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Orientation feature for fingerprint matching

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Abstract

This paper describes a fingerprint verification algorithm based on the orientation field. The orientation field of a fingerprint image has also been used for image alignment. Area around the core point has been employed as an area of interest for determining the orientation feature map. The algorithm has been tested on two databases (database available from University of Bologna, Biometrics Laboratory and FVC2002). The performance of the algorithm is measured in terms of receiver operating characteristics (ROC). For the University of Bologna database, at $\sim 0\%$ false acceptance rate (FAR) the genuine acceptance rate (GAR) observed is $\sim 78\%$ and at $\sim 11\%$ FAR, GAR is $\sim 97\%$. For the FVC2002 database at $\sim 0\%$ FAR the GAR observed is 75% and at $\sim 18\%$ FAR, GAR is 93%. Proposed algorithm yields better GAR at low FAR with reduced computational complexity. Because of simplicity in computations the algorithm can be easily implemented as an embedded automatic fingerprint identification system (AFIS).

Keywords: Orientation; Identification; Verification; False acceptance rate; False rejection rate; Genuine acceptance rate

1. Introduction

Among all the biometrics, fingerprint is most convenient, reliable, hence extensively used by forensic experts in criminal investigations. Fingerprints are believed to be unique across individuals, and across fingers of the same individual [1]. Even identical twins having similar DNA are believed to have different fingerprints. Because of this, there is increased use of automatic fingerprint verification systems in civilian as well as in law-enforcement applications. Fingerprint matching techniques can be broadly classified into two categories, minutiae-based and image-based.

A minutia-based technique aligns the two sets of minutiae points and determines the total number of matched minutiae [2]. Unfortunately, the minutiae-based approach contains many time consuming steps and relies heavily on the quality of input image. In fingerprint images, however, minutiae are not always clear even though the information of ridge directions and inter-ridge distances is preserved. The use of Gabor filter for texture classification and feature extraction has been proved its importance. Due to the multi-resolution capacity of Gabor transform it retains the textural features of an image. Since fingerprint image has strong oriented structure, Gabor filter has been used for representing the local ridge information.

We present an algorithm for fingerprint verification using image-based technique in which the variance feature of orientation field is used for matching. The test and trainee fingerprint images are aligned using the orientation, which makes the algorithm rotation invariant. The images in which the core point is located less than 50 pixels away from the image border have been rejected (both for training and testing). The area of interest for finding the orientation field is the area around the core point, hence, the segmentation to separate the foreground from background is not required. Since the area of interest is around core point, the algorithm becomes translation invariant.

This paper is organized in following manner. Section 2 describes the computation of orientation field and Section 3

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describes the fingerprint image registration process (training). Section 4 explains about the fingerprint matching, and in Section 5 algorithm results are presented.

2. Orientation field estimation

The orientation field of a fingerprint image represents the directionality of ridges [3]. Fingerprint image typically divided into number of non-overlapping blocks and an orientation representative of the ridges in the block is assigned to the block based on grayscale gradients in the block. The block size depends on the inter-ridge distance, i.e. it should include at least one ridge and one valley in a block. The block orientation can be determined from the pixel gradients by averaging or voting (optimization). The orientation field of block (i, j) is given by

$$\theta(i, j) = 0.5 \tan^{-1}\left(\frac{V_x(i, j)}{V_y(i, j)}\right), \tag{1}$$

where

$$V_x(i, j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} (G_x(u, v) G_y(u, v)) \tag{2}$$

and

$$V_y(i, j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} (G_x^2(u, v) - G_y^2(u, v)), \tag{3}$$

where w is the size of block, G_x and G_y are the gradient magnitudes in x and y directions, respectively. Sobel operators have been used for computations of G_x and G_y. The orientation field of a typical fingerprint image is shown in Fig. 1 (The orientation field is overlapped with the original fingerprint image).

Fig. 1. Orientation field of a typical fingerprint image.

Fig. 2. Typical core point located fingerprint image.

Fig. 3. Cropped image around core point.

3. Fingerprint image registration (Training)

Following steps have been followed for registration of fingerprint images (training).

Step 1: Core point detection.
Step 2: Image cropping around core point.
Step 3: Image smoothing.
Step 4: Computation of orientation field.
Step 5: Computation of feature vector (template).

A point of most curvature in a fingerprint image has been detected and considered as a reference (core) point [4]. A typical core point detected fingerprint image is shown in Fig. 2. A properly core point located fingerprint image has been considered for registration. An image of size 100 by 100 pixels around the core point has been cropped as shown in Fig. 3. The smoothing of cropped fingerprint image is carried out using a low pass filter, which helps in minimizing the effect of noise in gradient computation. The cropped image is divided into non-overlapping square blocks to compute orientation field using Eq. (1). The variance feature vector of orientation field is computed and is treated as a template or feature map.

$$\sigma_k^2 = \sum_{i=1}^{n} (\theta(i, k) - \mu_k)^2 \quad \text{for } k = 1, \ldots, m, \tag{4}$$

where μ_k is a mean of kth column of $\theta\ (i, j)$, m and n are number of columns and rows of θ, respectively. The feature vector is given by

$$\overline{v} = [\sigma_1^2 \sigma_2^2 \cdots \sigma_n^2]^{\mathrm{T}}. \tag{5}$$

4. Fingerprint image matching

The orientation field of test fingerprint image has been computed by following first four steps as described in Section 3. From the orientation field of test and trainee fingerprint images the amount of rotation of the test fingerprint with respect to the trainee fingerprint image is estimated. The efficient way of estimating the amount of rotation is proposed in this paper. The amount of rotation in a test fingerprint image is given by following equation:

$$\theta_r = \frac{(\theta'(1,1) - \theta(1,1)) + (\theta'(m,n) - \theta(m,n))}{2}, \tag{6}$$

where $\theta'(1,1)$ and $\theta(1,1)$ are orientations of first blocks of test and trainee fingerprint images, respectively. Similarly $\theta'(m,n)$ and $\theta(m,n)$ are orientations of block (m,n) of test and trainee fingerprint images, respectively. The test fingerprint image is then rotated by θ_r. The step 5 described in Section 3 is followed to compute the feature vector of the rotated test fingerprint image.

It has been observed that there is a little deviation between actual and estimated rotation angle as we go away from the core point and little more around the core point. The estimated angle of rotation for alignment gives better results with less computation. It has been observed that the amount of rotation for some fingerprint images in FVC2002 is more than 45°. The typical fingerprint images of trainee and test subject from FVC2002 database are shown in Fig. 4. The test and trainee fingerprint images are matched using the L_2 norm.

$$\begin{aligned} d &= \|\overline{\upsilon'} - \overline{\upsilon}\|^2 \\ &= \sum_{k=1}^{m} ({\sigma'_k}^2 - \sigma_k^2)^2, \end{aligned} \tag{7}$$

where $\overline{\upsilon'}$ and $\overline{\upsilon}$ are the feature vectors of test and trainee fingerprint images, respectively.

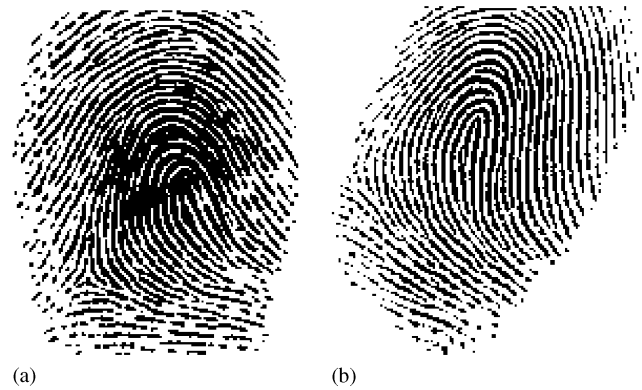

Fig. 4. Fingerprint images of the same subject from FVC2002 database.

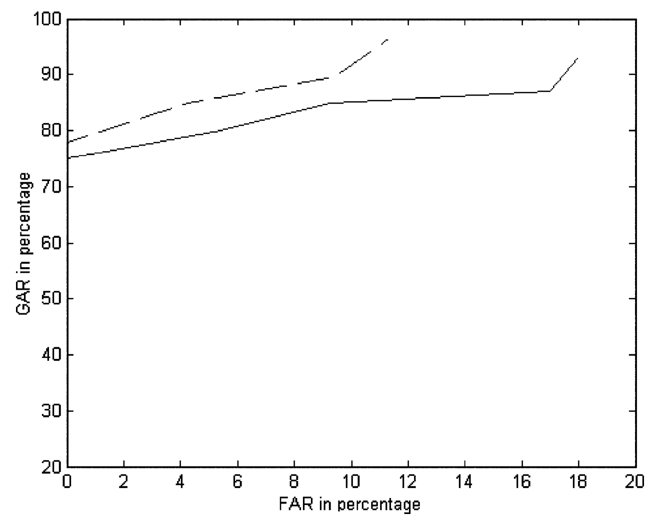

Fig. 5. Performance of algorithm on University of Bologna database (dashed line) and FVC2002 (solid line).

5. Experimental results and conclusion

We have used two different databases for experimentation provided by University of Bologna and FVC2002. The performance of algorithm has been measured in terms of FAR and false rejection rate (FRR) for various thresholds. The FAR and FRR for both databases are computed as follows.

N is the number of subjects with eight fingerprints each. Total fingerprint images are $T = 8 \times N$. A single template per subject has been considered for experimentation. Total trials carried out for finding true claims and imposter claims are $N \times (T-1)$, out of which total true claims are $N \times 7$ and imposter claims are (total trials – true claims).

FRR = (true claims rejected/total true claims) × 100 and FAR = (imposter claims accepted/total imposter claims) × 100 GAR = 100 − FRR in percentage.

For every possible combination the algorithm has been tested for computation of FAR and FRR.

University of Bologna database consists of images of 20 subjects with eight images of each subject. Total $20*8=160$ images. FAR and GAR at various values of thresholds are shown in Fig. 5. The GAR reported 96.33% at 11.3% FAR and 78% for 0.17% FAR. As compared to the fingerprint images from FVC2002 database fingerprint images of University of Bologna database are of good quality by means of amount of rotation in claimed fingerprint and average gray level.

We have considered Db1_a and Db1_b databases from FVC2002. Db1_a and Db1_b consist of total 800 and 80 fingerprint images, respectively. For experimentation 105 subjects with eight fingerprints of each out of 840 fingerprint images from both the databases have been used. For a single threshold total trials carried out for computations of FAR and FRR were $105 \times (840-1) = 88\,095$. Results reported for various thresholds on FVC2002 databases are given in Fig. 5.

The proposed algorithm produce better results at lower and higher values of FAR as compared to minutiae-based algorithms. As the algorithm takes fewer computations it can be implemented using the real-time processor.

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