Improving Fingerprint Recognition Performance Based on Feature Fusion and Adaptive Registration Pattern

Jie Tian[1,2,*], Yuliang He[1,2], Xin Yang[1,2], Liang Li[1,2], and XinJian Chen[1,2]

[1] Biometrics Research Group, Key Laboratory of Complex Systems and Intelligence Science
Institute of Automation, CAS, P.O.Box 2728, Beijing, 100080, China
[2] Graduate School of the Chinese Academy of Science Beijing, 100039, China
tian@doctor.com

Abstract. This paper proposes an adaptive registration pattern based fingerprint matching method dealing with the non-linear deformations in fingerprint. The *"registration pattern"* between two fingerprints is the optimal registration of every part of one fingerprint with respect to the other fingerprint. *Registration patterns* generated from imposter's matching attempts are different from those patterns from genuine matching attempts, although they share some similarities in the aspect of minutiae. In this paper, we combine minutiae, associate ridges and orientation fields to determine the *registration pattern* between two fingerprints and match them. The proposed matching scheme has two stages. An offline, training stage, derives a *genuine registration pattern base* from a set of genuine matching attempts. Then, an online matching stage registers the two fingerprints and determines the *registration pattern*. A further fine matching is conducted. In addition, the block orientation field is used as the global feature of a fingerprint to improve the performance of this method. And 2nd and 3rd relational structures between minutiae are applied to promote the fingerprint matching method. Experimental results evaluated by FVC2004 demonstrate that the proposed algorithm is an accurate one.

Keywords: adaptive registration pattern, relational structure between minutiae, fingerprint identification.

1 Introduction

A fingerprint, a pattern of ridges and valleys on the surface of a finger, has been used for individual identification upon legal purpose. With the increasing volume of information technology, automatic fingerprint identification becomes more popular in civilian applications, such as access control, financial security and verification of

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Corresponding author: Jie Tian ; Telephone: 8610-62532105; Fax: 8610-62527995.

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firearm purchasers, etc. A fingerprint is becoming an identity of human being. Automatic Fingerprint Identification Systems (AFISs) have been performed very well for years in ideal circumstances. However, limited memory is in an off-line AFIS, such as Personal Digital Assistant (PDA) and IC Card systems. It is important to design a reliable fingerprint identification method for AFISs.

A lot of work in fingerprint identification proposed a wide range of algorithms with different techniques. Fingerprint matching techniques can be broadly classified as minutiae-based or correlation-based technologies. Minutiae-based techniques attempt to align two sets of minutiae points and determine the total number of matched minutiae [1, 2, 3, 4]. Correlation-based techniques compare the global pattern of ridges and furrows to see if the ridges in two fingerprints align [5, 6, 7, 8]. The performance of minutiae-based technologies relies on the accurate detection of minutiae points and the use of sophisticated matching methods to compare two minutiae sets which undergo non-rigid transformations. However, for correlation-based techniques, the performance is affected by non-linear distortions and the presentation of noise present in image. It is usually known that minutiae-based techniques perform better than correlation-based ones. Correlation-based techniques involve several problems [9]: (a) A fingerprint image may contain non-linear warping because of the effect of pressing a convex elastic surface (the finger) on at surface (the sensor). Moreover, various sub-regions in the sensed image are distorted differently due to the non-uniform pressure applied by the user. It is difficult to compare two such distorted prints, even if with consideration of translation and rotation effects. (b) Based on the moisture content of the skin, the acquired image may vary with different sensor time to time and therefore making more complicated correlation process.

In this paper, we introduce a novel fingerprint verification algorithm based on adaptive registration pattern for alignment in matching and combined comprehensive minutiae and global texture feature, block orientation field. The algorithm first coarsely aligns two fingerprints and determines the *possible RP* by optimally registering each part of the two fingerprints. Next, inspects the *possible RP* with a *genuine RP space*. A further fine matching is conducted if the *RP* makes a genuine one. The multiply rules as a principle of fusion are exploited in fingerprint matching. The matching performance is greatly improved by these strategies.

This paper is organized as follows. First, the feature representation and extraction method is introduced. Next, the matching algorithm is explained. Experimental result of the algorithm and its applications are given in Section 4. Section 5 contains discussion and further work.

2 Fingerprint Presentation

The uniqueness of a fingerprint is determined by the topographic relief of its ridge structure and the presence of certain ridge anomalies termed as minutiae points. Typically, the global configuration defined by the ridge structure is applied to determine the class [10] of the fingerprint, while the distribution of minutiae points is used to match and to establish the similarity between two fingerprints [11, 1]. Automatic fingerprint identification systems, that match a query print against a large database of prints (which may consist of millions of prints), rely on the pattern of ridges in the query image to narrow the search in the database (fingerprint index), and on the minutiae points to determine an exact match (fingerprint matching). The ridge flow pattern itself is seldom used for matching fingerprints.

A good quality fingerprint usually contains about 60 minutiae which is enough for its uniqueness. However, a bad quality fingerprint may have very narrow foreground area without enough reliable minutiae to indicate its uniqueness. To the best of our knowledge, local fingerprint texture (ridges or valleys) features can improve the identification performance. Therefore, we use minutiae and associated local texture in our method. All local comprehensive minutiae in fingerprint F are denoted by a vector set $M^F = \{M^F_i = (x_i, y_i, \alpha_i, \beta_i, \varphi_{i1,\ldots}, \varphi_{iT}); T\geq 2, i=0, \ldots, m^F\}$, where: m^F is the number of minutiae in fingerprint F. For clarity, M^F_i denotes the ith minutia, presented by a feature vector $(x_i, y_i, \alpha_i, \beta_i, \varphi_{i1,\ldots}, \varphi_{iT})$ ($T\geq 2$, $1\leq i\leq m^F$, where 1) x_i and y_i are its coordinates respectively. α_i is the local ridge direction at M^F_i in the anticlockwise direction. β_i is the local grey variation of an area centred by M^F_i. 2) (x_{ik}, y_{ik}) ($k=1, 2, \cdots, T$), see Figure 1, are the points extracted from a ridge, which M^F_i locates, in equal step from its beginning point to its end. To represent local texture features of a local region centred at M^F_i, $\varphi_{ik}= \text{actan}((y_{ik} - y_i)/(x_{ik} - x_i))(k=1, 2, \cdots, T)$, the directions from M to (x_{ik}, y_{ik}) ($k=1, 2, \cdots, T$) in the anticlockwise direction, are introduced to describe the curvature of the ridge. β_i and φ_{ik} ($k=1, 2, \cdots, T$) describe the local texture properties of the local region associated with M^F_i, which accelerate aligning features during fingerprint matching.

The above defined comprehensive minutiae include local texture features and are dependent on their associated minutiae. It is hard to ensure their reliability although they enhance the uniqueness of a fingerprint. Therefore, it is feasible to use global feature for matching bad quality fingerprints to enhance performance of the matching method. In our experiments, we test a method using block orientation field [12] of a fingerprint as its global feature and to get inspiring results.

Comprehensive minutiae are combined with minutiae's n^{th} relative structures [13]. 3^{rd} order relational structures such as minutia-triangle employed in many methods [11, 2] require more computation expense than 2^{nd} order relative structures. Both structures are enough to represent the Euclidean distance-based relations among minutiae. With comparison to 2^{nd} order relative structures, 3^{rd} order relational structures have more features to represent the uniqueness of a fingerprint although more memory and time are needed. These relational structures combine isolated comprehensive minutiae as an aspect for matching.

3 Fingerprint Matching Based on Adaptive Registration Pattern

3.1 Coarse Matching

The task of the coarse global registration is to align the two fingerprints and find the possible corresponding point pairs between the two feature sets. We revised the registration method as described in [14] and introduce an *orientation field matching degree* feedback mechanism to improve the robustness of global alignment.

To estimate the registration parameter, we use the minutiae set to construct the local structure set: $\{Fl_1, Fl_2,\ldots, Fl_n\}$. Each local structure in the input fingerprint is compared with each local structure in the registration fingerprint. Each comparison generates a registration parameter and a similarity score:

$$MFl_{p,q} = (Fl_p^t, Fl_q^i, (dx, dy, rot, s_x, s_y), s_{p,q}) , \tag{1}$$

where the definition of the similarity score s_{pq} is the same with [15]. These comparisons give a possible correspondence list of feature points in two sets:

$$L_{corr} = \{(p_a^t, p_b^i, MFl_{p,q}) \mid p_a^t \in Fl_p^t, p_b^i \in Fl_q^i\} . \tag{2}$$

We cluster those registration parameters in $\{MFl_{p,q}\}$ into several candidate groups. Parameters in each group are averaged to generate a candidate global registration parameter. And the summation of similarity scores in each group becomes the power of each candidate registration parameter. The candidate parameters are sorted by their power and verified one by one using the orientation field information to choose the best global registration parameter.

3.2 Registration Pattern Determination

The next step is the determination of the *RP* that optimally registers each part of the two fingerprints. We take the input image as *"standard image"*, and take the registration fingerprint "a distorted image" versus standard one.

The feature set of the registration fingerprint is first aligned with the input fingerprint using the global alignment parameter we get in the last step. Next, we tessellate the overlap portion of the input image into seven non-overlap hexagons with radius=*R*. Then, we compute the optimal alignment parameter of the registration image with respect to each hexagon in the input image. The registration method is the same with that described in Section 3.1 except that: first, the searching space is greatly reduced, since the search region is restricted to the hexagon and its neighborhoods; second, sample points on associate ridges are utilized to provide more information for registration. The possible correspondence list is extended by the possible correspondences of sampled feature points. The illustration of the orientation and the type of the sample points are shown in Figure 1.

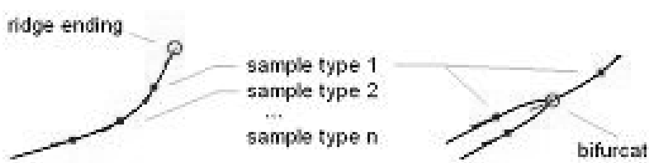


Fig. 1. Orientation and type of sample points on associate ridges

The registration parameters as a whole describe the *RP* between the two images:

$$RP = \{(dx_i, dy_i, rot_1, s_{xi}, s_{yi}); i = 1,..7\} \tag{3}$$

3.3 Learning Genuine Registration Patterns

Some different fingers may have similar flow patterns and many of their minutiae can be matched if we use a loose bounding box allowing the large distortion. However, when analyzing the two fingerprints in detail, we found that the *RP* was different from those from true matching. To learn the *genuine RPs,* we applied a set of distorted fingerprint images to derive a *genuine RP base (GRPB).* This set of images was extracted from NIST Special DB24 [16]. The database contains 100 MPEG-2 compressed digital videos of live-scan fingerprint data. Users are required to place their finger on the sensor and distort their finger exaggeratedly once the finger touched the surface.

(a) Registration image (b) input image (c) registration pattern

Fig. 2. A *genuine RP* derived from a true matching attempt

Those images from the same finger were matched to one to one and RPs were computed. These *RPs* formed our *GRPB*. In an experiment, we choose seven fix-sized hexagons with *R*= 45 pixels. In most cases, they cover most of the overlap portion. And the alignment parameters of these hexagons can well represent the whole *RP*. Figure 2 shows a *genuine RP* calculated by our algorithm from two images in NIST Special DB24.

3.4 Registration Pattern Inspection

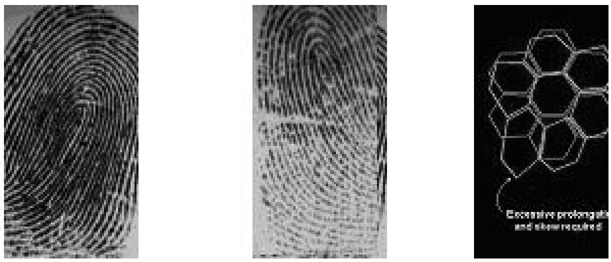
We define the distance between two *RPs*:

$$d(RP_i, RP_j) = \sqrt[2]{\sum_k \left[\begin{array}{l} \left(\dfrac{\left|dx_k^i - dx_k^j\right|}{s_d}\right)^2 + \left(\dfrac{\left|dy_k^i - dy_k^j\right|}{\lambda_d}\right)^2 + \\ \left(\dfrac{\left|ds_{xk}^i - ds_{xk}^j\right|}{\lambda_x}\right)^2 + \left(\dfrac{\left|ds_{yk}^i - ds_{yk}^j\right|}{\lambda_y}\right)^2 + \\ \left(\dfrac{|\, rot_k^i - rot_k^j \,|}{\lambda_r}\right)^2 \end{array} \right]} \tag{4}$$

And a *genuine RP space*:

$$S_{GRP} = \{RP \mid \exists RP_i \in GRPB, d(RP, RP_i) < Thr_{gspace}\}. \tag{5}$$

In our algorithm, each matching attempt generates a *possible RP*. If the *possible RP* belongs to S_{GRP}, a further fine matching is conducted. Otherwise, the matching attempt is rejected. Figure 3 shows a *fake RP* detected by our algorithm.



(a) Registration image (b) input image (c) registration pattern

Fig. 3. A *fake RP* was detected by our algorithm. The two fingerprints have some similarities in both minutiae and flow patterns. Inadequate contrast in the image stopped as rejecting it in the stage of coarse global registration, all those two fingerprints in fact belong to different types

3.4 Fine Matching

From the list of possible corresponding point pairs refined in the stage of *RP* determination, each feature point in the overlap portion of the registration fingerprint may have one or more corresponding feature points with the input fingerprint. The confliction of one feature point corresponding to more than one feature points can be solved by a simple rule: assign this feature point to the point which has the largest sum of similarity score with it. All the other correspondences are deleted. Then compute the matching score:

$$M = \frac{m}{\max(n_{input}, n_{template})} \times \sum s_i \tag{6}$$

where m is the number of matching feature points, n_{input} and $n_{Registration}$ are the numbers of feature points in the overlap portion of the input fingerprint and registration fingerprint respectively, and s_i is the similarity score in the final correspondence list.

For global texture feature, block orientation field, in this method, the mutual information (*MI*) method [18] is used to calculate the similarity between two fingerprints. However, the speed of this MI method is limited by the accuracy of the detected deformation model although it greatly increases the matching performance. Assume E denote the similarity between two fingerprints calculated with MI method. Their final similarity is obtained by fuse the relational structures and block orientation field, that is, a multiply rule, $F = M * E$, is used to estimate the final similarity.

4 Experimental Results

Feature selection and fusion play important role in matching. Two methods based on these schemes are proposed: the first one, denoted by “light” method, uses 2nd order relational minutia structures for local similarity measurement; another, denoted by “open” method, uses 3rd order relational minutia structures. In addition, the “open” method also use global feature, block orientation field, for matching. The two methods were submitted to FVC2004 [17] and tested by FVC2004. And their results were showed in Fig. 5 and Fig. 6. The “light” method is in the light team of FVC2004, and the “open” method is in the open team of FVC2004. The “open” method for the global features need more memory and time expenses in matching. Their testing results show that “light” method races 7 of the “light” team and the “open” method races 3 of the “open” team. Now the “light” method has been applied to the off-line AFISs, such as PDA, Mobile, lock, and so on. The demos of an off-line AFISs are showed in Fig.7.

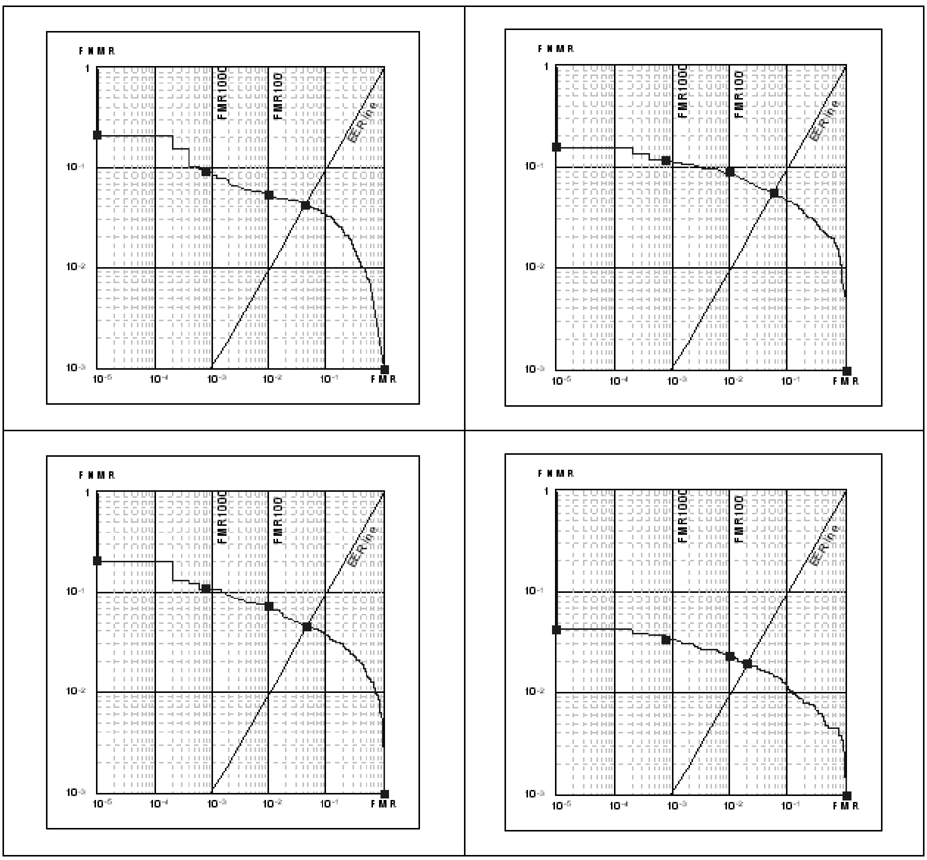


Fig. 5. Experimental results of “light” methods on FVC2004

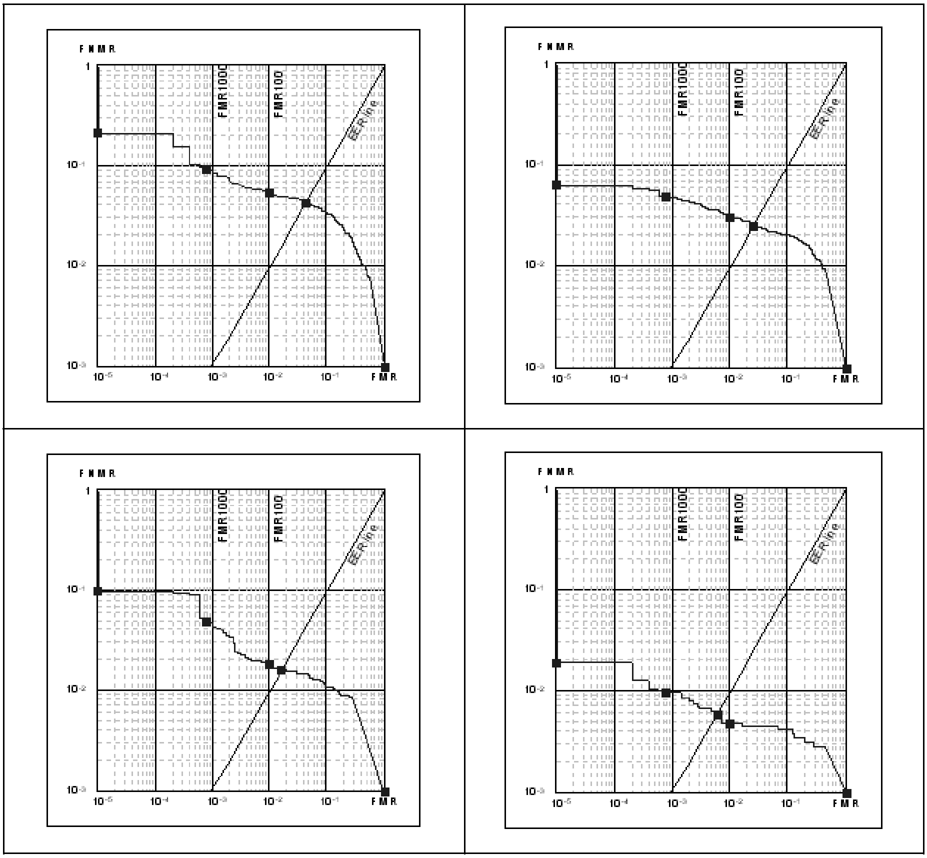


Fig. 6. Experimental results of “open” methods on FVC2004

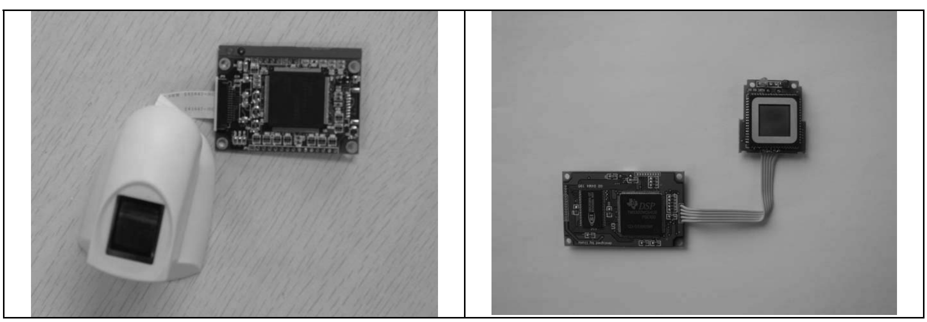


Fig. 7. Two demos of off-line AFISs

In addition, a biometric Information Toolkit (BITK, a toolkit for multi-biometric identification system (fingerprint + face + palm)) is under going. BITK obeys the rule of data flow, a principle of objective development. And BITK consists of source model，filter model and target model. The Source model is the beginning of data processing which only contains input without output. The functions are to read data from files, or other systems and devices storage. Filter model is the middle node of data processing. Its functions are to obtain data and output the processed results to the target model. All biometric data algorithms are included in this model, such as fingerprint enhancement, fingerprint matching, and so on. The target model is the ending step of data processing and it outputs or shows the results from the filter model.

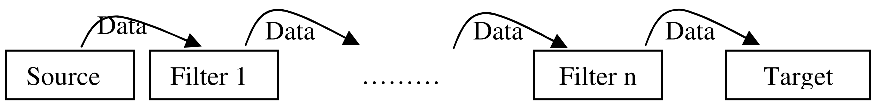


Fig. 8. Data Flow Model of BITK

Fig. 9. Multi-biometric identification system based on BITK

5 Conclusion and Future Work

We have introduced a novel fingerprint verification algorithm based on feature fusion and adaptive registration pattern. The inspection of *possible RP* successfully detected many dangerous imposter's matching attempts, which had similar flow pattern and minutiae configuration with the registration images. In addition, global feature of a fingerprint, triangular relational structures, and multiply rule of fusion, are applied to matching, which improves the performance of the method.

Our further works in biometric recognition will be done in the following fields: First, we'll improve false match in our match which sometimes occurs if there are lot of non-linear deformations and distortions caused by incorrect finger placement. Such situations are also the main cause for the high false matching rates (FMR) in traditional matching algorithms. Currently, a *possible RP* is inspected one by one check with the *genuine RPs*. We are deriving a knowledge base from these patterns. Second, sensitivity of our method is to bad quality fingerprints will be improved in terms of those with many false minutiae. For example, it is hard for these dry fingerprints to extract enough minutiae. Other novel global features should be further exploited into our methods. In addition, a multi-resolution search strategy will be employed as well to calculate the optimal deformations in the deformation space.

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