Available online at www.sciencedirect.com
SCIENCE DIRECT®
Pattern Recognition 38 (2005) 1665 – 1671
PATTERN RECOGNITION
THE JOURNAL OF THE PATTERN RECOGNITION SOCIETY
www.elsevier.com/locate/patcog

A robust fingerprint matching method

Jin Qi[a, b, *], Yangsheng Wang[b]

[a] *Department of Electrical Engineering, University of Electronic Science and Technology of China, Chengdu 610054, PR China*
[b] *Room 1211, National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences, P.O. Box 2728, Beijing 100080, PR China*

Received 18 June 2004; received in revised form 28 March 2005; accepted 28 March 2005

Abstract

This paper is concerned with accurate and efficient fingerprint matching. We have two main contributions:

(1) define a novel feature vector for each fingerprint minutia based on the global orientation field. These features are used to identify corresponding minutiae between two fingerprint impressions by computing the Euclidean distance between vectors.
(2) novel distortion-tolerant matching algorithm based on the closest triangle is developed. Furthermore, fingerprint directional field is also used to compute the final matching score combining with minutiae elaborately.

A series of experiments conducted on the public data collection, DB3, FVC2002, demonstrates the effectiveness of our method.

Keywords: Fingerprints; Matching; Features; Orientation field; Triangle

1. Introduction

In minutia-based fingerprint matching, two stages can be distinguished. First, registration aligns both fingerprints as well as possible. Most algorithms use a combination of translation, rotation and scaling for this task. After registration, the matching score is determined by counting the corresponding minutiae pairs between both fingerprints. Two minutiae correspond if a minutia from the test set is located within a bounding box or tolerant zone around a minutia from the template set. The matching score, which is a number in the range from 0 to 1, is calculated as the ratio of the number of matched minutiae to the total number of minutiae.

Registration stage is to recover the pose transformation between two fingerprints from the same finger. To estimate the transformation in minutia-based matching procedure, minutia correspondences must be obtained accurately. But the task is difficult to complete due to several complicating factors such as the rotation, translation and deformation of the fingerprints, the location and direction errors of detected minutiae from fingerprints as well as the presence of spurious minutiae and the absence of genuine minutiae. Several approaches to solve the problem have been proposed in the literature. These include methods based on structure matching [1–4], alignment matching [5–8], non-linear transformation [9,10]. The methods proposed in Refs. [5–8] 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. The local structure composed of several minutiae close to each other serves to obtain the minutiae correspondences in Refs. [1–4,9,10].

* Corresponding author. Tel.: +86 10 8287 2203x814; fax: +86 10 8261 9272.
E-mail addresses: jqi@nlpr.ia.ac.cn, jqi@mail.pattek.com.cn (J. Qi), wys@nlpr.ia.ac.cn (Y. Wang).

0031-3203/$30.00
doi:10.1016/j.patcog.2005.03.002

It is noted that the representation of local structure based on a group of minutiae is not robust because it relies on the interdependencies between minutia details, which can be missed or erroneously detected by a minutia extraction algorithm. In addition, determining the similarity of local structures is difficult because the correspondences between the elements in local structures cannot be known in advance.

The last stage, i.e. matching stage, is to establish the number of corresponding minutia pairs to compute the final matching score after registration. If two identical minutia point patterns are exactly aligned with each other, each pair of corresponding minutiae is completely coincident. In such a case, the matching task can be easily completed by counting the number of overlapping pairs. However, in practice, such a situation is not encountered. On the one hand, the location and direction errors introduced by the minutiae detection algorithm hinder the alignment algorithm to recover the relative pose transformation exactly, while on the other hand, the non-linear deformation of fingerprints which is an inherent property of fingerprint impressions can be accumulated to a large degree. With the existence of such a non-linear deformation, it is impossible to exactly recover the position of each input minutia with respect to its corresponding minutia in the template. Therefore, the matching algorithm needs to be elastic which means that it should be capable of tolerating, to some extent, the deformations due to the location and direction errors and non-linear deformations. Many matching algorithms have deliberated this non-linear deformation problem in order to improve their matching performance [3,4,6,9–14]. In Refs. [6,11] a variable matching boundary box is used. But the false matching rate (FMR) may increase as the size of matching box becomes larger. In Refs. [3,4], the matching certainty level of local minutiae structures is used to increase the reliability of the matching. As mentioned before, the local structure feature composed of a group of minutiae is not reliable due to depending on the interdependency of minutiae. A thin-plate spline model is used to describe the non-linear distortion between the two sets of possible pairs in Refs. [9,10]. The method is more complex than the rigid matching algorithm and has a heavy load of computation. In Refs. [12,13], a method is proposed that the ridge distances are normalized all over the image. Since it is not known in advance whether captured fingerprints contain any distortion, true normalization of the fingerprints is not possible.

With these in mind, we have two main contributions in this paper:

(1) In registration stage, a new method of fingerprint alignment is developed incorporating the global orientation field with minutiae properly. In contrast to the local structural features employed by the matching algorithms proposed in Refs. [1–4], the novel structure of each minutia we construct in this paper is not sensitive to noise because it only depends on the global finger print orientation field which is relatively robust to noise. Furthermore, our structure capturing the rich information on fingerprint ridge-flow pattern is more discriminative than the local minutia structure.We get the striking property that our structure can be represented as a minutia feature vector. Hence, obtaining the correct minutiae correspondences exactly becomes the computation of Euclidean distances between feature vectors. The task is straightforward.

(2) In matching stage, a novel matching method based on the closest triangles is proposed to compensate for the inexact registration. Our triangular matching technique is different from the approach in Ref. [14]. In Ref. [14], if there exists one pair of false matched triangles, the matching process cannot continue forward resulting in the false non-match case due to the strong interdependency between the triangles. In our matching method, the constructed triangles are independent from each other. Even if there is one pair of false matched triangles, our method can still work well due to the independency between triangles.

The rest of the paper is organized as follows. A detailed definition of our novel minutiae feature vector is presented in the following section. The triangular matching scheme based on the proposed minutia structure is developed in Section 3. This is followed by validation experiments conducted on the public domain collection of fingerprint images, DB3, FVC2002. Finally, concluding remarks are presented in Section 5.

2. Definition of the novel structure

In general, a minutia point M_k detected from a fingerprint can be described by a feature vector given by

$$F_k = (x_k \quad y_k \quad \psi_k), \tag{1}$$

where (x_k, y_k) is its coordinate, ψ_k is the local ridge direction. Note that in a fingerprint image, there is no difference between a local ridge orientation of 90° and 270°, since the ridges oriented at 90° and the ridges oriented at 270° in a local neighborhood cannot be differentiated from each other. Hence, the value of ψ_k is commonly set in the range from $-\pi/2$ to $\pi/2$ according to the following formula:

$$\psi_k = \begin{cases} \psi_k & \text{if } -\pi/2 < \psi_k < \pi/2, \\ \pi - \psi_k & \text{if } \pi/2 < \psi_k < \pi, \\ \psi_k + \pi & \text{if } -\pi < \psi_k < -\pi/2. \end{cases} \tag{2}$$

We define a function $\mathrm{d}\phi(t_1, t_2)$ for the difference between two directions or angles, t_1 and t_2, $-\pi/2 < t_1, t_2 < \pi/2$, keeping into account the effect of rotation of fingerprint image on the directions, as follows:

$$\mathrm{d}\phi(t_1, t_2) = \begin{cases} t_1 - t_2 & \text{if } -\pi/2 < (t_1 - t_2) < \pi/2, \\ t_1 - t_2 + \pi & \text{if } -\pi < (t_1 - t_2) < -\pi/2, \\ t_1 - t_2 - \pi & \text{if } \pi/2 < (t_1 - t_2) < \pi. \end{cases} \tag{3}$$

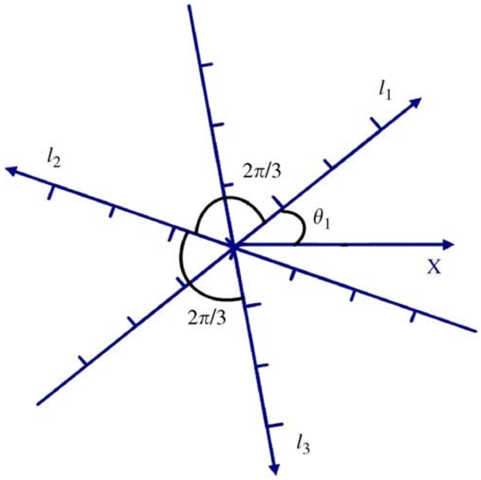

Fig. 1. Sampling points organized on three lines around a minutia detail.

Given a minutia point M_k with orientation ψ_k, we define our minutia structure as following procedures:

Let $\theta_1 = \psi_k$, $\theta_2 = \psi_k + 2\pi/3$ and $\theta_3 = \theta_2 + 2\pi/3$. We plot three lines l_1, l_2, and l_3 along the angles θ_1, θ_2 and θ_3 with respect to X axis through the minutia point M_k. A sampling step is done starting with the minutia point M_k along each line with sampling interval τ. The sampling action along each line stops till the latest sampling point falls in fingerprint background region, as illustrated in Fig. 1.

The sampling pattern consists of three lines l_m, $(1 \leqslant m \leqslant 3)$, with three positive directions θ_m, $(1 \leqslant m \leqslant 3)$, each one of them comprising $N^k_{l_m}$ sampling points P^k_{i,l_m}, $(1 \leqslant i \leqslant N^k_{l_m}, 1 \leqslant m \leqslant 3)$, equally distributed along the line l_m. Denoting by ω^k_{i,l_m} the local ridge orientation estimated in P^k_{i,l_m}, the relative direction ψ^k_{i,l_m} between minutia M_k and the sampling point P^k_{i,l_m} calculated by

$$\psi^k_{i,l_m} = \mathrm{d}\phi(\psi_k, \psi^k_{i,l_m}) \tag{4}$$

is independent from the rotation and translation of the fingerprint. The feature vector F_k of a minutia M_k that describes its structure characteristic with global fingerprint orientation field is given by

$$F_k = \left\{ \left\{ \psi^k_{i,l_m} \right\}_{i=1}^{N^k_{l_m}} \right\}_{m=1}^{3}. \tag{5}$$

The structure feature vector F_k is invariant to rotation and translation of the fingerprint.

Suppose F_i and F_j are the structure feature vectors of minutia *i* from input fingerprint and minutia *j* from template fingerprint, respectively. A similarity level is defined as

$$S(i, j) = \begin{cases} \dfrac{T - |F_i - F_j|}{T} & \text{if } |F_i - F_j| < T, \\ 0 & \text{otherwise}, \end{cases} \tag{6}$$

where T is the predefined threshold and $|F_i - F_j|$ is the Euclidean distance between feature vectors F_i and F_j. Note that the dimensions of them may be different from each other, and the Euclidean distance can be computed according to the minimum of their dimensions. The similarity level $S(i, j), 0 \leqslant S(i, j) \leqslant 1$, describes a matching certainty level of a structure pair instead of simply matched or not matched. $S(i, j) = 1$ implies a perfect match, while $S(i, j) = 0$ implies a total mismatch.

3. Fingerprint matching

Using the proposed minutia feature vectors, we develop a new triangular fingerprint matching algorithm making use of both fingerprint minutiae and orientation fields. Different from other minutia-based approaches our algorithm receives at the input two minutia lists and two orientation fields captured from two fingerprint impressions and delivers a matching score that expresses the degree of similarity between the two fingerprints. In order to align two point sets and two orientation fields before calculating the matching score, we need to identify a set of corresponding minutia pairs.

3.1. Corresponding minutia identification

The value of the similarity level between minutiae serves to identify corresponding pairs. The best-matched structure pair can be used as a corresponding point pair. Although not all well-matched structures are reliable, our experiments show that the best-matched structure pair of all minutia structures of template and input fingerprints is very reliable. The best-matched minutia structure pair (b_1, b_2) is obtained by maximizing the similarity level as

$$S(b_1, b_2) = \max_{i,j}(S(i, j)). \tag{7}$$

3.2. Registration

The registration stage is meant to recover the geometric transformation between the two fingerprint impressions.

In our work, the rigid transformation, i.e., translation vector $(t = [t_x, t_y]^{\mathrm{T}})$ and rotation angle (ψ), is recovered by the best-matched structure pair that exhibits the largest similarity value in Eq. (7). Let the best-matched minutia structure pair is denoted by (b_1, b_2), minutia b_1 from the input fingerprint and another b_2 from the template fingerprint. Hence we have

$$\psi = D(b_2) - D(b_1) \text{ and } t = P(b_2) - R_{\psi}(b_1), \tag{8}$$

where R_ψ denotes the 2×2 operator of counterclockwise rotation with ψ and the position and direction of a minutia b are denoted by $P(b)=[x(b), y(b)]^{\mathrm{T}}$ and $D(b)$, respectively. Applying the estimated geometric transformation onto the minutiae from the test fingerprint we obtain the list comprising the registered minutiae. Also, The orientation field from the test fingerprint will be aligned using the estimated transformation simultaneously.

3.3. Triangular pairing

Because of various factors that include the presence of local non-linear deformations and the errors induced by the minutia extraction algorithm, the corresponding minutiae cannot overlap exactly. Consequently, one must allow a certain tolerance between the positions and directions of corresponding minutiae by employing an elastic matching algorithm as proposed in Refs. [3,6,7]. Therefore, the matching should be elastic by using a 3-D bounding box B_g in the feature space instead of an exact matching. But the size of bounding box is tradeoff between the FMR and the false non-match rate (FNMR). It is so difficult to choose the desired and suitable box. In our method, two stages can be used to complete the minutiae pairing. First, a stricter box is chosen to get the initial corresponding minutiae pairs. Next, triangular match is available to attain the true corresponding minutiae pairs which are not found in the first stage.

3.3.1. Initial minutiae pairing

A small size bounding box B_g is chosen to get two corresponding minutiae lists L_1 and L_2 which are from the template fingerprint and the test fingerprint, respectively. Minutiae pairs are collected among the pairs with the largest similarity level values in Eq. (6), which, also fall in the bounding box B_g.

3.3.2. Triangular matching

In the initial minutiae pairing stage, some true corresponding minutiae may be not found due to the stricter box chosen. Now we must perform the triangular matching algorithm to deal with the situation. Before introducing the triangular match approach, we first see how to determine whether two triangles are similar.

Suppose there exist two triangles $\triangle ABC$ and $\triangle A'B'C'$ whose vertices are from the minutiae in L_1 and L_2, respectively. In convenience, We denote the direction of the ridge associated with the minutiae point A by $O(A)$ and the length of the line segment AB by $|\overline{AB}|$. Let

$$D\phi_l(\triangle ABC, \triangle A'B'C') = ||\overline{AB}| - |\overline{A'B'}|| + ||\overline{BC}| - |\overline{B'C'}|| + ||\overline{CA}| - |\overline{C'A'}|| \tag{9}$$

and

$$D\phi_o(\triangle ABC, \triangle A'B'C') = |O(A) - O(A')| + |O(B) - O(B')| + |(O(C) - O(C')|. \tag{10}$$

Two similarity levels $S_l(\triangle ABC, \triangle A'B'C')$ and $S_o(\triangle ABC, \triangle A'B'C')$ of $\triangle ABC$ and $\triangle A'B'C'$ can be defined as follows:

$$S_l(\triangle ABC, \triangle A'B'C') = \begin{cases} \frac{T_l - D\phi_l(\triangle ABC, \triangle A'B'C')/3}{T_l} & \text{if } \frac{D\phi_l(\triangle ABC, \triangle A'B'C')}{3} < T_l, \\ 0 & \text{otherwise,} \end{cases} \tag{11}$$

$$S_o(\triangle ABC, \triangle A'B'C') = \begin{cases} \frac{T_o - D\phi_o(\triangle ABC, \triangle A'B'C')/3}{T_o} & \text{if } \frac{D\phi_o(\triangle ABC, \triangle A'B'C')}{3} < T_o, \\ 0 & \text{otherwise.} \end{cases} \tag{12}$$

It is well known that the two similarity levels capture the information invariant to the rigid transformation and the relatively small non-linear deformation. It is time for us to detail our triangular matching method now. The main steps are as follows:

(1) Choose one minutia A_1, not in L_1 and not considered, from the template fingerprint.
(2) Choose one minutia B_1, not in list L_2 and not considered, from the relatively larger neighborhood N_{A_1} of minutia A_1 in registered test fingerprint.
(3) Get two minutiae A_2 and A_3, closest to minutia A_1, from the matched minutiae list L_1. Denote the corresponding minutiae of A_2 and A_3 as B_2 and B_3 from the matched minutiae list L_2, respectively.
(4) Compute the values of $S_l(\triangle A_1A_2A_3, \triangle B_1B_2B_3)$ and $S_o(\triangle A_1A_2A_3, \triangle B_1B_2B_3)$ according to Eqs. (11) and (12).
(5) If there exist $S_l(\triangle A_1A_2A_3, \triangle B_1B_2B_3) < T_{s1}$ and $S_o(\triangle A_1A_2A_3, \triangle B_1B_2B_3) < T_{s2}$, where T_{s1} and T_{s2} are threshold, we choose the B_1, which minimizes $S_l(\triangle A_1A_2A_3, \triangle B_1B_2B_3)$ and $S_o(\triangle A_1A_2A_3, \triangle B_1B_2B_3)$, as the corresponding minutia of minutia A_1.

Repeat above steps until all minutiae from the template fingerprint, not in the list L_1, are considered. Now we have completed the minutiae pairing task.

3.4. Orientation block pairing

As the orientation field estimation algorithm proposed in Ref. [6], the fingerprint image should be divided into a number of sub-blocks before computing the fingerprint orientation. With the registered orientation field, the procedure to identify the corresponding orientation block pairs is straightforward. Let (B_1, B_2) denote the corresponding orientation block pair, block B_1 from test fingerprint, block B_2

from template fingerprint, respectively. The similarity degree $S(B_1, B_2)$ of the two blocks B_1 and B_2 is calculated as follows:

$$D\phi(B_1, B_2) = |O(B_1) + \psi - O(B_2)|, \tag{13}$$

$$S(B_1, B_2) = \begin{cases} \dfrac{T_1 - D\phi(B_1, B_2)}{T_1} & \text{if } D\phi(B_1, B_2) < T_1, \\ 0 & \text{others,} \end{cases} \tag{14}$$

where ψ is computed with Eq. (8), T_1 is a threshold and the direction of a block B is denoted by $O(B)$.

3.5. Matching score computation

With the introduction of our novel minutia structures and registered fingerprint orientation fields the matching score M_s can be determined by both minutia matching score M_m and orientation field matching score M_o.

Let N_1 and N_2 denote the number of minutiae located inside the intersection of the two fingerprint images for test and template fingerprints, respectively. The minutia matching score M_m can be calculated according to the following equation

$$M_m = \frac{\sum_{i,j} S(i, j)}{\max\{N_1, N_2\}}, \tag{15}$$

where (i, j) is the corresponding minutiae pair, one from test fingerprint and another from template fingerprint, respectively, and $S(i, j)$ is computed according to Eq. (6).

The orientation field matching score M_o is defined by

$$M_o = \frac{\sum_{B_i, B_j} S(B_i, B_j)}{N}, \tag{16}$$

where (B_i, B_j) is the corresponding orientation block pair, one for test fingerprint and another for template fingerprint, respectively, N is the number of overlapped blocks of both fingerprints, and $S(B_i, B_j)$ is determined by Eq. (14).

The final matching score M_s is computed as follows:

$$M_s = \omega_m M_m + \omega_o M_o, \tag{17}$$

where (ω_m, ω_o) is a weight vector that specifies the weight associated with the minutia matching score M_m and the orientation field matching score M_o.

4. Experimental results

The experiments reported in this paper have been conducted on the public domain collection of fingerprint images, DB3 in FVC2002. It comprises 800 fingerprint images of size 300×300 pixels captured at a resolution of 500 dpi, from 100 fingers (eight impressions per finger).

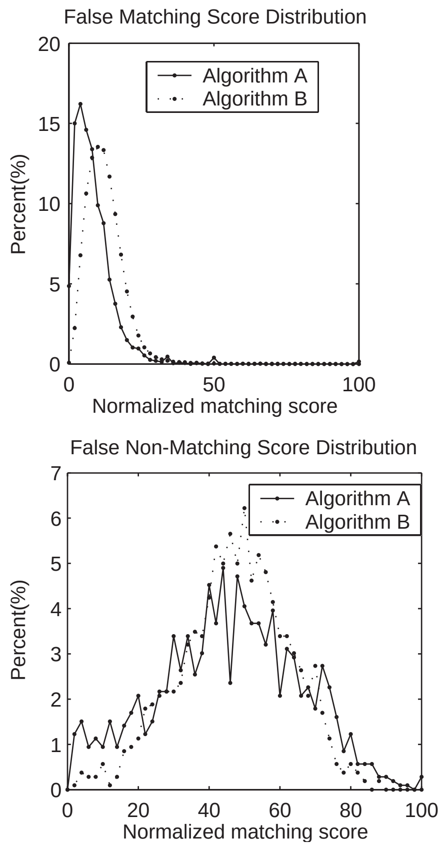

Fig. 2. The distribution curves of matching score on DB3 obtained with the algorithm A (solid line) and the algorithm B (dotted line).

A set of experiments have been conducted in order to show that both minutia information and orientation field information are complementary. First, denote our algorithm using only minutia information by A, which means to calculate matching score with Eq. (15); label our algorithm making use of both the minutia and orientation field as B, which computes the matching score according to Eq. (17). Matching experiments have been performed on DB3 using algorithms A and B. The distributions of false matching and false non-matching scores are shown in Fig. 2. The receiver operating characteristic (ROC) curves obtained by the two algorithms are illustrated in Fig. 3. We note that algorithm B outperforms the algorithm A. The only difference between the two algorithms consists of the method used for matching score computation. Consequently, these results reveal that the minutia information and orientation field information are complementary.

As mentioned above, we label our method as B. To show the effectiveness of our triangular matching approach, a comparative experiment has been conducted on DB3 with algorithm B and algorithm C without the triangular matching stage. Fig. 4 shows the matching performance in terms

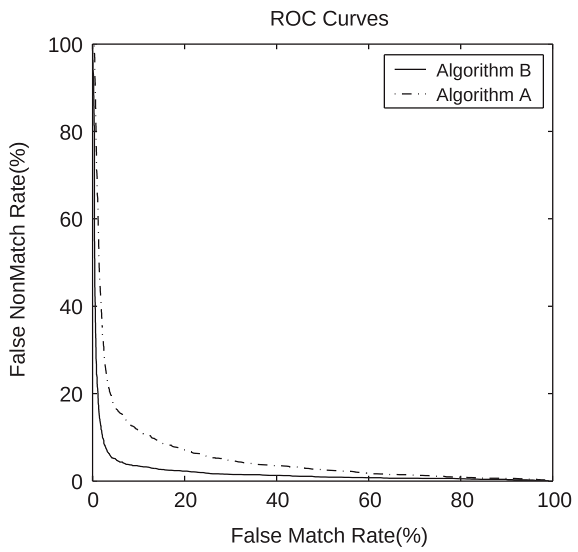

Fig. 3. ROC-curves on DB3 attained with the algorithm A (dash–dot line) and the algorithm B (solid line).

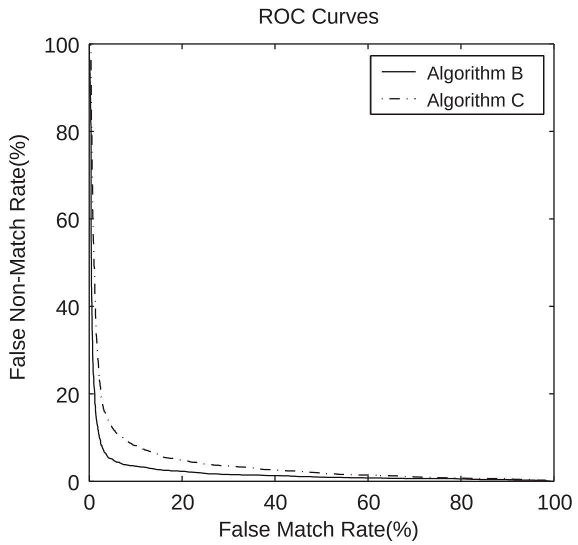

Fig. 4. ROC-curves on DB3 obtained with algorithm B (solid line) and algorithm C (dash–dot line).

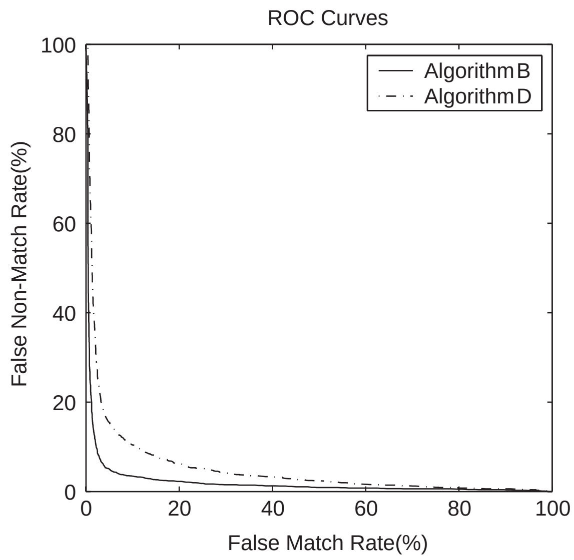

Fig. 5. ROC-curves on DB3 obtained with our matching method (solid line) and the algorithm D (dash–dot line).

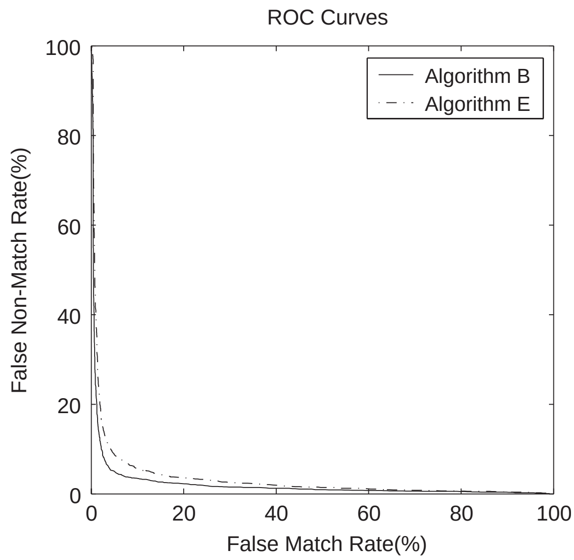

Fig. 6. ROC-curves on DB3 attained with our matching method (solid line) and the algorithm E (dash–dot line).

of ROC curves obtained with the two algorithms. The result demonstrates that triangular matching method works better.

Next, we conducted a set of experiments on DB3 meant to compare our algorithm with the approach proposed in Ref. [3], which matches fingerprints based on both the local and global structures of minutiae. For convenience we label the method in Ref. [3] as D. The algorithm D uses the local minutia structures for registration and computes matching score based on the similarity level of corresponding local structures. We have performed the two algorithms on DB3 and obtained the results expressed in terms of ROC curves, as shown in Fig. 5. The results demonstrate that our method is more effective than algorithm D.

Then, we compared the triangular matching method in Ref. [14] with our method. For convenience, the match scheme in Ref. [14] is denoted as E. The ROC curves is exemplified in Fig. 6. It is shown that our method does a better matching job than algorithm E.

Table 1
Comparison of our algorithm with algorithm PA26

Algorithm	EER (%)	Average enroll time (s)	Average match time (s)
Our algorithm	4.97	0.81	0.03
PA26	5.08	0.37	0.44

Finally, in Table 1 we compare our result with that of algorithm PA26 in DB3, which participated in the competition of FVC2002 and got the 12th place ranked by the equal error rate (EER). According to the ranking rule in terms of EER in FVC2002, our algorithm is in the first 12 places.

5. Conclusions

In this paper, we define novel minutia feature vectors that allow integration of orientation field information with the minutia details of fingerprints. The new feature vectors are rotation and translation invariant and capture more global information on fingerprint ridges and furrows pattern. Furthermore, it reduces the interdependencies between minutia details, which can be missed or erroneously detected by a minutia extraction algorithm. A new triangle-based fingerprint matching algorithm that relies on the proposed minutia vectors has been developed. The triangular match method proposed in this paper is robust to the inexact registration and non-linear deformation. In addition, the orientation field and minutiae are combined to compute the matching score. The experiments show that the two kinds of information are complementary and the method for computing matching score is effective.

The usefulness of our proposed approach is confirmed in the experiments conducted, which show good performance.

References

[1] Z. Chen, C.H. Kuo, A topology-based matching algorithm for fingerprint authentication, Proceedings of 125th Annual IEEE International Carnahan Conference on Security Technology, 1991, pp. 84–87.
[2] A.K. Hrechak, J.A. McHugh, Automatic fingerprint recognition using structural matching, Pattern Recognition 23 (8) (1990) 893–904.
[3] X. Jiang, W.Y. Yau, Fingerprint minutiae matching based on the local and global structures, Proceedings of the 15th International Conference on Pattern Recognition, vol. 2, 2000, pp. 1038–1041.
[4] A. Wahab, S.H. Chin, E.C. Tan, Novel approach to automated fingerprint recognition, IEE Proc. Visual Image Signal Process. 145 (3) (1998) 160–166.
[5] A.K. Jain, L. Hong, S. Pankanti, R. Bolle, An identity-authentication system using fingerprint, Proc. IEEE 85 (9) (1997) 1365–1388.
[6] A.K. Jain, L. Hong, R. Bolle, On-line fingerprint verification, IEEE Trans. Pattern Anal. Machine Intell. 19 (4) (1997) 302–313.
[7] N.K. Ratha, K. Karu, S. Chen, A.K. Jain, A real-time matching system for large fingerprint database, IEEE Trans. Pattern Anal. Machine Intell. 18 (8) (1996) 799–813.
[8] A. Ross, A.K. Jain, J. Reisman, A hybrid fingerprint matcher, Pattern Recognition 36 (2003) 1661–1673.
[9] A. Almansa, L. Cohen, Fingerprint image matching by minumization of a thin-plate energy using a two-step algorithm with auxiliary variables, Proceedings of the Fifth IEEE Workshop on Applications of Computer Vision, 04–06 December 2000, pp. 35–40.
[10] A.M. Bazen, S.H. Gerea, Thin-plate spline modeling of elastic deformations in fingerprints, Proceedings of the Third IEEE Benelux Signal Processing Symposium, 2002, pp. 1–4.
[11] X. Luo, J. Tian, Y. Wu, A minutia matching algorithm in fingerprint verification, Proceedings of the IEEE 15th International Conference on Pattern Recognition, 4 September 2000, pp. 833–836.
[12] A.W. Senior, R. Bolle, Improved fingerprint matching by distortion removal, IEICE Trans. Inform. Syst. (special issue on Biometrics) 7 (E84-D) (2001) 825–831.
[13] D. Lee, K. Choi, J. Kim, A robust fingerprint matching algorithm using local alignment, Proceedings of the 16th International Conference on Pattern Recognition, vol. 3, 2002, pp. 803–806.
[14] M.K. Zsolt, A fingerprint verification system based on trianglular matching and dynamic time warping, IEEE Trans. Pattern Anal. Machine Intell. 11 (22) (2000) 1266–1276.

About the Author—JIN QI received his B.Sc. degree and M.Sc. degree in Applied Mathematics from Sichuan Normal University, in 1999 and 2002, respectively. He is currently pursuing his Ph.D. degree in Computer Science in Institute of Automation, Chinese Academy of Sciences. In July 2002, he has finished his M.Sc. thesis: an Automatic ECG (Electrocardiograph) Recognition System. His research interests include Pattern Recognition, Computer Vision, Biometrics, Applied Mathematics, Image and Signal Processing.

About the Author—YANGSHENG WANG is a distinguished researcher in the National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences. He is currently the director of the CASIA-SAIT HCI Joint Laboratory. He has made significant contributions and published a large number of papers on the following topics: Statistical Pattern Recognition, Texture Analysis, Signal and Image Processing, 3D Reconstruction, Network Control, and Biometric Authentication.