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Fingerprint Ridge Orientation Estimation Based on Neural Network

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Abstract: - Ridge orientation is one of the fundamental features of a fingerprint image. Orientation estimation serves for feature extraction and matching and is the base of fingerprint recognition. Most existing orientation estimation methods are based on the characteristic of pixel intensity in a block. This paper uses neural network to learn the ridge orientation. The trained network has the property of responding to true ridge orientation with a large value and responding to the false ridge orientation with a small value. When estimating fingerprint ridge orientation, the responded values to each orientation at each image block are used to compute the fingerprint orientation field. The proposed method turns out more robust than the existing method.

Key-Words: - Fingerprint recognition, Ridge orientation, Neural network, Filtering, Orientation setection

1 Introduction

Fingerprint recognition is one of the technologies of biometric authentication. Though many advances on fingerprint recognition have been made in recent years, technologies of fingerprint recognition are still expected to be improved to meet the demands for faster, more robust, and more accurate system. Fingerprint matching typically goes through a series of processes, mainly including ridge orientation estimation, image segmentation, enhancement, ridge and minutiae detection, and matching [1,2]. Fingerprint image consists of directional ridges. Ridge orientation is the basic feature of a fingerprint image, and ridge orientation estimation is almost the prelude to fingerprint matching, since ridge orientation is used in almost all other steps. There are already some methods for fingerprint ridge orientation estimation in literatures [3-23]. Most of them are based on relationship of pixel intensity between pixels [3-16]. Among them, the most popularly used method for ridge orientation estimation is the gradient-based method or its variant [12-16]. This method computes the gradient vector of each pixel. The pixel intensity changes with the fastest speed along the gradient direction, and the length of the vector indicates the speed of the change. The ridge orientation estimated using gradient-based method is mainly dominated by the ridge edge pixels since they have large variation of pixel intensity along the gradient direction. The block ridge orientation can be computed by means of averaging the pixel gradients within the block. However, the pixels at the two parallel edges of a ridge have opposite gradients which will cancel each other when averaging the gradients. Therefore, the block orientation is computed by means of averaging the squared gradients, since the squared gradients at the two edges of a ridge point to the same direction. The gradient-based method is easy to be interfered by noise. In order to correct the false orientations caused by noise, [12] uses low pass filtering to smooth the orientation field. Fourier transform can also be used for orientation estimation [17]. The Fourier spectrum of a ridge block reveals two high peaks, connecting which the orientation of the line is orthogonal to the ridge orientation. There are some other methods trying to globally model the directional image in order to be able to predict orientation in very noisy area. Sherlock [18] generates the orientation field based on the location of singularities, including core and delta. This method fails to distinguish two fingerprints which have the same locations and numbers of singularities but the different orientation field pattern. This method is improved by Vizcaya [19] and Araque [20]. Modeling orientation is well used in generating fingerprints [20,21]. Modeling orientation based on the position of singularities fails when the image contains no singularities or their positions are falsely located. Gu [22] and Zhou [23] combine gradient-based method to model the directional image. That, in fact, is to use LMS to globally smooth the orientation field which is estimated using gradient-based method. This method is also dependent on the correct locating of the singularities and the estimation of their direction.

Estimating ridge orientation of noisy image is still a not full-solved problem. Gradient based method operates on the fact that for high quality ridges the gradient of most edge pixels has its direction almost orthogonal to the ridge orientation. However, low quality image block may contain edges which is not that of the ridges but of the noise caused by ridge interrupts, wet, dirt, etc. These spurious edges will produce false ridge orientations. And at the same time, modeling orientation field depends more or less on the locating of singularities which in return is dependent on the ridge orientation estimation itself. In order to correctly estimate ridge orientation in noisy ridge areas, we propose a machine learning based method which follows our previous work [24] that uses a neural network to evaluate the correctness of an estimated orientation. Section 2 describes the proposed method in detail. Section 3 is the experimental results. Section 4 is the conclusion.

2 Orientation Estimation

[24] proposed a method to estimate the fingerprint image quality by training a BP neural network which, containing 11 input nodes, 11 hidden nodes and 1 output node, responds to correct ridge orientation of ridge block (of high quality or manually recoverable) with a large value, and responds with a small value to those blocks which contain no ridges or contain manually unrecoverable ridges or are of falsely estimated orientations. The training method is demonstrated in [24]. For each image block, a feature vector $\langle C_1, C_2, ..., C_{11} \rangle$ [24] is computed to be fed into the network which will respond to the vector with a value. The responded value by the trained network to a specific block is depended on the orientation, because the items from C5 to C11 of the input vector $\langle C_1, C_2, ..., C_{11} \rangle$ [24] have a close relationship with the estimated ridge orientation. Suppose that the image is divided into unoverlapped blocks like in [24], and let W(i,j) denote the block at the *ith* row and the *jth* column. And the ridge orientation is quantified into 16 orientations: the *kth* orientation is $k \cdot \pi / 16 \ (0 \le k < 16)$. For each block W(i,j), 16 vectors, denoted as $\langle C_1, C_2, ..., C_{11} \rangle^k$ $(0 \le k < 16)$, can be computed, $\langle C_1, C_2, ..., C_{11} \rangle^k$ corresponding to the orientation $k \cdot \pi / 16$. For each block, feed the 16 vectors to the network and obtain 16 responded values, respectively. The trained network would generally respond with large values to the vectors corresponding to the orientation close to the true ridge orientation, and respond with small values to other vectors. We use these responded values to each block to estimate the ridge orientation.

In the following sections we use orientation number *i* for representing the orientation $i\pi / 16$. Let W be a image block. Net(W,i) represents the responded value of the trained network to the block W on orientation $i\pi / 16$. The process of estimating the orientation field is as follows:

(1) Estimate the responded value fields of the image *I* by the network on each orientation;
(2) Filtering the responded value fields in the orientation domain by low-pass filtering;
(3) Filtering the fields in the image domain by low-pass filtering;
(4) Orientation selection.

2.1 Computation of Responded Value Field

Let R[k](k=0,1,2,…,15) denote the responded value field of the image *I* by the network on the *kth* orientation ($k\pi / 16$), and R[k](i,j)=Net(W(i,j),k) represents the responded value by the network to the block W(i,j) (ith row and jth column) on the *kth* orientation. Fig.1 gives out the gray representation of responded value field of image FVC2000_DB1_104_8 on the 16 quantified orientations (0 , $\pi/16$, $\pi/8$, $3\pi/16$, $\pi/4$, $5\pi/16$, $3\pi/8$, $7\pi/16$, $\pi/2$, $9\pi/16$, $5\pi/8$, $11\pi/16$, $3\pi/4$, $13\pi/16$, $7\pi/8$ and $15\pi/16$). For a responded value field on a certain orientation in Fig.1, the white block indicates it is fairly possible that the corresponding ridge block is of the correct orientation.

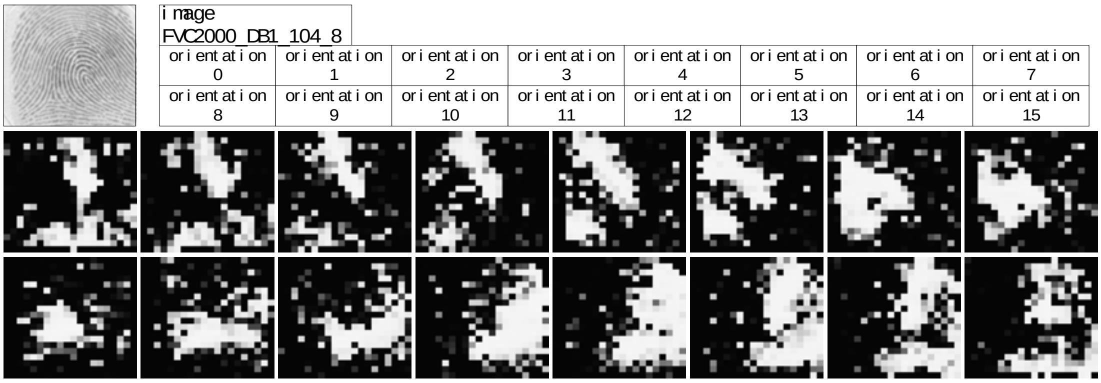

Fig.1 The responded value field by the network on 16 orientations of the image FVC2000_DB1_104_8.

2.2 Filtering on Orientation Domain

It is possible that some low quality ridge blocks are of large responded value on some false orientations. And this is reflected by the isolated bright blocks in Fig.1. These false orientations of large responded value are usually isolated and thus the isolated large value can be repressed by low-pass filtering on orientation domain. The responded values, R[k](i,j)(k=0,1,2,…,15), of the block W(i,j) on different orientations is filtered as in Eq.(1) where $\omega(u)$ is the low-pass filter, and get R'[k](i,j). Fig.2 shows the low-pass filtered results of original responded value fields which are shown in Fig.1.

$$R'[k](i,j)=\sum_{u=-1}^{1}\omega(u)\cdot R[k+u](i,j) \qquad (1)$$

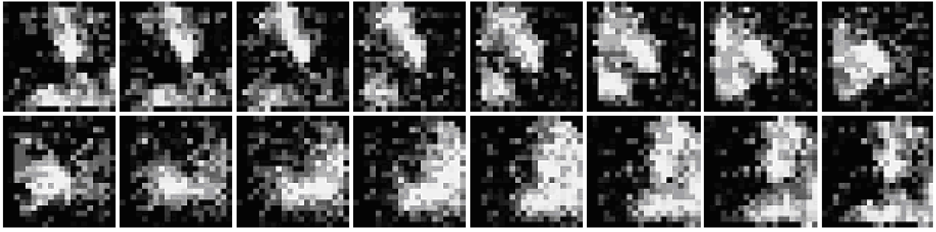

Fig.2 Low-pass filtered results, of fields in Fig.1, on the orientation domain

2.3 Filtering in Image Block Domain

As shown by Fig.2, the low-pass filtered responded field is still not smooth enough that some bright blocks are surrounded by black blocks and some black blocks are surrounded by bright blocks. However fingerprint ridge orientation usually changes smoothly between neighbor blocks. Hence, the low-pass filtered fields need to be filtered using 2-dimensional low-pass filter on the image block domain so that the filtered responded values change smoothly between neighbor blocks, which is accordant with the ridge orientation changing. Eq.(2) gives the process of low-pass filtering on the image block domain, where $R''[k](i,j)$ denotes the low-passed value of the block $W(u,v)$ on the *kth* orientation. Fig.3 shows the low-pass filtered results, of Fig.2.

$$R''[k](i,j)=\sum_{u=-1}^{1}\sum_{v=-1}^{1}\varpi(u,v)\cdot R'[k](i+u,j+v) \qquad (2)$$

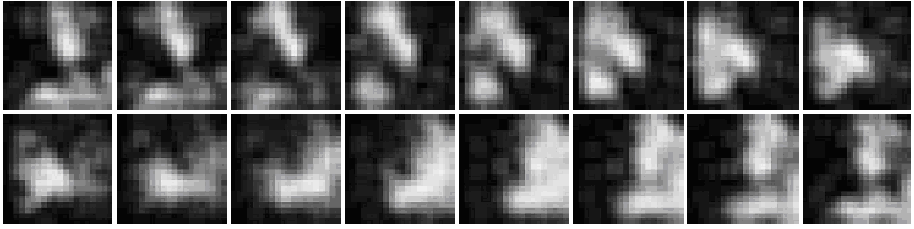

Fig.3 Low-pass filtered results, of images in Fig.2, on the image block domain.

2.4 Orientation Selection

Each image block has 16 responded values which are filtered on orientation domain and image block domain, and each value is corresponding to one of the 16 quantified orientations. Orientation selection is for each image block to select the orientation corresponding to the largest among the 16 values as the orientation of the block as given in Eq.(3) and (4).

$$R''[k](i,j)=\max\left(R''[l](i,j)\,\middle|\,0\le l\le 15\right) \qquad (3)$$

$$O(W(i,j))=k\cdot\pi/16 \qquad (4)$$

Fig.4 shows the final results of orientation estimation for image FVC2000_DB1_104_8 by the proposed method.

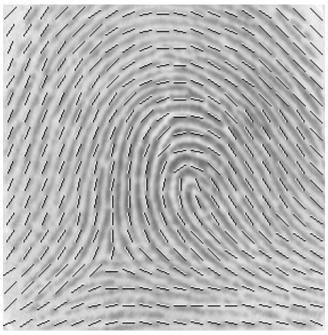

Fig.4 An example of orientation estimation.

3 Experiments

In this section, we compare two methods for estimating fingerprint orientation field: method A—Gradient based method [12-16] followed by Guassian low pass filtering [12]; method B—the proposed method. It is hard to evaluate the quality of a method for estimating orientation field. The quality of orientation estimation can be indirectly measured by computing the accuracy of feature detection, which, however, aside from orientation estimation, is dependent on segmentation and enhancement. Of course, computing the deviation between the orientation field by the proposed method and the one manually labeled can also be used for evaluating the orientation field estimation method. Yet manually labeling the orientation fields of a good many fingerprint images is an exhausting work, and it is no necessity, since the results of orientation estimation by two different methods can be obviously compared by visually inspection. In order to quantitatively compare the two methods, A and B, we count the number of blocks which contain ridges and have obviously incorrect orientations. The experiment uses 5 images which are shown in Fig.5. And for each image, the number of blocks of incorrect orientation is shown in Table 1 which shows that method B performs much better than method A. Fig.5 shows the orientation estimation results of those 5 images by the two methods, A (left column) and B (right column).

Table 1 Block counts of incorrect orientation

	the number of ridge blocks of incorrect orientation	
	method A	method B
image 1	25	0
image 2	18	3
image 3	10	2
image 4	60	15
image 5	62	0

4 Conclusion

Ridge orientation estimation is a necessary and fundamental step in fingerprint recognition. This paper proposes a method for fingerprint ridge orientation estimation using neural network from our previous work [24]. Experiments show that the proposed method leads to a great improvement in ridge orientation estimation.

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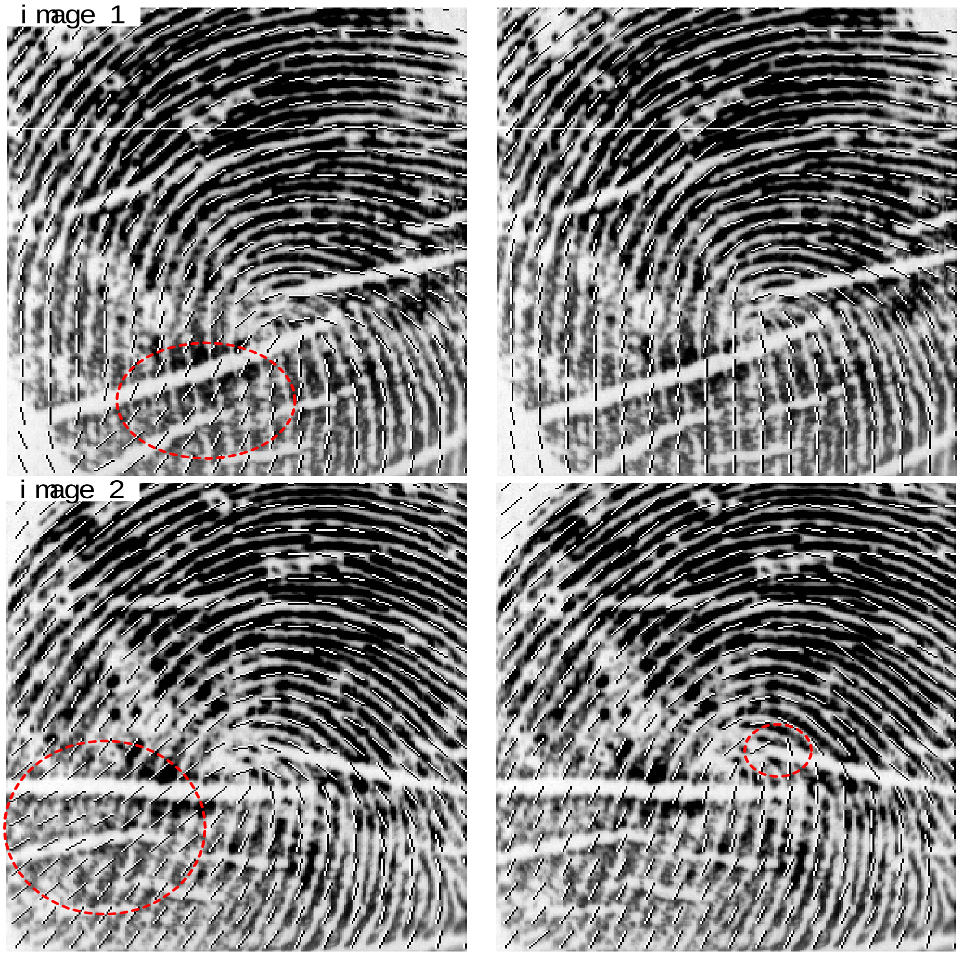
image 1
image 2

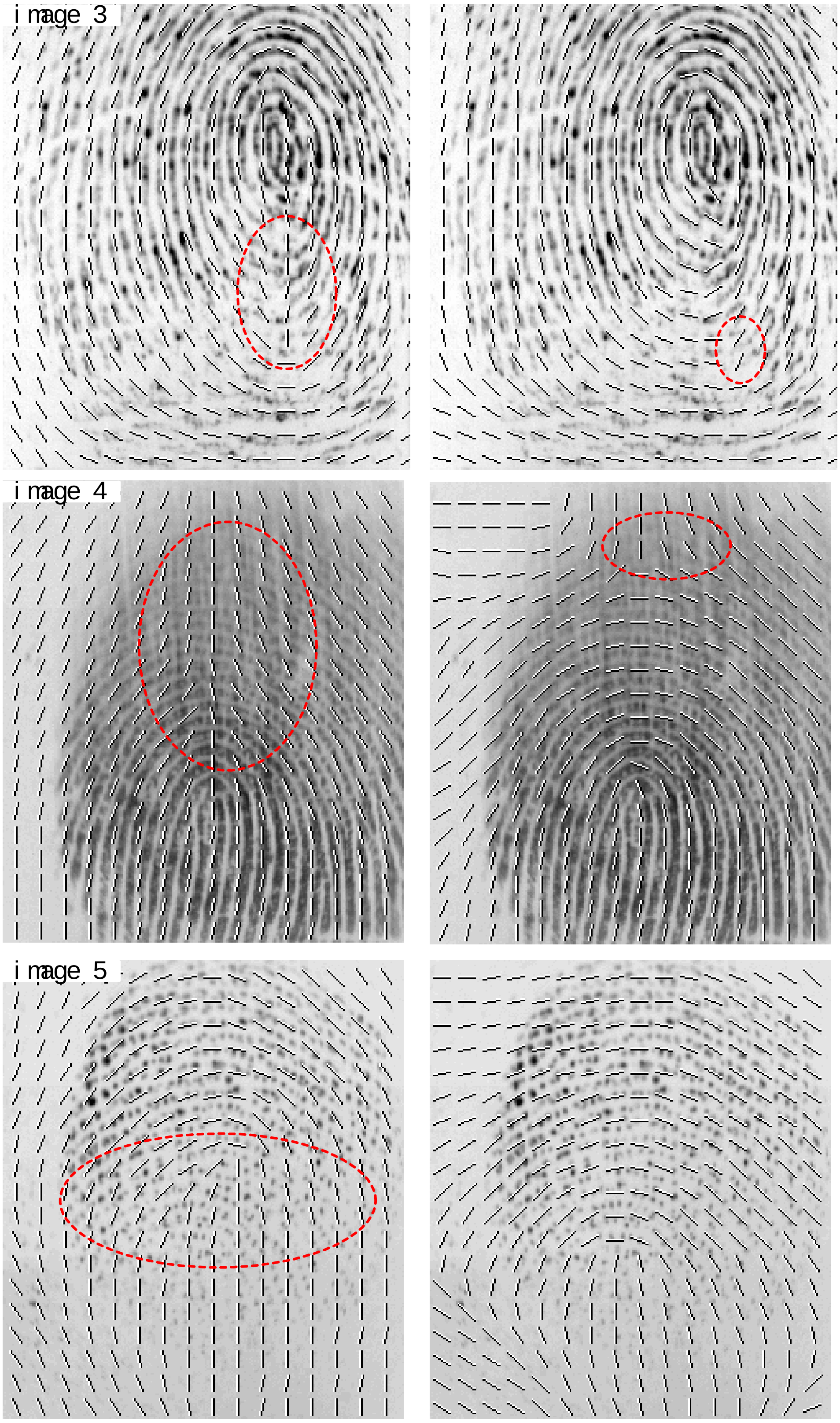

Fig. 5 Comparision of orientation estimation between method A (left column) and method B (right column). The dotted circles indicate that the orientations in circled region are incorrect, and vice versa.

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