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Removing the remaining ridges in fingerprint segmentation*

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Abstract: Fingerprint segmentation is an important step in fingerprint recognition and is usually aimed to identify non-ridge regions and unrecoverable low quality ridge regions and exclude them as background so as to reduce the time expenditure of image processing and avoid detecting false features. In high and in low quality ridge regions, often are some remaining ridges which are the afterimages of the previously scanned finger and are expected to be excluded from the foreground. However, existing segmentation methods generally do not take the case into consideration, and often, the remaining ridge regions are falsely classified as foreground by segmentation algorithm with spurious features produced erroneously including unrecoverable regions as foreground. This paper proposes two steps for fingerprint segmentation aimed at removing 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 for possible remove of the remaining ridge region. The proposed method proved effective in avoiding detecting false ridges and in improving minutiae detection.

Key words: Fingerprint segmentation, Recoverable ridges, Remaining ridges
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INTRODUCTION

Fingerprint identification typically goes through feature extraction and feature matching (Zhu *et al*., 2005b), with fingerprint segmentation being one of the steps for fingerprint feature extraction. A fingerprint image usually has to be segmented to remove regions of no interest 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 aimed 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 improve further the recognition accuracy. Most segmentation methods divide the fingerprint image into not-overlapped blocks and decide on the type (background and foreground) of each block (Chen *et al*., 2004; Hong *et al*., 1998; Klein *et al*., 2002; Mehtre and Murthy, 1986; Mehtre *et al*., 1987; Mehtre, 1989; 1993; Ong *et al*., 2003; Ratha *et al*., 1995; Tang *et al*., 2003; Wang *et al*., 2003). Some other methods are pixel-wise ones (Bazen and Gerez, 2000; 2001; Wang *et al*., 2004) 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 used gray variance and the histogram of pixel gradients in a sub-image block for segmentation (Mehtre and Murthy, 1986; Mehtre *et*

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al., 1987; Mehtre, 1989; 1993). For each sub-image block, Ratha *et al*.(1995) computed the variance of the projection signal at different directions. The foreground block has large variance along the direction orthogonal to the ridges and small variance along the direction parallel to the ridges. And background usually varies little along all directions. Hong *et al*.(1998) used 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 *et al*.(2002) computed gray mean, variance, gradient consistency and Gabor response for segmentation by using HMM. Ong *et al*.(2003) used the orientation coherence for coarse segmentation and then refined the results by Fourier-based enhancement, adaptive thresholding, and postprocessing. Chen *et al*.(2004) used clusters degree, mean and variance for segmentation by means of an optimized linear classifier. Tang *et al*.(2003) used mean and variance. Wang *et al*.(2003) used gray contrast, variance, gradient coherence and main energy ratio computed by using FFT for segmentation. Bazen and Gerez (2000; 2001) computed gray mean, variance and gradient coherence to pixel-wisely segment fingerprint image. Wang *et al*.(2004) used Gaussian-Hermite Moments. Yin *et al*.(2005) also used coherence, mean and variance. Jain and Ratha (1997) used the output of a set of Gabor filters for segmentation by adopting clustering. And Ren *et al*.(2002) detected feature dots somewhat like ridge edge points to segment fingerprint image. Quite different from the above segmentation methods, Yang *et al*.(2001) directly detected ridges and valleys and hence obtained the segmented image based on multi-scales roof edge detection.

Most existing segmentation methods aim to and can exclude regions containing no ridges ((d) in Fig.1) or of low quality and hence unrecoverable ((c) in Fig.1). Yet none of these methods consider exclusion of the remaining ridges ((e) in Fig.1), the afterimage of the previously scanned finger. And consequently, the remaining ridges are often mistaken as the foreground in case they have 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

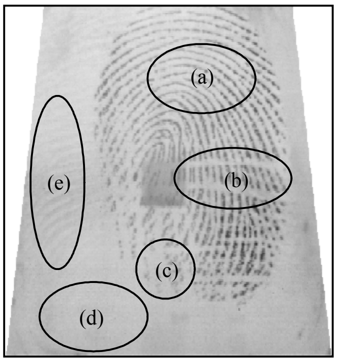


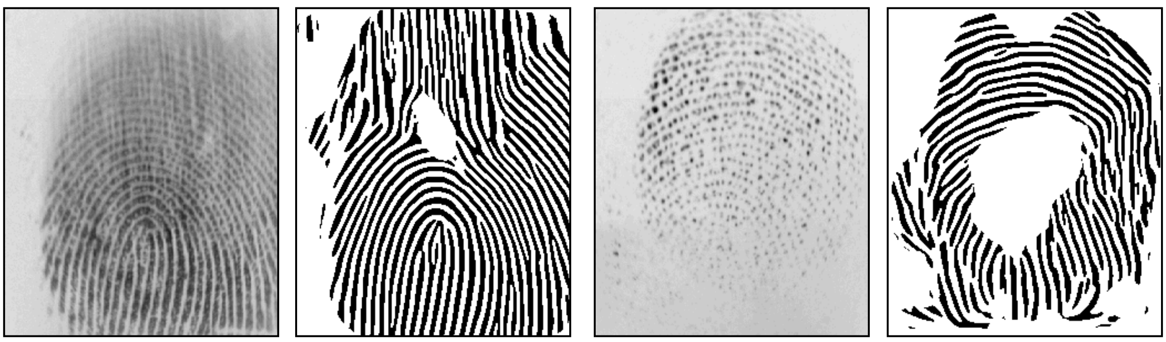
Fig.1 Fingerprint regions. (a) High quality ridge region; (b) Recoverable low quality region (the ridge interrupts are recoverable in this case); (c) Unrecoverable low quality region; (d) Non-ridge region; (e) Remaining ridge region

the types, recoverable and unrecoverable, and feed some samples, whose types 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 recovery is done by a certain algorithm, not manually, and therefore a manually recoverable ridge block may be unrecoverable for the specific algorithm since the algorithm cannot be more clever than the human brain. Recovering low quality ridges, e.g., enhancement using a texture filter by tuning its orientation and frequency (Ailisto *et al*., 2003; Hong *et al*., 1998; Zhu *et al*., 2004), usually depends on the correct computation of ridge orientation, incorrect computation of the ridge orientation means that the ridge cannot be recovered. Thus we propose to segment the fingerprint image through two steps. The first segments are according to the results of ridge orientation estimation. The high and low quality recoverable ridge regions, with their orientations correctly estimated, are identified as foreground in the first step. The foreground identified by the first step may contain the remaining ridge region, and the second step further excludes the remaining ridge region from the foreground. In the following sections describing 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.

PRIMARY SEGMENTATION

Fingerprint segmentation decreases computation time expended in image processing and improves the accuracy of feature (typically minutiae) extraction, because excluding non-ridge regions and unrecoverable ridge regions helps to (1) reduce CPU time, (2) avoid introducing false minutiae, and (3) keep recoverable ridge regions from being removed to avoid losing true minutiae. However, recoverable ridges are often actually not recovered in the enhanced image, because they are just manually but not algorithmically recoverable mainly due to their incorrectly estimated orientations. Figs.2a and 2b 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, which, in spite of the correct estimation of ridge orientations, are often considered unrecoverable and taken as background. Figs.2c and 2d show an example of taking manually recoverable ridges as background. Figs.2b and 2d are the segmentation results by VeriFinger 4.2 published by Neurotechnologija (hereinafter abbreviated as Neuro) (Neurotechnologija Ltd., 2004) which participated in FVC2002 (Maio *et al*., 2002) and FVC2004 (Maio *et al*., 2004) and came out top in both the contests. The main difficulty in fingerprint segmentation is to decide whether (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 that the orientation of each foreground block would be correctly computed, and as a result, those blocks with their orientations incorrectly estimated are practically not recoverable for the recovering algorithm, such as enhancement (Ailisto *et al*., 2003; Hong *et al*., 1998; Zhu *et al*., 2004) and ridge tracing (Jiang *et al*., 2001; Maio and Maltoni, 1997). Thus, it is reasonable that the ridge orientation estimation proceeds prior to the segmentation and that the blocks of incorrectly estimated orientation should be taken as background.

The proposed primary segmentation is based on the work of (Zhu *et al*., 2005a). Zhu *et al*.(2005a) 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 $<C_1, C_2, \ldots, C_{11}>$ 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 depends on the orientation, since the items from C_5 to C_{11} of the input vector $<C_1, C_2, \ldots, C_{11}>$ (Zhu *et al*., 2005a) have close relationship with the estimated ridge orientation. Suppose that the image is divided into non-overlapped blocks like in (Zhu *et al*., 2005a), 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



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

Fig.2 Examples of fingerprint image segmentation by VeriFinger 4.2 of Neuro (Neurotechnologija Ltd., 2004). (a) and (c) are the original images collected using SecuGen device; (b) and (d) are the segmented results of (a) and (c), respectively

$k \cdot \pi/16$ ($0 \le k < 16$). For each block $W(i,j)$, 16 vectors, denoted as $<C_1, C_2, \ldots, C_{11}>^k$ ($0 \le k < 16$), can be computed, $<C_1, C_2, \ldots, C_{11}>^k$ corresponding to the orientation $k \cdot \pi/16$. For each block, the 16 vectors are fed to the network and 16 responding values are obtained, 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 responding value to the kth vector ($<C_1, C_2, \ldots, C_{11}>^k$) of the block $W(i,j)$. We use these responding values to each block to estimate the ridge orientation and primarily segment the image (primary segmentation) as follows:

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

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

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

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

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

where $\omega(u)$ and $\varpi(u,v)$ are Gaussian filters used to smooth noisy responding 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 a background block if $M(W(i,j))=0$. t_m is a threshold value (0.5).

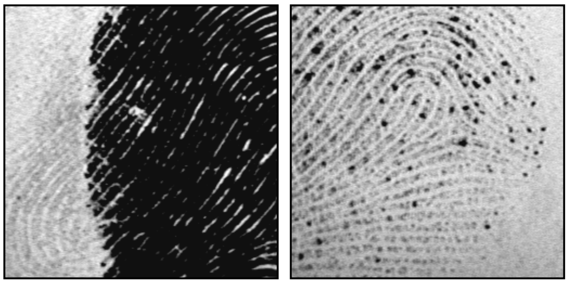
SECONDARY SEGMENTATION

The primary segmentation identifies and removes non-ridge blocks and unrecoverable ridge blocks (manually unrecoverable or having the incorrectly 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 one time segmentation, including the existing segmentation methods and the proposed primary segmentation as in Fig.3 showing an example of segmentation by existing method and the proposed primary segmentation which fail to remove the remaining ridges, since they often have clear structures and since it is possible that, for two fingerprints A and B as shown in Fig.4, the remaining ridges of fingerprint A have similar features 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 that in the true ridge block. The two differences are used by the secondary segmentation to further identify and remove the remaining ridges.

Let $LG(W)$ be the local average gray value of the

(a) (b) (c)

Fig.3 Segmentation failing to remove remaining ridges. (a) Original image FVC2004_DB2_35_4; (b) Result by Neuro (Neurotechnologija Ltd., 2004); (c) Result by the primary segmentation



(a) (b)

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

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 true ridge blocks without considering 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 *et al*., 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 $\{<LG(W_i), MG(W_i), LA(W_i), MA(W_i), y(W_i)>|1\le i\le N\}$: $y(W_i)=1$ 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 Eq.(8).

$$\begin{pmatrix} 1 & LG(W_1) & MG(W_1) & LA(W_1) & MA(W_1) \\ 1 & LG(W_2) & MG(W_2) & LA(W_2) & MA(W_2) \\ 1 & LG(W_3) & MG(W_3) & LA(W_3) & MA(W_3) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & LG(W_N) & MG(W_N) & LA(W_N) & MA(W_N) \end{pmatrix} \begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{pmatrix} = [y(W_1) \quad y(W_2) \quad y(W_3) \quad \ldots \quad y(W_N)]^{\mathrm{T}}, \tag{8}$$

where $<a_0, a_1, a_2, a_3, a_4>$ are the parameters to be solved. At the secondary segmentation, given a block W, compute $\hat{y}(W)$ by using Eq.(9).

$$\hat{y}(W) = a_0 + a_1 \cdot LG(W) + a_2 \cdot MG(W) + a_3 \cdot LA(W) + a_4 \cdot MA(W). \tag{9}$$

If $\mathrm{sign}(\hat{y}(W))=-1$, 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.5c shows the secondary segmentation result of Fig.3a with the remaining ridges not removed by Neuro and by the primary segmentation. More results are shown in Section 4.

EXPERIMENTAL RESULTS

The experiments use eight images, denoted as Images 1~8 respectively: Images 1~3 are shown in Figs.2a, 2c and 3a, respectively, and Images 4~8 are shown in Fig.5. 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 Figs.2b, 2d and 3b, respectively. Fig.5 shows the segmentation results of the other 5 images. Segmentation of fingerprint image serves to reduce the consumed time of image processing and improve the accuracy of minutiae detection. One 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 is the total number of minutiae contained in the image. The value of t is generally computed as the number of manually labelled 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.

CONCLUSION

Fingerprint segmentation is not a fully-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 by remaining ridges which are the afterimage of the previously scanned finger and are hard to be removed especially when they appear to be clear structures. It is difficult to correctly estimate the orientations of low quality ridge regions, and a manually recoverable region could be taken as background if its orientations are incorrectly estimated.

(a) (b) (c)

Fig.5 Examples of segmentation by the proposed method. (a) Result of Fig.2a; (b) Result of Fig.2c; (c) Result of Fig.3a

Table 1 *EI* comparison

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

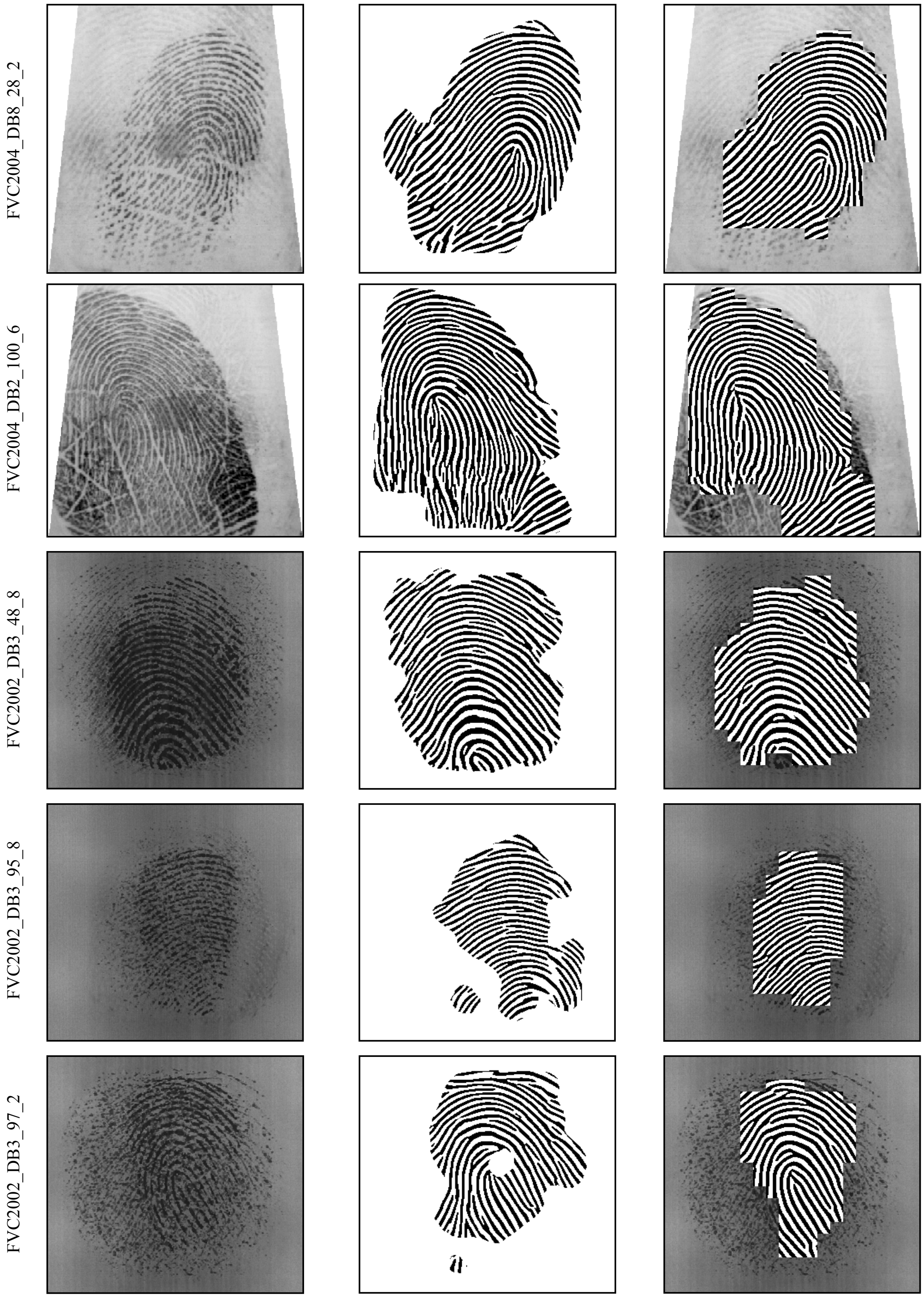


Fig.6 Comparison of segmentation between Neuro and the proposed method. Left column are the original images; Middle column are the results by Neuro; Right column are the results by the proposed method. Images in the left column, from top to bottom, are respectively denoted as Images 4, 5, 6, 7 and 8

Spurious minutiae are generally produced by inclusion of 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 previous work in (Zhu *et al*., 2005a), proposed a method of primary segmentation to exclude non-ridge regions and (manually or algorithmically) unrecoverable regions, and then proposed a secondary segmentation to reclassify the foreground blocks of the primary segmentation to remove the remaining ridges. Experiments showed that the proposed method leads to improved minutiae detection.

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