EXCLUDING THE REMAINING RIDGES OF FINGERPRINT IMAGE

En Zhu, Jianping Yin, Chunfeng Hu, Guomin Zhang
School of Computer Science, National University of Defense Technology, Changsha 410073, China

Jianming Zhang
Department of Computer Science, Hunan City University, Yiyang 413049, China
College of Computer and Communication, Hunan University, Changsha 410082, China

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Abstract: Fingerprint segmentation is usually to identify non-ridge regions and unrecoverable low quality ridge regions and exclude them as background so as to reduce the time of image processing and avoid detecting false features. In ridge regions, including high quality and low quality, there are often some remaining ridges which are the afterimage of the previously scanned finger and are expected to be excluded from the foreground. However, existing segmentation methods do not take the case into consideration, and often, the remaining ridge regions are falsely taken as foreground. This paper proposes two steps for fingerprint segmentation aiming to exclude the remaining ridge region from the foreground. The non-ridge regions and unrecoverable low quality ridge regions are removed as background in the first step, and then the foreground produced by the first step is further analyzed so as to remove the remaining ridge region. The proposed method turns out effective in avoiding detecting false ridges and in improving minutiae detection.

1 INTRODUCTION

Fingerprint segmentation is an important problem in fingerprint recognition. A fingerprint image usually has to be segmented to remove uninterested regions before some other steps such as enhancement and minutiae detection so that the image processing will consume less CPU time. A fingerprint image generally consists of different regions: non ridge region, high quality ridge region, and low quality ridge region. Fingerprint segmentation is usually to identify non-ridge regions and unrecoverable low quality ridge regions and exclude them as background so as to reduce the time of image processing and avoid detecting false features and further to improve the recognition accuracy. Most segmentation methods are block-wised ones (Mehtre, 1987; Mehtre, 1986; Mehtre, 1989; Mehtre, 1993; Ratha, 1995; Hong, 1998; Klein, 2002) which divide the fingerprint image into un-overlapped blocks and decide on the type (background and foreground) of each block. And some other methods are pixel-wised ones (Bazen 2000, Bazen 2001) which determine the type of each pixel. Fingerprint segmentation typically computes the feature (or feature vector) of each element, block or pixel, and then determine the element's type based on the feature (vector). The features used in fingerprint segmentation mainly include statistical features of pixel intensity, directional image and ridge projection signal, etc. Methre (Mehtre, 1987; Mehtre, 1986; Mehtre, 1989; Mehtre 1993) uses gray variance and the histogram of pixel gradients in a sub-image block for segmentation. For each sub-image block Ratha (Ratha, 1995) computes the variance of the projection signal on different directions. The foreground block is of large variance along the direction orthogonal to the ridges and is of small variance along the direction parallel to the ridges. And background is usually of small variance along all directions. Hong (Hong, 1998) uses the features, including frequency, variance and the average difference between the peaks and valleys, of the ridge projection signal along the direction orthogonal to the local ridges for segmentation. Klein (Klein, 2002) computes gray mean, variance,

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gradient consistency and Gabor response for segmentation by using HMM. Bazen (Bazen, 2000; Bazen, 2001) computes gray mean (Bazen, 2001), variance (Bazen, 2001) and gradient coherence (Bazen, 2000; Bazen, 2001) to pixel-wisely segment fingerprint image. Yin (Yin, 2005) also uses coherence, mean and variance. Jain (Jain, 1997) uses the output of a set of Gabor filters for segmentation by adopting clustering. Wang (Wang, 2004) uses Gaussian-Hermite Moments. Ong (Ong 2003) uses the orientation coherence for coarse segmentation and then refine the results by Fourier-based enhancement, adaptive thresholding, and postprocessing. And Ren (Ren, 2003) detects feature dots which are somewhat like ridge edge points to segment fingerprint image.

Most existing segmentation methods aim to and are able to exclude regions containing no ridges (e.g. Fig.1 (d)) or of low quality and hence unrecoverable (e.g. Fig.1 (c)). Yet none of these methods considers the excluding of the remaining ridges (e.g. Fig.1 (e)), the afterimage of the previously scanned finger. And consequently, the remaining ridges are often falsely taken as the foreground in the case that they are of clear or recoverable ridge structure. Another problem in fingerprint segmentation is how to know whether a low quality ridge block is recoverable or unrecoverable so as to guide the segmentation. The typical solution is to visually decide the types, recoverable and unrecoverable, and feed some samples, whose type are visually decided, into a classifier at its training stage, and the trained classifier would be used to classify the fingerprint regions. However, in fingerprint image processing, the process of ridge recovering is done by a certain algorithm not by manual, and therefore a manually recoverable ridge block maybe unrecoverable for the specific algorithm since the algorithm can not be cleverer than the human brain. Recovering low quality ridges, e.g. enhancement using a texture filter by tuning its orientation and frequency (Hong, 1998; Ailisto, 15; Zhu, 2004), usually depends on the correct computation of ridge orientation. Incorrect computation of the ridge orientation means that the ridge can not be recovered. Thus we propose to segment the fingerprint image through two steps: The first segments according to the results of ridge orientation estimation. The recoverable ridge regions, including high quality and low quality, with their orientations correctly estimated, are identified as foreground in the first step. The foreground identified by the first step may contain remaining ridge region, and the second step further excludes the remaining ridge region from the foreground. In the following sections which will describe the proposed algorithm in detail, we call the first step primary segmentation, and the second step secondary segmentation. Section 2 describes the primary segmentation. Section 3 describes the secondary segmentation. Section 4 contains the experimental results. Section 5 is the conclusion. And section 6 is the acknowledgement.

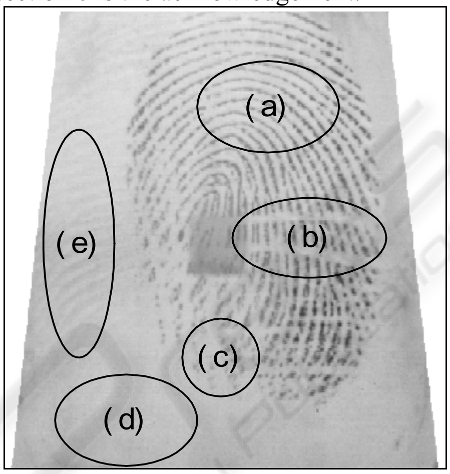


Figure: 1 Fingerprint regions: (a) high quality ridge region, (b) recoverable low quality region (the ridge interrupts are recoverable in this case), (c) unrecoverable low quality region, (d) non ridge region, (d) remaining ridge region.

2 PRIMARY SEGMENTATION

Fingerprint segmentation serves for decreasing the computational expenditure at image processing and for improving the accuracy of feature (typically minutiae) extraction, because excluding non-ridge regions and unrecoverable ridge regions helps to reduce CPU consumption and avoid introducing false minutiae, and keeping recoverable ridge regions not removed helps to avoid losing true minutiae. However, recoverable ridges are often actually not recovered in the enhance image, because they are just manually and not algorithmically recoverable mainly due to that their orientations are not correctly estimated. Fig.2 (a) and (b) show an example of taking algorithmically unrecoverable ridges, due to the incorrect estimation of ridge orientation, as foreground. Besides, it is hard to decide the recoverability of low quality ridges, and consequently, recoverable ridges, in spite of the correct estimation of ridge orientations, are often taken as background. Fig.2 (c) and (d) show an example of take manually recoverable ridges as background. Fig.2 (b) and (d) are the segmentation

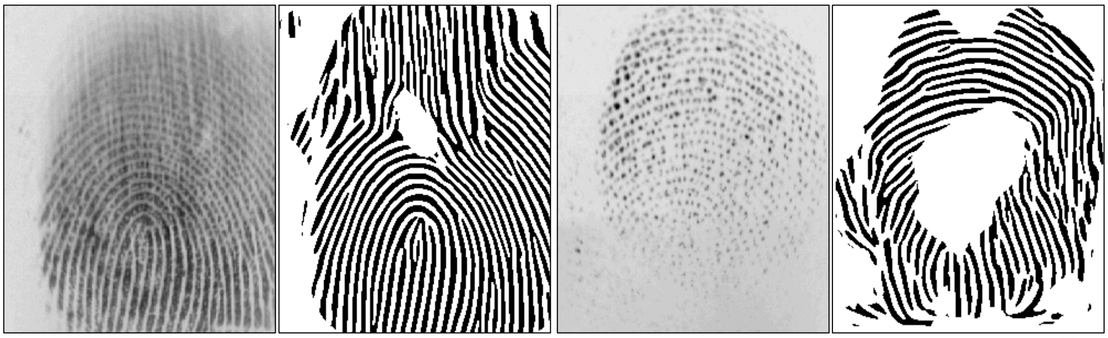


Figure 2: Examples of fingerprint image segmentation by VeriFinger4.2 of Neuro. (a) and (c) are the original images collected using SecuGen device, and (b) and (d) are the segmented results, respectively.

results by VeriFinger4.2 published by Neurotechnologija (hereinafter abbreviated as Neuro) (Neurotechnologija Ltd., 2004) which have participated in FVC2002 (Maio, 2002) and FVC2004 (Maio, 2004) and came top in both the two contests. The main difficulty in fingerprint segmentation is to answer whether the (low quality) ridge block is recoverable or unrecoverable by an automatic algorithm. A well trained classifier may be able to distinguish high quality ridges and manually recoverable low quality ridges from other type of regions. In the case of ridge orientation estimation following the image segmentation, although all the foreground blocks are of high quality or manually recoverable, none of the ridge orientation estimation algorithms can ensure the orientation of each foreground block would be correctly computed, and as a result, those blocks with their orientations falsely estimated are practically not recoverable for the recovering algorithm, such as enhancement (Hong, 1998; Ailisto, 2003; Zhu, 2004) and ridge tracing (Maio, 1997; Jiang, 2001). Thus, it is reasonable that the ridge orientation estimation proceeds prior to the segmentation and that the blocks of falsely estimated orientation should be taken as background.

The proposed primary segmentation is based on the work of (Zhu, 2005). (Zhu, 2005) Proposed a method to estimate the fingerprint image quality by training a neural network which 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. For each image block, a feature vector $\langle C_1, C_2, ..., C_{11} \rangle$ 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, since the items from C5 to C11 of the input vector $\langle C_1, C_2, ..., C_{11} \rangle$ (Zhu, 2005) have a close relationship with the estimated ridge orientation. Suppose that the image is divided into non-overlapped blocks like in (Zhu, 2005), 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. Let $R[k](i,j)$ be the responded value to the *kth* vector of the block W(i,j). We use these responded values to each block to estimate the ridge orientation and primarily segment the image (primary segmentation) as follows.

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

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

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

$$O(W(i,j)) = l \cdot \pi / 16 \quad (4)$$

$$M(W(i,j)) = \begin{cases} 1 & R''[l](i,j) \ge t_m \\ 0 & R''[l](i,j) < t_m \end{cases} \quad (5)$$

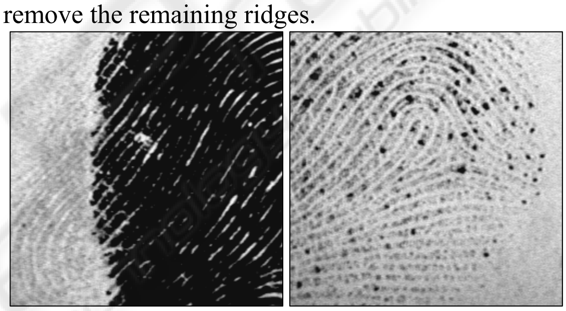
(a) (b) (c)

Figure 3: Segmentation failing to remove remaining ridges. (a) original image FVC2004_DB2_35_4, (b) result by Neuro, (c) result by the primary segmentation.

where $\omega(u)$ and $\varpi(u,v)$ are Gaussian filter and are used to smooth noisy responded values. $O(W(i,j))$ is the estimated ridge orientation. $M(W(i,j))$ denotes the result of the primary segmentation: $W(i,j)$ is a foreground block if $M(W(i,j))$ =1, and background if $M(W(i,j))$=0.

3 SECONDARY SEGMENTATION

The primary segmentation identifies and removes non-ridge blocks and unrecoverable ridge blocks (manually unrecoverable or having the falsely estimated orientations and thus algorithmically unrecoverable). The foreground of the primary segmentation contains ridge block of correct orientation. The remaining ridges of the fingerprint image tend to be included in foreground, if they have recoverable clear ridge structure and have their orientation correctly estimated. It is difficult to identify remaining ridges by once segmentation, including the existing segmentation methods and the proposed primary segmentation as in Fig.3 which shows the example of segmentation by existing method and the propose primary segmentation which fail to remove the remaining ridges, since remaining ridges often have clear structures and since it is possible, for two fingerprints A and B as in Fig.4, the remaining ridges of fingerprint A have the similar features with or even appear clearer than the true ridges of fingerprint B. Fortunately, within the same image, there are typical differences between the remaining ridges and the true ridges: (1) the average gray value of the remaining ridge block is generally bigger than that of the true ridge block; (2) the difference between ridge and valley in the remaining ridge block is smaller than in the true ridge block. The two differences are used by the secondary segmentation to further identify and remove the remaining ridges.



(a) (b)

Fig. 4 Remaining ridges and true ridges from two fingerprints have possible similar features. (a) Fingerprint A, the left part contains remaining ridges. (b) Fingerprint B, which contains true ridges which are of similar features, such as gray value and inter-ridge-valley difference, with the remaining ridges of Fingerprint A.

Let the LG(W) be the local average gray value of the block W. The global average gray value of all the foreground blocks would be

$$MG = \frac{\sum_{M(W(i,j))=1} LG(W(i,j))}{\sum_{W(i,j)} M(W(i,j))} \tag{6}$$

And let LA(W) be the local inter-ridge-valley gray difference of the block W. The global average inter-ridge-valley gray difference of all the foreground blocks is computed as

$$MA = \frac{\sum_{M(W(i,j))=1} LA(W(i,j))}{\sum_{W(i,j)} M(W(i,j))} \tag{7}$$

The first difference between the remaining ridge block and the true ridge block from the same image can be described by LG and MG: The value of $LG - MG$ is usually bigger at the remaining ridge block than at the true ridge block. And the second difference can be described using LA and MA: The value of $LA - MA$ is usually smaller at the remaining ridge block than at the true ridge block. Some blocks which have small LG value and large LA value can be taken as the true ridge blocks without regarding to the value of $LG - MG$ and $LA - MA$, and similarly, those blocks which have large LG value and small LA value can be taken as the remaining ridge blocks without considering the value of $LG - MG$ and $LA - MA$. Therefore, the secondary segmentation uses 〈LG , MG , LA , MA〉 to reclassify the foreground blocks of the primary segmentation. For the blocks from the same image, they have the same MG value and same MA value. LMS modal (Press, 1992) is used for the secondary segmentation. Suppose that N samples, including positive samples and negative samples, are selected for training the classifier and are denoted as $\{\langle LG(W_i), MG(W_i), LA(W_i), MA(W_i), y(W_i)\rangle | 1 \le i \le N\}$: $y(W_i) = 1$ if W_i is a positive sample (true ridge block), $y(W_i) = -1$ if W_i is a negative sample (remaining ridge block). The LMS modal is described by equation (8).

$$\begin{pmatrix} 1 & LG(W_1) & MG(W_1) & LA(W_1) & MA(W_1) \\ 1 & LG(W_2) & MG(W_2) & LA(W_2) & MA(W_2) \\ 1 & LG(W_3) & MG(W_3) & LA(W_3) & MA(W_3) \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & LG(W_N) & MG(W_N) & LA(W_N) & MA(W_N) \end{pmatrix} \begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{pmatrix} = \begin{pmatrix} y(W_1) \\ y(W_2) \\ y(W_3) \\ \cdots \\ y(W_N) \end{pmatrix} \quad (8)$$

where $\langle a_0, a_1, a_2, a_3, a_4 \rangle$ are the parameters to be solved. At the secondary segmentation, given a block W, compute $\hat{y}(W)$ as equation (9).

$$\begin{aligned} \hat{y}(W) = a_0 + a_1 \cdot LG(W) + a_2 \cdot MG(W) \\ + a_3 \cdot LA(W) + a_4 \cdot MA(W) \end{aligned} \quad (9)$$

If $sign(\hat{y}(W)) = -1$ where W is a foreground block in the result of the primary segmentation, take W as a background block and set $M(W) = 0$. Fig.5(c) shows the secondary segmentation result of image Fig.3(a) which has the remaining ridges not removed by Neuro and by the primary segmentation. More results are shown in Section 4.

4 EXPERIMENTAL RESULTS

The experiments use eight images, denoted as image1~8 respectively: image1, image 2, and image3 are shown in Fig.2(a), Fig.2(c) and Fig.3(a), respectively, and images 4~8 are shown in Fig.6. Fig.4 shows the segmentation results of the first 3 images by the proposed method. And their segmentation results by the Neuro are shown in Fig.2(b), Fig.2(d) and Fig.3(b), respectively. Fig.6 shows the segmentation results of the rest 5 images. Segmentation of fingerprint image serves for reducing the consumed time of image processing and improving the accuracy of minutiae detection. One of method to evaluate an automatic segmentation method is to compare the segmented image of the automatic algorithm with the manually segmented image and then estimate the segmentation accuracy of the automatic algorithm. Also, we can use the accuracy of minutiae detection for comparing two automatic segmentation algorithms. The accuracy of minutiae detection can be evaluated using EI (Error Index), EI=(a+b)/t where a is the number of lost minutiae, b is the number of spurious minutiae, and t the total number of minutiae contained in the image. The value of t is generally computed as the number of manually labeled minutiae. The smaller the value of EI is, the more accurate the algorithm is. We quantitatively verify the proposed segmentation method only using EI, since the accuracy of segmentation is obviously shown in Fig.5 and Fig.6. The Error Indexes of minutiae detection on each experimental image are listed in Table 1. The average EI of the two methods, Neuro and the proposed, on the experimental images are respectively 1.27 and 0.49. The proposed method produces spurious minutiae much less than Neuro and greatly decreases the EI value.

(a) (b) (c)

Figure 5: Examples of segmentation by the proposed method. (a)result of image Fig.2(a), (b)result of image Fig.2(c), (c)result of image Fig.3(a).

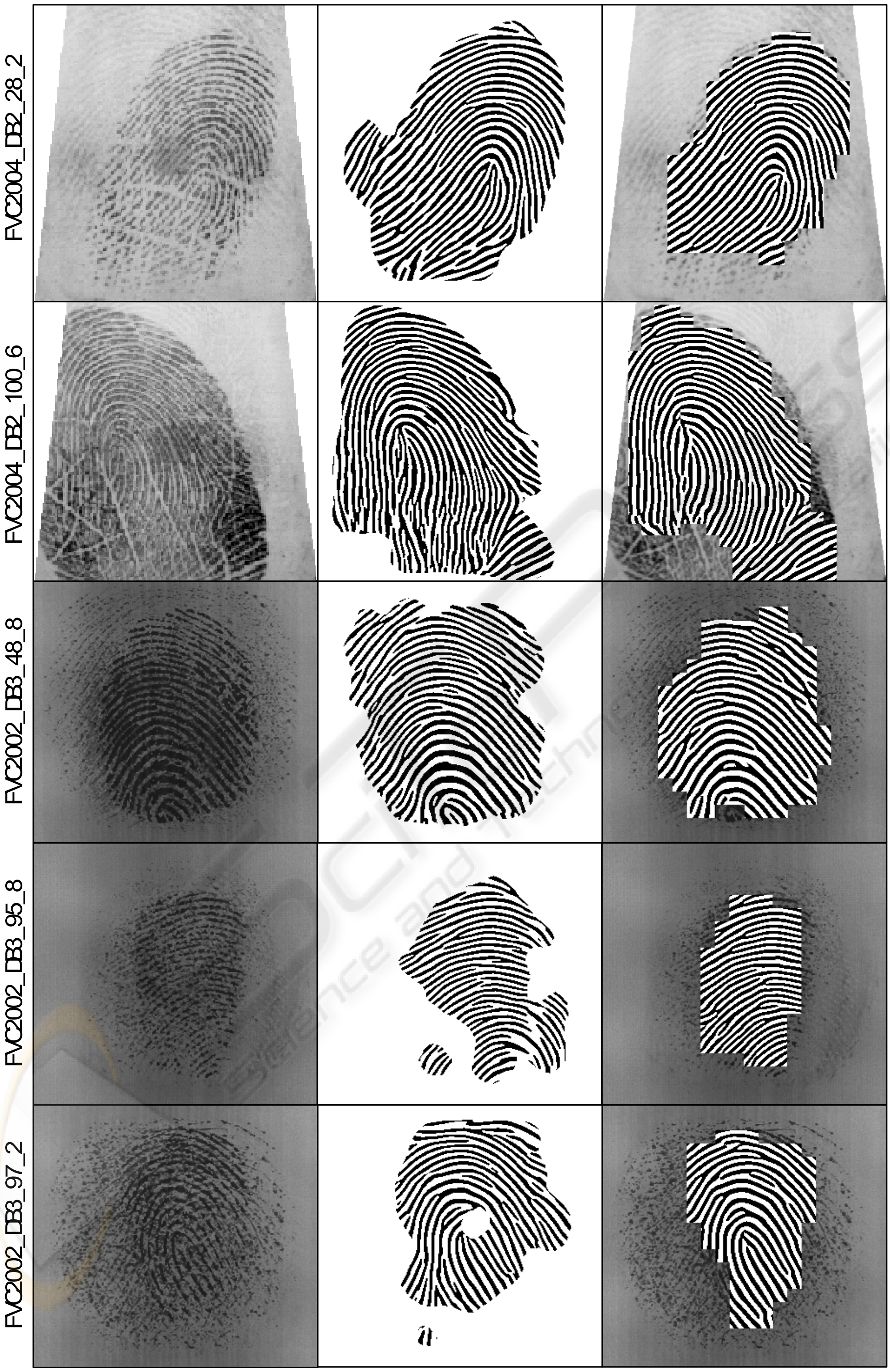


Figure 6: Comparison of segmentation between Neuro and the proposed. Left column is the original images; Middle column is the results by Neuro; Right column is the results by the proposed. The images in left column, from top to bottom, are respectively denoted as image4, image5, image6, image7 and image8.

Table 1: EI comparison.

Image	Manually labeled	Neuro				The proposed			
		True	Spurious	Lost	EI	True	Spurious	Lost	EI
Image1	26	13	25	13	1.46	13	2	13	0.58
Image2	11	3	32	8	3.64	9	4	2	0.55
Image3	29	27	8	2	0.34	26	2	3	0.17
Image4	17	12	10	5	0.88	9	4	8	0.71
Image5	35	29	24	6	0.86	29	2	6	0.23
Image6	17	13	10	4	0.82	10	7	7	0.82
Image7	12	11	12	1	1.08	11	1	1	0.17
Image8	10	6	13	4	1.70	9	6	1	0.70
Average	20	14	17	5	1.27	15	4	5	0.49

4 CONCLUSION

Fingerprint segmentation is not a full-solved problem in fingerprint recognition and mainly aims to reduce time expenditure of image processing and to improve minutiae detection. The main difficulties of fingerprint segmentation are that low quality regions are hard to be classified and that the fingerprint images are often interfered with remaining ridges which are the afterimage of the previously scanned finger and are hard to be removed especially when they appear clear structures. It is difficult to correctly estimate the orientations of low quality ridge regions, and a manually recoverable region should be taken as background if its orientations are falsely estimated. Spurious minutiae are generally produced by including manually or algorithmically unrecoverable ridge regions as foreground. In order to accurately remove unrecoverable regions and remaining ridges and as a consequence to improve the minutiae detection, this paper, following our previous work (Zhu, 2005), proposed a method, primary segmentation, to exclude non-ridge regions and (manually or algorithmically) unrecoverable regions, and then proposed the secondary segmentation to reclassify the foreground blocks of the primary segmentation to remove the remaining ridges. The experiments show that the proposed method leads to an improvement of minutiae detection.

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