A Robust Orientation Estimation Algorithm for Low Quality Fingerprints

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Abstract. It is a difficult and challenge task to extract the accurate orientation field for the low quality fingerprints. This paper proposed a robust orientation estimation with feedback algorithm to get the accurate fingerprint orientation. First, the fingerprint image is segmented into recoverable and unrecoverable regions. The following orientation field estimation and orientation correction algorithms were only processed in the recoverable regions. Second, the coarse orientation image is estimated from the input fingerprint image using the gradient-based approach. Then we computed the reliability of orientation from the gradient image. If the reliability of the estimated orientation is less than pre-specified threshold, the orientation will be corrected by the proposed mixed orientation model. The proposed algorithm has been evaluated on the databases of FVC2004. Experimental results confirm that the proposed algorithm is a reliable and effective algorithm for the extraction orientation field of the low quality fingerprints.

1 Introduction

The orientation field, as a global essential feature of a fingerprint image, it summarizes the overall pattern of a fingerprint's ridges and valleys and plays a very important role in fingerprint recognition processing [1]. Many orientation detecting techniques have been developed to obtain fast and reliable orientation field. N. Ratha et al[2] proposed a gradient based algorithm to compute the orientation field. They estimated the local orientation at each pixel based on an analysis of grayscale gradients in the block centered at the given pixel. Sarat C. Dass[3] utilized a Bayesian formulation for reliable and robust extraction of the directional field in fingerprint images with a class of spatially smooth priors. The spatial smoothness allows for robust directional field estimation in the presence of moderate noise levels. A.M. Bazen and S.H. Gerez[4] proposed an algorithm to estimate a high resolution directional field of

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fingerprints. The method computes both the direction in any pixel location and its coherence. It provides exactly the same results as the "averaged square-gradient method" that is known from literature.

Another type of algorithms has been advanced to model the overall orientation pattern globally, which are more adaptive to noise and corrupt in fingerprint images. Sherlock and Monro [5] represented the orientation based on a zero-pole model by mapping the image plane to a complex plane, where the core point was considered as pole and delta point as zero. These poles and zeros completely determine the overall fingerprint orientation. Li et al. [1] adapted the polynomial mode to refine the fingerprint orientation predicted by the coarse model. Zhou et al. [6] combined a polynomial model which is represented to reconstruct the overall orientation and a point charge model which modified the local orientation near the singular points, so that a more accurate orientation field could be obtained. Pedro et al. [7] divided the fingerprint image into several parts in terms of singular points. For different parts, a piecewise linear function was analyzed and applied.

The algorithms mentioned above could detect the orientation field successfully for the good and moderate quality fingerprint. However, the performance decreases greatly with the degradation of the fingerprint quality. This paper proposes a robust orientation estimation with feedback algorithm to get the accurate fingerprint orientation. First, the fingerprint image is segmented into recoverable or unrecoverable regions. The following orientation field estimation and orientation correction algorithm was only implemented in the recoverable regions. Second, the coarse orientation image is estimated from the input fingerprint image using the gradient-based approach. Then we computed the reliability of orientation from the gradient image. If the reliability of the estimated orientation is less than pre-specified threshold, the orientation will be corrected by the proposed mixed orientation model.

This paper is organized as following. Section 2 indicates out the details of orientation estimation of fingerprint images. Section 3 shows the performance of the proposed algorithm by experiments. Section 4 gives out our conclusion.

2 Fingerprint Orientation Estimation Algorithm

We proposed an orientation estimation with feedback algorithm to get the accurate fingerprint orientation. The flowchart of the proposed orientation estimation algorithm is shown in figure 1.

2.1 Segmentation of Fingerprints

In our algorithm, we classify each pixel in an input fingerprint image into a recoverable or an unrecoverable region. The fingerprint is divided into blocks of $w \times w$ pixels (w=12 in our algorithm). We select three features that contain useful information for segmentation. These three features are block clusters degree, block mean information and block variance. An optimal linear classifier has been trained for the classification per block and the criteria of minimal number of misclassified samples are used. Morphology has been applied as post-processing to reduce the number of classification errors [9].

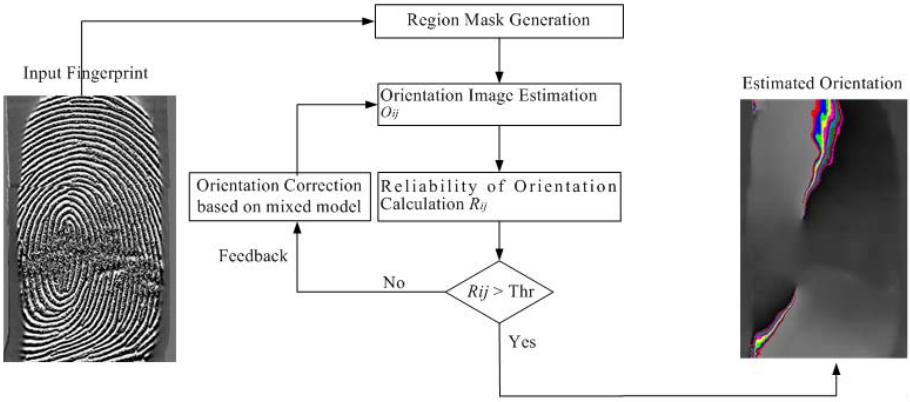


Fig. 1. The flowchart of the proposed fingerprint orientation estimation algorithm

2.1.1 Three Block Features

(1) The block clusters degree CluD

The block clusters degree CluD measures how well the ridge pixels are clustering. Using I as the intensity of image, the block clusters degree is defined as:

$$CluD = \sum_{i,j \in Block} sign(I_{ij}, \mathrm{Im}\,g_{mean}) \bullet sign(D_{ij}, Thre_{CluD}) \tag{1}$$

where $D_{ij} = \sum_{m=i-2}^{i+2} \sum_{n=j-2}^{j+2} sign(I_{mn}, \mathrm{Im}\,g_{mean})$, $sign(\alpha, \beta) = \begin{cases} 1 & if(\alpha < \beta) \\ 0 & otherwise \end{cases}$,

$\mathrm{Im}\,g_{mean}$ is the intensity mean of the whole image. $Thre_{CluD}$ is an empirical parameter, $Thre_{CluD}$ =15 in our algorithm.

(2) The block mean information $MeanI$

We use the difference of local block mean and global image mean as the second feature for fingerprints segmentation. The mean information $MeanI$ for each block is given by:

$$MeanI = (\frac{1}{w \bullet w} \sum_{Block} I) - \mathrm{Im}\,g_{mean} \tag{2}$$

(3) The block variance Var

The block variance Var is the third feature that is used. In general, the variance of the ridge-valley structures in the foreground is higher than the variance of the noise in the background. The block variance Var for each block is given by:

$$Var = \frac{1}{w \bullet w} \sum_{Block} (I - mean)^2 \tag{3}$$

2.1.2 Linear Classification Design

In this paper, we follow a supervised approach since the block features of samples in both areas are available. Using this method, a classification algorithm can be con-

structed that minimizes the probability of misclassifying. In our algorithm we use the criteria of minimal number of misclassified samples to classify the blocks. The criteria function can be defined as:

$$J(w) = \left\| (Xw - b) - \left| Xw - b \right| \right\|^2 \tag{4}$$

Our aim is to find a vector w to make the value of J(w) minimal. The detailed steps of algorithm can be seen from our previous work [9].

2.2 Coarse Orientation Field Estimation Based on Gradient

In our algorithm, the gradient-based approach proposed by Lin et al [8] was used to compute the coarse orientation Oij for each location (i,j). However, their block-wise scheme is coarse and cannot obtain fine orientation field. In order to estimate the orientation field more accurately, we extend their method into a pixel-wise one. For each pixel, a block with size (15*15) centered at the pixel is used to estimate the orientation of each pixel. To reduce the computational cost, a sliding window technique is implemented.

2.3 Reliability of Orientation Computing

An additional value rij is associated with each orientation element Oij to denote the reliability of the orientation. The value rij is low for noise and seriously corrupted regions and high for good quality regions in the fingerprint image. The reliability rij is derived by the coherence of the gradient Gij within its neighborhood. It is defined as follows:

$$r_{ij} = \frac{\left| \sum_W (G_{i,x}, G_{j,y}) \right|}{\sum_W \left| (G_{i,x}, G_{j,y}) \right|} = \frac{\sqrt{(G_{xx} - G_{yy})^2 + 4G_{xy}^{\ 2}}}{G_{xx} + G_{yy}} \tag{5}$$

Where $(G_{i,x}, G_{j,y})$ is the squared gradient, $G_{xx} = \sum_w G_x^{\ 2}$, $G_{yy} = \sum_w G_y^{\ 2}$, $G_{xy} = \sum_w G_x \cdot G_y$ and (G_x, G_y) is the local gradient. W is taken as 11*11 block around (i,j).

2.4 Orientation Correction Based on Mixed Model

We proposed a mixed orientation model to correct the estimated orientation where its reliability is less than threshold thr. Zhou et al. [6] proposed a combination model to estimate the orientation field. However, in their algorithm, the fingerprints were not segmented into recoverable and unrecoverable regions. When their algorithm was applied to unrecoverable region, it will result many spurious minutiae in the post processing although the orientation field could be modeled.

2.4.1 The Mixed Orientation Model

The mixed orientation model is consisted of two parts, polynomial model and singular model. Due to the smoothness of the original orientation field, we could choose

proper polynomial curves to approach it. As the value of fingerprints' orientation is defined on $[0,\pi)$, it seems that this representation has an intrinsic discontinuity [6]. We map the orientation field to a continuous complex plane [10]. Denote $\theta(x,y)$ as the orientation field. The mapping is defined as:

$$\mathrm{U} = \mathrm{R} + \mathrm{iI} = \cos(2\theta) + \mathrm{i}\sin(2\theta) \tag{6}$$

where R and I denote the real part and image part of the unit-length complex, U, respectively.

To globally approach the function R and I, a common bivariate polynomial model is chosen for them respectively, which can be formulated as:

$$(1\ x \cdots x^n)\cdot\begin{bmatrix} p_{00} & p_{01} & \cdots & p_{0n} \\ p_{10} & p_{11} & \cdots & p_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n0} & p_{n1} & \cdots & p_{nn} \end{bmatrix}\cdot\begin{pmatrix} 1 \\ y \\ \vdots \\ y^n \end{pmatrix} \tag{7}$$

where the order n can be determined ahead.

The singular area is the area near the singular points where the ridge curvature is higher than normal and where the direction of the ridge changes rapidly. So it is difficult to be modeled with polynomial functions. The orientation model proposed by Sherlock and Monro [5] is added at each singular point. We name Sherlock's model as the singular model. The model allows a consistent directional map to be calculated from the position of the cores and deltas only. In this model the image is located in the complex plane and the orientation is the phase of the square root of a complex rational function with the fingerprint macro-singularities (cores and deltas). Let $c_i\ (i=1..n_c)$ and $d_i\ (i=1..n_d)$ be the coordinates of the cores and deltas respectively; the orientation O' at each point (x,y) is calculated as:

$$O'(z) = O_0 + \frac{1}{2}\left[\sum_{i=1}^{n_d}\arg(z-d_i) - \sum_{i=1}^{n_c}\arg(z-c_i)\right] \tag{8}$$

where O_0 is the background orientation (we set O_0 =0), and the function arg(z) returns the argument of the complex number z (x,y).

To combine the polynomial model with singular model smoothly, a weight function is defined for singular model, its weight at (x, y) is defined as:

$$w = \begin{cases} 0 & if\ (\sum_{i=1}^{k} w_i > 1) \\ 1-\sum_{i=1}^{k} w_i & otherwise \end{cases} \tag{9}$$

$$w_i = \begin{cases} 0 & if\ (D_i(x,y) > r_i) \\ 1 - D_i(x,y)/r_i & otherwise \end{cases} \tag{10}$$

where k is the number of singular points, i is the ordinal number of singular points, $D_i(x, y)$ is the distance between point (x,y) and i-th singular point, $\boldsymbol{r}_i$ is i-th singular point's effective radius.

It is clear that for each point, its orientation is mainly controlled by singular model if it is near one of the singular points and it follows the polynomial model if it is far from the singular points.

Finally, the mixed model for the whole fingerprint's orientation field can be formulated as:

$$O_m = (1-w)\cdot\theta + w\cdot O' \tag{11}$$

If the reliability of the estimated orientation rij is less than threshold thr, we will using the orientation O_m derived from the mixed model instead of the original estimated orientation.

2.4.2 Detection of the Singular Points and the Estimation of the Parameters

In order to implement the orientation correction algorithm, the position and type of singular points are need to detected. In our algorithm, the Poincare index method is used to detect the singular points. In order to compute the singular points more robust, we pre-process the original orientation field with the low bandpass filters to decrease the noise and smooth the orientation flows.

To implement the mixed orientation model, many parameters need to be ascertained. Some of them are initiated and modified based on the experiments while others are computed by least square method.

3 Experimental Results

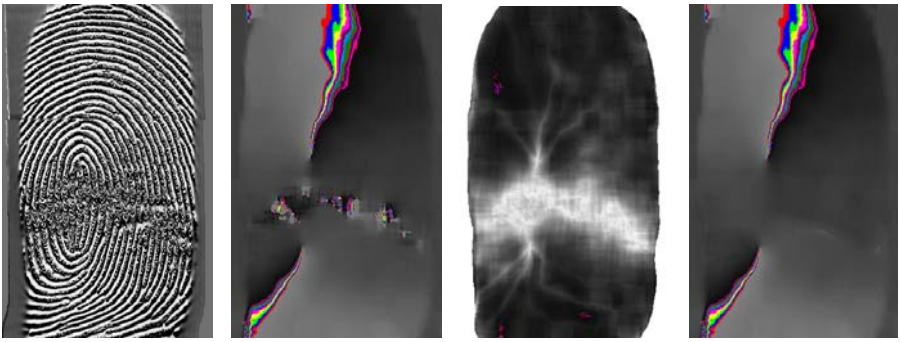
The proposed algorithm has been evaluated on the databases of FVC2004 [11]. As the limits of pages, only the results on FVC2004 DB3 were listed in this paper.

The fingerprints of FVC2004 DB3 were acquired through thermal sweeping sensor "FingerChip FCD4B14CB" by Atmel. The size of the image is 300*480 pixels with the resolution of 512 dpi. Figure 2 show an example of low quality fingerprint in FVC2004 DB3 and its experimental results using the proposed algorithm. It can be seen from figure 2 that the computed orientation field of this poor fingerprint is smoothly and precisely.

Experiments were also done to compare the orientation estimation algorithm with and without feedback method. The comparison results on FVC2004 DB3 are shown in figure 3. The EER was 1.64 for the algorithm with feedback method, while 3.60 for the algorithm without feedback method. It is proved that the feedback method improved the performance the recognition algorithm greatly. The average time for estimation a fingerprint orientation in FVC2004 DB3 is about 0.06 second on PC AMD Athlon 1600+ (1.41 GHz).

4 Conclusion

This paper propose an robust orientation estimation with feedback algorithm to get the accurate fingerprint orientation. The proposed algorithm has been evaluated on



(a) (b) (c) (d)

Fig. 2. Some experiment results of a fingerprint in FVC2004 DB3. (a)Original fingerprint (b)the coarse estimated orientation (c) the reliability of orientation (d) the corrected orientation

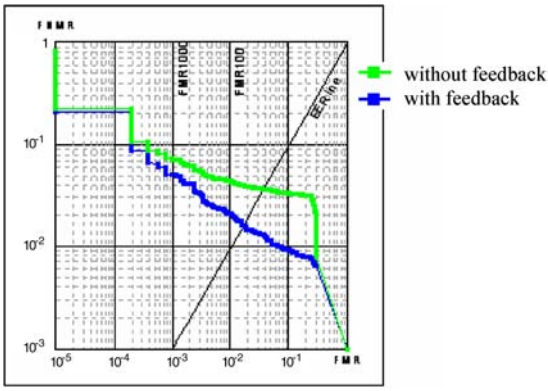


Fig. 3. The comparison the orientation estimation algorithm with and without feedback method on FVC2004 DB3

the databases of FVC2004. As the limits of pages, only the results on FVC2004 DB3 were listed in this paper. Experimental results confirm that the proposed algorithm is a reliable and effective algorithm for the extraction orientation field of the low quality fingerprints.

References

1. Li Jun, Yau Wei Yun, Prediction of Fingerprint Orientation, ICPR 2004, Aug. 2004 Volume: 4, Vol.4 On page(s): 436- 439
2. N. Ratha, K. Karu, S. Chen and A. K. Jain, A Real-time Matching System for Large Fingerprint Database, IEEE Trans. on Pattern Anal. Machine Intell., Vol. 18, No. 8, pp. 799-813, 1996.
3. Sarat C. Dass, Markov Models for Directional Field and Singularity Extraction in Fingerprint Images
4. A. Bazen, S. Gerez, “Systematic Methods for the Computation of the Direction Fields and Singular Points of Fingerprints”, Pattern Analysis and Machine Intelligence,2002, 24 (7), pp. 905-919

5. B. G. Sherlock and D. M. Monro; "A Model for interpreting fingerprint topology"; Pattern Recognition, Vol. 26, No. 7, pp. 1047-1993.
6. J. Zhou and J. W. Gu, A Model-based Method for the computation of Fingerprints' Orientation Field, IEEE Trans. On Image Processing, Vol. 13, No. 6, pp.821-835, 2004
7. P.R. Vizcaya and L.A. Gerhardt; "A nonlinear orientation model for global description of fingerprints"; Pattern Recognition, Vol. 29, No. 7, pp. 1221-1231.
8. L. Hong, Y. Wan, A. K Jain, Fingerprint Image Enhancement: Algorithm and Performance Evaluation. IEEE Trans. PAMI, 20(8), pp.777–789, 1998.
9. Xinjian Chen, Jie Tian, Jianggang Cheng, Xin Yang, Segmentation of Fingerprint Images Using Linear Classifier, EURASIP Journal on Applied Signal Processing, EURASIP JASP 2004:4 (2004) 480-494.
10. G.H. Granlund and H. Knutsson, Signal Processing for Computer Vision, Kluwer Academic Publishers, Boston, 1995.
11. Biometric Systems Lab, Pattern Recognition and Image Processing Laboratory, Biometric Test Center, http://bias.csr.unibo.it/fvc2004/.