Humanoid Fingerprint Recognition based on Fuzzy Neural Network

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Abstract: - Nowadays the computer speed is much faster than before, however well-trained humans are still the best pattern recognizer. In this paper we propose a fingerprint recognition method which is based on humanoid algorithms. Because fingerprint patterns are fuzzy in nature and ridge endings are changed easily by scars, we try to only use ridge bifurcation as fingerprints minutiae and also design a "fuzzy feature image" encoder by using cone membership function to represent the structure of ridge bifurcation features extracted from fingerprint. Then, we integrate the fuzzy encoder with back-propagation neural network (BPNN) as a recognizer which has variable fault tolerances for fingerprint recognition. Experimental results show that the humanoid fingerprint recognition system is robust, reliable and rapid.

Key-Words: - Humanoid fingerprint identification; Fuzzy system; Neural networks

1 Introduction

Nowadays, the advent of electronic business is influencing commerce at an ever increasing rate. The traditional identifications such as password, personal seals, financial cards, ID cards have the serious safety considerations in that they risk being faked, stolen or lost. According, we need a biometrics verification system that is safe, reliable, and convenient.

Biometrics verification systems use physiological or behavioral characteristics to verify the identity of a person automatically. Fingerprint is most popularly used in biometric identification systems, because it is a unique and unchangeable property throughout person's life [1]. Among all the various biometrics（e.q., face, palm, iris, fingerprints, etc.）, fingerprint identification is one of the most significant and reliable identification methods. It is obviously impossible that two people have the same fingerprint, i.e., the probability is 1 in 1.9E15 [2]. A fingerprint can be recognized by many different properties, such as ridges and bifurcation patterns, as well as local ridge anomalies [3].

By the American National Standards Institute proposes four classes of minutiae: ending, bifurcation, trifurcation, and undetermined [4].

The FBI makes use of only two, ridge ending and bifurcation. In the literature, these properties are commonly referred to as minutiae. Most fingerprint identification systems are based on minutiae matching, and there are two minutia structures that are most prominent: ridge endings and ridge bifurcations [5].

The ridge ending is defined as a point where the ridge ends abruptly. A ridge bifurcation is defined as a point where a ridge forks or diverges into branch ridges.

Because ridge endings are changed easily by scars, we only choose the bifurcation to be the minutiae of fingerprints.

2 Ridge Bifurcation Extraction

Due to the presence of noise in original fingerprint images, as well as poor image quality, we often fail to identify bifurcation area efficiently. To address this problem, we use image processing to reduce noise [6].

Through image processing, extracted features data can be more precise. This greatly increases identification accuracy. A system for bifurcation extraction of a fingerprint image is shown in Figure 1.

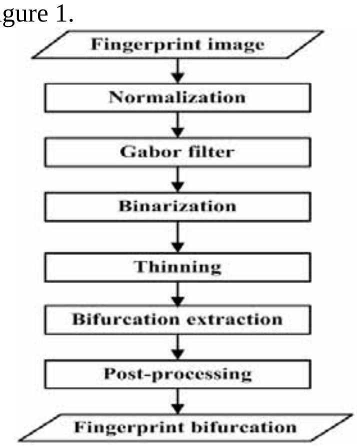

Fig.1. Bifurcation extraction.

3 Fuzzy Image Encoder

Fuzzy logic provides human reasoning capabilities to capture uncertainties that cannot be described by precise mathematical models [7]. And fuzzy logic can able to the reasoning with some particular form of knowledge [8].

Pattern identification is essentially the search for "the structure" in data, and fuzzy logic is able to model the vagueness of "the structure". There is an intimate relationship between the theory of fuzzy logic and the theory of pattern identification. The relationship is made stronger by the fact that fingerprint patterns are fuzzy in nature [9].

In a rule-based fuzzy system to inspect fingerprint, typical rules may be:

IF the bifurcations are **PLENTY** in the **UPPER-RIGHT CORNER** THEN the user id is **Alex.**

IF the bifurcations are **PLENTY** in the **LOWER-RIGHT CORNER** THEN the user id is **Bob.**

IF the bifurcations are **PLENTY** in the **UPPER-RIGHT CORNER** AND the bifurcations are **THIN** in the **LOWER-RIGHT CORNER** THEN the user id is **Charles.**

Therefore a "fuzzy feature image" encoder is applied for representing "the structure" of bifurcation point features extracted from fingerprints. The fuzzy encoder is a kind of transformation from crisp set to fuzzy set.

The fuzzy encoder consists of three main steps.

- First of all, a 512x512 fingerprint image is segmented into 8x8 grids, and the width of each grid is 64 pixels as shown in Fig. 2. A fuzzy set is associated with each grid region which is shown in Fig.3. We use cone membership function to design the fuzzy encoder. The process of the fuzzy encoder is described as the following three steps.

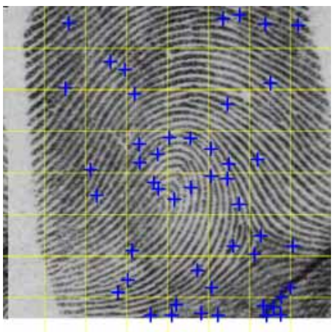

Fig.2. A sample image with the bifurcation points in 8x8 grids.

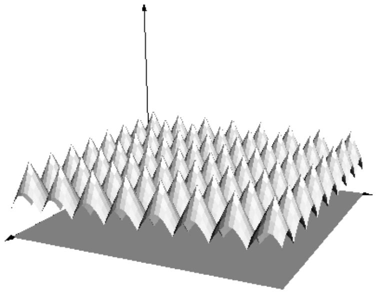

Fig.3. Membership functions of the fuzzy encoder.

- In the second step a membership value is considered for each fingerprint bifurcation, wherein a cone membership function is performed for each grid in order to present the structure of bifurcation features. The results of this analysis are used to get the membership value of the bifurcation to the fuzzy sets considered in previous step. The membership function of grid (i, j) is computed as:

$$\mu(i, j) = \sum_{n=1}^{m} \left(1 - \frac{Dis\tan ceToGridCenter_n}{GridWidth} \right) \cdots (1)$$

where $\mu(i, j)$ is the membership function of grid (i, j), m is the number of bifurcation points near the center of grid (i, j), and the Grid Width in this paper is 64 as shown in Fig.4.

- Finally, calculate the sum of membership degrees in each grid. Then the fuzzy image of fingerprint bifurcation structure is obtained in the third step.

The gray level value of fuzzy image is computed as:

$$F(i, j) = \begin{cases} 255 \quad if \quad \mu(i, j) \geq 1 \\ \mu(i, j) \times 255 \quad if \quad 0 \leq \mu(i, j) < 1 \cdots (2) \\ 0 \;\; if \;\; \mu(i, j) < 0 \end{cases}$$

Where $F(i, j)$ is the gray level value of grid (i, j) in a fuzzy image, which is shown in Fig.5.

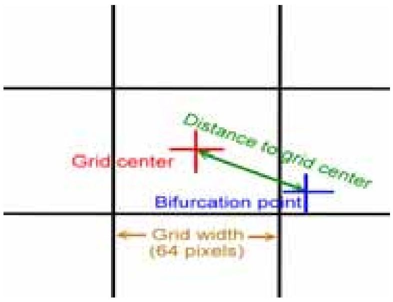

Fig. 4. Parameters of the membership function.

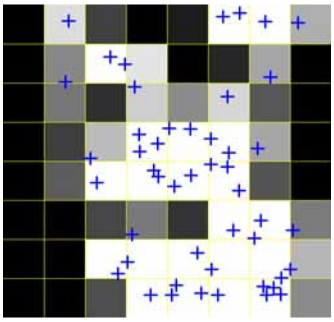

Fig.5. The fuzzy image of fingerprint bifurcation structure.

The rotation is a normal problem that occurs when a fingerprint is scanned for verification. The fuzzy image has fault tolerance for the rotation. If we rotate the fingerprint image 5 degrees in the clockwise direction as shown in Fig. 6, we can get almost the same fuzzy image of fingerprint bifurcation structure is shown as Fig 7.

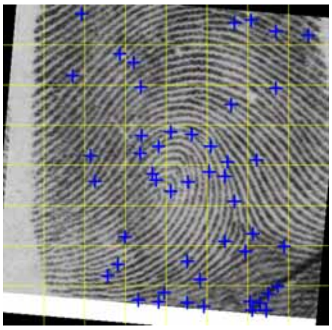

Fig.6. Rotate the fingerprint image 5 degrees in the clockwise direction.

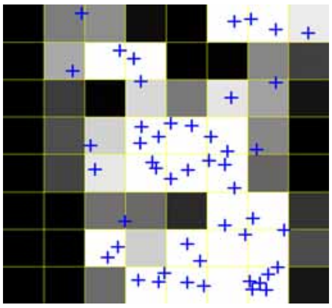

Fig.7. The fuzzy image of fingerprint bifurcation structure which is rotated 5 degrees in the clockwise direction.

4 Back-Propagation Neural Network

Neural networks offer exciting advantages such as adaptive learning, parallelism, fault tolerance, and generalization [7]. The neural network has capability to solving many important problems by simple computational elements [10]. The back-propagation (BP) algorithm is one of the most popular neural network learning algorithms. It has been used in a large number of applications [11]. Multilayer neural network with sigmoid hidden units have been extensively used for various applications since the BP algorithm was developed [12]. In this paper, we integrate the back propagation neural network (BPNN) with fuzzy encoder. This integration provides neural networks with "human-like" reasoning capabilities of fuzzy logic systems [13].

A typical BPNN has a multi-layer structure. An iterative weight-adjusting scheme is used to propagate backward the error term by modifying the weights of all the connections in the neural network （NN）structure in a stepwise fashion that is mathematically guaranteed to converge [14].

BPNN is the most widely used neural network system and the most well-know supervised learning technique. Basically, BPNN is comprised of three layers: input layer, hidden layers, and output layer. The BPNN algorithm is a systematic method for training multilayer artificial neural network. The objective of training the BPNN is to adjust the weights between these layers so that the application of a set of inputs produces the desired set of outputs [15].

The input layer is formed by the 64 neurons having the information of the pixel's values in the different fuzzy image grids. The number of hidden units was not determined by any mathematical approach. It was empirically determined to be 2 hidden layers and 10 neurons for each layer [16].

The activation function of the hidden and output units is a sigmoid function given by

$$f(x) = \frac{1}{1+e^{-x}} \quad \text{----------------------------------} \quad (3)$$

The values of each unit range between 0 and 1. They represent the normalized values of the corresponding [0~255] interval in each fuzzy image grid.

A rotated image is defined as a fingerprint image with its references x-axis and y-axis rotated and shifts. Rotation is a normal problem that occurs when a fingerprint is scanned for verification. The fuzzy logic and BPNN in this paper provides basic fault tolerance. If more fault tolerance abilities is required, we only need to add essential rotated samples while training, hence a variant fault tolerance system is implemented

As shown in Fig. 8, the BPNN of this system is composed of 4-layer neural networks. The algorithm based on efficient BPNN is as follows:

1. Set the network parameters:
   （1） Input layer size = fuzzy image size（8×8 = 64 neurons）
   （2） Layer number of hidden layers = 2
   （3） Neuron number of each hidden layer = 10
   （4） Learning rate = 0.3
   （5） Momentum factor = 0.6
   （6） Minimum root mean square error (RMSE) = 0.02
   （7） Maximum learning iteration number = 10000
2. Initialize a BPNN identification: Initialization of the weight matrix for hidden layer randomly.
3. Start training of a BPNN identification based on selected efficient base model parameters.
4. Save the training result to database.

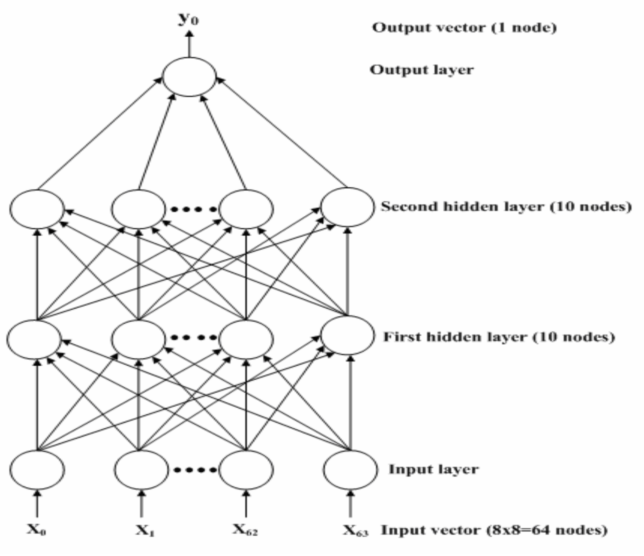

Fig.8. Back propagation neural network configuration.

5 Approach and Methods

Generally fingerprint identification and recognition system consist of 2 main parts:

(1) Fingerprint image processing
(2) Fingerprint identification

The step of fingerprint image processing is shown as Fig.9. And the step of fingerprint identification is shown as Fig.10.

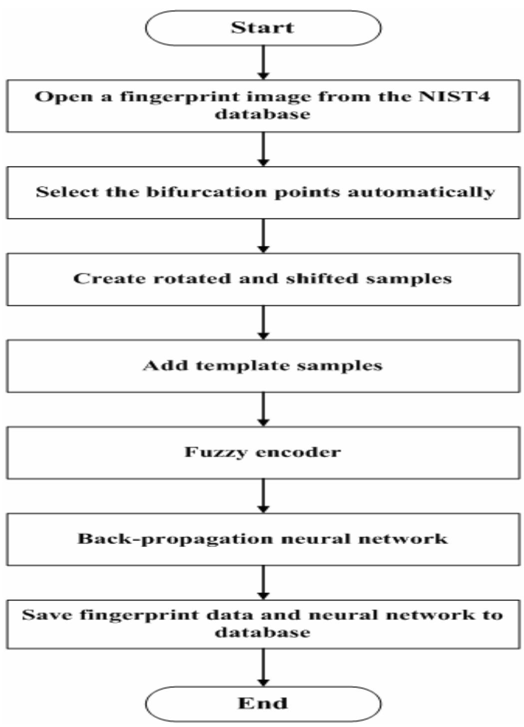

Fig. 9. The flow chart of adding new fingerprint data to database.

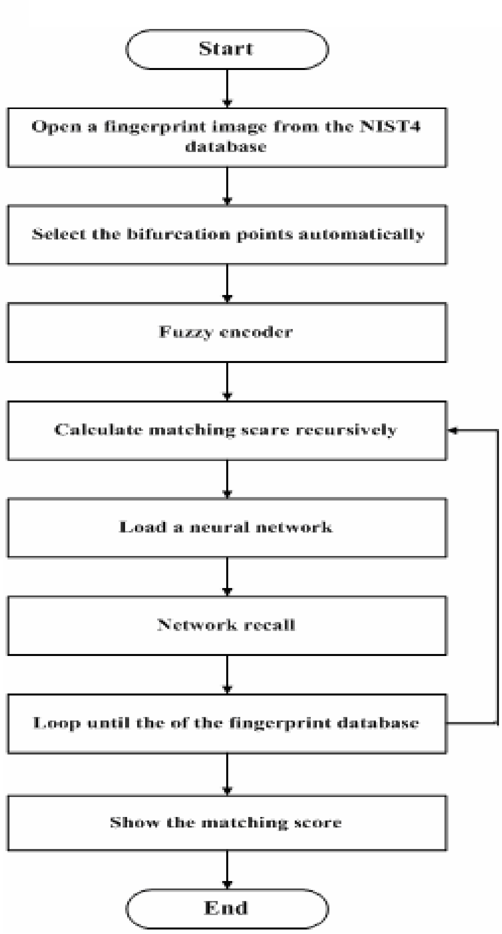

Fig.10. The flow chart of matching process.

6 Results and Discussion

The experiments have been conducted to evaluate the performance of this proposed fuzzy logic and neural network with NIST Special Database 4 fingerprint images. The fingerprint images were acquired and quantized into 512x512 by 500 dpi resolution with 256 gray levels in the test data set.

Fingerprints are usually divided into five distinct classes, namely, whorl, right loop, left loop, arch, and tented arch. A statistical analysis of the performances achieved by the proposed algorithm has been carried out using a number of 100 fingerprint images of each class. And a total of 500 fingerprint images are taken.

In fact, testing a fingerprint recognition algorithm requires a large database of samples （thousands or tens of thousands）. To overcome the problem of gathering large databases of fingerprint images for testing purposes, we use a synthetic fingerprint-image generation method for performance index. Generating testing fingerprints according to some parameters:

1) Random dropping of true minutiae.
2) Rotation degree.
3) Fingerprint shift.

The performance index that fingerprint identification has the following several items:

6.1 False rejection rate, FRR

One of the most important specifications in any biometric system is the false rejection rate (FRR). The FRR is defined as the percentage of identification instances in which false rejection occurs. This can be expressed as a probability. In this paper the FRR is 0 percent, it means that all of the authorized persons attempting to access the system will be recognized by that system. It's due to that all of the authorized persons have their own neural network model to do the identity in this system.

6.2 False acceptance rate, FAR

The false acceptance rate, or FAR, is the measure of the likelihood that the biometric security system will incorrectly accept an access attempt by an unauthorized user. A system FAR typically is stated as the ratio of the number of false acceptances divided by the number of identification attempts. In this paper the FAR is 0.23 percent, it means that 23 out of every 10,000 impostors attempting to breach the system will be successful. Stated another way, it means that the probability of an unauthorized person being identified an authorized person is 0.23 percent.

6.3 The processing time of each fingerprint image

A program which implements the procedures described in this work, was written in Boland C++ Builder 6.0 and run on and Pentium 4 3G processor. The CPU time including image processing and neural network training for each fingerprint is less than 5 second.

6.4 Matching speed

In this paper, we implement a high speed and accurate 1:N Fingerprint Matching algorithm. This system also allows 1:1 verification capability with a stored fingerprint template. Each identification can be carried with ease less than 0.07 second.

6.5 Dropping of true minutiae randomly

The effect for FAR and FRR by dropping of true minutiae randomly is shown in Fig.11. The FAR is 0 percent within [0% ~ 20%]. Therefore the fault tolerance for minutiae dropping is 20%.

6.6 Rotated image and shift image

The effect for FAR and FRR by image rotation is shown in Fig.12. The FAR is 0 percent within [-5° ~ +5°]. Therefore the basic fault tolerance for image rotation is ±5º. The effect for FAR and FRR by image shift is shown in Fig. 13. The FAR is 0 percent within [-10 pixels ~ +10 pixels]. Therefore the basic fault tolerance for image shift is ±10 pixels in this system.

6.7 Variable fault tolerance

In this paper the fault tolerant range can be expended easily. If the wider fault tolerance range is required, we only need to add essential rotated samples for neural network training. The Fig. 14 shows the basic fault tolerance for image rotation is ±5º (FRR1), but it can be expended easily to ±180º (FRR2) by adding essential training samples.

The results showed that fuzzy logic and neural networks have the ability to function and give correct results even with the existence of faults or noisy input data.

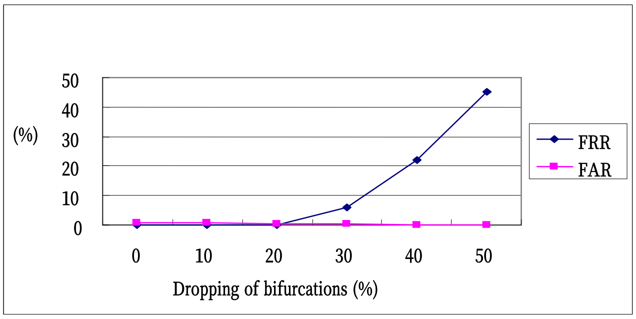

Fig.11. Dropping bifurcations randomly.

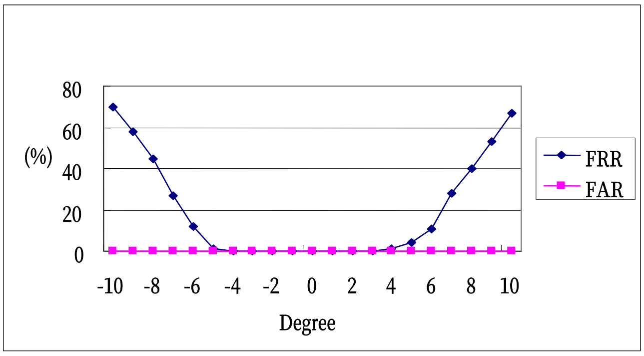

Fig.12. The effect of fingerprint rotation to the system.

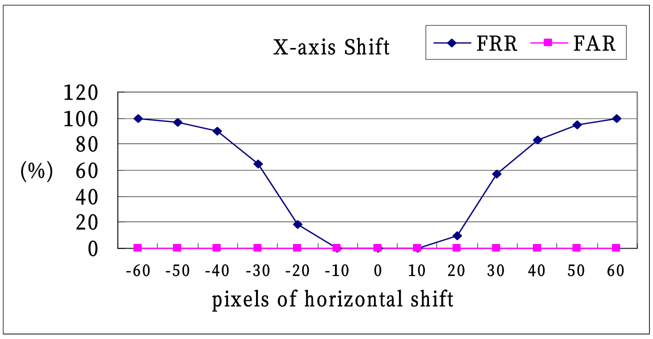

Fig.13-1. The effect of fingerprint shift to the system.

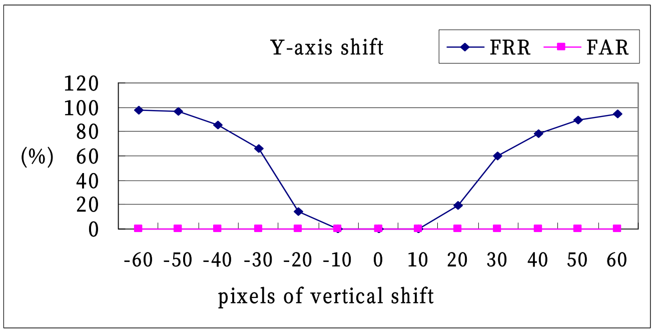

Fig.13-2. The effect of fingerprint shift to the system.

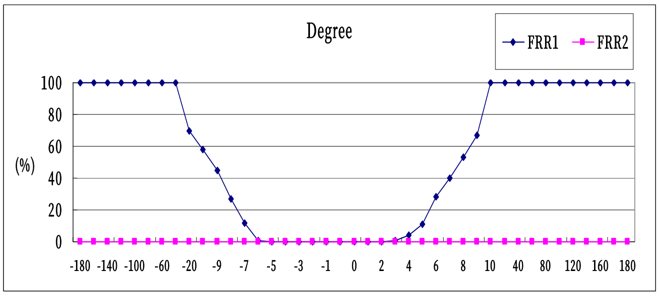

Fig.14. Variable fault tolerance.

7 Conclusion

In this paper, a humanoid method has been proposed for fingerprint recognition. We only use ridge bifurcation as fingerprints minutiae and a ridge bifurcation extraction algorithm with excluding the noise-like points ability is proposed. A fuzzy encoder by using cone membership function is designed to represent the structure of ridge bifurcation feature extracted from fingerprint. Then, we integrate the fuzzy encoder with BPNN as recognizer which has variable fault tolerances, including ridge bifurcation dropping, shift and rotation, for fingerprint recognition. Experimental results show that the proposed fingerprint recognition system is robust, reliable and rapid.

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