptation degree of particles according to Equation (6), the smaller T is, the greater the adaptation degree is.

$$T = \frac{\sum_{x=1}^{d}\left(g_x - (-1)\right)^2 + \sum_{y=1}^{d}\left(g_y - 1\right)^2}{c} \tag{6}$$

Where, g_x is the output results of different categories of compared irises through the neural network, g_y is the output results of the same category of compared irises through the neural network, a is the number of tested irises, b is the number of irises in the same (different) category as the comparison.

4) Sort T in ascending order.

5) The first 10 particles in the sequence do not change; Of the 11 to 19 particles in the sequence, one is kept randomly, and the remaining random pairs are then crossed, if $T(i') \leq T(i)$, then $i = i'$, otherwise $i = i$. The same goes for particle j; The last particle in the sequence is mutated so that if $T(i^*) \leq T(i)$, then $i = i^*$, otherwise $i = i$.

6) Update p_i and p_g.

7) Determine whether the end condition is met. If so, the iteration ends; If not, skip to step 2).

4. Iris recognition process

First, Harr wavelet is used to process the image, and its high-frequency information is used to describe the image. Arrange the three coefficient matrices corresponding to the horizontal, vertical and diagonal of the third layer, and then compress them to obtain the feature points and obtain the high-frequency coefficients[4]. Then, the difference of the high frequency coefficients of the characteristic points of the tested iris and the compared iris is input into the BP neural network, and the formula is as follows:

$$\boldsymbol{x_i} = \boldsymbol{C_{1-i}} - \boldsymbol{C_{2-i}}, i = 1,2,\ldots, \ 32 \tag{7}$$

Where, $\boldsymbol{x_i}$ represents the i-th component of the input vector, $\boldsymbol{C_{1-i}}$ is the high frequency coefficient of the iris to be measured, and $\boldsymbol{C_{2-i}}$ is the high frequency coefficient of the template iris.

The formula of the transmission function of BP neural network is:

$$\tanh(x) = \frac{\mathrm{e}^{\mathrm{x}} - \mathrm{e}^{-\mathrm{x}}}{\mathrm{e}^{\mathrm{x}} + \mathrm{e}^{-\mathrm{x}}} \tag{8}$$

The input of node j of the hidden layer of BP neural network is,

$$S_j = \sum_{i=1}^{32} \omega_{ij} x_i - \theta_j \, , j = 1,2,\ldots,12 \tag{9}$$

Where, ω_{ij} is the connection weight from the input layer to the hidden layer, and θ_j is the threshold value of the node j of the hidden layer.

The output is,

$$O_j = \tanh(S_j) \tag{10}$$

The input and output of the second hidden layer and output layer are the same principle as (9) and (10).

The closer the output value of BP neural network is to 1, the more similar the iris to be measured and the template iris. The closer it is to -1, the greater the difference between the iris to be tested and the template iris. When the output value is greater than the classification threshold, it is determined to be the same iris.

5. Experimental results

In this paper, iris library CASIA V4.0 is selected for experiments, which contains many sub-libraries and has very rich images. The experiment included 150 types of images, with a total of 2446 images. The classical neural network method, the neural network method improved by particle swarm optimization, the filter method and the method based on GAHPSO algorithm are used in the experiment. The experimental results were expressed by correct recognition rate (CRR), equal error rate (EER) and recognition time (T), as shown in the following table.

Table 1 Experimental result

Method	CRR	EER	T
Harr+ Neural network	97.35%	2.76%	5992
Harr+ PSO-Neural network	97.51%	2.35%	5851
Gabor filter+ Hamming	95.38%	1.79%	2910
Harr+ GAHPSO-Neural network	98.02%	4.46%	5694

5. Conclusion

It can be seen from the experimental results that the proposed method has higher accuracy than the classical neural network method and the PSO-optimized neural network method, indicating that the GAHPSO algorithm used in the proposed method can optimize the neural network well and improve its ability to classify iris images. In addition, the time is relatively short. The proposed method is more accurate than the filter class method, because with the expansion of iris recognition scale, a simple distance threshold is difficult to accurately distinguish a large number of distances. In summary, the proposed method can quickly and accurately carry out medium-scale iris recognition.

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