FINGERPRINT MATCHING BASED ON RIDGE SIMILARITY

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ABSTRACT

This paper proposes a method for fingerprint matching based on the local ridge similarity. Different from traditional methods which estimate rotation angle between a query and template minutia using orientation field, our approach estimates the local rotation angle directly from sampling points of ridges. After fitting samples by least square method, the optimal local rotation angle is obtained, moreover, the similarity between two ridges is measured by virtue of the fitting error. The best reference pair is then determined in the smoothed similarity histogram. Finally, a matching score is computed by projecting the query minutiae set to the template according to the best reference. The experimental results on the public fingerprint database, FVC2002 DB3(800 fingerprints, 8 impressions per finger) and a self-collected database(880 fingerprints, 5 impressions per finger), show that our approach is more effective compared with the conventional ridges-based approach.

***Index Terms*—** Fingerprint Matching, Parameters Estimation, Similarity Histogram

1. INTRODUCTION

As one of the most powerful biometric techniques, fingerprint identification has been widely researched due to the stability and uniqueness of fingerprint features[1]. During the past three decades, many significant improvements in automatic fingerprint identification system(AFIS) have been achieved, however, because of the quality and pose of fingerprints, the design of a robust and reliable AFIS is still a challenge task. Generally, an AFIS is composed of feature extraction and feature matching. Fingerprint matching which identify two impressions from a same finger play a significant role in the fingerprint identification. The main difficulty in fingerprint matching is how to obtain the accurate alignment between a query and template fingerprint.

Until now, various approaches for fingerprint matching have been proposed in the literature[1, 2, 3, 4]. Minutiae-based matching methods have been widely adopted since the stability and nice discrimination of minutiae features. Jiang[3] first built some local structures between the feature vectors and assigned the pair whose similarity was largest among all candidate minutiae pairs as the reference pair, and then matched the query and template fingerprint by constructing global feature vectors around the reference point. In [2], Ratha et. al. proposed an elastic matching algorithm, which first detect the peak in the generalized Hough space of alignment parameters formed by aligning two sampled thinning ridges and then count the number of matched minutiae using a fixed sized bounding box, the similar technique was also taken by [1]. Luo[5] modified this method by using a changeable sized bounding box. As an improvement to the generalized Hough method, Liu[4] developed a hierarchical Hough transform for fingerprint matching, which mainly to deal with two difficulties, i.e. missing matching pairs and duplicate matching problem. However, the traditional generalized Hough based approaches give poor rotation estimation due to the scale variance and distortion of fingerprint images.

As a 2D pattern matching, fingerprint matching generally need to determine three key parameters, namely x-translation, y-translation and rotation angle. In this paper, we proposed a novel matching approach to deal with noise and distortion of fingerprint image. First, the rotation angle between two thinning ridges associating with the corresponding minutiae is estimated by virtue of an effective technique(see more detail in the following section), and a similarity measure between two ridges is drawn during the estimation of rotation angle. Through constructing a similarity histogram using the ridge similarity measures, the reference pair between the query and template fingerprint is detected. And finally, minutiae pairing based on the reference pair gives a matching score to describe the similarity between the query and template fingerprint.

The rest of this paper is organized as follows. Section 2 presents the detail of fingerprint feature registration. The matching scheme based on the ridge similarity is developed in Section 3. The following section shows some experimental results. Finally, conclusions are drawn in Section 5.

2. FINGERPRINT REGISTRATION

In order to match a query fingerprint with the fingerprints from database, one popular method is to match the minutiae set extracted from fingerprint images. An end or bifurcation of ridge pattern(see Fig.1, the circles denote end minutiae and the deltas denote bifurcation minutiae), called minutia, which is a kind of intrinsic fingerprint feature. Usually, a minutia is represented as (x, y, φ), where x and y are the coordinates of the minutia, φ is the orientation of the local associated ridge.

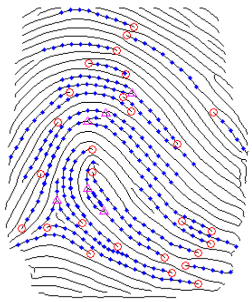


Fig. 1. Ridge sampling in the thinning image

In this paper, we match two sets of minutiae based on the local ridge similarity. Because of the unknown scale, translation and rotation of a fingerprint image, the local ridge should be considered, this is reasonable, since the deformation of a local ridge is relatively small. We sample a thinning ridge with an uniform interval L and represent the sample point by its x and y coordinates, as shown in Fig.1, the sampling points are denoted by solid dots. Assuming N points are sampled in the associated thinning ridge, we can denote a sampling ridge of the query fingerprint by $\mathcal{Q} = (x_0^q, y_0^q, x_1^q, y_1^q, \cdots, x_N^q, y_N^q)$, where x_0^q and y_0^q are the coordinates of the minutia, while $x_i^q (i = 1 \sim N)$ and $y_i^q (i = 1 \sim N)$ are the coordinates of the sampling points. In the same way, let $\mathcal{T} = (x_0^t, y_0^t, x_1^t, y_1^t, \cdots, x_N^t, y_N^t)$ denotes a ridge from the template fingerprint, where $x_i^t (i = 0 \sim N)$ and $y_i^t (i = 0 \sim N)$ have the similar meaning with Q. In order to align two ridges from the query and template fingerprint, besides considering the translation and rotation, the scale problem which is paid little attention by many papers also should be resolved. Under the ideal situation, for a matched minutia pair, (x_i^q, y_i^q) should correspond to (x_i^t, y_i^t) as follows:

$$s \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} x_i^q \\ y_i^q \end{bmatrix} + \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} = \begin{bmatrix} x_i^t \\ y_i^t \end{bmatrix}. \tag{1}$$

Where s is the scale factor, $\Delta\theta$ is the rotation angle, and $[\Delta x\ \Delta y]^T$ is the translation. In order to eliminate the translation, we subtract the (x_0^q, y_0^q) from (x_i^q, y_i^q), and the same operation also applied to (x_i^t, y_i^t). Therefore, the $[\Delta x\ \Delta y]^T$ can be removed from Eq.1. The sampling points in query ridge is denoted by $\widetilde{\mathcal{Q}}_i = (\widetilde{x}_i^q, \widetilde{y}_i^q) = (x_i^q - x_0^q, y_i^q - y_0^q)$, and the sampling points in template ridge denoted by $\widetilde{\mathcal{T}}_i = (\widetilde{x}_i^t, \widetilde{y}_i^t)$ in the same way. For convenience, we assign a_1 as $s\cos(\Delta\theta)$ and a_2 as $s\sin(\Delta\theta)$. As a result, Eq.1 is simplified to the following formula:

$$\begin{bmatrix} \widetilde{x}_i^q & -\widetilde{y}_i^q \\ \widetilde{y}_i^q & \widetilde{x}_i^q \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \widetilde{x}_i^t \\ \widetilde{y}_i^t \end{bmatrix} \tag{2}$$

We wish to estimate the scale s and the rotation angle $\Delta\theta$, therefore, we apply all sampling points to Eq.2. Thus, the least-square solution of the parameter $a = [a_1\ a_2]^T$ can be determined by solving the corresponding normal equations:

$$a = [A^T A]^{-1} A^T b \tag{3}$$

where

$$A^T = \begin{bmatrix} \widetilde{x}_1^q & \widetilde{y}_1^q & \cdots & \widetilde{x}_N^q & \widetilde{y}_N^q \\ -\widetilde{y}_1^q & \widetilde{x}_1^q & \cdots & -\widetilde{y}_N^q & \widetilde{x}_N^q \end{bmatrix}$$

and

$$b^T = \begin{bmatrix} \widetilde{x}_1^t & \widetilde{y}_1^t & \cdots & \widetilde{x}_N^t & \widetilde{y}_N^t \end{bmatrix}$$

We can estimate the rotation angle $\Delta\theta$ and the scale $s = \sqrt{a_1^2 + a_2^2}$ from Eq.3. To get a more explicit resolution of $[a_1\ a_2]^T$, we should notice the following equations:

$$A^T A = \begin{bmatrix} \sum((\widetilde{x}_i^q)^2 + (\widetilde{y}_i^q)^2) & 0 \\ 0 & \sum((\widetilde{x}_i^q)^2 + (\widetilde{y}_i^q)^2) \end{bmatrix}$$

and

$$A^T b = \begin{bmatrix} \widetilde{b}_1 \\ \widetilde{b}_2 \end{bmatrix} = \begin{bmatrix} \sum((\widetilde{x}_i^q * \widetilde{x}_i^t + \widetilde{y}_i^q * \widetilde{y}_i^t) \\ \sum((\widetilde{x}_i^q * \widetilde{y}_i^t - \widetilde{y}_i^q * \widetilde{x}_i^t) \end{bmatrix}$$

For convenience, we denote $A^T b$ by $[\widetilde{b}_1\ \widetilde{b}_2]^T$ in the above equation. Consequently, the rotation angle which aligns two ridges is calculated as follows:

$$\Delta\theta = \arctan(\frac{a_2}{a_1}) = \arctan(\frac{\widetilde{b}_2}{\widetilde{b}_1}) \tag{4}$$

Moreover, the scale factor can be computed as follows:

$$s = \frac{\sqrt{(\widetilde{b}_1)^2 + (\widetilde{b}_2)^2}}{\sum((\widetilde{x}_i^q)^2 + (\widetilde{y}_i^q)^2)}$$

Fig.2 shows the result when project samples from the query ridge to the template one, the solid points denote samples from template ridge, the circles represent the samples from query ridge, and the rotation version of the query ridge using Eq.2 is depicted by squares, for a comparison, we also plot the rotation without involving scale by deltas. Obviously, the version considering scale has smaller fitting error.

In order to measure the difference between two ridges, we calculate the fitting error under the optimal estimation of rotation angle and scale as follows:

$$\begin{aligned} E_{diff} &= ||Aa - b||^2 \\ &= \sum((\widetilde{x}_i^t)^2 + (\widetilde{y}_i^t)^2) - \frac{(\widetilde{b}_1)^2 + (\widetilde{b}_2)^2}{\sum((\widetilde{x}_i^q)^2 + (\widetilde{y}_i^q)^2)} \end{aligned} \tag{5}$$

Since the smaller E_{diff} indicate more similar between two ridges, thus, we measure the similarity between two ridges using the following formula:

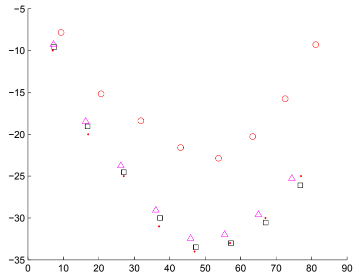


Fig. 2. The rotation between a query ridge and a template

$$E_{sim} = \frac{1}{1 + E_{diff}/C} \tag{6}$$

where C is a predefined constant, we assign C as 20.

From the view of computational efficiency, we register an end minutia and its sampling ridges by $M_e = (x_i, y_i, \varphi_i, x_i^1, y_i^1, \cdots, x_i^N, y_i^N, e_i^1, \cdots, e_i^N)$, where (x_i, y_i) and φ_i are the coordinate and local orientation of the minutia, respectively. x_i^j and y_i^j are the coordinate differences between the sampling point and the minutia, and e_i^j is defined as follows:

$$e_i^j = \sum_{k=1}^{j} ((x_i^k)^2 + (y_i^k)^2)$$

The introduction of e_i^j is to reduce the computational redundancy because the minuend and the denominator in Eq.5 is constant for matching different minutia combination. More attention should be paid to the of registration of bifurcation minutia, denoted by M_b, which is represented by three branches, the first branch is corresponding to the ridge when the two others form the least angle, and then clockwise register the other branches into M_b. From Fig.3, the points denoted by squares should first be registered, and then the points symbolized by circles and deltas are registered in sequence.

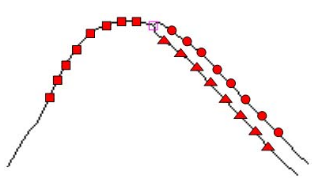


Fig. 3. The registration of the bifurcation minutia

3. FINGERPRINT MATCHING

Based on the estimation of rotation angle and the similarity measure between two ridges, we developed a scheme for fingerprint matching. The main task is to find the optimal translation and rotation parameters which align the query and template fingerprint. In this paper, we complete this task by detecting the peak in the similarity histogram which is built according to the local ridge similarity.

For a minutia M_q^i in a query fingerprint, we calculate the similarity between M_q^i and every minutia M_t^j in the template fingerprint using Eq.6. The translation parameter for a minutia pair is $(\Delta x_{ij}, \Delta y_{ij}) = (x_t^j - x_q^i, y_t^j - y_q^i)$, the rotation parameter $\Delta\theta_{ij}$ is calculated using Eq.4. The alignment between an end minutia and an end minutia is straightforward. However, for the alignment between an end and a bifurcation, we estimate two rotation angles, i.e.the ridge of the end minutia against the second branch and third branch of the bifurcation, and then assign the angle which corresponds to the maximal similarity as the rotation angle. As to the alignment between a bifurcation and a bifurcation, we calculate three rotation angles of corresponding branches, and then obtain the rotation angle by average the three angles. Since the transform between the query and template fingerprint is constrained into a certain range, we limit the translation parameter in a range of $[-H, H]$ and the rotation parameter in a range of $[-V, V]$. And then we discretize the translation and rotation parameters with proper interval H_d and V_d, respectively. Therefore, we can record the ridge similarity into a 3D array, denoted by $F(n_x, m_y, l_\theta)$, which is defined as follows:

$$F(n_{\Delta x}, m_{\Delta y}, l_{\Delta\theta}) = F(n_{\Delta x}, m_{\Delta y}, l_{\Delta\theta}) + E_{sim} \tag{7}$$

where $n_{\Delta x} = \lfloor (H + \Delta x)/H_d \rfloor$, $n_{\Delta y} = \lfloor (H + \Delta y)/H_d \rfloor$ and $n_{\Delta\theta} = \lfloor (V + \Delta\theta)/V_d \rfloor$, there, the function $\lfloor z \rfloor$ means taking maximal integer which is not more than the variable z. $F(n_{\Delta x}, m_{\Delta y}, l_{\Delta\theta})$ is first initialized with zeros, and accumulated by the minutia pairs of the query and template fingerprint. Since E_{sim} indicates the likelihood of the candidate pair as a matched pair, $F(n_{\Delta x}, m_{\Delta y}, l_{\Delta\theta})$ can be considered as a similarity histogram of the transform parameters.

To cope with the distortion and noise of fingerprint images, we smooth the similarity histogram $F(n_{\Delta x}, m_{\Delta y}, l_{\Delta\theta})$ by a Gaussian filter:

$$G(n, m, l) = A \cdot \exp(-\frac{(n^2 + m^2)}{\sigma_1^2} + \frac{l^2}{\sigma_2^2}).$$

Where A is a parameter that normalize the sum of Gaussian filter to one. And then we detect the peak in the smoothed similarity histogram. Assuming the coordinate corresponding to the peak is (n_p, m_p, l_p), which indicates the coarse transform parameters between the query and template fingerprint. Frequently, there are more than one candidate matched pair falling into the grid (n_p, m_p, l_p), we assign the one whose E_{sim} is maximal in those candidates as the reference pair. And finally, we project the query minutiae set to the template coordinate systems according to the reference pair.

We calculate the matching score between the query and template fingerprint using the following formula:

$$M_s = 2\frac{N_m}{(N_t + N_q)} \tag{8}$$

where N_m is the number of matched minutia pair which fill into a bounding box. N_t and N_q are the number of minutiae which fall into the overlapping area.

4. EXPERIMENTAL RESULTS

The algorithm presented in this paper has been tested on two databases. One is a public database, DB3 in FVC2002[6], which includes 800 fingerprint impressions from 100 finger(a finger provides 8 impressions) using capacitive sensor 100 SC, the size of image is 300×300. Another one is our private database, which is captured by optical sensor UaraU4000 and contains 880 fingerprint impressions from 176 fingerprints(a finger provides 5 impressions), the size of image is 356×328. Some examples of this database are showed in Fig.4.

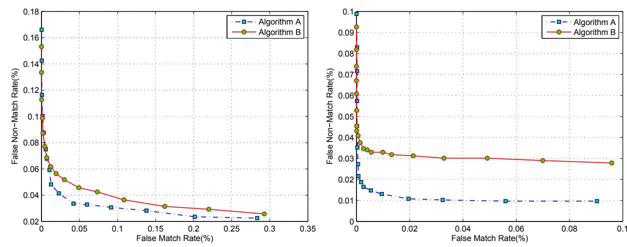
In the first database, we assign H as 150 and V as $\pi/3$, the shifting interval H_d is specified as 15, the rotation interval V_d is pointed to be $\pi/30$, and the size of smoothing filter is $5 \times 5 \times 3$ with $\sigma_1 = 0.8$ and $\sigma_2 = 0.6$. To measure the performance of our algorithm, we take the FVC rule. Each sample in the database is matched against the remaining samples of the same finger, thus, the total number of false non match(FNM) tests (in case no enrollment rejections occur) is: $100C_8^2 = 2800$. On the other hand, the first sample of each finger in the database is matched against the first sample of the remaining fingers, thus, the total number of false match(FM) tests (in case no enrollment rejections occur) is: $C_{100}^2 = 4950$. Fig.5(a) shows the receiver operating characteristic(ROC) curve.

In the second database, we set $H = 150$ and $V = \pi/3$. H_d is assigned as 12, V_d is pointed as $\pi/36$, and the size of smoothing filter is $3 \times 3 \times 3$ with $\sigma_1 = \sigma_2 = 0.6$. Using FVC rule, the total number of FNM tests is: $176C_5^2 = 1760$, and the total number of FM tests is: $C_{176}^2 = 15400$. Fig.5(b) gives the ROC curve. As a comparison, the performance of the generalized Hough method[7] also shown in Fig.5, where our method is denoted by algorithm A and the approach in [7] is denoted by algorithm B.

5. CONCLUSION

In this paper, we proposed an efficient method to match two fingerprint impressions. First, we represent the sampled ridge by the coordinate difference between the sample point and minutia. We deduced a novel approach to estimate the rotation parameter, which not only consider the rotation influence but also the scale variance. For more computational efficiency, we record the accumulation square sum of sample points. By construct a similarity histogram in the parameter space based on the ridge similarity, we detect the reference pair with maximum likelihood which corresponds to the peak in the similarity histogram. Finally, a match score is given to indicate the similarity of two fingerprint images. A set of experimental results show the effectiveness of our method.

Fig. 4. The samples from self-collected database. The fingerprint on the left has good image quality, the middle is moderate, and the right has low quality.



(a)FVC2002DB3 (b)Self-collected database

Fig. 5. The ROC curves of the matching score

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