

An Automatic Fingerprint Identification System using multiple classifiers

Abstract

Biometric applications have been wildly used nowadays. A fingerprint identification system is the most popular system due to the affordable price of a fingerprint scanner. An automatic fingerprint identification system (AFIS) using multiple classifiers is presented in this paper. The system consists of several steps: fingerprint enhancement, minutiae extraction, texture feature extraction, texture matching, and minutiae matching. The proposed matching system has been tested on a reasonably large fingerprint database and the experimental results show an effective performance.

1. Introduction

Among various fingerprint identification systems, the traditional methods based on minutiae have been widely used [3,5,8] because the topological structure of minutiae of a fingerprint is unique and invariant with aging. Jain et. al. proposed an novel alignment - based matching algorithm in [5] where the

authors used ridges associated with minutiae to obtain transformation parameters and elastic matching had been used for matching. The result was accurate but the system required a large storage because all ridges information must be saved. Another fingerprint identification approach, so called a filterbank - based fingerprint matching [6] used a bank of Gabor filters to capture the details in fingerprint as a compact fixed length Finger Code. The matching is based on Euclidean distance between two Finger Code, hence, it is faster than traditional method but reported a lower performance. In the filterbank - based approach, convolution with Gabor filters is the major computation to the overall feature extraction time. In this paper, we focus on a framework of an automatic fingerprint identification using multiple classifiers that consist of fingerprint classification, texture matching, and minutiae matching. The flow chart of our proposed hybrid fingerprint identification system is shown in Figure 1.

In Section 2, the fingerprint enhancement and minutiae extraction framework are explained. Section 3 discusses a fingerprint matching system using a filterbank. The multiclassifier fingerprint identification system is proposed in Section 4. The experimental result is shown in Section 5, followed by conclusions in Section 6.

2. Enhancement and Minutiae Extraction

2.1 Local Ridge Orientation (LRO) Estimation

The optimal ridge direction is defined as the directional field that shows the dominant local structure orientation. We propose an orientation angle approximation

frequency, horizontal detail, vertical detail, and diagonal detail coefficients, respectively.

Let Θ be an orientation angle, J_y and J_x are the vertical (LH) and horizontal (HL) wavelet coefficients, respectively. The estimate of the dominant orientation Θ at the center (n,r) of a $P \times P$ non-overlap block is given by,

$$\Theta_{nr} = 0.5 \tan^{-1} \left(\frac{\sum_{i=n-P/2}^{n+P/2} \sum_{j=r-P/2}^{r+P/2} 2 J_{x_g} J_{y_g}}{\sum_{i=n-P/2}^{n+P/2} \sum_{j=r-P/2}^{r+P/2} (J_{x_g}^2 - J_{y_g}^2)} \right) \quad (1)$$

The advantage of using wavelet coefficients for orientation angle estimation is that the LH and HL wavelet coefficients, which can be viewed as smoothed gradient information, can be directly calculated and treated as partial derivative results. More detail can be found in [9].

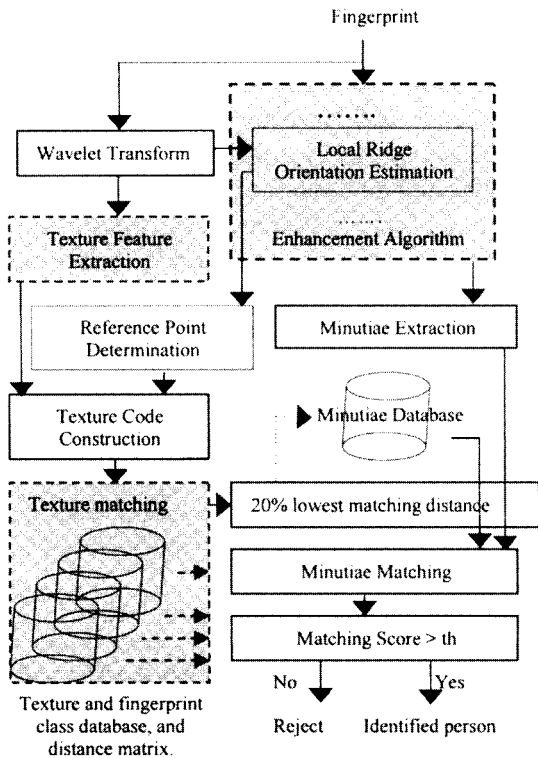


Figure 1: The proposed multiclassifier fingerprint identification system.

via Wavelet Transform. Level - 1 of a 2 - D wavelet represents 4 sub-bands, called LL, HL, LH, and HH, which correspond to low

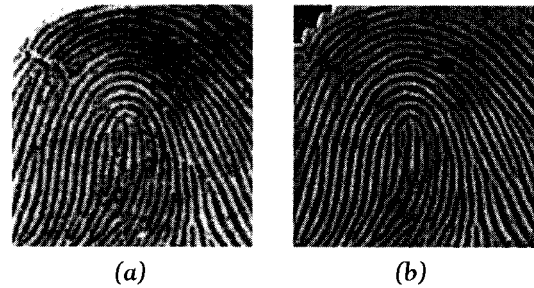


Figure 2: (a) Original image (b) Enhanced fingerprint.

2.2 Implementation of Spatial Filtering

The purpose of fingerprint enhancement filtering is to smooth (interpolate) the ridges along the same ridge line, characterize edges, and sharpened details in perpendicular of the ridge direction. The combination of any low-pass and high-pass filtering in perpendicular direction can be used to smooth and sharpen the images respectively. For simplicity, we choose a Gaussian kernel with zero mean and standard deviation (σ) in our implementation. The low-pass and high-pass Gaussian in spatial domain can be expressed as [4]:

$$G_L(x) = \frac{C}{\sqrt{2\pi\sigma_x^2}} \exp(-x^2/2\sigma_x^2), \quad (2)$$

$$G_H(y) = \frac{A}{\sqrt{2\pi\sigma_{y1}^2}} \exp(-y^2/2\sigma_{y1}^2) - \frac{B}{\sqrt{2\pi\sigma_{y2}^2}} \exp(-y^2/2\sigma_{y2}^2). \quad (3)$$

where $A \geq B, \sigma_{y1} > \sigma_{y2}$.

Hence, from the separable product property, 2 - D filters can be realized by the multiplication of Eqs. (2) and (3). Take for example, without loss of generality, let us assume that the ridges are perfectly horizontal. The 2 - D (mxm) filter that enhances horizontal ridges is given by,

$$G(x, y) = G(x)G(y), (-m+1)/2 \leq x, y \leq (m-1)/2, \text{ and } m \text{ is odd.} \quad (4)$$

The same analysis can be applied for enhancing other ridge directions with different orientation filters. By applying the appropriate filters, each directional ridge can be enhanced. By rotating this horizontal Gaussian filter mask, $G(x, y)$, with appropriate direction, enhancement filters for different fingerprint orientations can be found. More specifically, let N be the number of ridge directions, the directional filter can be written as $G_{\theta_i}(x, y)$, θ_i is the i^{th} rotation angle, and $i = \{1, 2, \dots, N\}$. From Section 2.1, the estimation of the ridge is quantized into eight different directions, hence, eight directional filters are needed in order to enhance the whole fingerprint images, $\theta_i = \pi i / 8$, $\{i = 0, 1, \dots, 7\}$.

2.3 Enhancement

The enhanced fingerprint image, $F_{en}(x, y)$, is determined by filtering fingerprint image, $I(x, y)$, with an appropriate directional filter mask, $G_{\theta_i}(x, y)$, where θ_i depends on the quantized ridge directions of the fingerprint image, $\Theta'(x, y)$. The enhancement can thus be expressed as:

$$F_{en}(x, y) = \sum_{u=-m/2}^{m/2} \sum_{v=-m/2}^{m/2} G_{\theta_i}(u, v) I(x-um, y-vm). \quad (5)$$

2.4 Post - Processing

Post processing consists of binarization, thinning, feature extraction, and false minutiae reduction. The details can be found in [3].

After post - processing, we obtain fifty minutiae (ending and bifurcation [1]) that have the highest coherency [4]. The estimate of the Coherency C_c at the center (n, r) of a $P \times P$ non - overlap block is given by,

$$C_c = \left(\frac{\left(\sum_{i=-P/2}^{P/2} \sum_{j=-P/2}^{P/2} (J_x^i - J_y^j) \right)^2 + \left(\sum_{i=-P/2}^{P/2} \sum_{j=-P/2}^{P/2} 2J_x J_y \right)^2}{\left(\sum_{i=-P/2}^{P/2} \sum_{j=-P/2}^{P/2} (J_x^i + J_y^j) \right)^2} \right)^{1/2} \quad (6)$$

where J_x and J_y are the vertical (LH) and horizontal (HL) wavelet coefficients, respectively.

The feature vector is constructed based on the type (ending and bifurcation), X - coordinate, Y - coordinate, and orientation of minutiae, see Figure 4. At each minutiae point (called reference minutiae), we generate a feature vector by collecting five nearest neighboring minutiae and calculate distance, different of ridge orientation, and ridge count between the reference and neighbor minutiae pair. We also store orientation difference and distance between core and reference minutiae. Hence, each fingerprint contains 50 vectors and each vector has 23 features, which are rotation and translation invariant. We can directly use them in minutiae matching stage.

3. Texture Feature Extraction

The texture feature extraction procedure is modified from [6]. Our texture feature extraction requires smaller computation and storage. Instead of using original fingerprint image, we obtain low frequency wavelet coefficient (LL band) from Section 2.1. The texture feature extraction is as following:

1) Calculate a reference point from Local Ridge Orientation (LRO) that is calculated in Section 2.1 using [3].

2) Divide an LL band of Wavelet coefficients into 5 concentric bands with respect to the reference point. Each band has 16 sectors and has 10 pixels wide (See Fig. 3, fingerprint A1).

3) Convolve an image with 8 directional Gabor filters. We set the filter frequency equal to the average ridge frequency of LL band Wavelet coefficient ($f=1/5$). The filter mask size of 11×11 is used for our experiment and a standard deviation of Gaussian envelope σ_x and σ_y is set to 2.0.

4) Rotate a feature vector 2 steps clockwise and 2 steps counter-clockwise and obtain a quantized rotated Finger Code. Each step is corresponded to 22.5 degree.

Each fingerprint has five feature vectors that can be used in matching stage. The major difference between our method and [6] is the use of LL band, the normalized value, and the reduced feature vector size. The Euclidean distance is used to obtain matching scores.

2) The matching distances have been sorted, twenty percent of the fingerprints that have minimum distance have been obtained into the next stage.

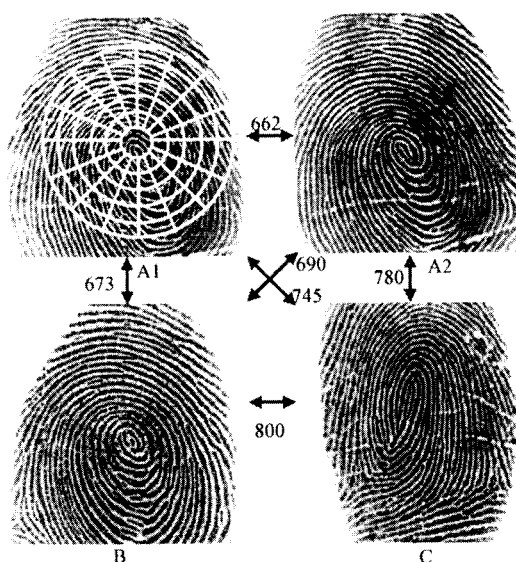


Figure 3: The example of texture distance between images. A1 and A2 is the same fingerprint with different impression. A1, A2 and B have similar characteristic ridge.

4. The Complete Matching System

We divide the complete matching system into 2 stages, a texture matching and a minutiae matching system.

4.1 Texture matching

We have observed statistically that the distance between two fingerprints, which have similar texture characteristics, is closer than fingerprints that have different texture characteristics (see Fig. 3). The texture matching in our paper has been adopted from [6]. The texture matching process based on our experiment using distance score is as following:

1) Given a set of fingerprint database, we categorize each fingerprint into classes, i.e., arch, left loop, right loop and double loop using the method in [7] and match each fingerprint against the others in the database.

4.2 Minutiae identification

The fingerprints obtained from Section 4.1 have been entered into a minutiae matching system. Given two sets of minutiae feature vector (one from query fingerprint and the other from the matched fingerprint called template that has a minimum distance), we further match each vector in query against one in template using the concept of correlation matching [8] and count the number of similarity. To avoid an inexactness, the matching should be tolerated to some bounding distance. The similarity value is incremented by one if all of the following criteria are met:

1) If a pair of reference and neighbor minutiae between query and template fingerprint have the same type (ending and bifurcation).

2) If the distance and orientation differences between core and reference

minutiae from both query and template are in a bounding distance. In our experiment, we empirically chose 40 pixels for a bounding distance and 22.5 degrees for orientation difference.

3) If a pair of reference and neighbor minutiae between query and template fingerprint is in a bounding distance. We empirically chose 15 pixels for a bounding distance, 22.5 degrees for orientation difference, and 1 for ridge count.

The reference minutiae that has similarity value equal or greater than one is marked in a corresponding pairs. Pose clustering has been used to calculate transformation in every pair of marked minutiae in query fingerprint to the correspondence pair minutiae in template fingerprint. The computed transformation parameters X and Y translation and rotation ϕ , are used to correct the image transformation. After transforming, we match two fingerprint minutiae against each other based on the bounding box and count the number of matched minutiae, see Figure 5. The fingerprint that has a highest matching score has been selected. If the number of matching score is greater than a certain threshold, we identify as a matched fingerprint. If the number of matching score is not greater than a certain threshold, the system identifies as a reject and retry has been requested.



Figure 4: The example of extracted feature (minutiae) with two fingerprints.

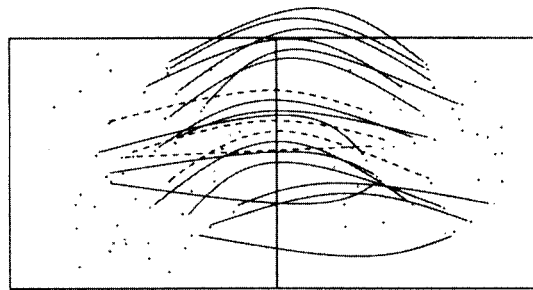


Figure 5: The example of matched minutiae with the same minutiae type (solid) and different minutiae type (dash)

5. Experimental and Evaluation Result

For the experiments, fingerprint images were collected from 100 people with 8 images for each person. 500 images were selected and processed to construct database. The texture feature and minutiae feature are obtained as described in Section 2 and 3. We construct a distance matrix and a matching system as in Section 4. The remaining 300 fingerprints that are not in the database were used to test the proposed algorithm. The simulation results with different threshold are shown in Table 1. Table 2 and 3 show the simulation results of an individual system. The lowest distance matching has been obtained from a texture matching and the highest matching score has been obtained from a minutiae identification.

Table 1: Simulation results using multiple classifier

Texture threshold value	Minutiae threshold value	False Acceptance (%)	False Reject (%)
-	10	0.04	5.5
-	12	0.02	6.5

Table 2: Simulation results using minutiae identification

Texture threshold value	Minutiae threshold value	False Acceptance (%)	False Reject (%)
-	10	0.04	6.3
-	12	0.02	7.2

Table 3: Simulation results using texture matching

Texture threshold value	Minutiae threshold value	False Acceptance (%)	False Reject (%)
50000	-	0.1	10.3
55000	-	0.07	9.8

6. Summary and Conclusions

We have developed a fingerprint matching system using multiple classifiers. The system consists of several sequential steps: fingerprint enhancement and minutiae extraction, texture feature extraction using filterbank, texture matching, and minutiae verification. Our system distinguishes itself from other approach at proposed orientation estimation using wavelet coefficient, texture

feature extraction, and multiple classifiers system, e.g. combining texture matching, fingerprint classifying, and minutiae verification. The experimental results are very convincing. The experimental results show better performance than a single classifier with a little time afford. The drawback of our system is the accuracy of fingerprint classification. In this paper, fingerprint classification is based on only the number and location of singularities. Singularities are not always detected completely if only a partial of fingerprint has been enrolled. The global ridge characteristics should be incorporated. Misclassification results in slow convert, thus, achieving high classification rate can speed up our proposed system. ☼

Reference

- [1] Sir Francis Galton, "Finger Prints," Macmillan and Co., 1892.
- [2] L. Hong, Y. Wan and A.K. Jain, "Fingerprint Image Enhancement: Algorithms and Performance Evaluation", **IEEE Transactions on PAMI**, Vol. 20, No. 8, pp. 777-789, August 1998.
- [3] S. Huvanandana, Changick Kim and J. N. Hwang, "Reliable and Fast Fingerprint Identification for Security Applications", IEEE International Conference on Image Processing (ICIP'2000), Vancouver, Canada, 2000.
- [4] Bernd Jahne, **Digital Image Processing: Concept, Algorithms, and Scientific Applications**, Springer, 1997.
- [5] A.K. Jain, L. Hong, and R. Bolle, "On-Line Fingerprint Verification" **IEEE Transactions on PAMI**, Vol. 19, No. 4, pp. 302-314, April 1997.
- [6] A.K. Jain, L. Hong, and R. Bolle, "Filterbank-based Fingerprint Matching" **IEEE Transactions on Image Processing**, Vol. 9, No. 5, pp. 846-859, May 2000.
- [7] K. Karu and A.K. Jain, "Fingerprint Classification", **Pattern Recognition**, Vol. 29, No. 3, pp. 389-404, 1996.
- [8] A. Wahab, S.H.Chin, and E.C.Tan, "Novel approach to automated fingerprint recognition", **IEE Proc.-Vis. Image Signal Process.**, Vol. 145, No. 3, pp. 160-166, June 1998.
- [9] S. Huvanandana, S. Malisuwan, and K. Rosesokon, "Orientation Approximation via Wavelet Transform", The third international Symposium on Communication and Information Technologies (ISCIT2003), Sept 2003, Songkra, Thailand.