Fingerprint Verification Based on Multistage Minutiae Matching

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Abstract

This paper proposes a novel and distortion-tolerant fingerprint verification technique based on multistage minutiae matching. In the first stage, the local similarities of minutiae between two fingerprints are evaluated by matching their local orientation fields and local minutiae topologic structures. In the second stage, the top 5 minutia pairs obtained in the first matching stage are used as the reference minutiae pairs to align two minutia sets, and a set of matched minutia pairs is obtained by matching the aligned two minutia sets. In the third stage, the set of matched pairs obtained in the second stage are matched again by matching two global topologic structures constructed based on the set of matched pairs. The final matching score is obtained based on the set of matched pairs obtained in the second matching stage and the separate matching scores calculated in three stages. Experiments on database of FVC2002 show that this fingerprint matching technique is effective.

1. Introduction

Fingerprints have long been used for person recognition due to their uniqueness and immutability. Minutia matching is the most well-known and widely used method for fingerprint matching. Several approaches to Minutiae-based fingerprints matching have been proposed in the literatures. Jiang and Yau proposed a minutia matching technique, in which the local structure was used to find the correspondence of two minutiae sets and increase the reliability of the global matching [1]. Jain et al. proposed an alignment-based matching algorithm, in which the ridges associated with the minutiae were used to align the input minutiae with the template minutiae and a bounding box was proposed to match the aligned minutiae [2]. Some improvements of this approach were proposed in [3]. Zsolt and Kovacs proposed a matching method based on triangular matching to cope with the strong deformation of fingerprint images due to static friction or finger rolling, and the matching was validated by Dynamic Time Warping [4]. Tico and Kuosmanen proposed a matching algorithm based on a fingerprint representation scheme that relies on describing the orientation field of the fingerprint pattern with respect to each minutia detail [5]. Ratha et al. proposed a matching technique based on graph representation constructed for both the input fingerprint and the template fingerprint using the fingerprint minutiae features [6].

The key aspect of all these methods is to obtain the minutiae correspondences accurately. However, using bounding box to pair minutiae may lead an inaccurate conclusion because the size of bounding box should be evaluated according to different fingerprint's nonlinear deformations, but this course is very difficult. The ridges and orientation from different fingers of different positions in the same fingerprint may be very similar. The local structure is less reliable feature because it is determined only by a small subset of the minutiae. Prints from the same finger may only have few similar structures due to the presence of spurious. Motivated by above observations, this paper proposes a novel method based on fingerprint matching in various aspects and using various features to improve the matching reliability. The proposed approach’s flowchart is depicted in Fig.1.

2. First stage matching

In this matching stage, we examine the local similarity of two fingerprints by matching their local orientation fields and local topologic structures.

The orientation field provides a rough description of the fingerprint pattern that can be estimated with reasonable accuracy even from noisy input images [2]. If a true alignment between two fingerprints is obtained, the orientation fields of two fingerprints in the overlapped common region can be matched with a high accuracy.
Given a minutia point \( m(x, y, \theta) \), we define the local orientation field, which is illustrated in Fig.2, as follows:

With the minutia point as center, we plot 4 concentric circles of radii \( r_i \), \( r_i = 3\tau \), \( r_i = r_{i-1} + 3\tau \), where \( \tau \) denotes the average fingerprint ridge period. Through the minutia point we also plot 4 lines \( l_j \), \( l_j = l_{j-1} + \pi/4 \) in a counterclockwise manner. Denoting the local ridge orientation estimated in the intersection point \( p_{ij} \) of circle \( r_i \) and line \( l_j \) by \( \theta_{ij} \), we define the local orientation field of a minutia as follows:

\[
D = \{ D_{ij} = d\phi(\theta_{ij}, \theta); 4 \geq i \geq 1, 8 \geq j \geq 1 \} \quad (1)
\]

where

\[
d\phi(t_1, t_2) = \begin{cases} 
  t_1 - t_2, & \text{if } -\pi < t_1 - t_2 < \pi \\
  2\pi + t_1 - t_2, & \text{if } t_1 - t_2 < -\pi \\
  2\pi - t_1 + t_2, & \text{if } t_1 - t_2 > \pi 
\end{cases} \quad (2)
\]

Let \( D_{ij} = 100 \) if the point \( p_{ij} \) falls in the fingerprint background region, such as the \( p_{43} \) and \( p_{44} \) in Fig.2.

Let \( D(a) = \{ \alpha_a \} \) and \( D(b) = \{ \beta_b \} \) denote the local orientation fields associated with two minutiae \( p_i \) and \( q_j \), respectively. A similarity function between two local orientation fields is defined as:

\[
S_o(p_i, q_j) = \frac{1}{K} \sum_{j=1}^{4} \sum_{i=1}^{8} s_{ij}
\]

where \( K \) is the total number of \( p_{ij} \) with \( \alpha_{ij} \neq 100 \) and \( \beta_{ij} \neq 100 \), and \( s_{ij} \) is calculated as:

\[
s_{ij} = \begin{cases} 
  \cos(2\alpha_{ij} - 2\beta_{ij}), & \alpha_{ij} \neq 100 \text{ and } \beta_{ij} \neq 100 \\
  0, & \alpha_{ij} = 100 \text{ or } \beta_{ij} = 100 
\end{cases} \quad (4)
\]

If the matching score \( S_o(a, b) \) is larger than a certain threshold \( T_s \), we match the local minutiae topologic structures \( T(a) \) and \( T(b) \) using the method presented in literature [1], otherwise we continue to match next pair of minutiae.

The integrated matching score of \( p_i \) and \( q_j \) is as follows:

\[
S_f(p_i, q_j) = \lambda S_o(p_i, q_j) + (1 - \lambda) S_m(p_i, q_j)
\]

where \( \lambda \) is a weight vector that specifies the weight associated with each component of the feature vector; \( S_m(a, b) \) is the matching score of \( T(a) \) and \( T(b) \).
3. Second stage matching

In this matching stage, we examine the global similarity of two fingerprints by alignment-based minutia matching algorithm.

To begin with, using the top 5 pairs obtained in first stage matching as reference pairs, we convert each minutia point to the polar coordinate system by following equation [1]:

\[
\begin{bmatrix}
  r_i \\
  e_i \\
  \theta_i
\end{bmatrix} = \begin{bmatrix}
  \sqrt{(x_i - x')^2 + (y_i - y')^2} \\
  d\phi\left(\tan^{-1}\left(\frac{y_i - y'}{x_i - x'}\right), \theta'\right) \\
  d\phi\left(\theta_j, \theta'\right)
\end{bmatrix}
\]

(6)

where \((x_i, y_i, \theta_i)\) is the coordinate of a minutia, \((x', y', \theta')\) is the coordinate of the reference minutia, \((r_i, e_i, \theta_i)\) is the representation of the minutia in polar coordinate system.

Let \(P = ((r_i, e_i, \theta_i), ..., (r_N, e_N, \theta_N))\) and \(Q = ((r_i, e_i, \theta_i), ..., (r_N, e_N, \theta_N))\) denote the converted set of \(M\) minutiae in the template fingerprint and the converted set of \(N\) minutiae in the input fingerprint, respectively.

Let each minutia \(p_i = (r_i, e_i, \theta_i)\) compare with each minutia \(q_j = (r_j, e_j, \theta_j)\) in \(Q\). If the \(q_j\) is in the bounding box of \(p_i\) and \(d\phi(\theta_i - \theta_j) \leq \theta_{\text{lim}}\), then the matching score of two minutiae is calculated using the (7), and the pair \((p_i, q_j)\) is added to matched pair set which is denoted as \(V = ((v_i^p, v_i^q), ..., (v_N^p, v_N^q))\), where \((v_i^p, v_i^q) = (p_i, q_j)\). In cases when a minutia has more than one matched minutiae, the pair with the maximal score is believed to be the correct one.

\[
S_i(p_i, q_j) = 2 - \frac{|e_i^p - e_i^q|}{0.3 * \max(e_i^p, e_i^q)} - \frac{d\phi(e_i^p, e_i^q)}{D}
\]

(7)

where \(D\) is the specified maximal angle difference.

To perform each matching test by choosing a candidate reference pair to align the two fingerprints, we can achieve a matched pair set. The set that have the most pairs will be chosen to the third stage matching. If there are more than one sets have the same most pairs number, the sum of matching scores in each set will be calculated as \((8)\) and the one with the highest value will be chosen.

\[
S = \sum_{i=1}^{K} S_i(v_i^p, v_i^q)
\]

(8)

4. Third stage matching

In this matching stage, we re-examine the global similarity by matching the global topologic structures constructed on the best-matched pair set obtained in the second matching stage.

Represent the best matched pair set \(V = ((v_i^p, v_i^q), ..., (v_N^p, v_N^q))\) as template topologic structure \(TS_p = (v_i^p, E_i^p)\) and input topologic structure \(TS_q = (v_i^q, E_i^q)\) respectively, where \(E_{ij}\) denote an edge between minutiae \(v_i^p\) and \(v_j^q\). The two structures are matched by matching the corresponding line, and the matching score of two edges are calculated as:

\[
S_{\text{edge}}(E_i^p, E_j^q) = 1 - \frac{d_{ij}}{0.2 * \max(d_{ij}^p, d_{ij}^q)}
\]

(9)

where \(d_{ij}\) is the distance between \(v_i^p\) and \(v_j^q\).

The matching score of \(v_i^p\) and \(v_i^q\) is the average matching score of two structure’s corresponding lines with \(v_i^p\) and \(v_i^q\) as the origin respectively, which can be calculated as

\[
S_i(v_i^p, v_i^q) = \frac{1}{K-1} \left( \sum_{j=1, j\neq i}^{K} S_{\text{edge}}(E_i^p, E_j^q) \right)
\]

(10)

Fig.3 illustrates the matching process of global topologic structure using four minutiae.

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Fig. 3. Illustration of global topologic structure matching
5. Resolution stage

Based on the best-matched pair set obtained in second matching stage, the matching score of two fingerprints can be calculated as:

\[
S = \frac{\sum_{i=1}^{N} (l + S_i(v^p_i, v^q_i) \times S_i(v^p_i, v^q_i) \times S_i(v^p_i, v^q_i))}{M + N}
\]

where \(s_i, s_p, s_q\) are the first stage matching score, the second stage matching score and the third stage matching score respectively. \((v^p_i, v^q_i) \in V\) is the matched pair obtained in the second matching stage. \(M\) and \(N\) are the minutia numbers of input fingerprint and template fingerprint respectively.

6. Experimental results

The FVC2002 DB1_A databases in which there are 100×8 images, is used to test the performance of our approach. The performance evaluation method in [7] is adopted. The total number of genuine and impostor matching attempts is \(((8*7)/2)*100=2800\) and \(((100*99)/2)=4950\), respectively. We realized the method proposed in literature [1] to compare with our approach. Our approach and literature [1] approach both use the same enhancement algorithm in literature [8]. The experimental results (Fig.4 and Table 1) show that the accuracy of our approach is better than the method proposed in literature [1].

### Table 1. Experimental results of DB1_A

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>EER</th>
<th>FMR100</th>
<th>FMR1000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Literature [1]</td>
<td>2.81%</td>
<td>4.18%</td>
<td>6.75%</td>
</tr>
<tr>
<td>Our approach</td>
<td>1.32%</td>
<td>1.53%</td>
<td>2.77%</td>
</tr>
</tbody>
</table>

Fig. 4. **Roc curve of two methods on DB1_A**

7. Conclusions

A novel fingerprint verification technique, which matches fingerprints in various aspects and using various features, is presented. In the first stage, we examine the local similarities of two fingerprints by matching their local orientation fields and local minutiae topologic structures. In the second stage, we examine the global similarity of two fingerprints by alignment-based minutia matching algorithm. In the third stage, we re-examine the global similarity by matching the global topologic structures constructed on the best-matched pair set obtained in the second matching stage. The final matching score is obtained based on the set of matched pairs obtained in the second matching stage and the separate matching scores calculated in three stages. The usefulness of the proposed approach is confirmed in the experiment conducted, which showed good performance in reliability and accuracy.

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References