Fingerprint Verification Based on Invariant Moment Features and Nonlinear BPNN

Ju Cheng Yang and Dong Sun Park*

Abstract: A fingerprint verification system based on a set of invariant moment features and a nonlinear Back Propagation Neural Network (BPNN) verifier is proposed. An image-based method with invariant moment features for fingerprint verification is used to overcome the demerits of traditional minutiae-based methods and other image-based methods. The proposed system contains two stages: an off-line stage for template processing and an on-line stage for testing with input fingerprints. The system preprocesses fingerprints and reliably detects a unique reference point to determine a Region-of-Interest (ROI). A total of four sets of seven invariant moment features are extracted from four partitioned sub-images of an ROI. Matching between the feature vectors of a test fingerprint and those of a template fingerprint in the database is evaluated by a nonlinear BPNN and its performance is compared with other methods in terms of absolute distance as a similarity measure. The experimental results show that the proposed method with BPNN matching has a higher matching accuracy, while the method with absolute distance has a faster matching speed. Comparison results with other famous methods also show that the proposed method outperforms them in verification accuracy.

Keywords: Absolute distance, BPNN, fingerprint matching, fingerprint verification, invariant moment features, neural network.

1. INTRODUCTION

Among all the biometric indicators, fingerprints have one of the highest levels of reliability and have been extensively used by forensic experts in criminal investigations. Fingerprint verification has emerged as one of the most reliable means of biometric authentication due to its universality, distinctiveness, permanence and accuracy.

Various approaches of fingerprint verification system have been proposed in the literature. Two main categories for fingerprint verification are minutiae-based methods [8,10] and image-based methods [1,7,9, 16-19]. The more popular and widely used techniques, minutiae-based methods, use a feature vector extracted from the fingerprints and stored as sets of points in a multi-dimensional plane. A feature vector may contain features of minutiae such as positions, orientations and types. It essentially consists of finding the best alignment between features of minutiae in templates and those in fingerprints under verification. The disadvantages of minutiae-based methods are that they may not utilize the rich discriminatory information available in the fingerprints and it may have a high computational complexity [14].

Image-based methods use different types of features from the fingerprint ridge patterns such as local orientation and frequency, ridge shape and texture information. The features may be extracted more reliably than detecting minutiae from fingerprints. Among various image-based matching methods, a Gabor filter based method [7] and its improved version [16] show relatively high performance comparing to previous works. In order to improve the matching accuracy even for rotated inputs, they used an approximated approach by representing each fingerprint with ten associated templates with different angles. Hence these methods inherently require a larger storage space and a significantly high processing time as well as the performance degradation from the approximation.

Tico *et al.* [17] propose a transform-based method

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using Digital Wavelet Transform (DWT) features, while Amornraksa et al. [1] propose using Digital Cosine Transform (DCT) features. The transform methods show a high matching accuracy for inputs identical to one in its own database. However, these methods have not considered the invariance to an affine transform to deal with different input conditions. Another method with the integrated Wavelet and Fourier-Mellin Transform (WFMT) [9] uses multiple WFMT features to deal with the variability of input fingerprint images. This method, however, is not suitable for all types of fingerprint images by choosing a core point as a reference point. In our previous work [19], the fingerprint verification using invariant moments with the learning vector quantization neural network is proposed. We use a fixed-size ROI to extract seven invariant moments as a feature vector. However, this method may not deal with the cases that a reference point is located near the rim of the fingerprint image, and the features form the whole ROI may not consider the effect of non-linear distortions.

To overcome the shortcomings of these methods, in this paper, a fingerprint verification system based on a set of invariant moment features and a nonlinear BPNN is proposed. A fingerprint image is first preprocessed to enhance an original image by Short Time Fourier Transform (STFT) analysis [2]. The algorithm simultaneously estimates all the intrinsic properties of the fingerprints to enhance the fingerprint image completely. In addition, it is also capable of connecting broken ridges and separating merged ridges, and this can improve a reliable detection of unique reference point.

A unique reference point for all types of fingerprints, including partial fingerprints, is to align a template to an input fingerprints before extracting features and it is determined by the complex filtering methods [12,15]. The complex filter is applied to ridge orientation field image to detect the position of a reference point with the maximum curvature. The orientation of this point is determined by using the Least Mean Square (LMS) orientation estimation algorithm [5], which estimates the orientation field using the gradient at each pixel and smoothes it with a Gaussian window.

Invariant moments are one of the principal approaches used in image processing to describe the texture of a region. The seven moments used in this paper are invariant to translation, rotation, and scale changes [4], so they are able to handle the various input conditions. To significantly reduce the effects from noise and non-linear distortions, and thus better preserves the local information, we use four sets of seven invariant moment features extracted from four partitioned sub-images of ROI. An ROI is a region centered with a reference point in an enhanced fingerprint image with its orientation field. The invariant features from four regions adjusted by its orientation field can improve the time-consuming alignment of transformation and rotation occurred at other methods [7,16].

A BPNN is adopted to verify the identification of an input fingerprint by measuring similarity between feature vectors of test fingerprint images and those of template images. The nonlinear neural network verifier is trained to determine whether the input matches to a template in a database. Using a nonlinear BPNN as a verifier may provide the flexible system with high matching accuracy. For a comparison study, an absolute distance measure which weights each element with the maximum of the each two input vectors is also used to evaluate the verification system in matching accuracy. The absolute distance is simple and fast and hence it has an advantage in matching speed. Comparing with some noted methods, our proposed method performs better of accuracy, too.

The paper is organized as follows: the fingerprint verification system is briefly reviewed in Section 2. In Section 3, the proposed verification system with feature extraction and matching methods are explained in details. Experimental results are shown in Section 4. Finally, conclusion remarks are given in Section 5.

2. INVARIANT MOMENTS ANALYSIS

Moment features can provide the properties of invariance to scale, position, and rotation [4]. We used moment analysis to extract invariant features from partitioned sub-images in an ROI. This section gives a brief description of the moment analysis.

For a 2-D continuous function f(x,y), the moment of order (p + q) is defined as

$$m_{pq} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} x^p y^q f(x,y)\,dxdy \qquad \text{for } p, q = 0, 1, 2, \ldots \tag{1}$$

The central moments are defined as

$$\mu_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x-\bar{x})^p (y-\bar{y})^q f(x,y)\,dxdy \tag{2}$$

where

$$\bar{x} = \frac{m_{10}}{m_{00}} \quad \text{and} \quad \bar{y} = \frac{m_{01}}{m_{00}}.$$

If f(x,y) is a digital image, then (2) becomes

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y), \tag{3}$$

and the normalized central moments, denoted η_{pq}, are defined as

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}, \text{ where } \gamma = \frac{p+q}{2}+1, \quad \text{for } p+q = 2,3,\ldots \tag{4}$$

A set of seven invariant moments can be derived from the second and third moments proposed by Hu [6]. As the equations shown below, Hu derived the expressions from algebraic invariants applied to the moment generating function under a rotation transformation. They consist of groups of nonlinear centralized moment expressions. The result is a set of absolute orthogonal moment invariants that can be used for scale, position, and rotation invariant pattern identification.

$$\begin{aligned}
\phi_1 &= \eta_{20} + \eta_{02}, \\
\phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2, \\
\phi_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - 3\eta_{03})^2, \\
\phi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2, \\
\phi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 \\
&\quad - 3(\eta_{21} + \eta_{03})^2] \\
&\quad + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 \\
&\quad - (\eta_{21} + \eta_{03})^2], \\
\phi_6 &= (\eta_{20} - \eta_{02})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 \\
&\quad - (\eta_{21} + \eta_{03})^2] \\
&\quad + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}), \\
\phi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12}) \\
&\quad [(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\
&\quad + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03}) \\
&\quad [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2].
\end{aligned} \tag{5}$$

3. PROPOSED FINGERPRINT VERIFICATION SYSTEM

The fingerprint verification system contains two stages: the off-line stage and the on-line stage, as shown in Fig. 1. In the off-line stage, fingerprint images of the different individuals to be verified are first processed by a feature extraction module and then the extracted features are stored as templates in a database for later use. In the on-line stage, a fingerprint image of an individual to be verified first processed by a feature extraction module; the extracted features are then fed to a matching module with one's identity ID, which matches them against

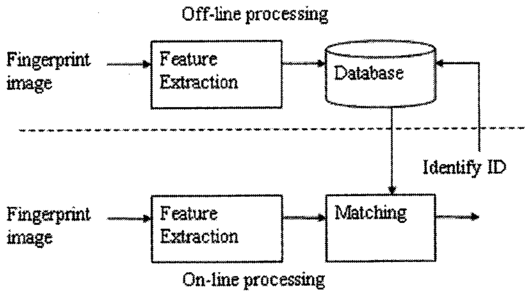


Fig. 1. Overview of the fingerprint verification system.

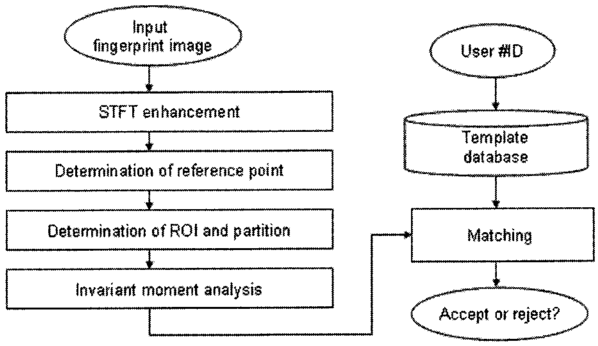


Fig. 2. Flowchart of the whole implementation scheme of the fingerprint verification system.

one's own templates in the database.

Both stages contain the same feature extraction module, which consists of four main steps as depicted as shown in Fig. 2: STFT enhancement, determination of reference point, determination of ROI and partition, and invariant moment analysis. At the last part of the whole verification system, the matching is implemented with absolute distance or BPNN.

3.1. STFT enhancement

The first step is to enhance the fingerprint image using STFT analysis [2]. The performance of a fingerprint matching algorithm depends critically upon the quality of the input fingerprint image. While the quality of a fingerprint image may not be objectively measured, it roughly corresponds to the clarity of the ridge structure in the fingerprint image, and hence it is necessary to enhance the fingerprint image. Since the fingerprint image may be thought of as a system of oriented texture with non-stationary properties, traditional Fourier analysis is not adequate to analyze the image completely as the STFT analysis does.

The algorithm for image enhancement consists of two stages as summarized below:

Stage 1: STFT analysis

1. For each overlapping block in an image, generate and reconstruct a ridge orientation image by computing gradients of pixels in a block, and a ridge frequency image through obtaining the FFT value of

the block, and an energy image by summing the power of FFT value;

2. Smoothen the orientation image using vector average to yield a smoothed orientation image, and generate a coherence image using the smoothed orientation image;

3. Generate a region mask by thresholding the energy image;

Stage 2: Enhancement

4. For each overlapping block in the image, the next four sub-steps are applied.
   a. Generate an angular filter Fa centered on the orientation in the smoothed orientation image with a bandwidth inversely proportional to coherence image;
   b. Generate a radial filter Fr centered on frequency image;
   c. Filter a block in the FFT domain, F=F × Fa × Fr;
   d. Generate the enhanced block by inverse Fourier transform IFFT(F);

5. Reconstruct the enhanced image by composing enhanced blocks, and yield the final enhanced image with the region mask.

3.2. Determination of reference point

In the second step, we determine the reference point from the enhanced image. The reference point is defined as "the point of the maximum curvature on the convex ridge [11]," which is usually located in the central area of fingerprint.

The reliable detection of the position of a reference point can be accomplished by detecting the maximum curvature using complex filtering methods [12,15]. They apply complex filters to ridge orientation field image generated from original fingerprint image. The reliable detection of reference point with the complex filtering methods as summarized below:

1. For each overlapping block in an image;
   a. Generate a ridge orientation image with the same method in STFT analysis;
   b. Apply the corresponding complex filter $h=(x+iy)^m g(x,y)$ centered at the pixel orientation in the orientation image, where m and $g(x,y)=\exp\{-((x^2+y^2)/(2\sigma^2))\}$ indicate the order of the complex filter and a Gaussian window, respectively;
   c. For $m=1$, the filter response of each block can be obtained by a convolution, $h*O(x,y)= g(y)*((xg(x))^t*O(x,y))+ig(x)^t*((yg(y)*O(x,y)))$, where $O(x,y)$ represents the pixel orientation in the orientation image;

2. Reconstruct the filtered image by composing filtered blocks.

It is worth to mention that the multi-resolution method [15] can overcome the orientation filed estimation error for the poor quality images. In this algorithm, however, since fingerprint images are enhanced first, the orientation fields from the enhanced images are accurate enough for reference point determination. So we just apply the complex filters on the orientation field of the enhanced image to increase the processing speed. The maximum response of the complex filter in the filtered image can be considered as the reference point. Since there is only one output, the unique output point is taken as the reference point.

(a) (b)

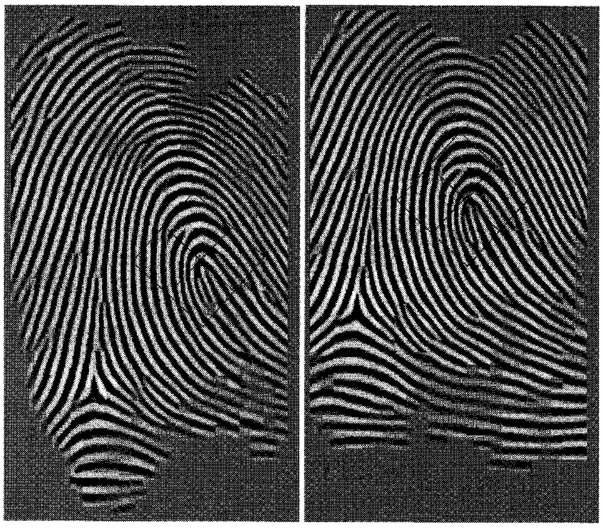
Fig. 3. (a) Original fingerprint (size 296x560) (b) determined reference point.

The LMS orientation estimation algorithm [5] is used to determine the orientation of reference point. It is mentioned that we use a pixel-wise method to instead the block-wise method as in [5]. Then, if we know the precise position of the reference point, we can determine its orientation accurately by the LMS orientation estimation algorithm. Therefore the position and the orientation ($\theta_0 \in [0^0, 180^0)$) in the enhanced image become those of a reference point.

An example of the experiments with an original fingerprint is shown in Fig. 3(a). The determined reference point is shown in Fig. 3(b). We can see the determined result is accurate both in position and orientation.

3.3. Determination of ROI and partition

The third step is to crop the fingerprint image based on the reference point into an ROI. In order to speed up the overall process, we use only a predefined area (ROI) around the reference point at the center for feature extraction instead of using the entire fingerprint. The center of the cropped image centers the position of the reference point and parallels the orientation of the reference point. Figs. 4(a) and (b) demonstrate the feature extraction from ROIs centered



(a) (b)

Fig. 4. (a) (b) demonstrate the feature extraction from ROIs centered on the determined reference point of an input fingerprint and a template one, respectively.

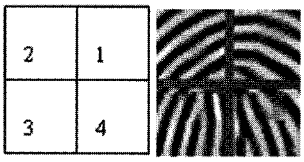


Fig. 5. Method for partitioning the ROI into 4 sub-images.

on the determined reference point of two input fingerprints of a person, respectively.

Since the ROIs centered on the same area around the reference point, the features are assured to be extracted, and they are invariant to rotation and translation. The size of the ROI can be experimentally determined. In this paper, a size of 64×64 ROI is used. In order to reduce the effects of noise and non-linear distortions, the ROI is partitioned into four smaller sub-images (4 quadrants) in an anticlockwise sequence as depicted in Fig. 5. So each sub-image has a size of 32×32.

3.4. Invariant moment features

At the fourth step, we apply the invariant moment analysis introduced in Section 2 on each sub-image respectively. For each sub-image, a set of seven invariant moments is computed, so four sets of invariant moments of the sub-images are extracted as features to represent a fingerprint.

Let $[\phi_{k1}, \phi_{k2} \dots, \phi_{k7}]$ (k= 1 or 2, 3, 4) as a set of invariant moments, the total feature vectors are the combination of the 4 sets of invariant moments V=[$\phi_{11}, \phi_{12} \dots, \phi_{17}, \phi_{21}, \phi_{22} \dots, \phi_{27}$, $\phi_{31}, \phi_{32} \dots, \phi_{37}$, $\phi_{41}, \phi_{42} \dots, \phi_{47}$]. The length of the total feature vectors is 28. An example of these invariant moment values is listed as in Table 1.

Table 1. Seven invariant moments with the different sub-images of the original fingerprint image (IM= Invariant Moment, S=sub-images).

IM(Log)	S1	S2	S3	S4
ϕ_1	6.659714	6.653635	6.662685	6.661865
ϕ_2	20.20554	22.17764	19.95373	21.51450
ϕ_3	25.54887	28.61435	27.35306	26.39129
ϕ_4	30.12149	29.69914	28.87533	30.23239
ϕ_5	58.06749	60.01645	57.39718	59.78171
ϕ_6	40.60153	40.83937	39.97735	41.17973
ϕ_7	59.20406	59.04040	57.90297	58.54520

3.5. Matching

3.5.1 Matching with absolute distance

Absolute distance is used to measure the similarity between the feature vectors of the input fingerprint with those of the templates fingerprint stored in the database.

Let $V_{f1} = \{a_1, a_2, \dots, a_n\}$ and $V_{f2} = \{b_1, b_2, \dots, b_n\}$ (n=28) denote the feature vectors of the two fingerprints to matched, T_m denotes the thresholds used in the matching process. The difference vector V_d of the two fingerprint feature vectors is calculated as in (6).

$$V_d = \left(\frac{|a_1 - b_1|}{\max(a_1, b_1)}, \frac{|a_2 - b_2|}{\max(a_2, b_2)} \dots\dots \frac{|a_n - b_n|}{\max(a_n, b_n)} \right) \quad (6)$$

We define the absolute distance of the two matching vectors as in (7).

$$R_m = \sum_{i=1}^{n} \frac{|a_i - b_i|}{\max(a_i, b_i)} \quad (7)$$

Then the final decision of matching result is determined by (8).

$$\begin{cases} \text{accept} & \text{if } R_m < T_m \\ \text{reject} & \text{if } R_m \geq T_m \end{cases} \quad (8)$$

In this equation the thresholds T_m varies according to the quality of the fingerprint images. The quality of fingerprint images can be varied depending on sensors, thus the threshold should be adjusted on a specific sensor. According to the experiment, the better the fingerprint image is, the larger T_m should be. In this paper, T_m is determined experimentally and set to 1.0.

3.5.2 Matching with BPNN

Instead of using the distance measures, a set of three-layer BPNNs are used to verify a matching between feature vectors of input fingerprint and those of a template fingerprint. The number of the BPNN is the same with the verifying persons. The structure of the BPNNs consists of input layer, one hidden layer and output layer.

For each input fingerprint and its template fingerprint, we compute maximum, minimum and average elements of the input vector V_{f1}, the template vector V_{f2} and the difference vector V_d as the input of the BPNNs. The maximum values are $V_{d\max}$, $V_{f1\max}$, $V_{f2\max}$, the minimum values are $V_{d\min}$, $V_{f1\min}$, $V_{f2\min}$, and the average values are V_{davg}, V_{f1avg}, V_{f2avg}. Since the output is to judge whether the input fingerprint is match or non-match according to the identity ID, we can take the matching process as a two-class problem. There are 9 input features and 2 output classes, so the input layer neurons and the output layer neuron are 9 and 1 respectively. The number of the hidden layer neurons is obtained empirically. In order to train the BPNN with a match or non-match case, we label the class values as 1 or 0. That is, 1 means the match and 0 means non-match. So the desired output values can be distributed intelligently by the BPNN.

In the training (off-line) stage, a set of $\{V_{d\max}$, $V_{f1\max}$, $V_{f2\max}$, $V_{d\min}$, $V_{f2\min}$, V_{davg}, V_{f1avg}, $V_{f2avg}\}$ are fed to the corresponding BPNN with indicating their corresponding class. The features are computed from the training data, each contains two feature vectors of the input fingerprint and template fingerprint as well as a difference vector of them. While, in the testing (on-line) stage, a set of $\{V_{d\max}$, $V_{f1\max}$, $V_{f2\max}$, $V_{d\min}$, $V_{f1\min}$, $V_{f2\min}$, V_{davg}, V_{f1avg}, $V_{f2avg}\}$ are fed to the BPNN to produce the output values. Similarly, the features are computed from the testing data, each contains two feature vectors of the test fingerprint and the corresponding template fingerprint with the querying ID as well as a difference vector of them. The element of the output values C_n is restricted in the range of [0, 1]. With the thresholds T_l and T_h, the matching result can be described as in (9).

$$\begin{cases} \text{accept} & \text{if } C_n \geq T_h \\ \text{reject} & \text{if } C_n < T_l \end{cases} \tag{9}$$

In this equation, the thresholds, T_h and T_l are the thresholds of 'accept' and 'reject' respectively. In the experiments, T_l was set to 0.005 and T_h was set to 0. 995.

4. EXPERIMENTAL RESULTS

The fingerprint image database used in this experiment is the FVC2002 fingerprint database set a [20], which contains four distinct databases: DB1_a, DB2_a, DB3_a and DB4_a. The resolution of DB1_a, DB3_a, and DB4_a is 500 dpi, and that of DB2_a is 569 dpi. Each database consists of 800 fingerprint images in 256 gray scale levels (100 persons, 8 fingerprints per person). For those reference points of the fingerprint images were near or on the border of the fingerprint images due to the small sensor sizes, the ROIs would be failed to acquire for computing the features, so we chose to replace the features using the average two features from the front and next impressions of the current impressions, the similar process can be extended to those containing more rejected impressions.

In the experiments of absolute distance matching, the average of the training samples per person was taken as the template fingerprint. The template feature vector of each person was computed from all the average feature vectors of the training fingerprints of the person. Training patterns were selected on the first 6 fingerprints of per person (6/8=75%) in each database, while all the 8 fingerprints of per person in each database were used for testing. That is, 600 (800×75%=600) patterns in each database was used for training, and tests were performed on all 800 patterns.

In the experiments of BPNN matching, 100 BPNNs each with 9 input layer neurons and 1 output layer neuron was trained on the 600 of patterns in each database, and test was performed on all patterns, too. So the training data contained 100×6=600 match samples and 99×6=594 non-match samples, totally 1194 samples for each BPNN. And the testing data contained 800 test samples. The training data and testing data were normalized by dividing the maximum values of each column into (0, 1] before training and testing network to avoid non-convergence. The training parameters were decided by experiments. Learning rate was set to 0.01, epoch was 5000, and mean absolute error was 0.001. Experimentally, the optimal number of hidden layer neurons was determined to 15.

The performance evaluation protocol used in FVC2002 is adopted in the experiments [13]. The Equal Error Rate (EER), revised EER (EER*), Reject Enroll (REJEnroll), Reject Match (REJMatch), Average Enroll Time (AETime) and Average Match Time (AMTime) are computed on the four databases. To compute the False Acceptance Rate (FAR) and the False Reject Rate (FRR), the genuine match and impostor match were performed. For genuine match, each test impression of each person was compared with the template of the same person. Since there are 100 persons, the number of matches was 100×8=800. For impostor match, the test impression of each person was compared with the template of other persons. The number of matches was 99×800=79200. The FRR and FAR are defined as follows:

$$FRR = \frac{\text{Number of rejected genuine claims}}{\text{Total number of genuine accesses}} \times 100\%, \tag{10}$$

$$FAR = \frac{\text{Number of accepted imposter claims}}{\text{Total number of imposter accesses}} \times 100\%. \tag{11}$$

The EER is used as a performance indicator. The EER indicates the point where the FRR and FAR are equal.

The tests were executed on Pentium IV 1GHz machines. The performances of our proposed method with two matching methods over the four databases of FVC2002 were shown in Tables 2 and 3, respectively. From the tables, we can find that the average EER values of absolute distance matching and that of BPNN matching over four databases are 4.91% and 3.69%, respectively. And the average enroll time of absolute distance matching and those of BPNN matching over four databases are 0.43 and 0.77 seconds, and the average match time are 0.10 and 0.19 seconds, respectively. So BPNN matching has a higher matching accuracy, while absolute distance matching has a faster matching speed. It is because that training the BPNN is much time consuming.

For evaluating the recognition rate performance, the Receiver Operating Characteristic (ROC) is used as another performance indicator. An ROC is a plot of Genuine Acceptance Rate (GAR=1-FRR) against FAR. In order to examine and prove the performance of the proposed method, a number of experiments comparing performance to other renowned methods were carried out on the FVC2002 database. Three matching methods, proposed in references [1,9], and [16], were selected for comparison.

(1) Method of Amornraksa [1]: the fingerprint matcher uses DCT features with the same parameters as in their paper.

(2) Method of Jin [9]: the fingerprint matcher uses WFMT framework with four multiple training WFMT features.

(3) Method of Sha [16]: This is the Gabor filter based method with the same parameters as in their paper.

For the experiments in the proposed method, the size of an ROI and the partitioned sub-images are identical with those introduced in the previous subsection. The BPNN is used as the matching method in this experiment.

Fig. 6 shows the ROC curves of the methods of Amornraksa, Jin, Sha and along with our proposed method on databases FVC2002 DB1_a. For the

Table 2. Performances of the proposed method with the absolute distance matching over the four databases of FVC2002.

database	EER	EER*	REJ_{Enroll}	REJ_{Match}	AE_{Time}	AM_{Time}
DB1_a	3.35%	3.35%	0.00%	0.00%	0.37sec	0.08sec
DB2_a	6.21%	6.21%	0.00%	0.00%	0.44sec	0.10sec
DB3_a	5.78%	5.78%	0.00%	0.00%	0.32sec	0.05sec
DB4_a	4.28%	4.28%	0.00%	0.00%	0.57sec	0.17sec
Average	4.91%	4.91%	0.00%	0.00%	0.43sec	0.10sec

Table 3. Performances of the proposed method with BPNN matching over the four databases of FVC2002.

database	EER	EER*	REJ_{Enroll}	REJ_{Match}	AE_{Time}	AM_{Time}
DB1_a	2.73%	2.73%	0.00%	0.00%	0.59sec	0.15sec
DB2_a	3.26%	3.26%	0.00%	0.00%	0.64sec	0.19sec
DB3_a	4.94%	4.94%	0.00%	0.00%	0.85sec	0.16sec
DB4_a	3.81%	3.81%	0.00%	0.00%	0.98sec	0.25sec
Average	3.69%	3.69%	0.00%	0.00%	0.77sec	0.19sec

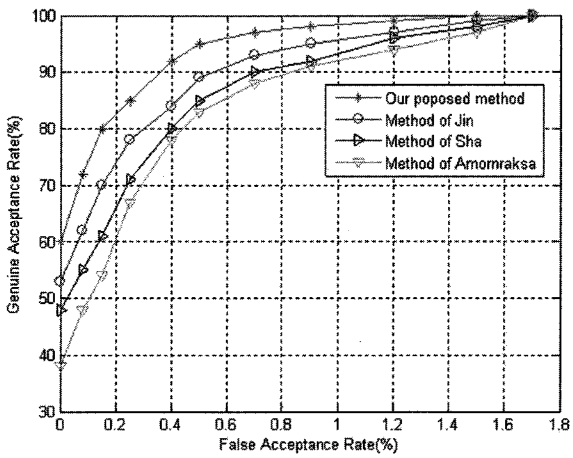


Fig. 6. ROC curves comparing the recognition rate performance of the proposed method with the methods of Amornranksa, Jin and Sha on database FVC2002 DB1_a.

Table 4. The GAR(%) under a FAR(%) value of 0.8% of the proposed method comparing with the method of Amornraksa, Jin, and Sha over the four databases of FVC2002.

Methods	DB1_a	DB2_a	DB3_a	DB4_a	Average
Method of Amornraksa	91.4%	85.7%	82.1%	92.6%	87.9%
Method of Sha	92.7%	88.9%	85.3%	93.2%	90.0%
Method of Jin	94.3%	92.4%	90.6%	94.9%	93.1%
Our proposed method	96.4%	95.8%	94.2%	97.3%	95.9%

experiments, as shown in the figure, since the curve of the proposed algorithm is above those of the other three methods, it means that the matching accuracy of the proposed algorithm is greater than the others.

Table 4 illustrates the average GAR(%) under a FAR(%) of 0.8% with the methods of Amornranksa, Jin, Sha and our proposed method are 87.9%, 90.0%, 93.1% and 95.9% respectively over the four databases of FVC2002. It shows that the average GAR(%) of our proposed method is more than 2.8% higher than any other methods.

5. CONCLUSIONS

In this paper, a fingerprint verification system based on invariant moment features and nonlinear BPNN is proposed. A preprocessing enhancement with the STFT analysis makes the algorithm highly robust to poor-quality fingerprint images and improves the matching accuracy.

Under the help of the enhancement, the reference point can be reliably and accurately determined with the complex filtering methods and LMS orientation estimation algorithm. Using the invariant moment analysis on sub-images, the extracted features have bound the effects of noise and non-linear distortions, while utilizing the invariant ability to the affine transformations of features to handle various input conditions.

Matching the fingerprints is implemented by two measures: absolute distance and BPNN. The maximum, minimum and average elements of the vectors of input fingerprint, template fingerprint and the difference vectors of them are used as the BPNN inputs. As an excellent nonlinear classifier, the BPNN can improve the whole matching performance.

The experimental results show that both absolute distance and BPNN can be used for fingerprint verification. The BPNN matching has a higher matching accuracy, while the absolute distance matching has a faster matching speed. Therefore, we can choose different matching methods for different application cases. Compared with some noted methods, we find that our proposed method also performs much better in matching accuracy. Further work should be proceeded to improve robustness and reliability of our proposed method.

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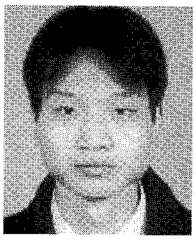

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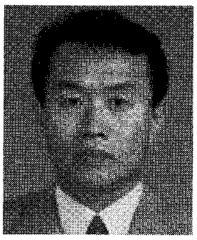

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