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Fingerprint Verification Using Perturbation Method

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Abstract

This paper describes a new, powerful technique of fingerprint verification based on a perturbation method. The proposed method consists of four parts. The first part performs local FFT band-pass filtering to enhance the cyclic ridge structure in respective local areas. The second part is optimal block-wise shift for preliminary matching. Then, the third part is application of GAT correlation to realize affine-invariant shape matching. Finally, the fourth part is detail matching by perturbation. The key ideas of our perturbation method are in three ways: extraction of core points from enrolled fingerprint images, setting local windows around the core point, and asynchronous perturbation of local windows for optimal detail matching between input and each enrolled fingerprint images. How to design the size of local windows, the range and direction of perturbation, and the matching criteria is crucial to the success of the proposed method. Experimental results using the public FVC2000 fingerprint image database demonstrate a sufficiently low equal error rate (EER) of 5.55% for false rejection and false acceptance comparable to those obtained by competing works.

1. Introduction

Identification of individuals based on their biological or behavioral characteristics, called *biometrics*, has lately been receiving increased attention. Accurate personal identification could deter crime and fraud, streamline business processes, and save critical resources. Here, biometrics includes face, fingerprint, hand geometry, iris, retinal pattern, voiceprint, hand vein, etc [1].

In particular, fingerprint verification [2] is the most prevalent with a biometric market share of 43.6% in 2006 [3]. These factors include: the fact that fingerprints are unique, small and inexpensive fingerprint capture devices, fast computing hardware, recognition rate and speed to meet the needs of practical applications.

Conventional fingerprint verification techniques are divided into two major approaches: minutiae matching versus pattern matching. The former approach extracts minutiae, i.e., ridge endings and bifurcations, and compares neighborhoods of nearby minutiae based on their loci, types, and directions for similarity between input and enrolled fingerprints. On the other hand, the latter approach performs matches on the basis of the local or global ridge pattern of the fingerprint.

Wakahara et al. [4] described a hierarchically unified fingerprint verification system of minutiae matching and pattern matching with emphasis on extraction of ridge direction distribution. Also, Hatano et al. [5] introduced the powerful idea of perturbation matching to improve the discrimination ability of fingerprint pattern matching.

This paper proposes a new, powerful pattern matching based method of fingerprint verification featuring an extended version of perturbation matching. The proposed method is composed of four hierarchically connected processes: local FFT band-pass filtering for image enhancement, optimal block-wise shift for global matching, GAT correlation [6] for absorbing linear distortion, and enhanced perturbation for detail pattern matching. We demonstrate successful experimental results using the public FVC2000 fingerprint image database.

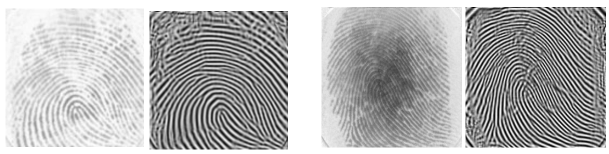
2. FVC2000 fingerprint database

The fingerprint database we used in experiments was released for FVC2000 (Fingerprint Verification Competition) [7]. The database consists of four sections (DB1, DB2, DB3, and DB4) and we used DB1 that was collected by low-cost optical sensor. This database has 110 fingers and 8 impressions per finger (880 fingerprints available). All fingerprints are 8-bits gray-scale images and the size is 300 × 300 pixels. In experiments, we resized each image to 256 × 256 pixels.

3. Fingerprint enhancement via local FFT band-pass filtering

Band-pass filters are used to pass only the dominant frequencies representing the periodicity of ridge patterns of each fingerprint image and selectively enhance their power components. Furthermore, we apply FFT band-pass filtering to respective local areas (16 × 16 pixels) overlapping each other and combine those filtering results by appropriate weighting. The advantage of local FFT band-pass filtering over global one is due to the fact that the dominant orientation of ridges in local areas is sharply located respectively.

Figure 1 shows examples of fingerprint enhancement by the proposed local FFT band-pass filtering method.



(a) (b)

Figure 1. Examples of fingerprint enhancement as applied to typical degradations, (a) and (b).

4. Preliminary matching using optimal block-wise shift and GAT correlation

Block-wise shift is based on gradient feature matching. First, the enhanced fingerprint image is divided into 16 × 16 blocks each of which has 16 × 16 pixels. Next, we calculate gradients by Roberts's cross-gradient operators [8] at each pixel. Then, a histogram of gradient directions quantized into 16 levels in each block is used as a gradient feature of the fingerprint image. Finally we match the input image against the enrolled fingerprint image by block-wise shift using an average inter-block distance $D(\Delta)$ given by

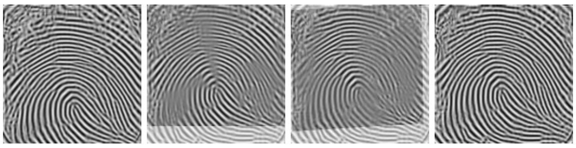
$$D(\Delta) = \frac{1}{N(\Delta)} \sum_{k} \sum_{i=0}^{15} \left(G_{k+\Delta}^{I}(i) - G_{k}^{E}(i) \right)^2, \qquad (1)$$

where Δ specifies a block-wise shift, and $G_{k+\Delta}^{I}(i)$ and $G_{k}^{E}(i)$ denote the input fingerprint feature at the $(k+\Delta)$-th block and the enrolled fingerprint feature at the k-th block, respectively. $N(\Delta)$ denotes the number of matched blocks between input and enrolled images for the shift Δ. Finally, the shift Δ that minimizes the value of $D(\Delta)$ determines an optimal block-wise shift.

GAT correlation [6] was introduced as a powerful computational model for determining an affine-invariant correlation value between two gray-scale images using the successive iteration method.

Here, we adopt the correlation value between input and enrolled fingerprint images using not gray levels but the above-mentioned gradient features. Then, the GAT correlation technique determines the optimal affine parameters that maximize the correlation value between the GAT-superimposed input fingerprint image and the enrolled fingerprint image. As a result, components of rotation, scale change, shearing, and translation are absorbed between input and enrolled fingerprint images.

Figure 2 shows an example of preliminary matching using optimal block-wise shift and GAT correlation.



(a) (b) (c) (d)

Figure 2. Example of preliminary matching. (a) Input fingerprint image. (b) Optimal block-wise shift. (c) GAT correlation matching. (d) Enrolled fingerprint image.

5. Verification using perturbation method

We propose a new perturbation method with the aim of detail verification between input and enrolled fingerprint images after preliminary matching. The proposed method consists of three steps: setting of local windows around core point, asynchronous perturbation of local windows, and employment of appropriate matching criteria for the perturbation matching.

5.1. Setting of local windows around core point

Core point is defined as "the north most point of the innermost ridge line" [2]. In our proposed method, we extracted a single core point for each of enrolled fingerprint images manually.

Next, we set four local windows for perturbation around the core point because the most distinctive characteristics of each fingerprint image appear around the core point. Concretely, each local window is located symmetrically around the core point excluding the central area of 10 × 10 pixels. The size of each local window ranges from 25 × 25 pixels to 50 × 50 pixels.

Figure 3 shows examples of setting of local windows around the core point.

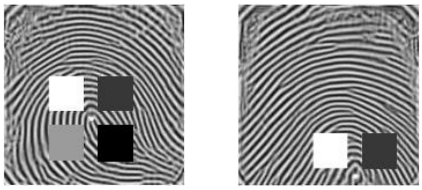


Figure 3. Examples of setting of local windows around the core point. White circles denote the manually extracted core points.

5.2. Selection of perturbation direction and dimension

The aim of asynchronous perturbation of four local windows is to absorb non-linear distortion and realize pixel-wise minute matching between input and enrolled fingerprint images. Hence, appropriate selection of perturbation direction and dimension is crucial to the success of the proposed perturbation method. We propose two different ways as follows.

The first one is use of a single perturbation direction perpendicular to the dominant ridge direction in each local window. The dominant ridge direction is determined by evaluating gradients at all pixels in the local window. Then, based on the investigation of intervals between adjacent ridge lines of fingerprints in the database FVC2000 DB1, we set the maximum dimension of perturbation in perpendicular direction at 12 pixels twice the average interval between ridge lines. Hence, the total number of back and forth perturbation is 25 (= 2 × 12 + 1) for each local window.

The second one is use of all directions in perturbation of local windows. Namely, each local window is moved around horizontally and vertically. Here, we denote the maximum dimension of perturbation by R. As a result, the total number of perturbation in all directions amounts to $(2R + 1)^2$. In experiments, we tried three values of R, i.e., 15, 20, and 25.

5.3. Matching criteria

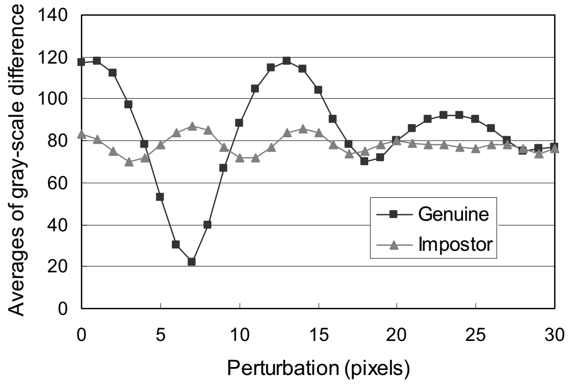
We adopt an average of pixel-wise gray-scale difference in each local window as a matching measure. Here, the average of gray-scale difference, d_k, for the k-th local window, is given by

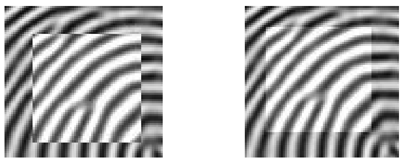
$$d_k = \frac{1}{N} \sum_{j} \sum_{i} | f_k(i,j) - g_k(i,j) |, \qquad (2)$$

where $f_k(i, j)$ and $g_k(i, j)$ denote gray levels of input and enrolled fingerprint images within the k-th local window, respectively. N denotes the number of pixels in the local window.

The perturbation method makes the most of the fact that due to the cyclic ridge structure the values of d_k also change cyclically as the local window moves through perturbation in a particular direction if the input fingerprint is genuine. On the other hand, the values of d_k do not exhibit the cyclic change if the input fingerprint is taken from an impostor.

Figure 4 shows relations between averages of gray-scale difference and perturbation in a particular direction.





(a) (b)

Figure 4. Relations between average values of gray-scale difference and perturbation in a particular direction. (a) Maximum gray-scale difference. (b) Minimum gray-scale difference.

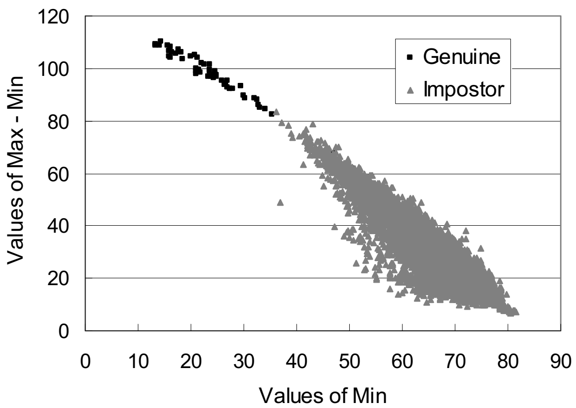


Figure 5. A typical scatter diagram of values of Max − Min vs. Min.

Here, we denote the maximum and minimum values of averages of gray-scale difference by Max and Min, respectively.

Then, from Fig. 4, it is found that the value of Min is very small and the value of Max − Min is very large if the input fingerprint is genuine. On the other hand, the value of Min is rather large and the value of Max − Min is small if the input fingerprint is taken from an impostor.

From the above consideration, we propose the matching criteria that the input fingerprint is classified as a genuine one if

$$\text{Min} \le Th_1 \quad \& \quad \text{Max} - \text{Min} \ge Th_2, \tag{3}$$

where Th_1 and Th_2 denote threshold values.

Figure 5 shows a typical scatter diagram of values of Min vs. Max − Min obtained by preliminary experiments made on 56 genuine pairs and 6,976 impostor pairs.

From Fig. 5, we can say that the above-mentioned matching criteria of (3) are promising. Optimal threshold values, Th_1 and Th_2, are determined in experiments.

6. Experimental results

We used a total of 880 fingerprints (110 fingers and 8 impressions) in FVC2000 DB1. Hence, in our fingerprint verification experiments we had a total of 110 × 8 × 7 (=6,160) genuine pairs and a total of 110 × 8 × 109 × 8 (=767,360) impostor pairs.

We evaluated the accuracy of the proposed method in terms of values of False Acceptance Rate (FAR) and False Rejection Rate (FRR) by varying two threshold values of Th_1 and Th_2 of (3).

Figure 6 shows ROC (Receiver operating characteristic) curves obtained by two different ways of perturbation: perpendicular direction vs. all directions.

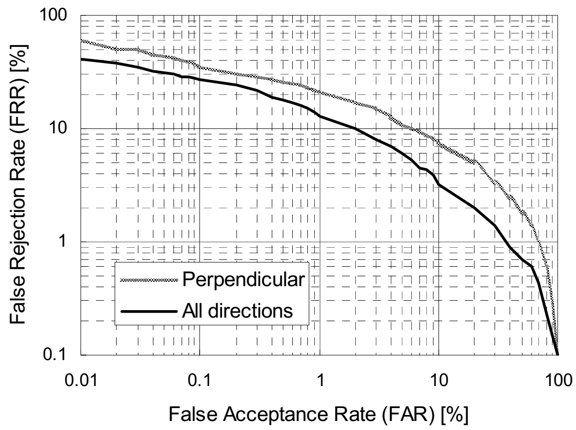


Figure 6. ROC curves.

From Fig. 6, it is clear that the perturbation method based on perturbation in all directions is far superior to that based on perturbation in a single perpendicular direction to ridge lines in each local window.

Table 1 shows Equal Error Rate (EER) and average matching time by the proposed perturbation method featuring perturbation either in perpendicular direction or in all directions. As described in 5.2, regarding the way of perturbation in all directions we tried three values of R, the maximum dimension of perturbation. Also, the average matching time specifies the processing time required only for the perturbation method on a 3.0GHz Pentium 4.

From Table 1, it is first found that perturbation in all direction surpasses perturbation in perpendicular direction to ridge lines in EER although the former is properly more time-consuming. The EER of around 5.5% by the former perturbation method (R=20.0) was obtained at Th_1 = 53.2 and Th_2 = 23.6. On the other hand, the EER of 8.32% by the latter perturbation method featuring perpendicular perturbation was obtained at easier threshold values of $Th_1 = 63.6$ and $Th_2 = 15.4$.

It is also found that the EER of the perturbation method in all directions did not change markedly as a function of the maximum dimension of perturbation, R. As was expected, the computational cost increased in proportion to $(2R + 1)^2$.

Finally, the obtained EER of 5.55% is comparable to those in the top group of FVC2000 [7].

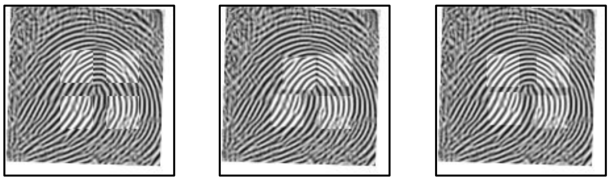
The total processing time required for matching between input and each enrolled fingerprint images was 5.29 sec on average (4.40 sec for enhancement, 0.46 sec for preliminary matching, and 0.43 sec for perturbation), while the top algorithm in FVC2000 finished the total matching process in 1.22 sec.

Table 1. EER and average perturbation matching time.

Perturbation direction	EER (%)	Ave. matching time (sec)
Perpendicular	8.32	0.015
All directions (R=15)	5.65	0.16
All directions (R=20)	5.57	0.28
All directions (R=25)	5.55	0.43

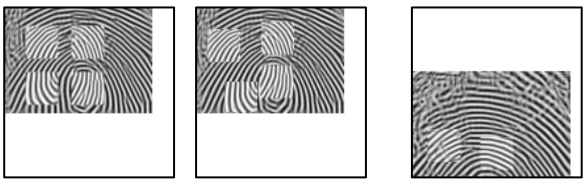
7. Discussion

The proposed perturbation method has two key features. One is asynchronous perturbation of four local windows around the core point. This realizes absorption of non-linear distortion, in particular, shearing due to the non-uniform pressure on the surface of a finger. The other is pixel-wise perturbation in all directions that realizes minute matching between input and enrolled fingerprint images around the core point.



(a) (b) (c)

Figure 7. Example of perturbation matching. (a) Original positions of four local windows. (b) Unsuccessful perturbation in perpendicular direction to ridge lines. (c) Successful perturbation in all directions.



(a) (b)

Figure 8. Examples of unsuccessful perturbation matching. (a) Genuine pair. (b) Impostor pair.

Figure 7 shows an example of successful perturbation matching in all directions against shearing, while perturbation in perpendicular direction to ridge lines failed in optimal matching.

On the other hand, Figure 8 shows examples of unsuccessful perturbation matching. The main causes of failure are the following two: (1) failure in preliminary matching due to a large amount of translation or rotation between a genuine pair, and (2) coincidence between an impostor pair due to a shortage of local windows.

8. Conclusion

Designing algorithms capable of extracting features and matching them in poor quality fingerprint images are still very challenging although a number of fingerprint verification systems are being used worldwide.

The proposed method was designed to realize pixel-wise minute matching and absorb non-linear distortion by introducing asynchronous perturbation of four local windows in all directions around the core point.

In experiments made on FVC2000 DB1 fingerprint database, the proposed method achieved an EER of 5.55% comparable to those obtained in the competition.

Future work is to improve the ability of preliminary matching against a large amount of linear distortion and select a necessary and sufficient number of local windows for enhanced perturbation. Also, a substantial reduction of computational cost is indispensable in practical applications.

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