IRIS Authentication using PSO

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ABSTRACT

The paper proposes a wavelet probabilistic neural network (WPNN) for iris biometric classifier. The WPNN combines wavelet neural network and probabilistic neural network for a new classifier model which will be able to improve the biometrics recognition accuracy as well as the global system performance. A simple and fast training algorithm, particle swarm optimization (PSO), is also introduced for training the wavelet probabilistic neural network. In iris matching, the CASIA iris database is used and the experimental results show that the feasibility and performance of the proposed method.

1. INTRODUCTION

Recently, the biometrics information using human appearance's or behavior's features for person authentication is becoming an important research topic in public security and information security domains. Compared to the digit Personal Identification Number (PIN), the critical data stored in the card can be protected more secure by using the biometric information. Generally, the biometric information includes the following: facial features, iris, voiceprint, fingerprints, and etc. Among these patterns, the iris recognition is a more reliable and stable for personal identification system [1-3]. The iris recognition system [1-11] consists of three sub-system: a iris detection system that include detecting, locating iris and extract iris circular ring, feature extraction system that composes of Sobel transform, and a Wavelet Probabilistic Neural Network (WPNN) used as pattern classifier.

When the dimension of the input vectors is very large, some preprocessing technique is usually required to reduce the computational workload and also to improve the generalization abilities of the network. In this paper, the wavelet probabilistic neural network can to compress the input data into a small number of coefficients and the proposed wavelet probabilistic neural network is trained by particle swarm optimization (PSO).

PSO [18-19] is an evolutionary computation technique developed by Kenney and Eberhart in 1995. This algorithm simulates bird flocking or fish schooling behavior to achieve a self-evolution system. It can search automatically the optimum solution in the vector space. But the searching process is not randomness. According to the different problems, it decides the searching way by the fitness function. This paper will develop an optimal design of WPNN based on PSO. Finally, the scaling factor and translation factor of wavelet basis and the smoothing factor of Gaussian function will be optimized by PSO. Simulation results show the performance of the proposed WPNN.

2. IRIS IMAGE ACQUISITION

The iris image, as shown in Fig. 1 (a), does not only contain abundant texture information, but also some useless parts, such as eyelid, pupil, and etc. Because the iris is between the pupil (inner boundary) and the sclera (out boundary), the pupil is usually taken as circle. To localize the iris, we propose a simple and efficient method. The procedure is as following:

1. A new image is the representation of the original image by 2-D wavelet, and its size is only quarter of the original image.

2. The edge of pupil in new image is detected by Sobel transform.

3. The center coordinates and the radius of the pupil is determined by Hough transform.

4. The iris circular ring is obtained by the position of pupil.

In the above mentioned methods, the first step reduces the dimensionality of image to improve the efficiency of extracting iris image. The second and third steps provide an approach to localize the position of the pupil. But the position of pupil is in the new image, the twice center coordinates and radius of the pupil is the position of pupil in original image. When the center coordinates and the radius of the pupil in original is obtained, the iris circular ring is extracted to as features.

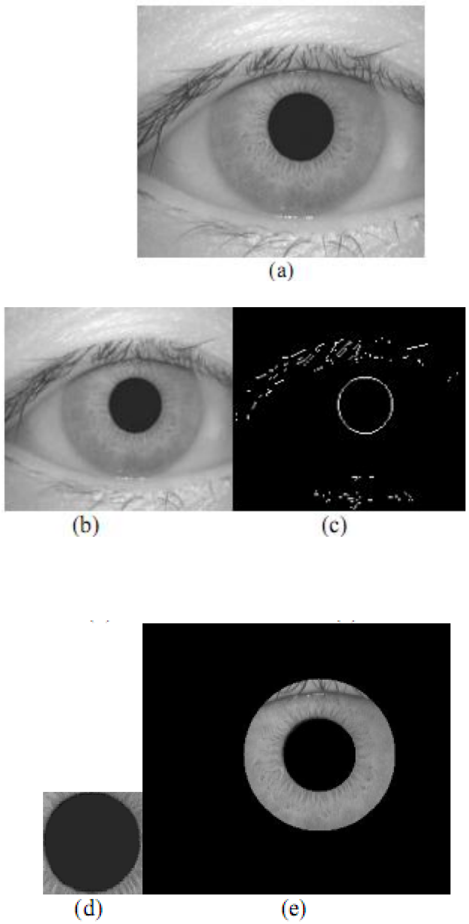

Fig 1. Iris localization. (a) Original iris image (b) New image after wavelet transform (c) New image after Sobel transform (d) Pupil image (e) Iris image

The more iris circular ring is extracted, the more information is used as feature. The recognition performance is much better, but the efficiency is slightly affected. In the next section, the detailed description of the iris feature extraction method is presented [11].

3. IRIS TEXTURE FEATURE EXTRACTION

Iris texture has abundant texture information for iris identification or matching [1-11]. We propose a very efficient algorithm to extract iris feature for iris recognition. The proposed method is based on the iris features existing in high frequency. The proposed method is different from traditional 2-D iris feature extraction method. Firstly, The Sobel transform is used to extract iris texture; the texture information is transformed 1-D energy profile signal. Finally, the WPNN is used as a classifier in iris recognition system.

The purpose of Sobel transform is used to extract the iris texture. The vertical projection is used as preprocessing to make texture image to 1-D energy profile signal. Each iris image is projected onto the 1-D energy profile signal. The signal is more concentrated and as feature vectors. Finally, the WPNN is selected as the pattern recognition classifier because its high performance and high efficiency.

Sobel transform

The iris image is captured in different size from different people. It is not convenient for iris recognition, and the recognition performance is also affected. In the cause of the convenience of computation and achieving the high recognition performance, each captured iris circular ring number from different iris image is the same and the iris ring is unwrapped to a rectangular block as Fig. 2 (a) with a fixed size. To capture the texture of iris, we adopt the Sobel transform to analyze texture shown as Fig.2 (b).

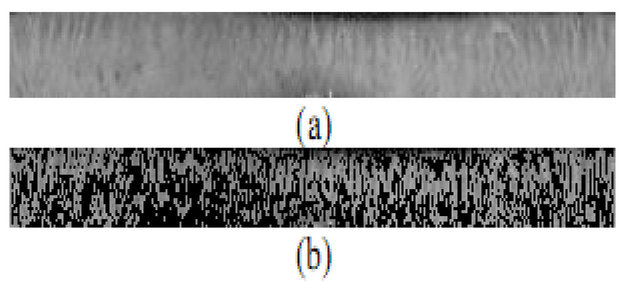

Fig.2 (a) Unwrapped iris image; (b) Unwrapped iris image after Sobel transform

Vertical projection

To reduce system complexity, we adopt vertical projection to obtain 1-D energy profile signal. The exploit the benefits driving from concentrated energy, every row is accumulated as energy signal. This method is evaluated on the CASIA iris databases, which contains a set of iris images as Fig. 2 (a) from Chinese.

Let X be an iris image of size mxn, m is the number of iris circular ring, and n is pixels of each iris circular ring.

$$X = \begin{vmatrix} X_{1x1} \ldots\ x_{1xn} \\ . \qquad . \\ . \qquad . \\ X_{mx1} \ldots\ X_{mxn} \end{vmatrix} \qquad (1)$$

After vertical projection, the 1-D energy signal Y is obtained.

$$Y = [y_1 \ldots y_n] \qquad (2)$$

The m is very smaller than the n. Thus, the information of iris texture after vertical projection is abundant than the information of iris texture after horizontal projection. So, We adopt the vertical projection to extract the 1-D energy signal as feature vector.

4. WAVELET PROBABILISTIC NEURAL NETWORK

WPNN combines wavelet neural network [20-23] and probabilistic neural network [15] for an iris recognition classifier. Fig. 3 presents the architecture of a four-layer WPNN, which consists feature layer, wavelet layer, Gaussian layer, and decision layer. In feature layer, X1… XN are as sets of feature vectors or input data, and N is the dimension of data sets. The wavelet layer is a linear combination of several multidimensional wavelets. Each wavelet neuron is equivalent to a multidimensional wavelet, and the wavelet in the following form

$$\phi_{a,b}(x) = \sqrt{a}\phi\left[(x-b) / (a)\right] \quad a,b \in R \qquad (3)$$

is a family of function generated from one single function □ □ $\phi(x)$ by the scaling and translation, which is localized in both the time space and the frequency space, is called a mother wavelet and the parameters are named the scaling and translation factors, respectively.

In Gaussian layer, the probability density function of each Gaussian neuron is the following form

$$f_1(x) = (1 / (2\pi)^{(2/p)} \sigma^P)\,(1/n_1) \sum_{i=0}^{n} \exp(-(X-S^i_j)^2 / (2\sigma^2)) \qquad (4)$$

1) Where X is the feature vector, p is the dimension of train set, n is the dimension of input data, j is jth data set, S^i_j is the train set, and ε is the smoothing factor of Gaussian function.

When the input data is changed, we do not change the architecture of WPNN or train the factors. It is suitable for biometric recognition classifier. Finally, the scaling factor, translation factor and smoothing factor are randomly initialized at beginning and will be optimized by PSO algorithm.

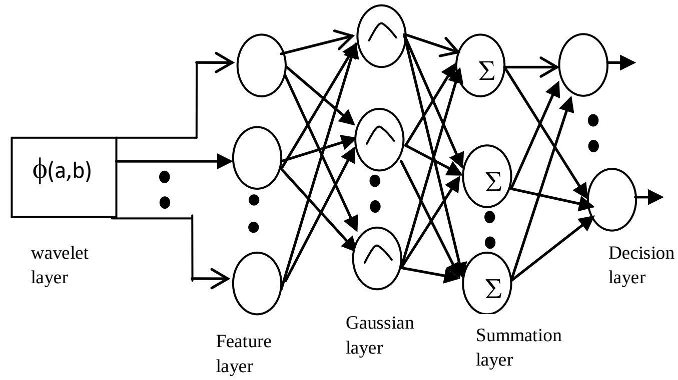

Fig.3 Architecture of a four-layer WPNN

5. LEARNING ALGORITHM

PSO is a new bio-inspired optimization developed by Kenney and Eberhart in 1995[18-19]. PSO exploits cooperative and social behavior's heuristics, such as shoal of fishes, flock of birds and swarm of insects. The basic algorithm involves the starts from a population of distributed individuals, named particles, which tend to move toward the best solution in the search space. The particles will remember the best solution encountered and the best solution of swarm. At each interaction, every particle adjusts its velocity vector, based on its momentum and the influence of both its best solution and the best solution of swarm. At time unit t, the position of ith particle xi, i =1,2,…,M, (M is the number of particles) moves by addition of a velocity vector vi, which is a function of the best position (the best fitness) found by that particle, (pi , for individual best) and of the best position found so far among all particles of swarm(g, for global best). The movement can be formulated as:

$$V_i = w(t)v_i(t-1)+c_1(p-x_i(t-1))+c_2u_2(g-x_i(t-1)) \qquad (5)$$

$$x_i(t-1)=x_i(t)+ v_i(t) \qquad (6)$$

acceleration constants, and $\mu \varepsilon (0,1)$ the uniformly distributed random numbers.

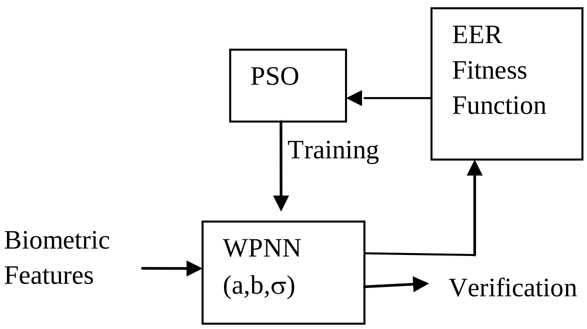

Fig.4 WPNN training using PSO

The PSO is used for training the single neuron to optimize WPNN model as shown in Fig.4. We encode the wavelet neuron by two factors, including scaling factor and translation factor of wavelet neuron and Gaussian neuron by smoothing factor. PSO, in offline mode, searches the best set of factors in the three dimensional space.

6. EXPERIMENT PROCEDURE AND ITS RESULTS

In this section, we refer to our method of combining Sobel transform, vertical projection with WPNN for iris recognition. The iris database used in the comparison is the CASIA iris database). The database contains 756 iris images acquired of 108 individuals (7 images per individual). In the following experiments, a total of 324 iris images (three iris images of each person is extracted) were randomly selected as the train set and the remains as the test set from the remaining images.

6.1 Evaluation on Iris verification with the proposed method

In a real application, the iris verification experiment classifies an individual as either a genuine user (called an enrollee) or an impostor. Thus, the experiment has two types of recognition errors: it either falsely accepts an impostor or falsely rejects an enrollee. We define two types of error rate. The false acceptance rate (FAR) is the probability that an unauthorized individual is authenticated. The false rejection rate (FRR) is the probability that an authorized individual is inappropriately rejected.

FAR = (number of false acceptances) /(number of impostor attempts) (7)

FRR = (number of false rejections) /(number of enrollee attempts) (8)

The performance of iris verification is estimated with the Equal Error Rate (EER). When FAR is equal to the FRR, the EER is obtained as Fig.5. The high performance of iris verification system is in low EER.

The results show in Table 1. In these experiments, the best EER is 3.36% and the average EER is 5.36%. These results illustrate the superiority of the proposed method. These observations demonstrate that the iris recognition techniques can be suitable for low power applications showing that the complexity of the proposed method is very low

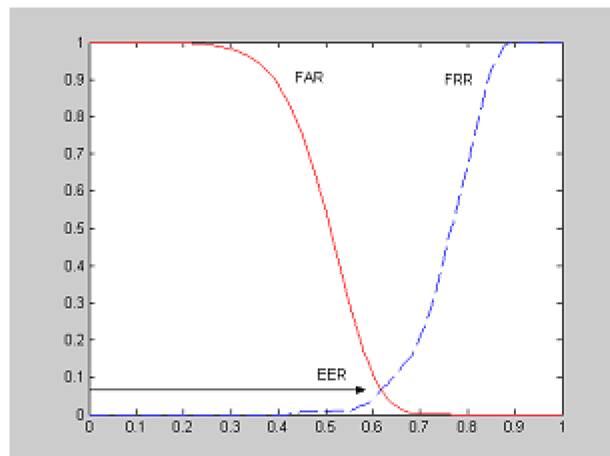

Fig. 5 Equal Error Rate (EER)

Table 1 The recognition performance of WPNN

Method	**Proposed**
Average EER	5.33%
Best EER	3.36%

6.2 Evaluation on Iris Identification with Existing Methods

From Table 2, we show the performance of our new method is much better than that of our previous method. The proposed method combines a very simple algorithm and WPNN, which can significantly outperform established iris recognition system on standard datasets. Owing to high efficiency and simplicity of the proposed method, it is very suitable for low power applications or HW platforms having small portions of memory available (smartcard).

Table 2 Compared with the previous method and proposed method

Method	Proposed	Previous
Average EER	5.33%	5.56%
Best EER	3.36%	4.36%

7. CONCLUSION AND FUTURE WORK

The paper proposes a wavelet probabilistic neural network as iris recognition classifier. The WPNN combines wavelet neural network and probabilistic neural network. We use PSO for adjusting the parameters of WPNN. We only need a few parameters as the weights of WPNN and the evaluation of WPNN is based on CASIA iris database. From the simulation results described in experiments, it is clear that the proposed method has high efficiency. The complexity of feature extraction method for iris recognition is excellently low. The proposed method provides excellently effective, and achieves a considerable computational reduction while keeping good performance. We have proved the proposed method can achieve very fast iris recognition. In future, we will further improve the recognition performance of iris recognition and apply it to embedded system.

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