A ROBUST MATCHING METHOD FOR DISTORTED FINGERPRINTS

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ABSTRACT

This paper proposes a robust method to match distorted fingerprints. We first aligned the query and template fingerprints. To cope with the deformation brought by distorted fingerprints, we trained the distribution of orientation difference at a series of concentric circles around the corresponding pairs, and calculate the posterior probability of matched class using Bayesian method. We compute the score of unmatched absolute reliable minutiae by doubling the size of bounding box. At finally, we fuse the both scores with the score of matched minutiae using the multiplication rule. The experiments have been conducted on the public fingerprint collection, DB3 in FVC2002, and the results present that our method outperforms the conventional matching algorithm.

***Index Terms*—** fingerprint matching,orientation field, minutiae

1. INTRODUCTION

Among all the biometrics, Fingerprint has been widely researched currently due to the stability and uniqueness of fingerprint features [1], generally, an automatic fingerprint identification system(AFIS) composed of feature extraction and feature matching, fingerprint matching identify two fingerprints using extracted features through some elaborate ways, which play an important impact on the accuracy of an AFIS.

In the past three decades, various fingerprint matching methods have been proposed in the literatures [1–5], Jiang [4] first built some local structures with neighbor minutiae to find the corresponding point, and then constructed global feature vectors around the corresponding point to match the tested fingerprints. However, the local structures are sensitive to noise and deformation of fingerprint, hence the different fingerprints may produce quite similar local structures and the fingerprints from a same finger may lose a lot of local structures. M.Tico [2] designed a fingerprint matching method based on some kind of orientation-based minutia descriptor, which integrated orientation information and proved to be more reliable and robust to noise, however, the different between the minutia descriptors may vanish if two minutiae located too near in a fingerprint, thus the false corresponding pairs may be achieved by this method. In [1],Jain proposed an elastic matching algorithm, which first align two fingerprints based on the ridges associating with a minutia and then count the number of matched minutiae using a fixed sized bounding box, nevertheless, the ridge is sensitive to noise during the processing of ridge extraction, Luo.et.al [3] improved this method by using a changeable sized bounding box. However, since the deformation of fingerprints, minutiae pairing is difficult to be completed no matter using the fixed sized bounding box or changeable sized bounding box.

In this paper, we proposed a new matching method to cope with the noise and deformation of fingerprint. Based on our previous work of fingerprint alignment [5], we focus on measuring the similarity between two fingerprints to complete the task of fingerprint verification. Orientation field is a more robust feature to noise, however, through the observation of fingerprint alignment in our experiments, it could be found that the similarity of orientation fields between two fingerprints from a same finger is affected by the distance from the points in the fingerprint foreground to the corresponding point, generally, the longer distance between the point and corresponding point may diminish the similarity of orientation. We establish a set of probability models to encode this relation, and then calculate the posterior probability of each class based on the models. From the view of minutia, fingerprint matching means to find paired minutiae as many as possible, on the contrary side, the lesser minutiae failing to match means more possibility to be the same finger. In order to find the minutiae which is impossible to be matched by any minutiae, first, we take a strategy of scoring to label these absolute reliable minutia(ARM), and then double the size of bounding box, if there no any minutiae no matter the genuine minutiae or pseudo minutiae on other fingerprint fall into the doubled bounding box, we claim that the ARM fail to be matched and calculate a score to indicate the extent of matching failure. See more detail on the following section. Finally, we fuse the above scores with the minutiae matched score provided by [5] to give a comprehensive score which obtains better performance.

The rest of this paper is organized as follows. Section 2 presents the more detail of Modelling orientation deformation. The minutia scoring to label ARM also been given in this section. A matching scheme based on posterior probability of orientation difference and the matching failure of ARM is developed in section 3. The following section gives some experimental results on the public database of fingerprint image, DB3 in FVC2002 [6]. The conclusion of this paper presented in section 5.

2. FEATURES FOR MATCHING

2.1. Modelling Orientation Difference

Due to the deformation of fingerprint, the dissimilarity of ridges between the input fingerprint and template fingerprint may be enhanced with the increase of distance between the point in foreground and the corresponding point. The relation between the distance and dissimilarity obviously nonlinear, in order to overcome the influence brought by the deformation, we model the orientation difference between the query fingerprint and the template one. We sample the overlapping region of both fingerprints at a series of circles which center on the corresponding point, see Fig.1.

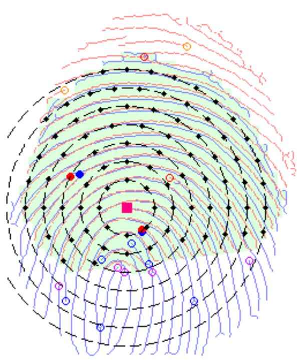
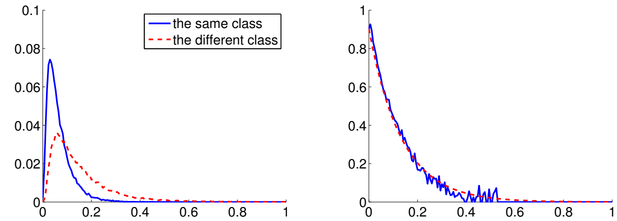


Fig. 1. Sampling on the aligned fingerprints, the dashed curve is the sampling circle, the black solid dot denote the sampled points. The fingerprints is came from 13_1.tif and 13_4.tif, DB3, FVC2002.

The least radius of sampling circle in our experiment is 24 pixels, while the interval of each radius is 16 pixels, so we can assume the sampling points on different circle is independent each other. Since orientation fields are changing slowly in the neighborhood of sampling points, the interval between sampling points should be assigned to a relative large value, thus, the sampling points in a same circle can be seen as independent. Assuming the orientation field of the query fingerprint is Ψ_R, and the template one is Ψ_T, we measure the difference $\Delta\varphi$ of a sampling point using the following equation:

$$\Delta\varphi = d(\Psi_R(x', y'), \Psi_T(x, y)) \tag{1}$$



(a) (b)

Fig. 2. (a)The condition distribution of $\Delta\varphi_i$ (b) The posterior distribution of class c_0, the dashed line is the exponent fitting curve.

Where $d(.,.)$ is defined as follows:

$$d(\alpha, \beta) = \begin{cases} \pi - (\alpha - \beta) & if \frac{\pi}{2} < \alpha - \beta \\ |\alpha - \beta| & if -\frac{\pi}{2} < \alpha - \beta \leq \frac{\pi}{2} \\ \pi + (\alpha - \beta) & if \alpha - \beta \leq -\frac{\pi}{2} \end{cases}$$

While x and y are the coordinates of a minutia, x' and y' are the projective coordinates of (x, y) according to the corresponding pairs. As to each circle, we obtain an orientation difference vector $(\Delta\varphi_i^1, \Delta\varphi_i^2, \cdots, \Delta\varphi_i^{N_i})$, where i indicate the i^{th} circle, and N_i is the number of sampling points in each circle. We use d_i to denote the sampling circle, so the posterior probability of c_k in each circle can be expressed as following:

$$P_{ki} = P(c_k|\Delta\varphi_i^1 \cdots \Delta\varphi_i^{N_i}, d_i) \tag{2}$$

Where $k = 0, 1$, c_0 denote the same class, i.e. the query fingerprint and template one belong to a same finger, while c_1 denote the different class. Since $\Delta\varphi_i^j$ and $\Delta\varphi_i^l$ are independent, using Bayesian rule [7], we can get:

$$P_{ki} = \frac{1}{P(c_k)^{(N_i - 1)}} \prod_{j=1}^{N_i} P(c_k|\Delta\varphi_i^j, d_i) \tag{3}$$

Where the $P(c_k)$ is the prior probability of each class, since we have no knowledge about each class, the $P(c_k)$ can be set to 0.5, and can be removed from P_{ki}, so the post probability can be defined as following:

$$P(c_k|\Delta\varphi_i, d_i) = \frac{P(\Delta\varphi_i|c_k, d_i)}{P(\Delta\varphi_i|c_k, d_i) + P(\Delta\varphi_i|c_{(1-k)}, d_i)} \tag{4}$$

In this paper, we train $P(\Delta\varphi_i|c_k, d_i)$ by the training database provided by FVC2002, which contains 80 fingerprints of DB3. The Fig.2(a) shows the distributions of $P(\Delta\varphi_i|c_k, d_i)$ which is the probability distributions of circle whose radius is 56, the distribution of $P(c_0|\Delta\varphi_i, d_i)$ is plotted in Fig.2(b), we fit $P(c_0|\Delta\varphi_i, d_i)$ by a exponent curve, which also be depicted in Fig.2(b) by the dashed line.

Each circle can be regarded as a classifier, so we can construct the Bayesian classifiers [7] as follows:

$$P(c_k|D) = \sum_{i \in H} P_{ki} \cdot P(d_i|D) \tag{5}$$

Where D denotes the sampled orientation difference vector $(\Delta\varphi_1^j, \Delta\varphi_2^j, \cdots, \Delta\varphi_i^j, \cdots, \Delta\varphi_M^j)$, in which $\Delta\varphi_i^j$ is the orientation difference vector of the i^th circle.$P(d_i|D)$ is the probability of the hypothesis in the final classification, it can also be considered as a weight of each circle in the classifier. In this paper, we point $P(d_i|D)$ as the equal correct rate(ECR)(i.e. 1 subtract the equal error rate(EER)),

2.2. Minutia Scoring Factors

Conventional matching method [1,5] compute matching score using the matched minutiae. On the other hand, less minutiae fail to be matched means more similar between the inquired fingerprints and template one. The second strategy we took to cope with deformation is counting the number of ARM under the sense of doubled bounding box. We label ARM by minutia scoring.

First, orientation coherence [8] describe the strength of the estimated orientation field, the coherence reached 1 if the gradient vectors within a block are parallel to each other, while it arrived at 0 if they diffuse equally over all directions. Second, because of segmenting error and the noise brought by preprocessing, those minutiae who close to boundary are less reliable then the interior minutiae. Third, the longer ridges indicate more reliable of minutiae. Finally, a minutia has higher score if there are no other minutiae appeared around it.

Combining the above four factors, we can decide weather a minutia is absolute reliable or not. A minutia satisfied the following four constraints, $coh > 0.2$, $lenbk > 16$, $len > 16$ and $min = 0$, is considered as an ARM, where coh is the orientation coherence given by [8], len denotes the length of ridge associating the minutia, lenbk is the distance between the minutia and the boundary, while min is the number of minutiae which fall into the circle whose center is the tested minutia and radius is 12 pixels.

3. THE SCHEME OF FINGERPRINT MATCH

Based on the orientation difference model and ARM, we develop a scheme to describe the similarity between the query fingerprint and the template one. First, the corresponding pair has been identified by our previous work [5]. A minutia M_k in a query fingerprint can be presented as the following vector:

$$F_R^i = (x_R^i, y_R^i, \varphi_R^i)$$

Where x_R^i and y_R^i are its coordinates in the fingerprint image, φ_R^i is the orientation of the associating ridge. So the feature vector of an inputting fingerprint can be expressed as $(F_R^1, F_R^2, \cdots, F_R^N, \Psi_R)$, where Ψ_R is the block orientation field. In the same mean,the fingerprint feature vector of the template is $(F_T^1, F_T^2, \cdots, F_T^M, \Psi_T)$. In our scheme, the final score to describe the similarity is a combination of three scores: the score of matched minutia (MMs), the score of orientation matching (OMs) and the score of ARM failing to be matched(MFs). The MMs can be defined as follows:

$$MMs = 2\frac{\sum_{i \in R, j \in T} S_{ij}}{(M+N)} \tag{6}$$

Where R and T are the minutiae set of query fingerprint and template one,respectively. M and N are the number of minutiae which fall into the overlapping area, S_{ij} is given as following:

$$S_{ij} = \begin{cases} 1 & if x_R^{'i} - x_T^j < B_x, y_R^{'i} - y_R^j < B_y and \\ & \quad d(\Psi_R^{'i} - \Psi_T^j) < B_f \\ 0 & otherwise \end{cases}$$

Where (B_x, B_y, B_f) is the bounding box vector, the $x_R^{'i}$ and $y_R^{'i}$ are the projective coordinates of x_R^i and y_R^i according to the corresponding pairs, the projective transform obey the following formula:

$$\begin{aligned} x_R^{'i} &= x_T + (x_R^i - x_R) \cdot \cos(\Delta\theta) - (y_R^i - y_R) \cdot \sin(\Delta\theta) \\ y_R^{'i} &= y_T + (x_R^i - x_R) \cdot \sin(\Delta\theta) - (y_R^i - y_R) \cdot \cos(\Delta\theta) \end{aligned}$$

Where x_R^i and y_R^i are the coordinates of the minutia, x_R and y_R are the coordinates of reference point in the query fingerprint, while x_T and y_T are the coordinates of reference point in the template fingerprint, $\Delta\theta$ is the orientation difference between the two reference points.

The OMs can be defined as the posterior probability belonging to the same class:

$$OMs = \frac{P(c_0|D)}{P(c_0|D) + P(c_1|D)} \tag{7}$$

Where $P(c_0|D)$ and $P(c_1|D)$ are given by Eq.5. The MFs is defined as following:

$$MFs = 2\frac{\sum_{i \in AR, j \in AT} S_{ij}}{(M+N)} \tag{8}$$

Where the AR and AT are the ARM sets of query fingerprint and template one, respectively. And bounding box in Eq.8 adopt the double size used in Eq.6

The final matching score fuse the above three scores as following:

$$Ms = MMs \cdot exp(-w_0(1 - OMs)) \cdot exp(-w_1 MFs) \tag{9}$$

Where w_0 and w_1 are the weights that reflect the different important influence on the final matching.

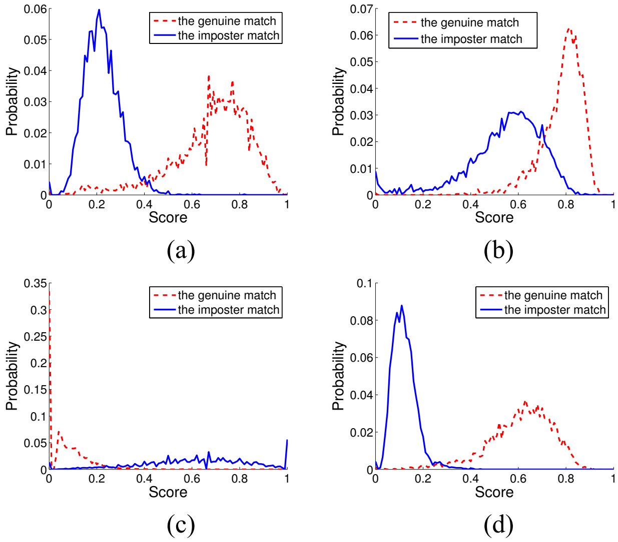


Fig. 3. The distributions of various matching score,(a)MMs (b)OMs (c)MFs (d)Ms

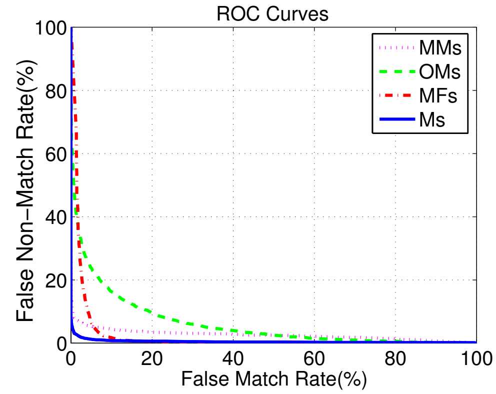


Fig. 4. The ROC curves of various matching score

4. EXPERIMENTAL RESULTS

The performance of our method has been tested on the public database, DB3 in FVC2002[6], which contains 800 fingerprint images from 100 fingers(a finger provides 8 impressions) using capacitive sensor 100SC. (Bx, By, Bf) is assigned as $(10, 10, 0.33)$, and (w_0, w_1) is specified as $(1.9, 0.08)$.

Fig.3(a) shows the distribution of MMs, the dashed line is the score distribution of the same finger, while the solid line is the different finger. Fig.3(b) and Fig.3(c) show the score distribution of OMs and MFs, respectively. As a fusing result, Fig.3(d) demonstrates the score distribution of Ms. All scores have been normalized to $[0, 1]$. Fig.4 plot the ROC curve of Ms, the ROC curves of MMs, OMs and MFs are also be depicted for a comparison. From the Fig.4, we can compute the EER of various matching method. The EER of MMs is 5.29% [5], while the EER of OMs and MFs are 13.19% and 5.49%, respectively. As shown in Fig.4, the precision of Ms outperforms all the single score, and the EER attain at 2.08%, which testify the effectiveness of our method.

5. CONCLUSIONS

In this paper, we develop a novel method to measure the similarity between two fingerprints. Based on the conventional matching method, we introduced two effective characteristics. We cope with the deformation of orientation field through modelling the difference of orientation field, and obtained the posterior probability of two classes using Bayesian method. To hurdle the deformation of minutia, we take an opposite way to conventional fingerprint matching, first, we label ARM in a given minutiae set by scoring the minutia, second, we double the size of bounding box and count the ARM failing to be matched in the sense of doubled bounding box. Finally, we fused the three scores by multiplication rule. The experimental results show the nice performance of our method.

6. REFERENCES

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