Fingerprint Enhancement Scheme For Low - Assurance Images Through Learning

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Abstract— **The Biometrics indicators, Fingerprints are one of the highest levels of reliability and have been extensively used by forensic experts in criminal investigations. Anyway the performance of these techniques relies heavily on the quality of input fingerprint. But already existing STFT (short-time Fourier transform) analysis is not much perfect and best suit, to recover these unrecoverable regions of the fingerprint. Usually, fingerprint images are enhanced by one stage in either the spatial or the frequency domain. However, the enhanced performances are not satisfactory because of the complicated ridge structures that are affected by unusual input contexts. In this paper, we propose a novel and effective two-stage enhancement scheme in both the spatial domain and the frequency domain by learning from the underlying images. To remedy the ridge areas and enhance the contrast of the local ridges, we first enhance the fingerprint image in the spatial domain with a spatial ridge-compensation filter by learning from the images. In a proposed two-stage scheme to enhance the low quality fingerprint image in both the spatial domain and the frequency domain based on learning from the images…we use FFT(Fast Fourier Transform) algorithm to overcome the problem**

Index Terms—**Fingerprint enhancement, learning, privacy in biometrics systems, two-stage filtering.**

I. INTRODUCTION

BIOMETRICS, i.e., described as the science of recognizing an individual based on his or her physical or behavioral traits, is beginning to gain acceptance as a legitimate method for the determination of an individual's identity.Fingerprint recognition has emerged as one of the most reliable means of biometric authentication because of its universality, distinctiveness, permanence and accuracy. The performance of fingerprint recognition techniques relies heavily on the quality of the input fingerprint images. Fingerprint images are frequently of low quality because of the contexts of the image-acquisition process. Among all the biometric indicators, fingerprints are one of the highest levels of reliability and have been extensively used by forensic experts in criminal investigations. Fingerprint recognition has emerged as one of the most reliable means of biometric authentication because of its universality, distinctive-ness, permanence, and accuracy. The quality of a fingerprint image may be poor or significantly different because of various factors, such as wetness and dryness, pressure strength, smears, and so on, which lead to different types of degradation in fingerprint images.

should be, and some parallel ridges are not well separated. Thus, fingerprint-enhancement approaches are needed to deal with all of these factors.

Generally speaking, fingerprint recognition algorithms are roughly classified into two classes : minutiae-based and image-based methods, which primarily use minutiae information or a reference point along with a number of ridge attributes for recognition. The wrong ridge structural information can be fatal to both classes of recognition algo-rithms since it can change the information of the minutiae points and reference points, and it may also cause some errors in feature extraction. To reduce the possibility of recognition error, a robust enhancement algorithm is required, especially for low-quality fingerprint images. In order to overcome the shortcomings of the existing algorithms on the fairly poor fingerprint images with cracks and scars, dry skin, or poor ridges and valley contrast ridges, we propose a novel and effective two-stage enhancement algorithm for low-quality fingerprint images, in this paper, by integrating spatial- and frequency-domain filters. The method adequately uses the information of the first enhanced image for the estimation of second filters' parameters. The procedure is not to simply concatenate two enhancement steps, while both of them have enhanced contributions. The first-stage filter, i.e., a ridge-compensation filter, intends to use the context information of the local ridges to connect broken ridges and separate merged ridges. It remedies the ridge areas and enhances the ridge con-trast. Although this processing enhances the ridges, it blurs the images because the mask of the filter uses the neighbor information. Thus, a second-stage, i.e., a tuned bandpass filter that is separable in the radial and the angular-frequency domains, is applied to the first enhanced image to improve the finger-print image completely because of the fast and sharp attenua-tion of the filter in both the radial and the angular-frequency domains. It is highlighted that the bandpass filter is designed by learning the filters' parameters from both the original image and the first-stage enhanced image instead of acquiring from the original image solely, which will benefit the performance of the enhancement. The contribution of this paper is that our fingerprint enhancement scheme is based on the learning from the images; thus, it is able to handle the various input contexts, such as fingerprint with cracks and scars, dry skin, or poor ridges and valley contrast ridges, for user authentications.

II. Related Works On Fingerprint Enhancement

Human experts routinely use the context information of fin-gerprint images, such as ridge continuity and regularity to help in identifying them. This means that the underlying morpho-genetic process that produced the ridges does not allow for irregular breaks in the ridges except at ridge endings. Because of the regularity and continuity properties of the fingerprint im-age, occluded and corrupted regions can be recovered using the contextual information from the surrounding area. Such regions are regarded as “recoverable” regions. The efficiency of an automated enhancement algorithm depends on the extent to which they utilize the contextual information. Some filters for these enhancement tasks are classified either in the spatial domain or in the frequency domain. According to the classification of the filters, the existing enhancement processing is roughly classified into either spatial-domain filtering or frequency-domain filtering.

A. Spatial-Domain Filtering

The most popular approach to fingerprint enhancement, which was proposed in, is based on a directional Gabor filtering kernel. The algorithm uses a properly oriented Gabor kernel, which has frequency-selective and orientation-selective properties, to perform the enhancement. These properties al-low the filter to be tuned to give maximal response to ridges at a specific orientation and frequency in the fingerprint image. However, unlike Fourier bases or discrete cosine bases, using Gabor elementary functions has the following problems: Gabor elementary functions do not form a tight frame; they are bi-orthogonal bases; and there is no rigorously justifiable reason for choosing the Gabor kernel over other directionally selective filters, such as directional derivatives of Gaussians or steerable wedge filters.

B. Frequency-Domain Filtering

Unlike spatial-domain techniques, filters in the frequency do-main can be used to calculate convolutions effectively from the entire image rather than from a small area of the filtered point in the spatial domain. This section deals with some other filters that are defined explicitly in the frequency domain. Each whole image is convolved with eight location-independent precomputed filters at the intervals of 45°. However, the algorithm does not utilize the full contextual information that is provided by the finger-print image. The contextual filtering is actually accomplished at the stage labeled “selector,” which uses the local orientation information to combine the results of the filter bank using ap-propriate weights for each output. In addition, the algorithm requires computing and retaining 16 prefiltered images. Thus, it is quite time consuming and not suitable for real applications.

In the proposed scheme, fingerprint image enhancement uses STFT analysis. . It acquires the block frequency through the STFT analysis and estimates the local ridge orientation too. A directional bandpass filter is employed to enhance the fingerprint image in blocks. However, because of the complex input contexts of the low-quality image, not all of the unrecoverable regions of the fingerprint can be recovered clearly, as it is difficult to accurately estimate some parameters of the filters through a simple STFT analysis. Thus, the algorithm needs to be improved to enhance the unrecoverable regions of low-quality images.

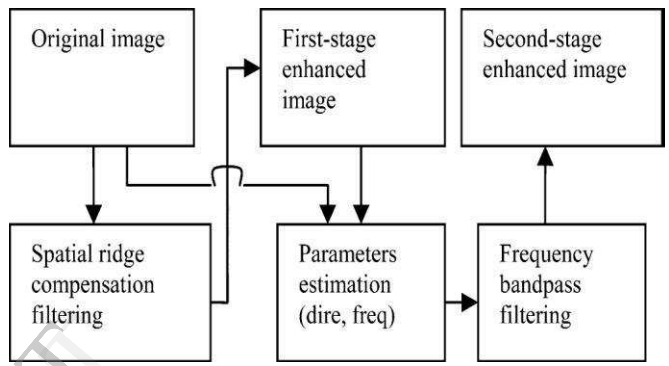


Fig. 1. Diagram of the whole process of the proposed two-stage enhancement scheme (dire = ridge direction, freq = ridge frequency).

III. Proposed Two-Stage Enhancement Scheme

To overcome the demerits of the existing enhancement algorithms a new and effective scheme with two consecutive stages (Fig. 1) is using. The algorithm first enhances the images in the spatial domain with a spatial ridge-compensation filter and, then, enhances the images in the fre-quency domain. The parameters (ridge direction and frequency) for the frequency bandpass filters are estimated from the orig-inal image and the first-stage enhanced image.

A. First-StageEnhancement:SpatialRidge-Compensation Filter

The first stage performs ridge compensation along the ridges in the spatial field. This step enhances the fingerprint’s local ridges using the neighbor pixels in a small window with a weighted mask along the orientation of the local ridges. Each pixel in the fingerprint is replaced with its weighted neighbor sampling pixels in a small window and with the controlled con-trast parameters along the orientation of the local ridges. Meanwhile, the filter enhances the gray-level values of ridges’ pixels along local ridge orientation.

The main idea of the first-stage enhancement scheme is to

$$\mathrm{fltimg}(i,j) = \frac{\sum_{m=-(w-1)/2}^{(w-1)/2} \sum_{n=-(h-1)/2}^{(h-1)/2} \mathrm{norimg}(i', j')}{(((w-1)\times\beta+\alpha)\times h)}$$

$$i' = i + m\cos(O(i,j)) + n\sin(O(i,j))$$
$$j' = j - m\sin(O(i,j)) + n\cos(O(i,j))$$

estimate unbiased local orientation and compensate the possible defects by using the local orientation. The scheme consists of three steps: local normalization, local orientation estimation, and local ridge-compensation filtering.

1) Local Normalization: This step is used to reduce the local variations and standardize the intensity distributions in order to consistently estimate the local orientation. The pixelwise opera-tion does not change the clarity of the ridge and furrow structures but reduces the variations in gray-level values along ridges and furrows, which facilitates the subsequent processing steps. The global normalization method is also used for the fingerprint en-hancement employing a Gabor filter.

For each pixel (i, j) in a subimage, which is acquired by di-viding the fingerprint image into subimages first, the normalized image is defined as follows:

$$\mathrm{norimg}(i,j) = M_0 + \mathrm{coeff} * (\mathrm{img}(i,j) - M)$$
$$\mathrm{coeff} = \frac{V_0}{V}.$$

Here, img(i, j) is the gray-level value of the fingerprint image in pixel (i, j), norimg(i, j) is the normalizing value in pixel (i, j), and coeff is the amplificatory multiple of the normalized image. M is the mean of the subimage, and V is the variance of the subimage. M_0 and V_0 are the desired mean and variance values, respectively.

2) Local Orientation Estimation: This step determines the dominant direction of the ridges in different parts of the finger-print image. This is a critical processing, and errors occurring at this stage are propagated to the frequency filter. We used the gradient method for orientation estimation and an orientation-smoothing method with a Gaussian window to correct the estimation. Because of the ambiguity of the orientation values for each position, an orientation-smoothing method with a Gaussian window is used to correct the estimation, rather than a simple averaging.

3) Local Ridge-Compensation Filter: With the estimated orientation values in place, the final step compensates the ridge artifacts using a local ridge-compensation filter with a rotated rectangular window to match the local orientation. For each pixel (i, j) in the normalized image, the computing formula for the ridge-compensation filter is defined as follows:

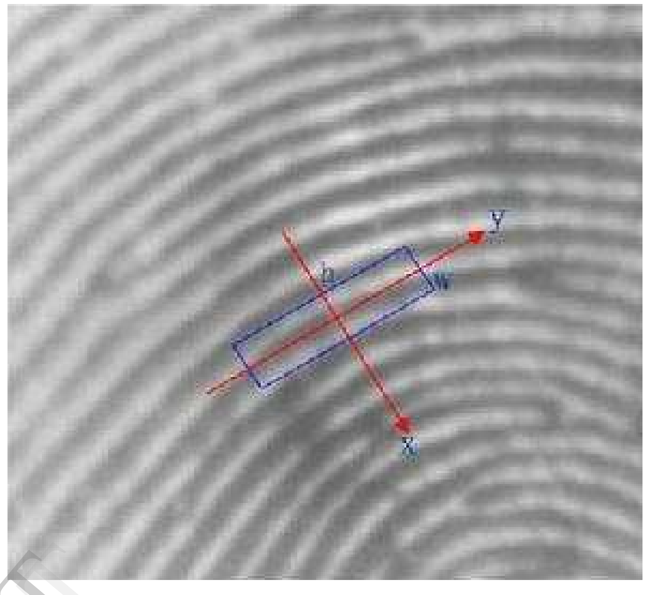


Fig. 2. Demonstration of an enhanced window along the local ridge orientation.

B. Second-Stage Enhancement: Frequency Bandpass Filter

Although the result of the first spatial filter increases the ridge contrast in the direction perpendicular to the ridges, this processing may blur the image as well. Thus, a second-stage enhancement with a tuned bandpass filter is proposed to en-hance the fingerprint image serially. The frequency bandpass filters used are separable in the radial and angular domains, respectively. The processing is able to enhance the fingerprint image both in the radial and the angular domains and enhance the ridges completely. The enhancement of fingerprint images with bandpass filters may take advantage of the regularity of the spatial structure by filtering the image with a position-dependent bandpass fre-quency filter whose passband is matched everywhere with the local ridge orientation and local ridge frequency. Instead of us-ing the entire image, we apply the frequency filters to the blocks to utilize all of the local frequency and local orientation infor-mation.

Using polar coordinates (ρ, φ) to express the filters as a sepa-rable function, the frequency bandpass filters $H(\rho, \varphi)$ used are separable in the radial and the angular domains, respectively and are given as follows:

$$H(\rho, \varphi) = H_\rho(\rho) H_\varphi(\varphi)$$

$$H_\rho(\rho) = \frac{1}{\sqrt{2\pi}\rho_{BW}} \exp\left(-\frac{(\rho - \rho_c)^2}{2\rho_{BW}}\right)$$

$$H_\varphi(\varphi) = \begin{cases} \cos^2 \dfrac{\pi(\varphi - \varphi_c)}{2\varphi_{BW}}, & \text{if } |\varphi| < \varphi_{BW}, \\ 0, & \text{Otherwise.} \end{cases}$$

In our enhancement scheme, the coherence measurements are adapted to estimate the angular bandwidth of the directional filter. The scheme is summarized as follows

1) *Local orientation estimation by learning*: This step determines the dominant direction of the ridges in different parts of the fingerprint image by learning from the images. The orientation estimation is similar with Step 2 in the first-stage filtering, which used the gradient method for orientation estimation. However, the new orientation $\theta(x, y)$ is corrected in the enhanced image after the first-stage enhancement. The formula for the computation of the new orientation $\theta(x, y)$ is as follows:

$$\theta(x, y) = \begin{cases} \text{corr } \theta(x, y), & \text{if } |\text{corr } \theta(x, y) - \text{orig } \theta(x, y)| < t, \\ \dfrac{\sum_{(i,j) \in W} \text{corr } \theta(x, y)}{(W \times W)}, & \text{else} \end{cases}$$

where orig $\theta(x, y)$ is the orientation of a pixel in the original image, corr $\theta(x, y)$ is the orientation of the corresponding pixel in the enhanced image, t is a threshold value, and W is the window size.

2) *Local frequency estimation by learning*: This step is used to estimate the interridge separation in different regions of the fingerprint image. The local frequency is estimated by applying FFT to the blocks by F = FFT (block_img) , and the local frequency is pixel processing. . A frequency error-correcting process is applied when the estimated frequency to be outside of the range is assumed to be in-valid. The obtained frequency is also used to design the radial filter.

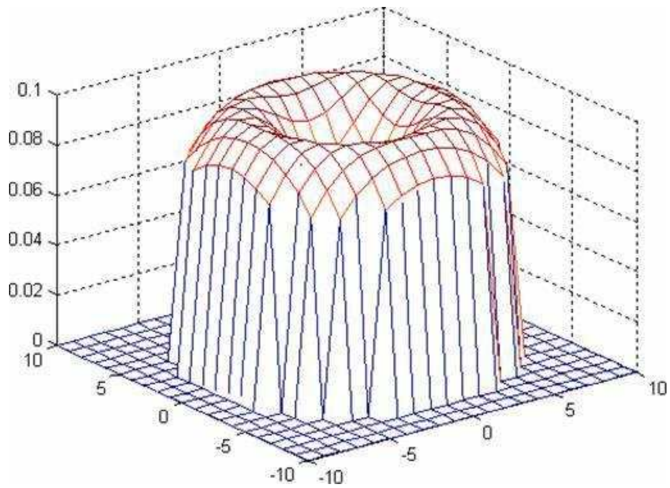


Fig.3. Designed radial filter in the frequency domain

3) *Coherence image*: The coherence indicates the relationship between the orientation of the central block and those of its neighbors in the orientation map. The coherence is related to the dispersion measure of circular data. The coherence is high when the orientation of the central pixel $\theta(x, y)$ of a window is similar to each of its neigh-bors $\theta(x_i, y_i)$, and W is the window size. The obtained coherence image is used to determine the bandwidth of the angular filter.

4) *Frequency bandpass filtering*: First, the whole smooth-ing filtered image is divided into overlapping subim-ages, and for each subimage, the following operations are performed.
    a) FFT domain: The FFT of each subimage is ob-tained by removing the dc component, F = FFT (block_fltimg).
    b) Angular filter: The angular filter Fa is applied, which is centered on the local orientation image and with the bandwidth inversely proportional to the coherence image using .
    c) Radial filter: The radial filter Fr is applied, which is centered on the local frequency image using .
    d) Filtered image: The block is filtered in the frequency domain, i.e., F = F × Fa × Fr.
    e) Reconstructed image: The enhanced image is reconstructed by Enhimg = IFFT (F).

The reconstructed image is the final enhanced image by the proposed two-stage enhancement algorithm. Finally, a morphological-based segmentation method is used to seg-ment the foreground from the background

IV. Experimental Results

A. Experimental Results of the First-Stage Enhancement

The local normalization has benefits for this enhancement algorithm. It is obvious that the locally normalized image has better results than the globally normalized image in enhancing the contrast between the ridges and the valleys in the low-quality image. The local normalization should be more effective with images that are partly contaminated. In the experiments, first, we applied our first-stage enhancement al-gorithm and, then, followed the chain-code-based minutiae-extraction method. To show that our proposed method is effective combined with this minutiae-extraction method, we com-pared the results with two input contexts: the original image and our proposed first-stage enhanced image. . When our proposed enhanced image is used as input, the number of false and missing minutiae is less than that when the original image is used. The following terms are defined for the purpose of comparing the experimental results:

The following terms are defined for the purpose of comparing the experimental results:

1) true minutia: a minutia point detected by an expert, m_t ;
2) false minutia: a minutia “ma” that does not coincide with m_t being a false minutia;
3) dropped minutia: when a minutia m_t is not detected in “ma,” with m_t being a dropped minutia;

Based on aforementioned experimental results, we can draw the conclusion that our proposed first-stage enhancement scheme is effective as a preprocessing process. After the imple-mentation of a sophisticated minutiae-based method, the whole system will have better performance compared with the method that does not use the enhancement.

B. Experimental Results of the Two-Stage Enhancement Algorithm

Some results of the proposed two-stage enhancement algo-rithm using fingerprints from four subdatabases of the FVC2004 database are shown in Fig. 4. In order to show that our proposed first-stage enhanced algo-rithm benefit the second-stage enhancement, experiments with combining some two filters were conducted. The simulation results are shown by using the combination of two filters: Hong’s Gabor filter + second-stage filter, Chikkerur’s STFT + second-stage filter, and our proposed ridge-compensation filter + second-stage filter.

To further provide quantitative analysis of the enhanced al-gorithms, two experiments were conducted for comparison.

1) Experimental Results of the Two-Stage Enhancement Method Combined With a Sophisticated Minutiae-Based Method:

The proposed system extracts minutiae from the original image or from different enhanced images. The ex-periments were conducted several times (five times here) for statistical analysis. Table II presents a comparison of the statistics (aver-age and standard deviation) of TMR, FMR, DMR, and EMR percentage of the system’s performance combined with no en-hancement, Gabor filters, Gabor filters + second stage, STFT, STFT + second stage, and our two-stage enhancement meth-ods over the FVC2004 databases.

TABLE II Statistics Of Tmr (%), Fmr (%), Dmr (%), And Emr (%) Performance Of The System Combined With No Enhancement, Gabor Filters, Gabor Filters + Second Stage, Stft, Stft + Second Stage, And Our Two-Stage Enhancement (*U* = Average, Std = Standard Deviation)

	TMR (%)		FMR (%)		DMR (%)		EMR (%)	
	u	*std*	*u*	*std*	*u*	*std*	*u*	*std*
No enhancement	36.4	0.19	34.5	0.49	17.7	0.65	11.4	0.48
Gabor filter enhancement	90.3	0.45	4.21	0.10	3.52	0.13	1.97	0.42
Gabor filter+2nd stage enhancement	91.1	0.24	3.89	0.06	3.21	0.07	1.80	0.21
STFT enhancement	92.5	0.36	3.30	0.09	2.11	0.17	2.19	0.15
STFT +2nd stage enhancement	93.4	0.29	3.12	0.10	1.80	0.12	1.68	0.20
Our two-stage enhancement	95.4	0.47	2.33	0.10	1.14	0.13	1.13	0.28

Fig. 4. Results of the proposed two-stage enhancement algorithm that is ap-plied to fingerprints from four FVC2004 databases DB1–DB4. (a), (c), (e), (g) Original images. (b), (d), (f), (h) Our two-stage enhanced images.

2) Experimental Results of the Two-Stage Enhancement Method Combined With an Image-Based Verification Method:

A fingerprint verification method that uses tessellated invari-ant moment features is tested combined with the proposed method and some well-known enhanced algorithms. All of the experiments are based on the tessellation of region of interest with 16 tessellated cells, and each cell has 16 × 16 pixels; the similarity measurement is the eigenvalue-weighted cosine (EWC) distance.

A good fingerprint enhancement is very important mainly for image-based fingerprint matchers, because the image-based matcher depends on the accuracy of the reference point detection.

To evaluate the performance of the verification system, the false reject rate (FRR) and the false acceptance rate (FAR) are computed:

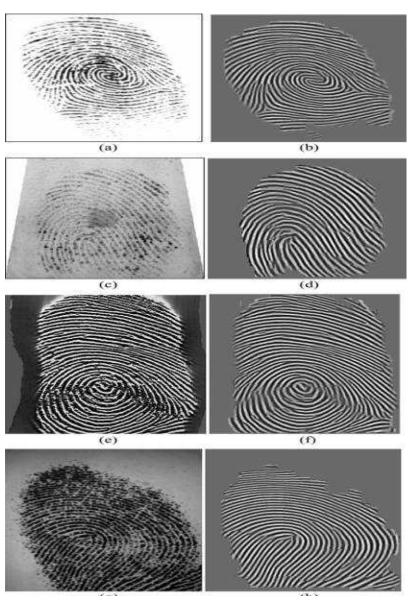
$$\mathrm{FRR} = \frac{\text{Number of rejected genuine claims}}{\text{Total number of genuine accesses}} \times 100\%$$

$$\mathrm{FAR} = \frac{\text{Number of accepted imposter claims}}{\text{Total number of imposter accesses}} \times 100\%.$$

The equal error rate (EER) is used as a performance indicator. The EER indicates the point where the FRR and FAR are equal:

$$\mathrm{EER} = \frac{(\mathrm{FAR} + \mathrm{FRR})}{2}, \quad \text{if } \mathrm{FAR} = \mathrm{FRR}.$$

In the experiments, each subdatabase (800 finger-print patterns) of FVC2004 database is divided into a training set and a testing set using a 25% jackknife method. The im-postors and genuine distributions were generated; then, the FRR and FAR were computed according to (16) and (17). The EER of a system can be used to give a threshold-independent per-formance measure. The lower the EER, the better the system's performance, and the EER is the half of the total errors when FAR equals FRR [10].The same experiments were repeated four times by selecting different fingerprints for training and testing, and then the statistics (average and standard deviation) of the EER(%) were computed by considering the four experimental results.



V. Conclusion And Further Work

In this paper, an effective two-stage enhancement scheme in both the spatial domain and the frequency domain for low-quality fingerprint images by learning from the images has been proposed. Emphasizing the enhancement of the low-quality im-ages, the first-stage enhancement scheme has been designed to use the context information of the local ridges to connect or separate the ridges. Based on this spatial filtering, the broken ridges will be connected and the merged ridges will be sepa-rated Effectively; thus, the fingerprint ridges can be remedied and recovered well. In the second-stage processing, the filter is separable in the radial and angular domains, respectively. Its parameters have adequately been determined by the information of both the original image and the enhanced images of the first stage instead of acquiring from the original image solely. Thus, the proposed two-stage scheme enhances the fingerprint images significantly. The experimental results show that the proposed scheme is able to handle various input contexts and achieves the best performance in combination with two nominated verification algorithms.

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