

DIRECTIONAL FILTER BANK-BASED FINGERPRINT IMAGE ENHANCEMENT USING RIDGE CURVATURE CLASSIFICATION

Joon Jae Lee¹, Byung Gook Lee¹, Chul Hyun Park²

¹Division of Computer and Information Engineering, Dongseo University,
Busan, Korea

{jjlee, lbg}@dongseo.ac.kr,

²Mobile Communication, Samsung Electronics, Gumi, Korea
park95@purdue.edu

Abstract: In fingerprints, singular regions including core or delta points have different directional characteristics from non-singular regions. Generally, the ridges of singular regions change more abruptly than those of non-singular areas, thus in order to effectively enhance fingerprint images regardless of region, local ridge curvature information needs to be used. In this paper, we present an improved Directional Filter Bank (DFB)-based fingerprint image enhancement method that effectively takes advantage of such ridge curvature information. The proposed method first decomposes a fingerprint image into 8 directional subbands using the DFB and then classifies the image into background, low curvature, and high curvature regions using the directional energy estimates calculated from the subbands. Thereafter, the weight values for directional subband processing are determined using classification information and directional energy estimates. Finally, the enhanced image is obtained by synthesizing the processed subbands. The experimental results show that the proposed approach is effective in enhancing both singular and non-singular regions.

1. INTRODUCTION

Owing to developments in fingerprint scanning technologies [1], recently fingerprint based person identification or verification could be deployed successfully in many forensic or civilian applications. However, even fingerprint images acquired by modern fingerprint sensors include various kinds of noise components, thus fingerprint image enhancement is still considered as a crucial step for reliable fingerprint feature extraction.

The aim of fingerprint image enhancement is not to produce a good visual appearance of a fingerprint image but to facilitate the subsequent ridge extraction. Therefore, not only suppressing noise but avoiding undesired side effects is very important in fingerprint image enhancement [2]. To accomplish this aim of image enhancement, many approaches have been suggested. O'Gorman et al. proposed a contextual filter whose parameters are automatically determined from image features such as ridge

width [3]. Sherlock et al. suggested a fingerprint image enhancement method using directional Fourier filtering [4]. This method suppresses both directional and frequency noises effectively in the Fourier transform domain, but it has the disadvantage that it requires Fourier transform and inverse Fourier transform operations as many as the number of predefined directional band pass filters. Hong et al. attempted to remove directional and frequency noises in the spatial domain by using a set of Gabor filters, which have oriented and frequency selective characteristics [5]. In this method, they assume that ridge-valley structures have a sinusoidal shape along the direction normal to ridges, thus non-singular regions satisfying this assumption relatively well can be successfully enhanced while singular regions generally forming a high curvature are prone to be distorted. In addition, due to blockwise operation of the Gabor-filter based methods, some blocking artifacts appear especially in borders between the blocks with high differences in directions or qualities.

In order to effectively remove directional noises of fingerprints, several directional filter bank (DFB) [6][7]-based methods have been proposed [8]. The method in [8] decomposes a fingerprint image into 8 directional subbands using the DFB, and next is calculated a weight value for each directional subband block using the directional energy ratios and then each directional subband block is multiplied by a weight and synthesized each subband is processed. Finally, the enhanced image is obtained by synthesizing the processed directional subbands. Though it can remove directional noise quite a lot, this method could be unreliable because it is not easy to distinguish the regions of normal fingerprint and undesired noise features. Additionally, since the DFB-based methods do not use local ridge curvature information, it has a poor performance in enhancing singular (high curvature) areas though it enhances well non-singular (low curvature) regions. If the method by [7] is used for fingerprint enhancement, it has an advantage of multiresolution structure which consists of a combination of the Laplacian pyramid and the DFB, but it is not maximally decimated.

Therefore, based on DFB of [8] due to its simple structure and efficient processing time, we propose an improved fingerprint image enhancement method that effectively exploits local ridge curvature information. The proposed method gets such ridge curvature information using the DFB and the local directional subbands are processed differently according to local ridge curvatures. The enhanced image is obtained by synthesizing the processed directional subbands. In the next section, the proposed method is described in detail, and the experimental results and conclusions are given in section 3 and 4, respectively.

2. FINGERPRINT IMAGE ENHANCEMENT

The proposed methods are composed of directional decomposition, subband processing, and synthesis stages. In the analysis stage, an input image is decomposed into 8 directional subband outputs using the 8-band DFB, and segmentation is performed to differentiate foreground regions from background ones and high curvature regions from low curvature ones. As a result of segmentation, a segmentation array is generated. In the subband processing stage, the decomposed directional subband images are processed using a segmentation array and directional estimates of each block. In

the synthesis stage, the processed subbands are synthesized and the enhanced image is obtained.

2.1 Directional Decomposition Using DFB

Directional decomposition of a fingerprint image is performed by the DFB that decomposes an image efficiently and accurately into several directional subbands. Fig. 1 shows the frequency partition map of the 8-band DFB and an example of directional decomposition by the DFB. The size of each directional subband image is illustrated in Fig. 1(c). For an $N \times N$ image, the size of each subband becomes $N/4 \times N/2$ or $N/2 \times N/4$ according to its direction. The down sized subbands result from quincunx down samplers and the rectangular shapes of the subbands are due to post sampling for removing the frequency scrambling by down sampling. Though there are a lot of methods that perform directional filtering such as Gabor filters and directional Fourier filters, the DFB has several advantages over the other methods in that the directional separation is accurate and the procedures are efficient. The more detail description about the DFB used in this paper can be found in [6].

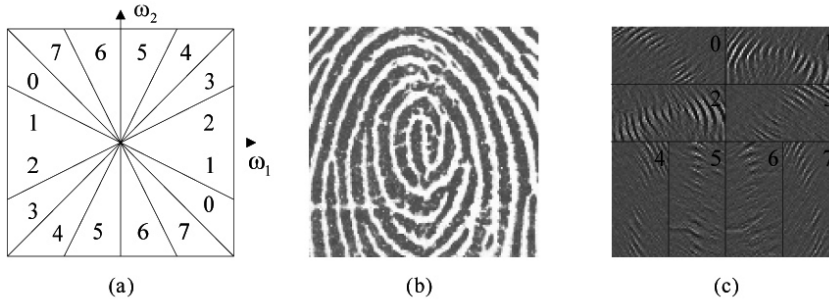


Fig. 1. An example of directional decomposition by 8-band DFB. (a) Partition map of the 8-band DFB, (b) original image, and (c) decomposed directional subband images of (b).

2.2 Classification

The proposed method separates foreground regions from background ones by finding blocks where sum of the directional energy estimates is more than a certain threshold (Th). Let $s_{i,j}^\theta(x, y)$ denote the coefficient at position (x, y) of subband θ corresponding to an image block $B_{i,j}$. The directional energy estimate of the image block $B_{i,j}$ associated with subband θ is defined as

$$e_{i,j}^\theta = \sum_{x,y \in B_{i,j}} |s_{i,j}^\theta(x, y) - \mu_{i,j}^\theta| \quad (1)$$

where $\theta \in \{0, 1, 2, \dots, 7\}$ and $\mu_{i,j}^\theta$ is the mean value of the corresponding subband block coefficients. Once the directional energy estimates of a block are calculated, we determine whether the block belongs to foreground regions or not as follows:

$$A_s(i, j) = \begin{cases} 1, & \text{if } \sum_{k=0}^7 e_{i,j}^\theta > Th, \\ 0, & \text{otherwise,} \end{cases} \quad (2)$$

where $A_s(i, j)$ is a segmentation array that shows the characteristics of a block $B_{i,j}$. If $A_s(i, j)=0$, the block $B_{i,j}$ belongs to background regions, while if $A_s(i, j)=1$, it belongs to foreground regions. In our experiment, we set the block size for segmentation to 16x16.

Thereafter, to divide the foreground regions into low curvature areas and high curvature ones, the proposed method calculates a block orientation image $o_{i,j}$ by finding the direction with the maximum energy from each block. Since the directional energy values are usually affected by noise components, in order to get a more reliable orientation of the block the extended neighborhood regions are considered for calculating the block orientation. Let $o_{i,j}$ denote the orientation of a block $B_{i,j}$, then the block orientation is given as follows:

$$o_{i,j} = \theta, \quad \text{if } E_{i,j}^\theta = \max_{\theta'} \{E_{i,j}^{\theta'}\}, \quad 0 \leq \theta, \theta' \leq 7, \quad (3)$$

$$E_{i,j}^\theta = \frac{1}{(2m+1)^2} \cdot \sum_{k=-m}^m \sum_{l=-m}^m e_{i+k, j+l}^\theta \quad (4)$$

where $E_{i,j}^\theta$ is the average directional energy estimate of the neighborhood region of the block $B_{i,j}$. An example of orientation images is given in Fig. 2. We can see that the orientation image calculated from average directional energy estimates is more reliable than the one by the directional energy estimates.

After obtaining an orientation image on a 8x8 block basis, the proposed method differentiates high curvature areas from low curvature ones by checking out the directional difference ($dd_{k,l}$) between two adjacent 8x8 blocks as follows:

$$A_s\left(\frac{l}{2}, \frac{l}{2}\right), A_s\left(\frac{l}{2} + k, \frac{l}{2} + l\right) = \begin{cases} 2, & \text{if } 45^\circ \leq dd_{k,l} \leq 135^\circ \text{ and } d_s < d_{th}, \\ 1, & \text{otherwise,} \end{cases} \quad (5)$$

where $dd_{k,l} = |\theta_{i,j} - \theta_{i+k, j+l}|$, $(k, l) = (-1, 0), (0, -1), (0, 1), (1, 0)$, and d_s is a distance from the nearest singular point. According to the above equations, every 16x16 block including at least one high curvature 8x8 block becomes a high curvature area. In case that a local orientation field is affected by noise, the region could be a high curvature area even though it belongs to low curvature areas. For that reason, the proposed method defines high curvature areas as the regions where adjacent two block regions show a high curvature and they are within a certain distance d_{th} from the nearest singular point. Limiting the high curvature area in a singular point area enables the proposed method to effectively differentiate the singular regions from noisy ones unless the singular point region is affected severely by noise. Since an orientation image is already obtained, detection of singular points can be performed simply by calculating a Poincare index for each local region [9]. As a result of classification, a segmentation array is generated and each element has a value between 0 and 2.

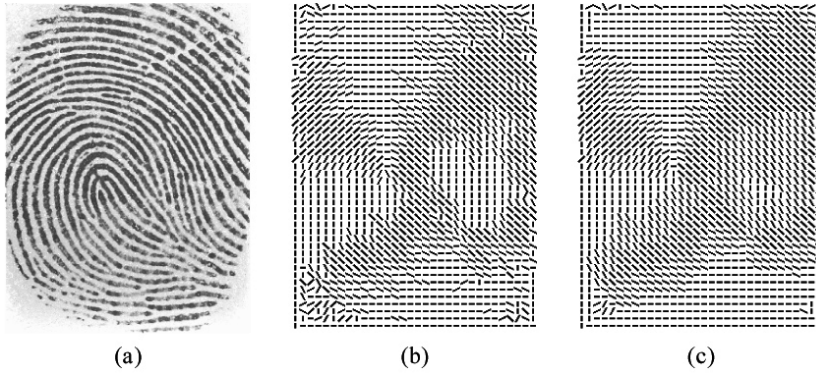


Fig. 2. Examples of orientation images calculated using the DFB. (a) Original image, (b) orientation image calculated using the corresponding block region only, and (c) orientation image calculated using the extended block region.

2.3 Processing and Synthesizing Directional Subbands

In general, in a block of low curvature areas directional energy is concentrated on about one direction, whereas in high curvature areas directional energy is concentrated on more than one direction. To enhance high curvature regions effectively, the proposed adjusts the number of directional subbands to be used for local region reconstruction according to ridge curvatures. In case that block size is fixed, high curvature regions can be represented well by using more number of directional subbands for local subband reconstruction than that for low curvature regions. Let w_{ij}^θ denote the weight value for θ -directional subband (s_{ij}^θ) corresponding to a block B_{ij} , then the weight values for a local region are determined as follows:

$$w_{i,j}^\theta = \begin{cases} 1, & \text{if } \theta \in D_{i,j}, \\ 0.5, & \text{else if } \{(\theta \pm 1) + n_o\} \bmod n_o \in D_{i,j} \text{ and } \theta \notin D_{i,j}, \\ 0, & \text{otherwise,} \end{cases} \quad (6)$$

$$D_{i,j} = \{k \mid E_{i,j}^k \geq \hat{E}_{i,j}^n\}, \quad 0 \leq \theta, k \leq 7, \quad (7)$$

$$n = \begin{cases} n_L, & \text{if } A_s(i, j) = 1, \\ n_H, & \text{else if } A_s(i, j) = 2, \end{cases} \quad (8)$$

where $D_{i,j}$ is a set of indices indicating the orientations with dominant energy in each block and the directions within the top n energies are the elements of $D_{i,j}$, n_o is the number of orientations, and $\{\hat{E}_0, \dots, \hat{E}_7\}$ is a down sorted version of $\{E_0, \dots, E_7\}$. In the experiments, we set n_L and n_H to 1 and 2, respectively. Since if only dominant directional subbands are used for reconstruction some artifact could occur, linear interpolation between the dominant orientation and its adjacent orientation is performed to reduce such artifacts as in Eq. (6) [8]. In the proposed method the block size is fixed

as 16×16 and the number of directions with dominant energy varies from 1 to 2 according to a segmentation array value. All weight values for background regions ($A_s(i,j)=0$) are set to 0. The decomposed directional subbands are multiplied by the calculated weight values and the enhanced image is obtained by synthesizing the processed subbands. The block diagram for the proposed fingerprint image enhancement method is given in Fig. 3.

Since the directional filtering procedure sets the coefficients of directional subband blocks that do not belong to dominant directions to 0, we can see some artifacts in the directionally filtered image. In order to reduce such artifacts, the proposed method performs smoothing using a 3×3 mean filter after directional filtering.

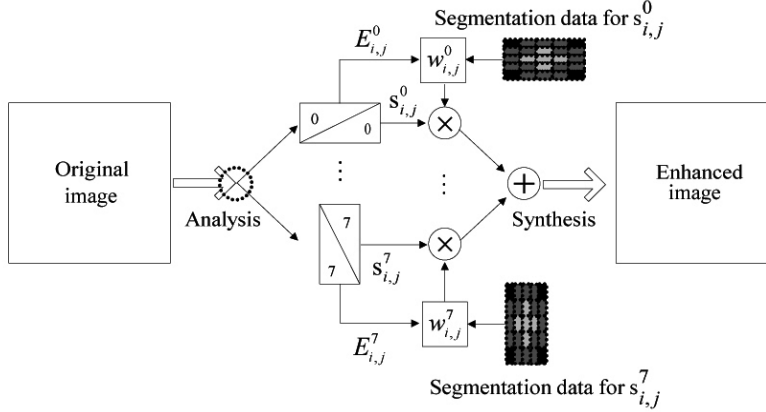


Fig. 3. Block diagram for the proposed method.

3. EXPERIMENTAL RESULTS

The proposed method was first evaluated using the 5 fingerprint images sampled from FVC2000 2a database. The aim of fingerprint image enhancement is to facilitate the following fingerprint feature extraction, so we not only visually observed the enhanced images but investigated how the proposed method affects accurate fingerprint feature extraction. Since the fingerprint features we want to extract here are fingerprint minutiae such as bifurcations and ending points, we evaluate the proposed method analyzing the accuracy of the extracted minutiae after applying the proposed fingerprint image enhancement method to fingerprints.

Once the enhanced image is obtained, it is binarized and thinned. From the thinned image, minutiae can be detected simply by analyzing neighborhood pixels. In our experiments, we compared the proposed methods with the Gabor filter bank-based method [5], and the results are shown in Table 1. As shown in Table 1, the two methods had a similar error rate. To be more specific, the Gabor filter bank-based method showed a good performance in enhancing non-singular and oily regions, whereas severe blocking artifacts or ridge distortion appeared frequently in singular or high curvature regions. For the proposed method, it showed a better performance in enhancing singular areas than the Gabor filter bank-based method. In non-singular (or

low curvature) regions, it showed a reasonably good performance though it was a bit inferior to the Gabor filter bank-based method especially in enhancing the oily regions. In the case that two dominant directions are used for local subband reconstruction, the singular regions are enhanced better than the case that one dominant direction is used, but the broken ridges are not connected well. In Fig. 4, we can see that the proposed method using local ridge curvature information has a better enhancing performance than the previous methods.

Table 1. Error rate of each method. M: Number of missing minutiae, S: Number of spurious minutiae. DFB-based (I): DFB-based enhancement using one dominant direction [6], DFB-based (II): DFB-based enhancement using two dominant directions, DFB-based (adaptive): Proposed method

Method	1		2		3		4		5	
	M	S	M	S	M	S	M	S	M	S
Gabor filter-based [5]	0	3	2	10	6	3	3	5	0	7
DFB-based (I)	1	3	3	9	0	2	4	2	2	5
DFB-based (II)	0	4	2	11	0	2	2	4	0	8
DFB-based (adaptive)	0	4	2	10	0	2	2	2	0	6

4. CONCLUSIONS AND FUTURE WORK

We have proposed an improved DFB-based fingerprint image enhancement method that is effective in enhancing both singular and non-singular regions. The proposed method segments the foreground region of a fingerprint image into low curvature and high curvature regions, then processes local directional subbands differently according to where the local region belongs. Experimental results show that the proposed approach suppresses the major noise components of fingerprints effectively regardless of region. In order to improve the enhancing performance of the proposed method, further study on segmenting the singular and non-singular regions more reasonably is required.

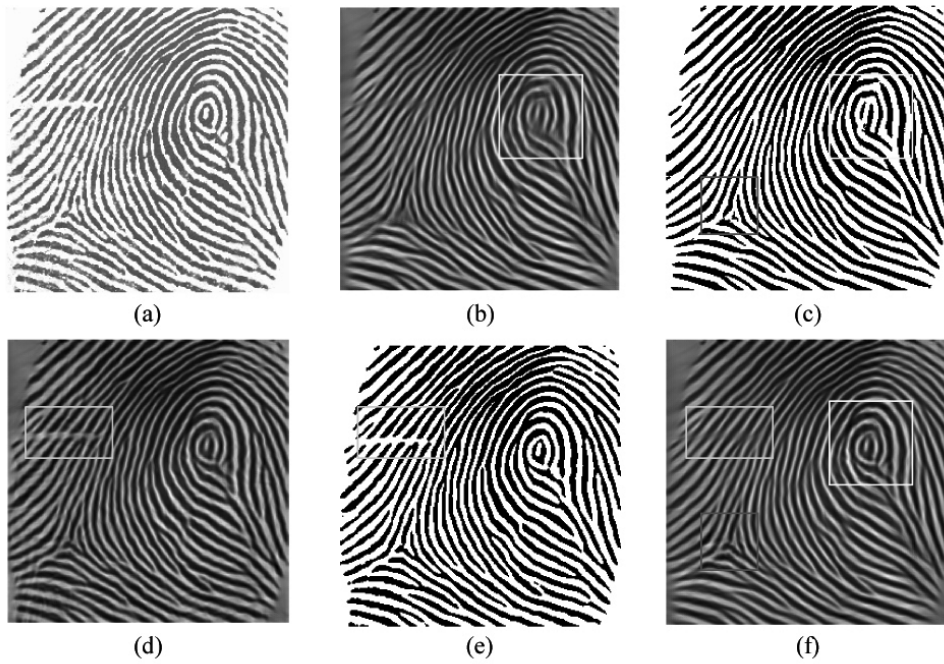


Fig. 4. Comparison of the enhancement methods. (a) Original image, (b) enhanced image using one dominant direction, (c) binarized image of (b), (d) enhanced image using two dominant directions, (e) binarized image of (d), (f) enhanced image by the proposed method, (g) binarized image of (f), (h) enhanced image by the Gabor filter bank-based method, and (i) binarized image of (h).

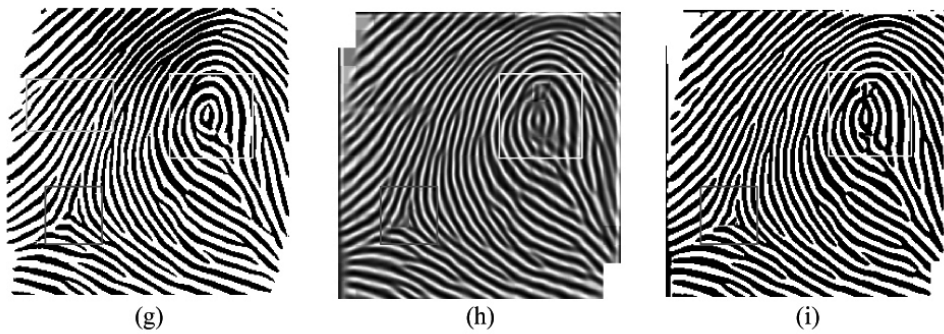


Fig. 4. (Continued).

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