Fingerprint Matching by Incorporating Minutiae Discriminability

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Abstract

Traditional minutiae matching algorithms assume that each minutia has the same discriminability. However, this assumption is challenged by at least two facts. One of them is that fingerprint minutiae tend to form clusters, and minutiae points that are spatially close tend to have similar directions with each other. When two different fingerprints have similar clusters, there may be many well matched minutiae. The other one is that false minutiae may be extracted due to low quality fingerprint images, which result in both high false acceptance rate and high false rejection rate. In this paper, we analyze the minutiae discriminability from the viewpoint of global spatial distribution and local quality. Firstly, we propose an effective approach to detect such cluster minutiae which of low discriminability, and reduce corresponding minutiae similarity. Secondly, we use minutiae and their neighbors to estimate minutia quality and incorporate it into minutiae similarity calculation. Experimental results over FVC2004 and FVC-onGoing demonstrate that the proposed approaches are effective to improve matching performance.

1. Introduction

Although fingerprint recognition has been studied for many years and very effective solutions are nowadays available, fingerprint recognition cannot be considered a fully solved problem, and the design of accurate, interoperable and computationally light algorithms is still an open issue[13].

Among various fingerprint matching algorithm, minutiae-based matching algorithms are the most popular approaches since they are widely believed that minutiae are the most discriminating and reliable features. The key procedure of all these methods is to obtain the minutiae correspondences accurately. Due to several factors such as the rotation, translation and deformation of the fingerprints as well as the presence of spurious minutiae and the absence of genuine minutiae, the minutiae correspondences are very ambiguous. Researchers have developed kinds of local features such as ridge, orientation, minutiae and so on to reduce this ambiguity. The methods proposed in[10][9], make use of ridges associated with each minutia to get the correspondences. However, the ridge is less discriminatory feature because the ridges from different fingers or different positions in the same fingerprint may be very similar, and the ridge is easy to be affected by noise and distortion. Rotation-invariant orientation feature vectors is built by estimating the orientation distances of the sampling points surrounding a minutia and the minutia itself[19],[15], which is less affected by noise and distortion. Local minutiae structures use neighboring minutiae to increase the distinctiveness of minutiae, which can be classified into nearest neighbor-based[12],[11] and fixed radius-based[4], [16]. Recently Cappelli et al.[3] proposed 3D data structures (called Minutiae Cylinder-Code) to represent Local minutiae structures, which combine the advantages of both neighbor-based and fixed radius-based structures.

However, fingerprint minutiae tend to form clusters[17][18]. Moreover, minutiae in different regions of the fingerprint are observed to be associated with different region-specific minutiae directions, and minutiae points that are spatially close tend to have similar directions with each other[5]. These factors make the minutiae in similar regions have larger local similarity and result in many minutiae correspondences in imposter matches, which make it difficult to distinguish minutiae from such regions by local features, as shown in Figure.1. Another challenging problem in minutiae-based fingerprint matching is low-quality fingerprint matching. The performance

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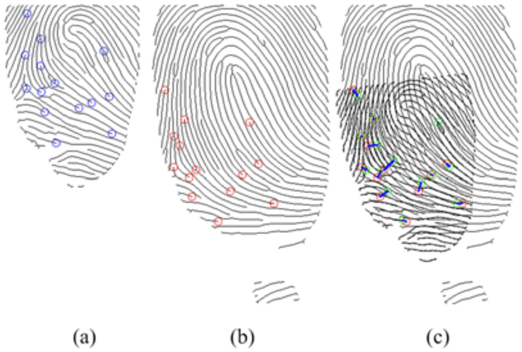

Figure 1. An illustration of imposter match. (a) and (b) are two skeleton images, (c) is the matching results of (a) and (b).

Figure 2. An illustration of low quality fingerprint image. (a) Gray fingerprint image (b) skeleton of (a).

of minutiae-based fingerprint matching relies heavily on the minutiae extraction process. During minutiae extraction, false minutiae may be extracted due to lower fingerprint image quality such as dry or wet fingers, as shown in Figure.2. Removing spurious minutiae is a very difficult problem because genuine minutiae may be removed simultaneously. In current minutiae matching algorithms, each minutia contributed equally to the fingerprint matching score. Therefore, existence of spurious minutiae will lead to more matched minutiae pairs for imposter matches, and more unmatched minutiae for genuine matches.

In this paper we will analysis minutiae discriminability from minutiae distribution and minutiae quality, and incorporate minutiae discriminability in minutiae matching algorithm. The rest of the paper is organized as follows: Section 2 provides feature extraction and fingerprint representation. Section 3 describes the proposed minutiae matching algorithm. The experimental results are reported in section 4 and conclusions are drawn in section 5.

2. Feature extraction and representation

All the features of a fingerprint are represented as $F = \{M, C\}$, where M is the local feature set related with minutiae and C is the convex hull of fingerprint foreground ($C = \{(x_i, y_i)\}_{i=1}^{N_c}$, where N_c is the number of vertices of the convex hull, (x_i, y_i) are the x and y coordinates of the ith vertex). Local features are detected on the thinned ridge map and the orientation field. The set of local features is denoted as $M = \{(m_i, Q_i, c_i, f_i)\}_{i=1}^{N}$, where N denotes the number of detected minutiae, $m_i = (x_i, y_i, \theta_i)$ includes x, y coordinates, direction respectively, f_i denotes the transform-invariant orientation feature vector corresponding to the ith minutiae, Q_i denotes minutia quality and c_i denotes the index of low discriminative type. In the following, we discuss minutiae quality and classification in detail.

2.1. Low discriminative minutiae detection

Minutia are usually treated as randomly distributed points over the foreground region of fingerprint image during the matching process. While this assumption is not the actual situation for a real world fingerprint images. Minutiae points that are spatially close tend to have very similar directions with each other [5]. We further find out that this spatial distribution characteristics of minutiae leads to high false acceptance rate with high probability, as shown in Figure 1. In our observation, such minutiae gathering regions usually occur in front of core point in left loop and right loop fingerprints and upper delta point in all fingerprints, which we call region A and region B, respectively. In this case, since the images quality are both good and local structure features are also well matched, it is hard to distinguish it from genuine match.

In this paper, we call this kind of minutiae as low discriminative minutiae and have different matching strategies for them. The following steps describe how we detect such kinds of minutiae in details:

Step 1: For each minutia m_i, compute the average minutiae direction difference $d\theta_i$ between m_i and its neighboring n minutiae. All the minutiae that satisfy $d\theta_i < \pi/4$ are selected as seed minutiae and add m_i to Q.

Step 2: For each seed minutia m_i, initialize an minutiae set Q with m_i and a stack S with m_i, respectively, and use the following expanding algorithm to find its similar minutiae.

- Step 2.1: If S is empty, then goto Step 2 for the next seed minutia, otherwise pop a minutia m_j from S.
- Step 2.2: Search for the neighboring minutia m_k of m_j that is not in Q. If position distance and direction distance of m_j and m_k are less than POS_T and DIR_T, respectively, push m_k into S, add m_k to Q and continue Step 2.2, otherwise return to Step 2.1, where POS_T and DIR_T are predetermined threshold values.

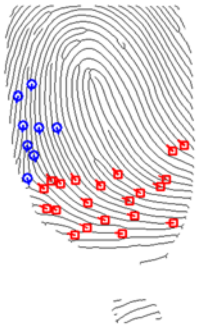

Figure 3. An illustration of low discriminative minutiae detection. Blue circle denotes minutiae from region B and red square denotes minutiae from region A.

Step 3: Judge that minutiae in Q is from region A or B by the minutiae distribution;

Step 4: If the size of set Q is larger than a threshold, then all the minutiae in Q are treated as low discriminative minutiae (A or B). It is worth noting that threshold for region A is larger than that for region B.

Figure.3 illustrates a detection result of Figure.1(b), in which blue circle denotes minutiae from region B and red square denotes minutiae from region A.

2.2. Minutiae quality

The performance of the matching algorithm highly depends on the fingerprint image quality as well as minutiae quality. For poor fingerprint image, some spurious minutiae may still exist after fingerprint enhancement and postprocessing. However, it is hard to distinguish spurious minutiae from genuine ones. When at least one of the compared two fingerprints is of low-quality, the expected minutiae pairs are more than high quality fingerprints. For imposter matches, more matched minutiae pairs means larger matching score. For genuine matches, more false minutiae will lead to more unmatched minutiae which lead to smaller matching score. Intuitively, high quality minutiae pairs should contribute more to matching score, meanwhile high quality unmatched minutiae should also contribute more penalty to matching score. It is necessary to propose a method to measure minutiae quality. While near the low-quality minutiae, there are usually some other minutiae. Therefore, we propose to use the neighboring minutiae to measure minutiae quality. First, nearest n (in our experiments n=3)minutiae center around the minutia m_i is found and the average distance d_i between the neighbor minutiae and the center minutia m_i is calculated. Then, the following piecewise function is adopted to measure minutiae quality.

$$Q_i = f_1(d_i, D_{T_1}, D_{T_2}) = \begin{cases} 0 & \text{if } d_i < D_{T_1}, \\ 1 & \text{if } d_i > D_{T_2}, \\ \frac{d_i - D_{T_1}}{D_{T_2} - D_{T_1}} & \text{otherwise.} \end{cases} \tag{1}$$

where D_{T_1} and D_{T_2} are two parameters which are determined by experience.

3. Minutiae Matching

3.1. Minutiae Similarity

In this section, we improve our previous local minutiae structure similarity estimation[2],[1] by incorporating minutiae quality. Suppose that there are N^I minutiae in the input fingerprint feature set $F^I = (M^I, C^I)$ and there are N^T minutiae in the template fingerprint feature set $F^T = (M^T, C^T)$. The calculation of local minutiae structural similarity between m_p^I and m_q^T has two stages.

In stage (1), minutia m_p^I and its neighbors are mapped on the coordinate system of m_q^T. Let $N(m_p^I, r) = \{m_{p_i}^I\}_{i=1}^{n_p}$ denote the set of the neighboring minutiae circled m_p^I within r radius in input fingerprint, including m_p^I, $N(m_q^T, r+\Delta r) = \{m_{q_j}^T\}_{j=1}^{n_q}$ denote the set of the neighboring minutiae circle m_q^T within $r+\Delta r$ radius in the template fingerprint including $m_{q_j}^T$ and T_r represent the corresponding rigid transformation from m_p^I to m_q^T. Each minutia $m_{p_i}^I$ in $N(m_p^I, r)$ is mapped to $m_{p_i}^{\prime I}$ using T_r. Then, the contribution of $m_{p_i}^I$ with respect to minutia m_p^I is calculated as

$$C_{p_i} = f_2(D(m_{p_i}^{\prime I}, m_{q_{ki}}^T), d_1, d_2) \cdot f_2(\Lambda_2(\theta_{p_i}^{\prime I}, \theta_{q_{ki}}^T), \theta_1, \theta_2) \tag{2}$$

where,

$$m_{q_{ki}}^T = \arg \max_{m_{q_j}^T \in N(m_q^T, r+\Delta r)} f_2(D(m_{p_i}^{\prime I}, m_{q_j}^T), d_1, d_2) \cdot f_2(\Lambda_2(\theta_{p_i}^{\prime I}, \theta_{q_j}^T), \theta_1, \theta_2) \tag{3}$$

where d_1 and d_2 are two distance thresholds, θ_1 and θ_2 are two direction distance thresholds, and function f, D and Λ_2 are defined as,

$$f_2(x, th_1, th_2) = 1 - f_1(x, th_1, th_2). \tag{4}$$

$$D(m_p, m_q) = \sqrt{(x_p^I - x_q^T)^2 + (y_p^I - y_j^T)^2} \tag{5}$$

$$\Lambda_2(\theta_p^I, \theta_q^T) = \begin{cases} \theta_p^I - \theta_q^T & \text{if } |\theta_p^I - \theta_q^T| \le \pi, \\ \theta_p^I - \theta_q^T - 2\pi & \text{if } (\theta_p^I - \theta_q^T) > \pi, \\ \theta_p^I - \theta_q^T + 2\pi & \text{otherwise.} \end{cases} \tag{6}$$

If C_{p_i} is larger than 0, $m^I_{p_i}$ is regarded as a local matched minutia.

In stage (2), we define two other neighboring minutiae sets: $N(m^T_q, r)$ and $N(m^I_p, r+\Delta r)$. They are similar as in stage 1. We use the same symbol T_r to represent the relative rigid transformation from m^T_q to m^I_p. Each minutia $m_{q_j} \in N(m_q, r)$ is mapped to $m'^T_{q_j}$ using T_r. The contribution of m_{q_j} to the minutia m_q is calculated as follows

$$C_{q_j} = f(D(m^I_{p_{kj}}, m'^T_{q_j}), d_1, d_2) \cdot f(\Lambda_2(\theta^I_{p_{kj}}, \theta'^T_{q_j}), \theta_1, \theta_2) \tag{7}$$

where,

$$m^I_{p_{kj}} = \arg \max_{m^I_{p_i} \in N(m^I_p, r+\Delta r)} f(D(m^I_{p_i}, m'^T_{q_j}), d_1, d_2) \cdot f(\Lambda_2(\theta^I_{p_i}, \theta'^T_{q_j}), \theta_1, \theta_2) \tag{8}$$

The structural similarity between m^I_p and m^T_q is measured using the following formula

$$MS_{pq} = \frac{\sum_{m^I_{p_i} \in N(m^I_p, r)} Q^I_{p_i} \cdot C_{p_i} \cdot TQ^T_{p_i}}{M_p + bias} \cdot \frac{\sum_{m^T_{q_j} \in N(m^T_q, r)} Q^T_{p_j} \cdot C_{q_j} \cdot TQ^I_{p_j}}{M_q + bias}, \tag{9}$$

where

$$M_p = \sum_{m^I_{p_i} \in N(m^I_p, r)} Q^I_{p_i} \cdot TQ^T_{p_i} \tag{10}$$

$$M_q = \sum_{m^T_{q_j} \in N(m^T_q, r)} Q^T_{p_j} \cdot TQ^I_{p_j} \tag{11}$$

$Q^I_{p_i}$ is the quality of minutia m_{p_i} in input fingerprint, while $TQ^T_{p_i}$ is the quality of transformed minutia m'_{p_i} in template fingerprint, $bias$ is a parameter to reduce similarity of two minutiae with small overlapped region. The calculation of $TQ^T_{p_i}$ is classified into four different conditions:

1. If m'_{p_i} is outside the convex hull of the template minutiae set. $TQ^T_{p_i}$ is zero.

2. If m_{p_i} is a local matched minutia, $TQ^T_{p_i}$ is set as the quality of minutia $m^T_{q_{ki}}$, i.e. $TQ^T_{p_i} = Q^T_{p_{ki}}$

3. If m_{p_i} is not a local matched minutia and the distance between m'_{p_i} and its nearest neighbor is large than $D_{T_2}/2$, $TQ^T_{p_i}$ is set as the quality of its nearest neighbor.

4. Otherwise, $TQ^T_{p_i}$ is set 1 directly.

The calculation of $TQ^I_{p_j}$ is similar to $TQ^T_{p_i}$.

The local orientation-based descriptor proposed by Tico and Kuosmanen [19] has been used to find potential matches. In this method, the descriptor consists of the orientation distances between the minutia and the sampling points around the minutia in a circular pattern. Suppose that m^I_p is a minutia in the input fingerprint, m^T_q is a minutia in the template fingerprint, and $f^I_p = \{\alpha_{k,l}\}$ and $f^T_q = \{\beta_{k,l}\}$ are their corresponding transform-invariant feature vectors. The orientation similarity between these two feature vectors is calculated as

$$OS_{pq} = 1/K \sum_{l=1}^{L} \sum_{k=1}^{K_l} s(\Lambda_1(\alpha_{k,l}, \beta_{k,l})) \tag{12}$$

where $\Lambda_1(\theta_1, \theta_2)$ is the orientation distance between θ_1 and θ_2, and $s(x)$ denotes a similarity value with respect to the orientation difference x as follows.

$$s(x) = e^{-x/(\pi/16)} \tag{13}$$

Two similarity functions are combined to measure the similarity between the minutiae pair by the product rule

$$s_{pq} = OS_{pq} \cdot MS_{pq} \tag{14}$$

If m^I_p and/or m^T_q are from low discriminative region A or B, there usually are many matched minutiae pairs. Matching score (17) is not only decided by matched minutiae number but also minutiae similarity. Therefore, we can reduce matching score by reducing the similarity of minutiae from region A or B. s_{pq} is revised by the following way.

$$s_{pq} = \begin{cases} \mu_A \cdot s_{pq} & \text{if } m^I_p \text{ or } m^T_q \text{ is from region A} \\ \mu_B \cdot s_{pq} & \text{if } m^I_p \text{ or } m^T_q \text{ is from region B} \end{cases} \tag{15}$$

3.2. Minutiae pairing and Matching score computation

Let $\{p_k\}_{k=1}^{N_I}$ and $\{q_l\}_{l=1}^{N_T}$ denote two minutiae sets from input and template fingerprint respectively, and $s = \{s_{kl}\}_{k=1,l=1}^{N_I,N_T}$ denote the set of similarity degrees between two minutiae sets. However, a minutia may exhibit a large similarity degree with more than one minutia. In order to identify the most distinguishable pairs of corresponding minutiae, the similarity degree set s is normalized by the method proposed by Feng [6] as

$$ns_{pq} = \frac{s_{pq} \cdot (N^T + N^I - 1)}{\sum_{k=1}^{N^I} s_{kq} + \sum_{k=1}^{N^T} s_{pk} - s_{pq}} \tag{16}$$

There are usually two methods for minutiae alignment: alignment by one minutiae pair or alignment by two minutiae pairs. Two minutiae pairs based-alignment is more accurate to estimate translation and rotation parameters. First, minutiae pairs are sorted in decreasing order of NS and the top K minutia pairs are used as the reference pair candidates. For every two reference minutiae pairs, the average

Table 1. Results of the proposed matching algorithm over FVC2004 databases (%)

Databases	EER	FMR100	FMR1000	ZeroFMR
DB1	1.69	2.04	4.57	7.00
DB2	2.99	4.32	6.43	8.07
DB3	1.34	1.75	4.32	5.93
DB4	1.25	1.29	2.18	6.71

Table 2. Average results comparison of proposed algorithm with that of top three participants of FVC2004 (%)

Algorithms	EER	FMR100	FMR1000	ZeroFMR
Proposed	**1.82**	**2.35**	**4.38**	**6.93**
P101	2.07	2.54	4.70	6.21
P047	2.10	2.96	4.61	6.59
P071	2.30	2.73	5.10	10.01

translation and rotation are used to align two minutiae sets. The score of each alignment is calculated using the following formula.

$$score = \frac{2\sum_{k=1}^{n} s_{i_k j_k}}{CN^I + CN^T}(1 - \exp(-n/\sigma)) \qquad (17)$$

where n denotes the number of matched minutiae, $\{(i_k, j_k)\}_{k=1}^{n}$ denotes the matched minutiae pair set, CN^I and CN^T denote the number of minutiae that should be matched for the input fingerprint and the template fingerprint respectively, and σ is a control parameter. The maximal score of these alignments is selected as the matching score.

4. Experimental results

We conduct a series of experiments on FVC2004 and online evaluation version FVC-onGoing to evaluate the performance of the proposed algorithm.

4.1. Performance on FVC2004

There are four databases in FVC2004. Each database set contains 800 fingerprint images captured from 100 different fingers, 8 images for each finger. The performances of the proposed algorithm on four FVC2004 databases are shown in Table.1. We see that our algorithm perform well on all four databases, especially on DB1 which is well known for its low image quality and large distortion. We also compare the average performance of our algorithm with that of top three participants of FVC2004 in Table.2. According to the ranking rule in terms of EER in FVC2004, our algorithm can rank the first place and is much better than P101. The detailed performances of FVC2004 algorithms can be seen from the website [8].

Table 3. Performance comparison of MntModel 1.0 with other submitted algorithms over FV-HARD (%)

Algorithms	EER	FMR100	FMR1000	ZeroFMR
EMB9200 2.3	0.70	0.65	1.25	2.39
GBFRSW 1.3.2.0	0.74	0.74	1.44	2.82
MntModel 1.0	**1.26**	**1.37**	**2.80**	**4.91**
MM_FV 3.0	1.53	1.81	3.04	4.08

4.2. Performance on FVC-onGoing

FVC-onGoing is a web-based automated evaluation system for fingerprint recognition algorithms[14]. Tests are carried out on a set of sequestered datasets and results are reported on-line by using well known performance indicators and metrics. FVC-onGoing provides two benchmark areas, these are fingerprint verification and fingerprint matching, to evaluate fingerprint recognition algorithms. In fingerprint verification, algorithms submitted to these benchmarks are required to enroll fingerprints into proprietary or standard templates and to compare such templates to produce a similarity score. In fingerprint matching, no fingerprint enrollment (feature extraction) is required, only the minutiae matching algorithms are evaluated using a standard minutiae-based template format [ISO/IEC 19794-2 (2005)]. In each benchmark, there are mainly two benchmarks. One of them is STD, in which fingerprint images are acquired in operational conditions using high-quality optical scanners. The other one is HARD, which contains a relevant number of difficult cases (noisy images, distorted impressions, etc.) that makes fingerprint verification more challenging.

We submitted our algorithm, which named “MntModel 1.0” on FVC-onGoing website, to both benchmark areas. The submitted algorithms are the same except the orientation field. For fingerprint matching, we reconstructed fingerprint orientation field by using the method proposed by Feng[7], while for fingerprint verification, we use the original orientation field.

The comparison results are reported in the Table 3, 4, 5 and 6. Except our algorithm, all the compared algorithms are coming from commercial area. According to EER, our algorithm can rank 3, 4, 4 and 5 over FV-HARD, FV-STD, FMISO-HARD and FMISO-STD, respectively. In FMISO-HARD and FMISO-STD, our algorithm’s ZeroFMR is very comparative, which ranks 1 and 2, respectively. For the same input minutiae set, our algorithm can reduce the false acceptance more efficiently.

5. Conclusion

In order to improve the performance of minutiae-based fingerprint matching algorithm, we take the minutiae discriminability into account. In the light of minutiae distri-

Table 4. Performance comparison of MntModel 1.0 with other submitted algorithms over FV-STD (%)

Algorithms	EER	FMR100	FMR1000	ZeroFMR
GBFRSW 1.3.2.0	0.12	0.04	0.16	1.76
EMB9200 2.3	0.18	0.11	0.19	0.40
MM_FV 3.0	0.28	0.18	0.39	0.99
MntModel 1.0	**0.29**	**0.17**	**0.51**	**2.01**

Table 5. Performance comparison of MntModel 1.0 with other submitted algorithms over FMISO-HARD (%)

Algorithms	EER	FMR100	FMR1000	ZeroFMR
Triple_M_ISO 1.2	1.10	1.64	3.16	11.61
EMB9200 2.41	1.11	1.15	2.08	4.74
SFCore 1.0	1.41	1.58	2.70	19.81
MntModel 1.0	**1.59**	**1.76**	**2.82**	**4.71**

Table 6. Performance comparison of MntModel 1.0 with other submitted algorithms over FMISO-STD (%)

Algorithms	EER	FMR100	FMR1000	ZeroFMR
EMB9200 2.41	0.23	0.16	0.29	0.70
Triple_M_ISO 1.2	0.23	0.23	0.36	1.61
SFCore 1.0	0.26	0.18	0.35	1.22
Tiger ISO 0.1	0.32	0.23	0.45	1.35
MntModel 1.0	**0.38**	**0.33**	**0.51**	**1.07**

bution characteristic, we discover two low discriminative regions in fingerprint and propose an effective approach to detect minutiae in such regions. In order to improve low quality fingerprint matching, we propose to use neighbors of a minutia to measure its quality and incorporate the quality to minutiae similarity calculation. Experimental results over FVC2004 and FVC-onGoing demonstrate that the proposed approaches demonstrate the proposed approaches is effective. However, matching processes including minutiae similarity calculation, alignments and orientation reconstruction all are time consuming. The main direction in the future is to speed up the algorithm.

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