Fingerprint Registration Using Centroid Structure and Line Segments [1]

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Summary
In this paper a novel distortion-tolerant fingerprint registration method based on centroid structure vector (CSV) and Vector Line Segment (VLS), is proposed. In this method, minutia features of the query fingerprint are clustered into various clusters and a set of VLS is extracted. Several likely transformations between the query and the template images are estimated by using VLS sets. Then, CSV under each likely transformation is constructed by using the centroids of minutia clusters. The fine transformation is finally determined by the number of VLS pairs together with the similarity level of CSV. Experiment results show that this algorithm is an effective and efficient one for aligning fingerprints with a small number of minutia and heavy distortions. Such situations are often encountered in forensic applications.

Key words:
Fingerprint, Registration, Clustering, Minutia.

Introduction

Fingerprint registration means to recover the geometric transformation between two fingerprint images (the query and the template images) to align the two fingerprints and their features, and it is an important stage in most of fingerprint matching algorithms [1]. Although there exist some orientation field (OF)-based [1] and texture-based [2] fingerprint registration methods, most of fingerprint matching algorithms that provide real-time processing and high confidence are so far based on minutiae registration. The major reason for the wide usage and popularity of the minutiae-based registration is that the minutiae of a fingerprint are the most discriminating and reliable features [3, 4].

The minutia extracted from a fingerprint image can be characterized by a list of attributes that includes: (1) the type of minutia (ending or bifurcation), (2) the minutia position, (3) the minutia direction which is defined as the angle that the ridge associated with the minutia makes with the horizontal axis [5], (4) the local structure composed of the neighboring minutiae, (5) the global structure constructed by all minutiae.

Minutia-based registration is a difficult problem for the following reasons:

- The positions and orientations of the minutiae may be changed due to the effect of pressing a convex elastic surface (the finger) on a flat surface (the sensor).
- The overlapped areas between two fingerprints (for example Latent and Tenprint Images) may be disconnective.
- Some genuine minutiae may be missed and some spurious minutiae may be present.

A number of approaches for minutia-based registration have been proposed in the literature. These include methods based on a reference minutia pair [5, 6, 7] and on a local structure pair [8, 9, 10]. In [6] and [7], the minutia pair that results in the maximum number of the matching pairs is chosen as the reference pair. The authors reported good performance. However, the number of matching pairs obtained can not be considered reliable because the genuine minutiae may not have counterpart and the spurious minutiae may have a few counterpart due to deformation of the fingerprints and defects of the feature extraction algorithm. The method proposed by Tico and Kuosmanen [5] uses the minutia pair that exhibits the largest possibility value to estimate geometric transformation. In [8] and [9], the best-matched structure pair serves as the correspondence of the two fingerprints. However, we can argue that the local structure is not a well distinct feature because it is determined only by a small subset of the minutiae. The local structure may have many similar structures in the mate image and a spurious structure pair may become the “best-matched” structure pair. In [10], the transformation parameter is estimated by clustering and also only based on the local structure.

This paper presents a novel minutia-based fingerprint registration method which take both local structures (vector line segments) and the global structure (centroid structure) into account. As the minutiae of the query image

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are clustered according to the distance between minutiae, a set of vector line segments, each of which is composed of two minutiae from one cluster, is first constructed. Several likely transformations between the query and template fingerprints are estimated based on the paired vector line segments (one-to-many mapping possibly). The centre of the cluster, in which each minutia has a corresponding minutia in the template fingerprint, is then calculated and used to construct the Centroid Structure Vector CSV. The number of vector-line-segment pairs with the same transformation parameter together with the similarity level of CSV finally determines the global geometric transformation parameter. Although the step of transformation parameter clustering in our method is similar to that of Germain et al [10], the combination of VLS and CSV totally different from the local structure used by Germain et al. makes our alignment algorithm unique and robust. Due to inexact extraction of minutia positions and nonlinear deformations, the registration algorithm should be capable of tolerating, to some extent, the deformations. Usually, such an elastic registration can be achieved by placing a bounding box around each template minutia, which specifies all the possible positions of the corresponding template minutia with respect to the query minutia [11]. This method does not provide a satisfactory performance in practice, because local deformations may be small while the accumulated global deformations can be quite large. In [12], an adaptive bounding box is employed to compensate the minutia localization errors and nonlinear deformations. In our registration algorithm, under the global transformation a group of local transformation parameters is also generated for corresponding feature cluster pairs. Different bounding boxes will be used at the local and global transformations.

The paper is organized as follows. In section 2, 3 details attendant to the Centroid Structure Vector and Vector Line Segment are described. The registration algorithm is described in section 4. Section 5 gives the experimental results, and discussions are presented in section 6.

2. Centroid Structure

Let *F* be a set of minutiae which consists of F_k, *k=1,…,M*. A minutia F_k extracted from a fingerprint image can be described by a feature vector FV_k with position $p_k(x_k, y_k)$ and local ridge direction ϕ_k:

$$FV_k = (p_k(x_k, y_k), \phi_k)^T \tag{1}$$

To simplify the description of our algorithm, we define a function $Sub(\phi_1, \phi_2)$ for the difference between two angles, ϕ_1 and ϕ_2, $-\pi \le \phi_1, \phi_2 < 2\pi$, as follows:

$$Temp = (\phi_2 - \phi_1)\bmod(2\pi)$$

$$Sub(\phi_1, \phi_2) = \begin{cases} Temp, & if\ -\pi < Temp \le \pi \\ temp + 2\pi, & if\ temp \le -\pi \\ 2\pi - temp, & if\ temp > \pi \end{cases} \tag{2}$$

The set of query minutiae, F^q, is first clustered into several feature clusters (Figure 1b) FC_i, *i=1, 2, …, N*. The clustering method used here is Hierarchical Clustering Method. The centroid C_i of FC_i is defined as:

$$C_i = (p_i(x_i, y_i), \phi_i)^T = \frac{1}{m_i} \sum_{FV \in FC_i} FV \tag{3}$$

where m_i is the number of minutiae in FC_i and FV is the feature vector of a minutia from FC_i. A centroid structure is illustrated in Figure 1d, and is described by edge d_{ij}, radial angle θ_{ij} and ridge direction φ_{ij} between two centroids. d_{ij}, θ_{ij} and φ_{ij} are calculated using X.D.Jiang's [9] equations (3, 4, 5) respectively. Centroid Structure vector CSV is defined as:

$$\begin{aligned} CSV &= (cv_{12}, cv_{13}, \cdots cv_{ij}, \cdots cv_{N-1N})^T, i < j \\ cv_{ij} &= (d_{ij}, \theta_{ij}, \varphi_{ij})^T \qquad i, j = 1,2, \cdots N \end{aligned} \tag{4}$$

Let $CSV(q)$ and $CSV(t)$ denote two $CSVs$ from the query fingerprint and template fingerprint respectively. Let D_{nf} denote the maximum distance by which two matching edges are allowed to differ in their Euclidean distance. Let Φ_{nf} denote the maximum allowed difference in rotation angle. We use the following formula to evaluate the similarity between two corresponding $CSVs$:

$$\begin{aligned} CsvDis(q,t) &= \frac{1}{N_{csv}} \sqrt{\sum_{i=1, i \ne j}^{N} \sum_{j=1}^{N} Dcv_{ij}^T \cdot Dcv_{ij}} \\ Dcv &= \left(\frac{d_q - d_t}{D_{nf}}, \frac{\theta_q - \theta_t}{\Phi_{nf}}, \frac{\varphi_q - \varphi_t}{\Phi_{nf}}\right) \end{aligned} \tag{5}$$

where N_{csv} is the number of elements of the CSV.

If each minutia in one feature cluster FC_i^q from the query fingerprint has a corresponding minutia in the feature cluster FC_i^t from the template fingerprint, FC_i^q and FC_i^t are corresponding feature cluster pair and the centroid C_i^q of FC_i^q and centroid C_i^t of FC_i^t are the corresponding centroid pair. Two centroid structures from two images of the same finger will be similar. Compared with the directly constructed global structure using all minutiae, the centroid structure is simpler. As a result, the similarity level computation between two CSV is speedy.

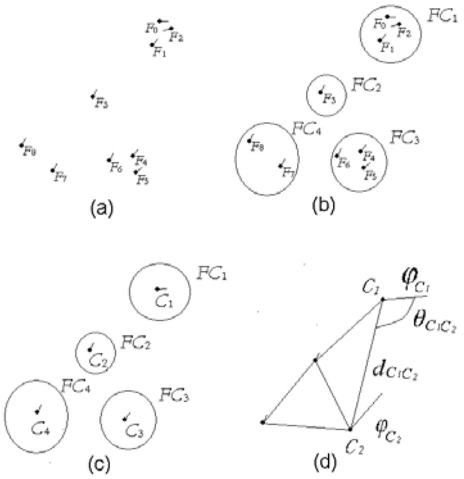

Fig. 1 The minutia clustering and CSVs. (a) The original minutia set. (b) The minutia feature clusters. (c) The cluster centers. (d) The centroid structure

If each minutia in one feature cluster FC_i^q from the query fingerprint has a corresponding minutia in the feature cluster FC_i^t from the template fingerprint, FC_i^q and FC_i^t are corresponding feature cluster pair and the centroid C_i^q of FC_i^q and centroid C_i^t of FC_i^t are the corresponding centroid pair. Two centroid structures from two images of the same finger will be similar. Compared with the directly constructed global structure using all minutiae, the centroid structure is simpler. As a result, the similarity level computation between two CSV is speedy.

3. Vector Line Segment

Definition 1: In the rectangular coordinate system if two minutiae from the same feature cluster, are apart a distance D and $D_{\min} \le D \le D_{\max}$, this two minutiae forms a line segment, or LS.

Vector Line Segment VLS similar to the minutia local structure with 1-nearest neighbor in [9], can be described with the relative distance d_{ab}, minutia direction φ_{ab} and radial angle θ_{a_ab} between two minutiae (see Fig. 2)

Suppose that there are VLS^q constructed by two minutiae F_a^q and F_b^q from the query fingerprint and VLS^t constructed by two minutiae F_a^t and F_b^t from the template one. Two VLSs are corresponding pair if the following relations are all satisfied,

$$\begin{aligned} \partial d &= abs(VLS^q.d_{ab} - VLS^t.d_{ab}) < T_d \\ \partial\varphi &= abs(sub(VLS^q.\varphi_{ab}, VLS^t.\varphi_{ab})) < T_\varphi \\ \partial\theta &= abs(sub(VLS^q.\theta_{ab}, VLS^t.\theta_{ab})) < T_\theta \end{aligned} \quad (6)$$

where T_d, T_φ and T_θ are thresholds for distance, minutia direction and radial angle respectively. The distance between VLS^q and VLS^t is then defined as follows, which is also used to evaluate the similarity level between the two VLSs:

$$VlsDis(q,t) = \sqrt{(\frac{\partial d}{D_{nf}})^2 + (\frac{\partial\varphi}{\Phi_{nf}})^2 + (\frac{\partial\theta}{\Phi_{nf}})^2} \quad (7)$$

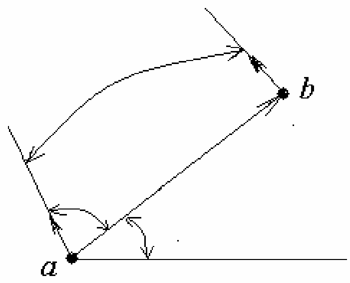

Fig. 2 The vector line segment.

Suppose TP as the transformation related to two corresponding VLSs from the query fingerprint and the template fingerprint respectively. TP is represented by 3-tuple $TP=(\Delta\theta,\Delta x,\Delta y)$ and calculated by

$$\begin{aligned} &\Delta\theta = (sub(F_a^q.\varphi_a, F_a^t.\varphi_a) + sub(F_b^q.\varphi_b, F_b^t.\varphi_b) \\ &+ sub(VLS^q.\theta_{ba}, VLS^t.\theta_{ba}))/3 \\ &\Delta x = f_x(x,y,\Delta\theta) = ((F_a^t.x_a + F_b^t.x_b) \\ &- ((F_a^q.x_a + F_b^q.x_b)\cos(\Delta\theta) \\ &- (F_a^q.y_a + F_b^q.y_b)\sin(\Delta\theta)))/2 \\ &\Delta y = f_y(x,y,\Delta\theta) = ((F_a^t.y_a + F_b^t.y_b) - \\ &((F_a^q.y_a + F_b^q.y_b)\cos(\Delta\theta) \\ &+ (F_a^q.x_a + F_b^q.x_b)\sin(\Delta\theta)))/2 \end{aligned} \quad (8)$$

Definition 2: Suppose that there are a corresponding VLS pair A with transformation $TP_A=(\Delta\theta_A,\Delta x_A,\Delta y_A)$ and another corresponding VLS pair B with transformation $TP_B=(\Delta\theta_B,\Delta x_B,\Delta y_B)$. We think that B is consistent with A if the following formulas are all satisfied,

$$\begin{aligned} &abs(\Delta\theta_B - \Delta\theta_A) < T_{\Delta\theta} \\ &abs(\Delta x_B - \Delta x_A) < T_{\Delta x} \\ &abs(\Delta y_B - \Delta y_A) < T_{\Delta y} \end{aligned} \quad (9)$$

where $\Delta x_A = f_x(x_A, y_A, \Delta\theta_A)$, $\Delta x_B = f_x(x_B, y_B, \Delta\theta_A)$, $\Delta y_A = f_y(x_A, y_A, \Delta\theta_A)$ and $\Delta y_B = f_y(x_B, y_B, \Delta\theta_A)$. $T_{\Delta\theta}$, $T_{\Delta x}$ and $T_{\Delta y}$ are thresholds.

Line Segments are the local structures used in our alignment algorithm. Generally speaking, the more minutiae a local structure contains, the more discriminative information it has. However in case that there are few (e.g. less than 15) minutiae extracted from the fingerprint image, or there are spurious minutiae generated from poor-quality images, which are often encountered situations for latent fingerprint images, choosing a local structure with only two minutiae may be a good alternative. VLS is simple and independent from rotation and translation of the fingerprint. The deformation of the line segment is not serious since VLS consists of minutiae from a small area. Although two fingerprints from different fingers may have many similar VLSs due to their simple structure, many of the local structure correspondences will generate the same transformation parameters and accumulate a large number of votes for the hypothesized match only when a genuine match exists. In other words, only when two fingerprints are from the same finger, many corresponding VLS pairs will have consistent transformations. In our algorithm, the most likely transformation will be acquired by transformation parameter clustering similar to Germain's [10].

4. Registration Algorithm

Firstly, we estimate a set of transformation parameters by exploiting the consistency of VLS pairs. Then, we find the most possible transformation of two fingerprints by taking the similarity level of two CSVs into account.
The steps of our registration algorithm are given below:

1) **Constructing the query VLS set**: Let f_i and f_j denote the number of times minutiae i and j have been selected respectively. S_Q is the set of VLS^q from the query fingerprint. N_{vls} is the number of elements of S_Q. M is the number of minutiae extracted from the query fingerprint.

```
Step 1: N_vls = 0
    For 1≤i≤M { f_i = 0}
    f_max = 2 and N_max = 80
Step 2: For 1≤i≤M { If ( f_i < f_max and N_vls < N_max)
        { For 1≤j≤M {
            If ( f_j < f_max and meet definition 1
                and VLS^q ∉ S_Q)
            { Add VLS^q to sets S_Q ; f_i = f_i + 1;
              f_j = f_j + 1; N_vls = N_vls + 1 }}}}
Step 3: if ( f_max >= 6 or N_vls >= N_max ) { Goto Step4}
        Else { f_max = f_max + 1; Goto Step 2}
Step 4: end
```

2) **Searching for corresponding VLS pairs:** Let S_T be the set of VLS^T from the template fingerprint. S_T^q is the set of VLS^T that corresponds with the VLS^q. TN is the pre-specified maximum number of the elements in S_T^q.

```
For all q∈S_Q {
  N_t = 0
  For all t∈S_T {
    If <q, t> is a corresponding pair {
      If N_t < TN {Add t to S_T^q   N_t = N_t + 1}
      Else Given t_m ∈ S_T^q and
        VlsDis(q,t_m) = Max{VlsDis(q,t_a) | t_a ∈ S_T^q}
        {
          if VlsDis(q,t_m) > VlsDis(q,t)
            {Replace t_m with t}
          }}}
```

3) **Estimating a set S_{Tr} of transformations**: Suppose we have a corresponding VLS pair $A<q,t>$, $q\in S_Q$, and $t\in S_T^q$. Let S_{Con}^A denote a set of corresponding VLS pairs consistent with $A<q,t>$ according to Definition 2, N_q^A be the number of VLS^q in S_{Con}^A and N_t^A be the number of corresponding VLS pairs. Note that N_t^A may be greater than N_q^A since one VLS^q might have a number of corresponding $VLS^T s$ in S_T^q. Then the transformation $E_A=(\Delta\theta_A^E,\Delta x_A^E,\Delta y_A^E)$ of S_{Con}^A can be calculated by

$$\begin{aligned}\Delta\theta_A^E &= \frac{1}{N_t^A}\sum_{m=1}^{N_t^A}\Delta\theta_m\\ \Delta x_A^E &= \frac{1}{N_t^A}\sum_{m=1}^{N_t^A}\Delta x_m\\ \Delta y_A^E &= \frac{1}{N_t^A}\sum_{m=1}^{N_t^A}\Delta y_m\end{aligned} \tag{10}$$

where $\Delta x_m = f_x(x_m, y_m \Delta\theta_A^E)$ and $\Delta y_m = f_y(x_m, y_m \Delta\theta_A^E)$. And a score is assigned to the above transformation by the following equation:

$$Tran\_Score^A = w_1 \times N_q^A + w_2 \times N_t^A \tag{1}$$

where w_1 and w_2 are the weights of N_q^A and N_t^A respectively. We choose the top N_{tr} transformations according to $Tran\_Score$ on a descent order to form a set S_{Tr}.

4) **Estimating the transformation of two fingerprints using CSV**

Two kinds of bounding boxes with different sizes are used in this step to tolerate, to some extent, the deformations:

i. For each transformation $E_A \in S_{Tr}$, if minutia F_a^q from the query feature cluster FC_i^q has a matched minutia F_a^t in the template fingerprint within a coarse bounding box, called the global bounding box, F_a^t is added into the template feature cluster FC_i^t , otherwise F_a^q is removed from FC_i^q. Repeat until no minutia can be added and be removed.

ii. The coarse centroids C_i^q of the query feature cluster FC_i^q and C_i^t of the template feature cluster FC_i^t, are computed respectively using equation (3). Under the local transformation defined by centroid pair $< C_i^q, C_i^t >$ and with the fine local bounding box repeat the step i.

iii. Respectively construct CSV_A^q and CSV_A^t using the query feature clusters and the template feature clusters obtained in step ii.

The transformation score $FgTran\_Score^A$ of the two fingerprints will be determined by $Tran\_Score$ of E_A and $CsvDis(q,t)$ together. The final transformation E_{fg} of the two fingerprints is the $E_m \in S_{Tr}$ that has the maximum $FgTran\_Score$.

5. Experimental Results

The experiments reported in this paper have been conducted on DB1, DB2 from FVC2002 competition [13] and NIST Special Database 27(NIST SD27). DB1 and DB2 are captured using an optical sensor and contain 110 unique fingers, with 8 impressions of each finger respectively. The evaluation sets consist of 2,800 genuinely matching pairs and 4,950 non-matching pairs respectively. NIST SD27 contains latent fingerprints from crime scenes and their matching rolled fingerprint mates. In all there are 258 latent cases. The results of our alignment algorithm are compared to those of alignment algorithm based on a reference minutiae pair (RMPA) similar to H.Ramoser's [7]. Table 1 gives the alignment statistics. The implementation of our algorithm with VC6.0 has an average computational time of 0.003 sec for the alignment step on a 2.0 GHz PC. It is clear that the performance of our algorithm is better than that of RMPA.

Note that when there are a few (e.g. less than fifteen) minutiae scattered in a large area, extracting VLSs is easier than constructing local structures containing more than two genuine minutiae in a small area. Fig.3 shows two such examples. Nearly half of the fingerprint images in NIST SD27 have less than 15 minutia and most of them have heavy deformations. At such circumstances, visual inspection showed that for NIST SD27, only two alignments, i.e. 0.7%, given by the proposed algorithm are wrong. This exhibits its advantages.

6. Conclusions

A novel technique of fingerprint registration has been presented using centroid structure vector and vector line segment in this paper. The use of both the local and global transformation parameters makes our algorithm be able to tolerate, to some extent, the nonlinear deformation. The primary advantage of this approach is its good performance under a wide variety of circumstances. In particular, it is robust to align fingerprints with a small number of minutiae that are distributed in a large area of the fingerprint image.

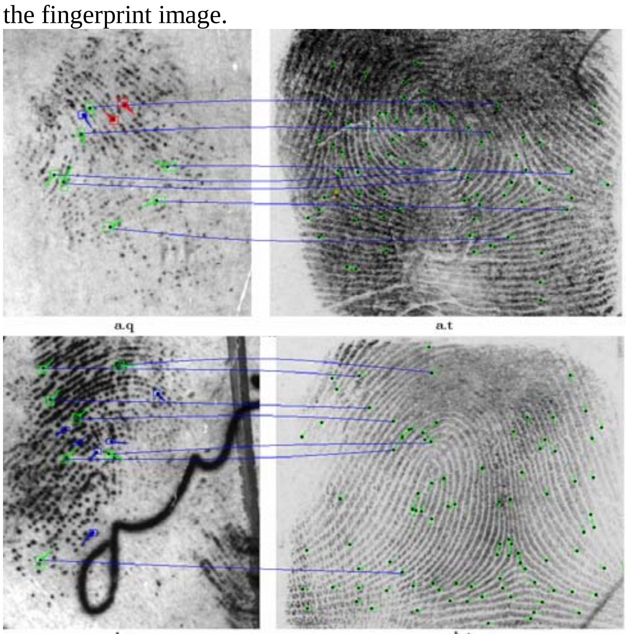

Fig. 3 a.q and a.t and b.q and b.t are two examples of image pair from the same finger. The spurious and missing minutiae are marked by blue and red respectively..

Table 1: Performance comparision

Database	Correct rate of alignment (%)		Average Times (ms)	
Algorithm	ours	RMPA	ours	RMPA
NIST SD27	99.3	93.6	2.6	3.1
DB1	99.8	95.4	2.8	3.5
DB2	99.6	95.9	2.8	3.5

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