A Fusion Algorithm of the Incomplete Fingerprints Matching based on Fuzzy Criterion

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Abstract

In this paper, a fusion method based on fuzzy criterion is proposed for incomplete fingerprint matching due to skin distortions. Firstly, according to the properties of competition of the local fingerprint, complementation and redundancy of the global fingerprint, the proposed scheme is based on orientation entropy and Poincare Index to detect the reference point of fingerprints, and then extract ROI. Secondly, this paper presents a fusion matching scheme which is based on fuzzy criterion. In order to improve the matching accuracy, the fusion matching scheme uses fuzzy theory as a criterion to integrate decisions from different algorithms. Experiment results executed on FVC2002 prove the proposed scheme is effective for fingerprints identification. In addition, it is robust to resolution and rotation.

Keywords: incomplete fingerprint matching, information fusion, fuzzy criterion

1. Introduction

Fingerprint-based identification is the most widely used biometric authentication technology (e.g., face, fingerprint, hand geometry, iris, retina, signature, voice print, hand vein, gait, ear, odor, keystroke dynamics, etc. [1,2]), because of the uniqueness, immutability and portability of fingerprints. However, the acquired fingerprints often have dirty parts, scars, creases and so on. For incomplete fingerprint, the loss of information and serious nonlinear deformation cause great difficulties in incomplete fingerprint recognition. So it is imperative to do some researches on this project [3,4,5].

The fingerprint is unique for every individual and it is convenient and mature to capture. Methods of fingerprint matching can be coarsely categorized into: minutia-based, correlation-based and hybrid-based. The minutia-based methods [6,7,8,9] are based on the best alignment and the largest similarity of the surrounding minutia information (e.g. minutiae type, direction and relative distance). However, these methods rely on the accurate extraction of minutia and the used matching algorithm to a great extent. Correlation-based algorithms [10,11] match the global patterns of ridges and valleys to determine whether the ridges are aligned. The input and template fingerprint images are superimposed and the correlation between the corresponding pixels is computed for different alignments (e.g., various displacements and rotations). These methods require less computational complexity than minutia-based methods, but they are vulnerable to variations in position, scale, and rotation. The hybrid-based methods [12] use both minutia and feature information. They combine minutia and feature matching results to generate a final matching score. These methods also depend on the precise detection of minutia and the used matching algorithm.

Fingerprint matching is still a very difficult problem, which mainly due to the large variability and skin distortions. In this paper, the method of the reference point detecting of all classes is improved, and the method is free to resolution and rotation. Then, to improve the matching accuracy, this paper represents a fusion matching scheme which is based on fuzzy criterion. The fusion scheme could adjust the similarity scores obtained using minutiae-based matching algorithms and correlation-based algorithms. As a result, our scheme can integrate decisions from different algorithm, and utilize the advantages of every algorithm.

The paper is organized as follows. In Section 2, some related works are presented. In section 3, our method is described in detail. Section 4 provides the experimental results to analyze the performance. And the conclusion is in Section 5.
2. Related works

2.1. Minutiae-based Algorithm

The minutiae matching problem can also be viewed as a point pattern matching problem which has been extensively studied yielding families of approaches known as algebraic geometry, Hough transform, relaxation, operations research solutions, energy-minimization, and so on. The local minutiae feature representation has been used for point pattern fingerprint matching [8]. This approach describes each minutiae as a local structure, which is called a minutiae descriptor. The minutiae descriptor comprises information about the orientation field sampled in a circular pattern around the minutiae point. The circular pattern consists of \( L \) concentric circles of radii \( r_i (1 \leq i \leq L) \). Each circle comprising \( K_i \) sampling points, which are equally distributed along its circumference, described as \( p_{k,l} (1 \leq k \leq K_i) \). As the rotation and translation during fingerprint input, the minutiae descriptor is nearly invariant. Hence, it can characterize the minutiae location and solve the problem of the fingerprint distortion on the acquisition sensor.

The similarity function is defined as follows [13]:

\[
S(a,b) = \left( \frac{1}{K} \sum_{l=1}^{L} \sum_{k'=1}^{K} \exp(-16A(\alpha_{l,j}, \beta_{l,j})) \right)
\]

where the \( a \) and \( b \) are the minutiae descriptors, which \( a = \{ \alpha_{l,j} \}, \ b = \{ \beta_{l,j} \}. \) And \( A(\alpha_{l,j}, \beta_{l,j}) \) is the distance between angles, with values between 0 and 1, \( K = \sum_{l=1}^{L} K_i \).

2.2. Correlation-based Algorithm

Correlation-based algorithm, usually, may be susceptible to the quality of image and non-linear distortion. The fingerprint distortion and the noise problems are usually addressed by computing the correlation locally instead of globally. The correlation theory is described as follows:

\[
T \otimes_{correlation} I = F^{-1} \left( F(T) \cdot \frac{F(I)}{|F(I)|} \right)
\]

Where \( T \) and \( I \) are the two fingerprint images corresponding to the template and the input fingerprint, respectively. Where \( F() \) is the Fourier transform of an image, \( F^{-1}() \) is the inverse Fourier transform, \( SPOF \) means the Symmetric Phase Only Filter.

2.3. The hybrid-based methods

In [12], the matching scores generated by comparing the minutiae sets and the ridge feature maps, are combined in order to generate a single matching score. They adopted the following sum rule. Let \( S_m \) and \( S_r \) indicate the similarity scores obtained using minutiae matching and ridge feature map matching, respectively. Then, the final matching score, \( S \), is computed as

\[
S = \alpha S_m + (1 - \alpha) S_r
\]

where \( \alpha \in [0,1] \). For the experimental results reported in this paper, \( \alpha \) was set to 0.5. It is possible to vary \( \alpha \) to assign different weights to the individual matchers.

3. The proposed methods

3.1. Segmenting and Finding a region mask
Firstly, we remove background region and get a region mask of foreground region. Mean and variance based algorithm can significantly reduce the number of basic image entities, and due to the good discontinuity preserving filtering characteristic, the salient features of the overall image are retained [1]. Moreover, a novel image segmentation method is devised and some new features are proposed to represent the local ridge structure of a fingerprint [14]. But mean and variance based algorithm does not work well on too wet or too dry fingerprint images. Steps for mean and variance based algorithm are summarized as follows:

(1) Divide the fingerprint image $I(i, j)$ into non-overlapping blocks with size $M \times N$. Compute the mean value $Mean_i$ for each block using Equation (4)

$$Mean_i = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} I(i, j)}{M \times N}$$  \hspace{1cm} (4)

(2) Compute the variance value $Var_i$ for each block from equation (5)

$$Var_i = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (I(i, j) - Mean_i)^2}{M \times N}$$  \hspace{1cm} (5)

(3) Select empirically a threshold value working on different images. If the $Var_i$ is greater than threshold value, the block is considered as foreground, otherwise it belongs to background. Figure 1 show the segmented images based on mean and variance algorithm.

3.2. Orientation field estimation

By the conventional approach, the orientation map is analyzed blockwise. In each block, a dominant orientation is estimated through gradients of every pixel. The equations[13] are

$$V_x(x, y) = \sum_{x-w/2}^{x+w/2} \sum_{y-w/2}^{y+w/2} 2\partial_x \xi(u, v) \partial_x \eta(u, v)$$  \hspace{1cm} (6)

$$V_y(x, y) = \sum_{x-w/2}^{x+w/2} \sum_{y-w/2}^{y+w/2} \left( \partial_y \xi(u, v) - \partial_y \eta(u, v) \right)$$  \hspace{1cm} (7)

$$\theta(x, y) = \frac{1}{2} \tan^{-1} \left( \frac{V_y(x, y)}{V_x(x, y)} \right)$$  \hspace{1cm} (8)

where $w$ is the size of the block centered at $(i, j)$. And $\partial_x, \partial_y$ are gradients along the horizontal and vertical directions. There are many approaches to calculate gradients, such as using Sobel operator or Marr-Hildreth operator. The obtained orientation map is usually smoothed through a low-pass filter.

3.3. Extracting the edge of the orientation field
The orientation of the ridge flow changes abruptly in the singular region. Therefore, reference points could be located at the trip points of the orientation field (see as Figure 3). And extraction is preformed in the edge of orientation jumping regions instead of the whole orientation field. Here, the orientation field is considered as an intensity image and Log operator is used to detect the edge of the orientation jumping regions.

Figure 3. 1st Smoothed orientation image. 2nd the edge of the smoothed orientation jumping regions. 3rd labeling the trip points in the fingerprint image.

3.4. The Poincare Index Method

The Poincare index method takes the values 1/2, −1/2, and 0 for a core point, a delta point, and an ordinary point, respectively. The operation is carried on block-wise. For each block centered at pixel \((i, j)\) in the orientation field, the cumulative change of orientation \(PI(i, j)\) can be computed along an enclosed curve (contains \(N_p\) points) using equation 9. If the value of \(PI(i, j)\) is equal to 1/2, the pixel \((i, j)\) is considered as a core point. Usually if there is more than one core in a very small region, an average core point can be computed instead. The Poincare Index method may induce the displacement of the core point because of smoothing the estimated orientation field. To resolve the problem, we extend the area centered at the average core point based on the curvature information adaptively. And the center of each block contained in the extended area is considered as a core point. Therefore, a reference point set \(S_1\) could be gotten. Figure 4 is just an example of the extension. This will have a detailed description below.

\[
PI(i, j) = \frac{1}{2\pi} \sum_{k=1}^{N_p} \Delta(k)
\]

where

\[
\Delta(k) = \begin{cases} 
\delta(k) & \text{if } \lvert \delta(k) \rvert < \pi/2 \\
\pi + \delta(k) & \text{if } \delta(k) \leq -\pi/2 \\
\pi - \delta(k) & \text{otherwise}
\end{cases}
\]

\[
\delta(k) = O(x_{(k+1) \text{mod } N_x}, y_{(k+1) \text{mod } N_y}) - O(x_i, y_i)
\]

Figure 4. The reference point set \(S_1\) based on the Poincare Index method

3.5. Orientation entropy measurement

Information entropy is used to measure the uncertainty of orientation filed. A reference point is defined as the point that has maximum curvature in the most internal ridge, while orientation
entropy in the local area measures directional difference in a local area. Orientation entropy in the local area $\omega$ is defined:

$$H(\omega) = -\sum_{(u,v)} \rho_{O(u,v)} \log(\rho_{O(u,v)})$$  \hspace{1cm} (11)$$

where

$$\rho_{O(u,v)} = \frac{\left( \sum_{(i,j) \in A} \Delta [O(i,j) - O(u,v)] \right)^{-1}}{\sum_{(i,j) \in A} \left( \sum_{(i',j') \in A} \Delta [O(i',j') - O(u,v)] \right)^{-1}}$$  \hspace{1cm} (12)$$

Predefine a threshold value $T$, for each block, if the block’s orientation entropy is larger than $T$, the center of this block is decided as a possible reference point (shown as Figure 5) and another reference point set $S_2$ could be obtained.

Figure 5. The reference point set $S_2$ gotten from the orientation with gradient dispersion

### 3.6. Detection of reference point and ROI

As shown in the 3rd image of Fig.5, it is difficult to decide the reference point in $S_2$ is a core point or a delta point. Therefore, we combine the orientation entropy and the Poincare Index to detect the reference point more precisely. Meanwhile, a sub-image 96×96 centered at the reference point is extracted as the ROI (as shown in Figure 6). The criterion is as following: If $S_1$ is not empty, and then it is supposed that there is a core point at least in the input fingerprint. If the expanded area centered at the average core point exceeds a predefined area or the number of the intersection of $S_1$ and $S_2$ is larger than the predefined number, stop the extension to $S_1$. The intersection is determined as the reference point set $S$. Its centroid is considered as the detected reference point. If there isn’t a reference point in $S_1$, the threshold value $T_1$ is chosen. If orientation entropy centered at the pixel $(i,j)$ is larger than $T_1$, then the pixel $(i,j)$ is decided as a reference point.

Figure 6. The results of ROI

### 3.7. Fusion scheme

Minutiae-based algorithm is the most common and widely used technique, which aligns two sets of minutiae considering the directional image around the minutiae. Minutiae-based matching essentially aims at finding the alignment between the template and the input minutiae feature sets and results in the maximum number of minutiae pairings. In the alignment, the proposed scheme provides the robust reference point. As the rotation and translation during fingerprint input, the minutiae descriptor is nearly invariant. However, it is complex and computational.

Correlation-based algorithm is based on the global patterns of ridges and valleys to determine whether the ridges are aligned. Moreover, it requires less computational complexity than minutia-based methods, but vulnerable to the quality of image and non-linear distortion. In
our scheme, ROI extracted with Poincare Index and Orientation entropy is free to resolution and rotation.

As is depicted above, the advantages and disadvantages of two algorithms are different, so we fuse the matching results from two algorithms. Then fusion scheme with fuzzy criterion is as follows:

\[
F(S_{\alpha}, S_{\beta}) = \frac{S_{\alpha}S_{\beta}}{1 - S_{\alpha} - S_{\beta} + 2S_{\alpha}S_{\beta}}
\]  

where \(S_{\alpha}\) is the normalized similarity scores obtained using minutiae-based matching algorithm, and \(S_{\beta}\) is from correlation-based algorithm.

4. Experiment results

To evaluate the proposed scheme, we tested on the fingerprint images with low quality in FVC2002, which consists of four collections (labeled DB1, DB2, DB3, and DB4, respectively) of fingerprint images. Each contains 800 images from 100 individuals. The fingerprint images used here were obtained from the FVC2002 (Fingerprint Verification Competition) databases [16].

As shown in Figure 7, compared with another two algorithms, the proposed scheme is evaluated by the False Match Rate (FMR) and False Non-Match Rate (FNMR). As is shown, the EER of the fusion scheme is better than the single method. Experiment results prove the proposed scheme is effective for fingerprints identification.

![Figure 7. Retrieval performance on FVC2002 for our proposed algorithm and the two matching algorithms (minutiae-based and correlation-based)](image)

5. Conclusions
The large loss of information and serious nonlinear deformation cause great difficulties in incomplete fingerprint recognition. The single matching algorithm is not suitable for all fingerprint situations. In this paper, a fusion method based on fuzzy criterion is proposed for incomplete fingerprint matching. Firstly, according to the local and the global fingerprint information, the proposed scheme detects the reference point of a fingerprint based on orientation entropy and Poincare Index, and then extracts ROI. Secondly, this paper presents a fusion matching scheme which is based on fuzzy criterion. In the matching step, the proposed scheme provides the robust reference point for the minutiae-based algorithms. Besides, ROI extracting with Poincare Index and Orientation entropy is used in correlation-based algorithms. Then, the fusion scheme based on fuzzy criterion adjusts the similarity scores obtained using separate minutiae-based and correlation-based matching algorithms, and obtains the optimum estimation. Experiment results prove the fusion matching scheme is robust for the incomplete and nonlinear distortions fingerprint.

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7. References