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Iris Recognition based on SA-PSO Algorithm

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Abstract

With the progress of The Times, iris recognition has been widely used in military, commercial and other fields, it has promoted people's life from many aspects. However, with the expansion of iris recognition scale, the accuracy of iris recognition only using distance algorithm can not meet people's requirements. To solve this problem, this paper proposes a second recognition method based on SA-PSO algorithm on the basis of single recognition. In this method, filter and distance algorithm are used to exclude different iris images, and then wavelet and neural network are used for accurate authentication. Experimental results show that the proposed method has improved the recognition speed and accuracy.

Keywords

Iris Recognition; Biometrics; Gabor Filter; PSO Algorithm; Neural Network.

1. Introduction

Iris is an important part of the human eye. It looks like a ring and contains rich texture features such as centripetal groove and color spots, which can be used to accurately identify people. Iris recognition includes four steps: image quality assessment, pre-processing, iris feature extraction and matching. Image quality evaluation is to judge whether the image quality meets the recognition standard through several indicators to avoid the poor image quality and the recognition result impression. Pre-processing usually includes iris positioning, normalization, noise reduction and other operations. The positioning is to determine the location of the inner and outer boundaries of the iris, and the normalization is to map different sizes of iris into the same size rectangle, and then noise reduction to eliminate noise interference as much as possible. Feature extraction is to transform image information into digital information, which is easy to compare. Feature matching is to match the extracted information in a certain way so as to determine the recognition result [1]. Feature extraction and matching are the key to iris recognition. Iris is very safe and easy to recognize because iris is hardwired to DNA and stable throughout life.

With the expansion of iris recognition scale, the distance similarity situation also increases correspondingly, the accuracy of distance class method can not meet people's requirements. In order to solve this problem, this paper proposes a second recognition method based on SA-PSO algorithm on the basis of single recognition.

2. SA-PSO Algorithm

2.1. SA Algorithm

The idea of simulated annealing (SA) algorithm comes from the process of burning solid annealing. In the process of heating up, the internal energy of the solid gradually increases, and there is an extreme value, when the temperature slowly decreases, the irregular movement of the particles in the solid gradually decreases, the internal energy of the solid gradually

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decreases and reaches a relatively stable state. SA algorithm is based on the principle of this phenomenon to operate, it will optimize the problem and annealing principle, the optimization of the iterative process as the combustion of solid cooling energy to reach the equilibrium state process [2].

The objective function E(x) is regarded as the internal energy of the current burning solid, x is the optimal solution of the optimization problem, and it is regarded as the microscopic state of the particles in the current solid. The algorithm starts with an initial solution and iteratively searches for the optimal solution. When the exit condition is satisfied, the iterative process is terminated and the optimal value is output. The current solution x_{old} will generate a new solution x_{new} through random perturbation in the iteration, and the value of the objective function will determine whether x_{new} replaces x_{old} or not. If $E(x_{\text{new}}) \le E(x_{\text{old}})$, then x_{new} replaces x_{old} ; If $E(x_{\text{new}}) > E(x_{\text{old}})$, then x_{new} can determine whether to replace x_{old} according to the relationship between P and random number, and P is usually determined according to Metropolis criterion:

$$P = \exp\left(-\frac{E\left(x_{\text{new}}\right) - E\left(x_{\text{old}}\right)}{kT}\right) \tag{1}$$

Where, K is The Boltzmann constant with a value of 1.3806505×10^{-23}, and T is the temperature at this time (degree Celsius).

It can be seen from the above equation that when the temperature is high and P is large, the algorithm is more likely to accept the poor solution x_{new} at this time. In other words, the algorithm can escape the local optimal solution. Then, as the temperature decreases, P starts to decrease, and the probability that the algorithm will accept a better solution is increasing. This combination can find the optimal value efficiently. When the temperature of solid annealing is slowly decreased, the algorithm process should also be so to improve the accuracy.

2.2. PSO Algorithm

Particle swarm optimization (PSO) algorithm is derived from bird predation behavior and is an iterative computing technology. First, a random set of massless particles with two properties, speed and position, each particle can be regarded as a bird. It searches for the optimal position in space and shares its information with other particles (birds), while the population also searches for the overall optimal position, and all particles change their state through multiple iterations according to the above two optimal positions [3]. The formula of PSO algorithm is:

$$v_i(t+1) = v_i(t) + c_1 r_1 \left[p_i(t) + x_i(t) \right] + c_2 r_2 \left[p_g(t) - x_i(t) \right] \tag{2}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{3}$$

Where: i = 1,2... ,m,m is the total number of particles in the group, v_i is the velocity of particle I, x_i is the position of particle I, r_1 and r_2 are random numbers in the interval (0,1), c_1 and c_2 are self and social learning factors respectively, t is the number of iterations, p_i is the historical optimal of this particle, and p_{g} is the historical optimal of the whole group.

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In order to improve the performance of the algorithm, the inertia factor ω is added, which is closely related to the local exploration and global search ability of the particle [4]. The formula of adding inertia factor ω is:

$$v_i(t+1) = \omega \times v_i(t) + c_1 r_1 \left[p_i(t) + x_i(t) \right] + c_2 r_2 \left[p_g(t) - x_i(t) \right] \tag{4}$$

2.3. SA-PSO Algorithm

PSO algorithm is easy to fall into the local optimal, while SA algorithm has a certain randomness and can jump out of the local optimal, so researchers combined the two and proposed a simulated annealing combined particle swarm optimization (SA-PSO) algorithm. This algorithm can not only get better solutions, but also leave poor solutions with appropriate probability, thus balancing the contradiction between local and global.

The algorithm steps are as follows:

1) Initialization. The annealing speed δ, learning factors $c_1$and c_2, inertia weight ω and other parameters are initialized.

2) Set particle swarm. The population size is m, and their position and speed are initialized.

3) Get their fitness based on $F(x)$ and current fitness based on p_i and p_g.

4) The initial annealing temperature T is obtained according to the fitness $F(p_g)$ of the current global optimal position p_g.

5) Calculate the annealing fitness of each particle at the current temperature. The formula is:

$$f_{SA}(P_i) = \frac{e^{-\frac{f(p_i)-f(p_d)}{T}}}{\sum_{i-1}^{n} e^{-\frac{f(p_i)-f(p_d)}{T}}} \tag{5}$$

6) Select a p_i instead of p_g according to the roulette idea, that is, the optimal value of a particle replaces the global optimal value at this time. Firstly, the cumulative probability of annealing algorithm is calculated according to formula (6).

$$F(j) = \sum_{i=1}^{j} f_{SA}(P_i) \tag{6}$$

Then, according to F(x), p_r satisfying the requirement is selected instead of p_d, satisfying the conditions are:

$$F(r-1) < \text{rand}() < F(r) \tag{7}$$

Where, rand () is a random number between [0,1].

7) Update the velocity position of each particle.

8) Calculate fitness and update p_i and p_g.

9) After that, the annealing operation is carried out according to formula (8).

$$T = \delta t \tag{8}$$

10) Determine whether the end condition is met, if so, the end and output the return value; If not, skip to Step 5) to the next round of the loop.

The flow chart of SA-PSO algorithm is:

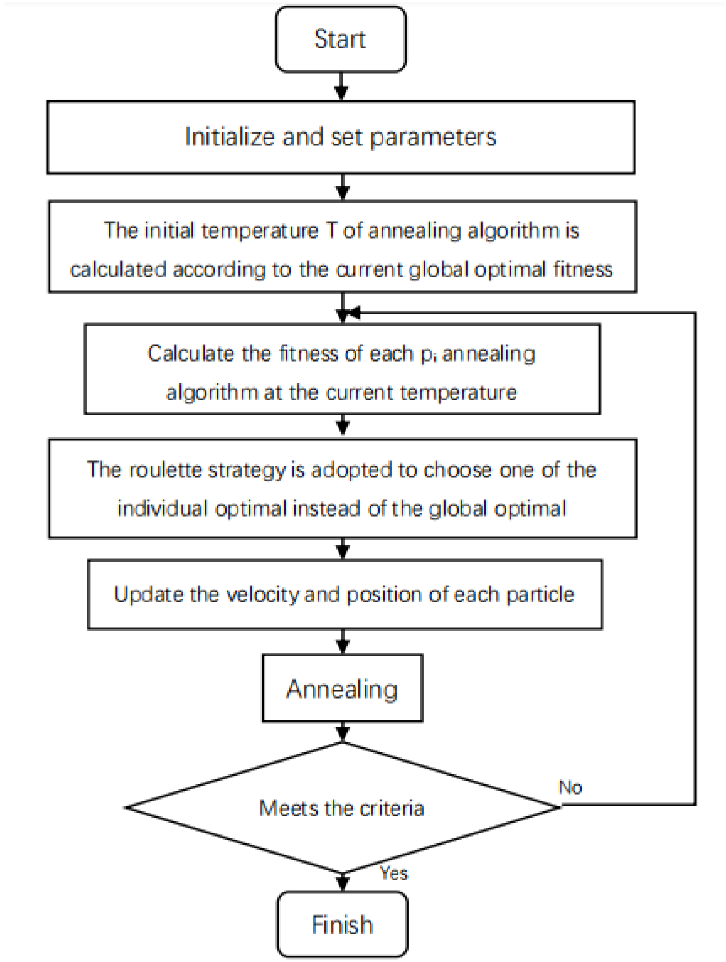

Figure 1. Flow chart of SA-PSO algorithm

3. First Iris Recognition

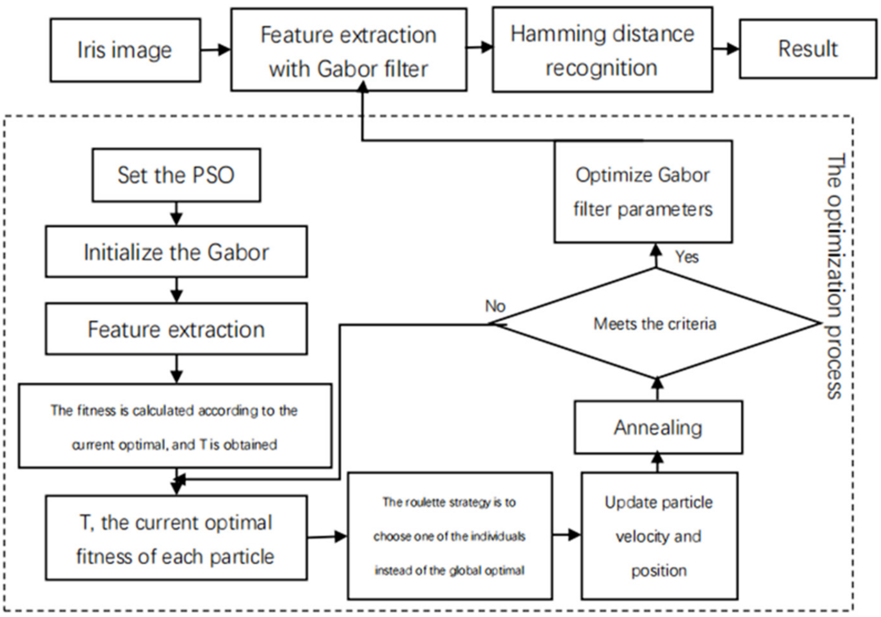

Figure 2. Initial identification process diagram

Before iris feature extraction and matching, it is necessary to preprocess the images qualified in the quality evaluation. In order to better determine the location of the inner and outer boundaries of iris, this paper adopts the method of secondary positioning, first to determine the approximate range of the boundary, and then to get accurate positioning. Below, we will identify the pre-processed images.

The picture of the initial identification process shown in Figure 2.

3.1. Gabor Filter Parameter Adaptive

Gabor filter has a very good effect on texture feature extraction, and its performance is closely related to parameter setting. Many researchers directly use empirical parameters, which is very convenient, but low in accuracy and universality. Therefore, in this paper, Sa-PSO algorithm is adopted to optimize the maximum frequency k_{max} of the filter and the frequency difference f_v between cores.

In addition to selecting a reasonable particle population size and learning factor for SA-PSO algorithm, the setting of initial temperature and annealing speed is also closely related to the performance of the algorithm. The former has a direct influence on the annealing fitness of particles, and then affects the probability that the algorithm accepts poor solutions after the random solution is generated. The initial temperature can be set higher and then cooled slowly, so the temperature can be set according to formula (9). Annealing speed should be slow, to carefully find the optimal solution, this paper set the annealing speed of 0.96.

$$\mathrm{T} = -\frac{f\left(P_{pd}\right)}{\ln 0.2} \tag{9}$$

The parameter optimization process is:

1) Initialization. The population size m was set and initialized. Each particle was treated as an initial Gabor filter (including a set of k_{max} and f_v). The parameters c_1, c_2 and δ were set. In this paper, the particle size is set as 30, the initialization speed is set as [-50,50], the number of iterations is set as 300, and the two factors are set as 1.4944.

2) The comparison iris of the same type and different type extracted from the iris library was trained as the test iris, and the 5×8 filter bank was used to extract iris features. The hamming distance between iris and iris of the same kind and between iris of different kinds was calculated and compared respectively, and the adaptation degree of recognition was obtained accordingly.

a_1 iris was selected from the corresponding iris database to test, b_1 iris of the same type and b_1 iris of different type were compared, and the adaptation degree was obtained according to formula (10) after feature extraction.

$$T_1 = \frac{1}{\bar{a}_1}\left[\sum_{x=1}^{b_1}\left(HD_x - 1\right)^2 + \sum_{y=1}^{b_1}\left(HD_y - D\right)^2\right] \tag{10}$$

Where, HD_x and HD_y are hamming distances between iris of different and same categories respectively. The smaller the T_1, the greater the degree of adaptation.

3) Carry out particle swarm evolution for particle i, and calculate T1 of current particle p_i and particle p_g according to the above formula. If $T_1\left(x_i\right) \le T_1\left(p_1\right)$, then $p_i = x_i$; If it's $T_1\left(x_i\right) \le T_1\left(p_1\right)$, then it's $p_g = x_i$.

4) The initial annealing temperature T is obtained according to the fitness of the current global optimal position p_g.

5) Calculate the annealing fitness of each particle at the current temperature.

6) Choose a p_i instead of a p_g according to the idea of roulette.

7) Update the velocity and position of each particle.

8) Calculate the degree of adaptation and update p_i and p_g.

9) Conduct annealing operation according to formula (8). The annealing rate is 0.96.

10) Determine whether the end condition is met, if so, the end and output the return value; If not, skip to Step 5) to the next round of the loop.

3.2. Feature Extraction with Gabor Filter

The Gabor filter bank selects a combination of 5 frequencies and 8 directions. Due to the large scale of iris recognition, in order to read more information and reduce the correlation between image dimensions, PCA algorithm was first used to compress the dimension of iris image before feature extraction, and the image from 256×32 was compressed to 256×1.

After that, the steps of feature extraction of SA-PSO-Gabor filter are as follows:

1) Number the frequencies and directions of these filters in ascending order.

2) The 256×1 image was processed with the above 40 filters.

3) The 256 filters with the largest response amplitude of feature points were selected for encoding, and the corresponding frequencies and directions of the filters were coded into 3-bit binary codes respectively. Then, the obtained two codes are pieced together into 6-bit binary codes in the order of first frequency and then direction, which are used to represent the characteristics of each sub-block.

4) Finally, the 256 feature points were sequentially spliced to form 1536-bit iris feature coding.

3.3. Hamming Distance Matching

After the feature coding is obtained, the hamming distance XOR calculation is carried out based on formula (11) with the feature coding of contrast template iris, and the value of n is 1536.

$$HD = \frac{1}{n}\sum_{i=1}^{n} C_1 \oplus C_2 \qquad (11)$$

The smaller the HD, the more similar the iris. When the similarity rate is greater than the threshold, the iris is eliminated. When the similarity rate is less than the threshold value, the second recognition is entered.

4. Iris Recognition Again

Re-identification process diagram shown in Figure 3.

4.1. Haar Wavelet Feature Extraction

Haar wavelet can be used to decompose images in different spatial directions and different frequency bands. In this paper, it is used to extract the features of iris images for secondary recognition. First, the image is decomposed by Haar filter, and then the high frequency information is used to reflect the decomposition result. For iris feature extraction, there are too many high frequency coefficients in the first and second layers of Haar wavelet, which is at a disadvantage in terms of space complexity. In order to extract more information even when the iris coding is not long [5], the high frequency coefficients in the third layer are used for feature extraction. The image of Haar wavelet decomposition is shown in Figure 4:

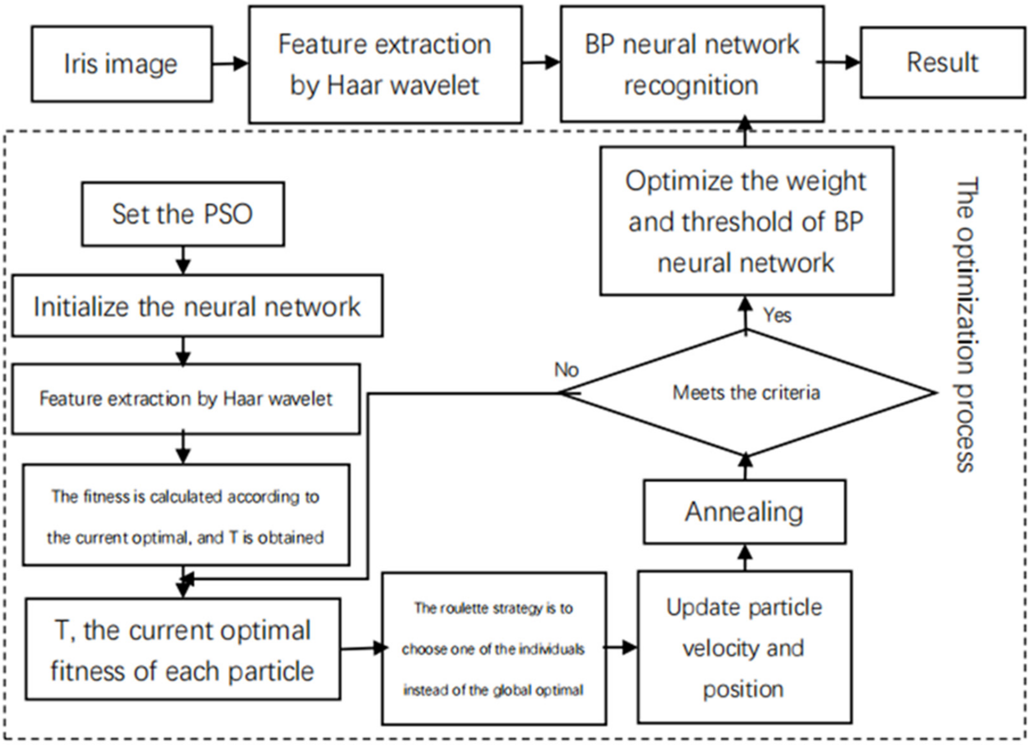

Figure 3. Identify process diagram again

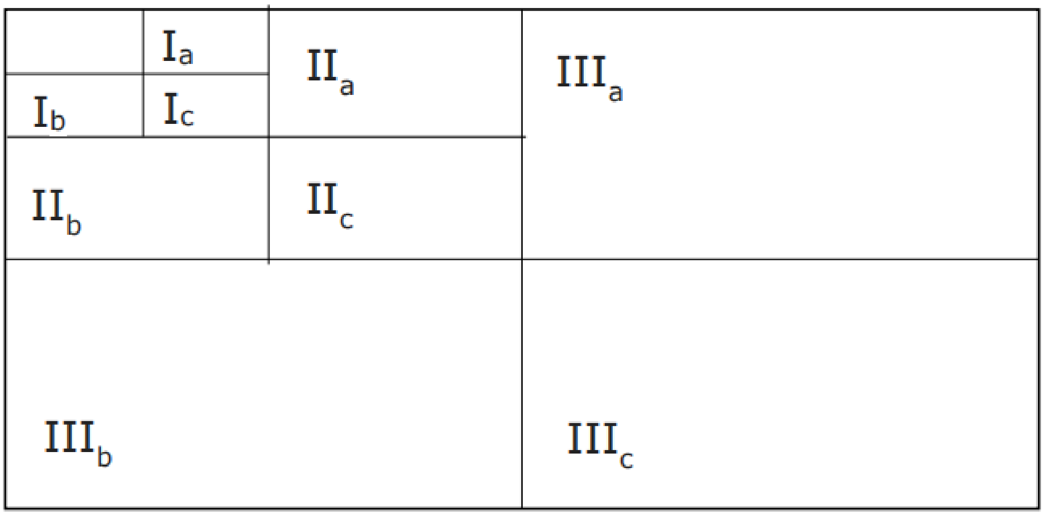

Figure 4. Image of Haar wavelet decomposition

Where, I, II and III respectively represent the coefficient matrix of the first, second and third layers, and subscripts a, b and c correspond to horizontal, vertical and diagonal high frequency subgraphs. III_a, III_b and III_c were selected in this paper. The three coefficient matrices were vertically arranged and then compressed to 32×1 dimension by PCA to generate 32 feature points. The high-frequency coefficients of these feature points were used to represent the features of iris.

4.2. Neural Network Connection Weight Adaptive

BP neural network is a multi-layer feedforward network, which includes output layer, hidden layer and output layer. When the information is propagated forward, the input layer enters the hidden layer after receiving the data, calculates it layer by layer, and then enters the output layer. If the value does not meet the expectation, the error is transmitted back and adjusted. Repeat the process and stop learning when the condition is met.

Among them, the hidden layer can be several layers, which contain several neurons, through which information is obtained between layers. In order to ensure the network performance and make the structure as compact as possible, this paper selects the double-hidden layer structure and sets up 12 nodes at each layer. Set the number of nodes at the input layer to 32 and the number of nodes at the output layer to 1. The weight of BP neural network will also directly affect the network performance, so this paper uses SA-PSO to optimize the connection weight of the network.

The transfer function is selected as $\tanh(x)$, which is nonlinear and its output is bounded, suitable for the input of the next layer. The function is expressed as:

$$\tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{12}$$

The graph of this function is:

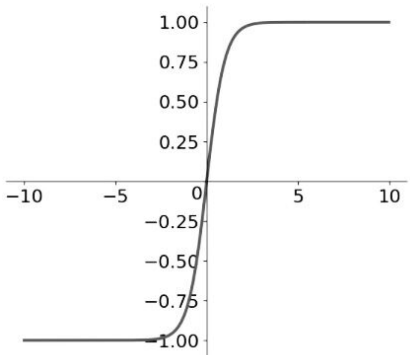

Figure 5. Image of tanh(x) function

The parameter optimization process is:

1) Initialization. Set the population size and regard the particle as a neural network. According to the network structure, it can be known that the network weights between layers are 384, 144 and 12, a total of 540. Set parameters such as c_1 and c_2. The initial velocity of the 15 particles set in this paper is within [-1,1], the number of iterations is set as 300, and the two factors are set as 1.4944.

2) The iris of the same kind and different kinds extracted from the iris database were used as test iris for training with neural network, and the recognition adaptation was obtained according to the results of different iris of the same kind and the same iris of the same kind calculated by neural network.

a_2 iris was selected from the corresponding iris database to test, b_2 iris of the same type and b_2 iris of different type were compared, and the adaptation degree was obtained according to formula (13) after feature extraction.

$$T_2 = \frac{1}{a_2}\left[\sum_{x=1}^{b_2}\left(g_x - (-1)^2\right) + \sum_{y=1}^{b_2}\left(g_y - 1\right)^2\right] \tag{13}$$

Among them, g_x is the result of different categories of comparative iris after neural network calculation, and g_y is the result of the same category of comparative iris after neural network calculation. The smaller the T, the greater the degree of adaptation [6].

3) Evolve particle i, and calculate the T_2 of current particle p_i and particle p_g according to the above formula. If $T_2(x_i) \le T_2(p_i)$, then $p_i = x_i$; If it's $T_2(x_i) \le T_2(p_g)$, then it's $p_g = x_i$.

4) -10) Same as in Section 3.1.

4.3. BP Neural Network Recognition

In this paper, the input vector of BP neural network is the difference between the high frequency coefficient values of the test iris image and the contrast template iris feature points. The calculation formula is:

$$x_t = T_t - C_t, t = 1, 2, \cdots, 32 \tag{14}$$

Where, x_t represents the tTH component of the input vector, T_t represents the high frequency coefficient of the iris to be measured, and C_t represents the high frequency coefficient of the template iris.

Taking into the transfer function, the input of each node in the first hidden layer in this paper is composed of the input of 32 nodes in the input layer, and the input of each node is the input of the input layer of the node multiplied by the corresponding weight, where the input vector of the ith node is:

$$s_i = \sum_{t=1}^{32} \omega_{t-i} \times x_t \tag{15}$$

Where, ω_{t-i} represents the weight of the t th node of the input layer connected to the i th node of the layer, $i = 1, 2, \cdots 12$.

The output vector of this node is:

$$Z_i = \frac{1 - e^{-2xs_i}}{1 + e^{-2xs_i}} \tag{16}$$

The input of each node of the next hidden layer is composed of the input of 12 nodes of the first hidden layer, and the input of each node is the output of the node multiplied by the corresponding weight, where the input vector of the jTH node is:

$$s_j = \sum_{i=1}^{12} \omega_{i-j} \times z_i \tag{17}$$

Where, ω_{i-j} represents the weight of the output of the ith node of the previous layer connected to the jTH node of this layer, $j = 1, 2, \cdots 12$.

The output vector of this node is:

$$Z_j = \frac{1 - e^{-2\times s_j}}{1 + e^{-2\times s_j}} \tag{18}$$

The input of the output layer is composed of the input of 12 nodes in the second hidden layer. The input of each node is the output of the node multiplied by the corresponding connection weight. The input vector of x_3 is:

$$s_3 = \sum_{j=1}^{12} \omega_{j-3} \times z_j \tag{19}$$

Where, ω_{j-3} represents the weight of the output of the jTH node of the upper layer connected to the layer.

The output vector is:

$$Z_3 = \frac{1-e^{-2\times s_3}}{1+e^{-2\times s_3}} \tag{20}$$

Because the hyperbolic tangent function tanh () is chosen as the excitation function in this paper, the closer the output value is to 1, the more similar the iris to be measured will be to the template iris to be measured. The closer the output value is to -1, the greater the difference between the iris to be tested and the template to be tested. When the output value is greater than the threshold, the iris is the same.

5. Experimental Results and Summary

In this paper, iris images in CASIA V4.0 were selected and 160 categories were selected. The 2500 images were respectively tested by the three methods proposed in this paper: the quadratic recognition method SA-PSO-Gabor + Hamming + Harr + BP neural network, the neural network algorithm Haar + SA-PSO-neural network, and the filter algorithm PSO-Gabor + Hamming. The experimental results were represented by CRR, EER and T to compare the performance of the algorithms. The experimental results are shown in Table 1:

Table 1. Experimental results

Iris recognition algorithm	CRR	EER	T
SA-PSO-Gabor+Hamming+Harr+BP Neural Networks	99.34%	0.67%	0.5931×10^4
Haar+SA-PSO-Neural Networks	98.79%	1.24%	0.6810×10^4
PSO-Gabor+Hamming	92.65%	7.76%	0.3964×10^4

It can be seen from the experimental results that the proposed algorithm has a higher CRR and a lower EER, which means it has a higher correct recognition ability and a shorter recognition time when the recognition rate is guaranteed.

Compared with distance algorithms, the proposed method has further network training, which greatly improves the accuracy. Compared with neural network algorithms, the method presented in this paper is more targeted when first recognizing the iris images with a large gap and then training them in the network. Moreover, the time of network algorithm is longer than that of distance algorithm, and the iris image has been reduced in the second recognition, so the recognition time is reduced. The algorithm in this paper has improved the recognition accuracy and speed.

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