Image Quality Measures for Fingerprint Image Enhancement

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Abstract. Fingerprint image quality is an important factor in the performance of Automatic Fingerprint Identification Systems(AFIS). It is used to evaluate the system performance, assess enrollment acceptability, and evaluate fingerprint sensors. This paper presents a novel methodology for fingerprint image quality measurement. We propose limited ring-wedge spectral measure to estimate the global fingerprint image features, and inhomogeneity with directional contrast to estimate local fingerprint image features. Experimental results demonstrate the effectiveness of our proposal.

1 Introduction

Real-time image quality assessment can greatly improve the accuracy of an AFIS. The idea is to classify fingerprint images based on their quality and appropriately select image enhancement parameters for different qualities of images. Good quality images require minor preprocessing and enhancement. Parameters for dry images (low quality) and wet images (low quality) should be automatically determined. We propose a methodology of fingerprint image quality classification and automatic parameter selection for fingerprint enhancement procedures.

Fingerprint image quality is utilized to evaluate the system performance [1–4], assess enrollment acceptability [5] and improve the quality of databases, and evaluate the performances of fingerprint sensors. Uchida [5] described a method for fingerprint acceptability evaluation. It computes a spatial changing pattern of gray level profile along with the frequency pattern of the images. The method uses only a part of the image - "observation lines" for feature extraction. It can classify fingerprint images into only two categories. Chen et al. [1] used fingerprint quality indices in both the frequency domain and spatial domain to predict image enhancement, feature extraction and matching performance. They used the FFT power spectrum based on global features but do not compensate for the effect of image-to-image brightness variations. Based on the assumption that good quality image blocks possess clear ridge-valley clarity and have strong Gabor filters responses, Shen et al. [3] computed a bank of Gabor filter responses for each image block and determined the image quality with the standard deviations of all the gabor responses. Hong et al. [6] applied sinusoidal wave model to dichotomize fingerprint image blocks into recoverable or unrecoverable regions. Lim et al. [2] computed the local orientation certainty level using the ratio of the maximum and minimum eigen values of gradient covariance matrix and the orientation quality using the orientation flow.

In this paper, we propose a limited ring-wedge spectral measure to estimate the global fingerprint image features. We use the inhomogeneity and directional contrast to estimate local fingerprint image features. Five quality levels of fingerprint images are defined. The enhancement parameter selection is based on the quality classification. Significant improvement in system performance is achieved by using the proposed methodology, equal error rate(EER) is droped from 1.82% to 1.22%.

2 Proposed Quality Classification Features

In Figure 1, sample fingerprint images of different qualities are taken from Database DB1 of FVC 2002. The dry image blocks with light ridge pixels in fingerprints are due to either slight pressure or dry skin surface. Smudge image blocks in the fingerprints are due to wet skin environment, unclean skin surface or heavy pressure,(Figure 1(c)). Other noise is caused by dirty sensors or damaged fingers. The following five categories are defined:

- Level 1- (good) clear ridge/valley contrast; easily-detected ridges; precisely-located minutiae; easily-segmented.
- Level 2- (normal) Most of ridge can be detected; ridge and valley contrast is medium; fair amount of minutiae; possesses some poor quality blocks (dry or smudge).
- Level 3- (Smudge/Wet) not well-separated ridges.
- Level 4- (Dry/lightly inked) broken ridges; only small part of ridges can be separated.
- Level 5- (Spoiled) totally corrupted ridges.

2.1 Global Quality Measure: Limited Ring-Wedge Spectral Energy

The images with the directionality pattern of periodic or almost periodic wave can be represented by the Fourier spectrum [1, 7]. A fingerprint image is a good example of such type of texture. The FFT spectrum features can be simplified by expressing them in polar coordinates. We represented the spectrum with the function S(r, θ), where r is the radial distance from the origin and θ is the angular variable. If fft2 represents the 2-D discrete Fourier transform function and fftshift moves the origin of the transform to the center of the frequency rectangle, then the FFT spectrum S(r, θ) can be expressed as follows:

$$S(r, \theta) = log(1 + abs(fftshift(fft2(img)))) \tag{1}$$

In [1], the FFT power spectrum based global feature does not compensate the effect of image-to-image brightness variations. The global index measures the entropy of the energy distribution of 15 ring features, which are extracted using Butterworth low-pass filters. We convert $S(r, \theta)$ to 1-D function $S_\theta(r)$ for each direction, and analyze $S_\theta(r)$ for a fixed angle. Therefore, we can obtain the spectrum profile along a radial direction from the origin. A global descriptor can be achieved by summing for discrete variables:

$$S(r) = \sum_{\theta=0}^{\pi} S_\theta(r) \tag{2}$$

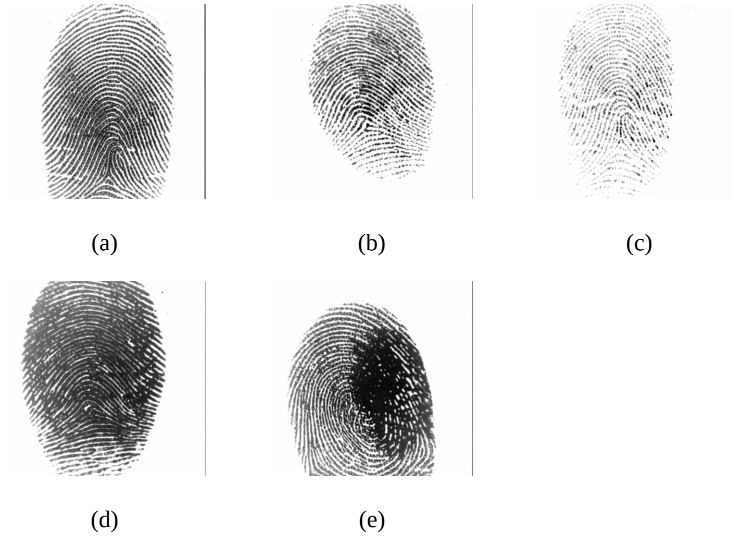


Fig. 1. Typical sample images of different image qualities in DB1 of FVC2002. (a)Good quality, (b) Normal, (c) Dry , (d) wet and (e) Spoiled

Figure 2 shows the spectra for one pair of fingerprint images (one has good quality, the other has low quality) from the same finger. We observe that there exists a characteristic principal peak around the frequency of 40. Based on actual computations and analysis of sample patterns, we compute the band energy between frequency 30 and frequency 60, which we will call ”limited ring-wedge spectral measure”. The difference between good quality and low quality images is significant as indicated by the existence of strong principal feature peak (the highest spectrum close to the origin is the DC response) and major energy distribution. The new global feature described above effectively indicates the clear layout of alternate ridges and valleys patters. However, it still can not classify fingerprint images, which are of generally good quality but contains low quality blocks or which are of generally low quality but contain good quality blocks. A statistical descriptor of the local texture is necessary for such classification of fingerprint images.

2.2 Local Quality Measure: Inhomogeneity and directional contrast

To quantify the local texture of the fingerprint images, statistical properties of the intensity histogram [7] are well suited. Let I_i, L, and $h(I)$ represent gray level intensity, the number of possible gray level intensities and the histogram of the intensity levels, respectively. Mean(m), standard deviation(σ), smoothness(R) and uniformity(U) can be expressed as in equations 3-6. We define the block *Inhomogeneity*(inH) as the ratio of the product between mean and *Uniformity* and the product between standard deviation and smoothness.

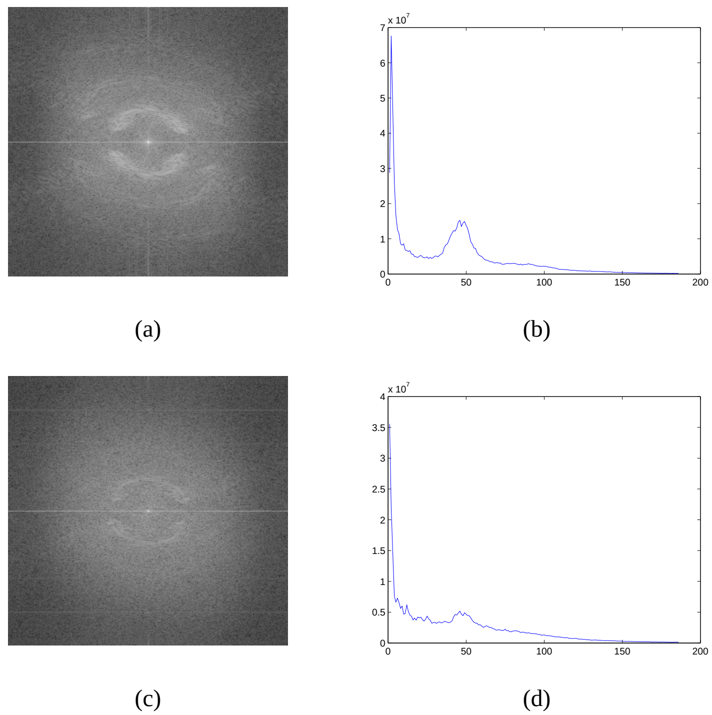


Fig. 2. Spectral measures of texture for good impression and dry impression for the same finger. (a) and (b) are the corresponding spectra and the limit ring-wedge spectra for Figure 1(a), respectively; (c) and (d) are the corresponding spectra and the limit ring-wedge spectra for Figure 1(c), respectively.

$$m = \sum_{i=0}^{L-1} I_i h(I_i) \tag{3}$$

$$\sigma = \sqrt{\sum_{i=0}^{L-1} (I_i - m)^2 h(I_i)} \tag{4}$$

$$R = 1 - \frac{1}{1 + \sigma^2} \tag{5}$$

$$U = \sum_{i=0}^{L-1} h(I_i)^2 \tag{6}$$

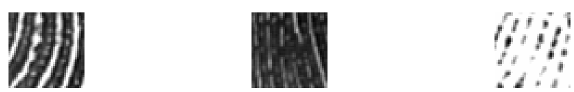
$$inH = \frac{m \times U}{\sigma \times R} \tag{7}$$

In [8], low contrast regions map out smudges and lightly-inked areas of the fingerprint, and there is very narrow distribution of pixel intensities in a low contrast area; low flow maps flags blocks where the DFT analyses could not determine a significant ridge flow. We used the modification of ridge-valley orientation detector [8] as a measure of local directional contrast. Directional contrast reflects the certainty of local ridge flow orientation, and identify spoiled regions (Figure 1(d)). According to [8] for each pixel we calculated the sum of pixel values for 8 directions in 9×9 neighborhood, s_i. The values of s_{max} and s_{min} correspond to most probable directions of white pixels in valleys and black pixels in ridges. We averaged the values of ratios s_{min}/s_{max} for block pixels to obtain the measure of directional contrast. By visual examination we determined the value of threshold for this average, and if the average is bigger than threshold then the block does not have good directional contrast. The minutiae, which are detected in these invalid flow areas or are located near the invalid flow areas, are removed as false minutiae.

3 Adaptive Preprocessing Method

Fingerprint preprocessing is performed based on the frequency and statistical texture features described above. In the low quality fingerprint images, the contrast is relatively low, especially for light ridges with broken flows, smudge ridges/valleys, and noisy background regions. A high peak in the histogram is usually generated for those areas. Traditional histogram equalization can not perform well in this case. Good quality originals might even be degraded. An alternative to global histogram equalization is local adaptive histogram equalization(AHE) [7]. Local histogram is generated only at a rectangular grid of points and the mappings for each pixel are generated by interpolating mappings of the four nearest grid points. AHE, although acceptable in some cases, tends to amplify the noise in poor contrast areas. This problem can be reduced effectively by limiting the contrast enhancement to homogeneous areas. The implementation of contrast limited adaptive histogram equalization(CLAHE) has been described in [9]. If contrast enhancement is defined as the slope of the function mapping input intensity to output intensity, CLAHE is performed by restricting the slope of the mapping function, which is equivalent to clipping the height of the histogram. We associate the clip levels of contrast enhancement with the image quality levels, which are classified using the proposed global and local image characteristic features. We define the block as good block with *Inhomogeneity*(inH) less than 10 and average contrast(σ) greater than 50 (See Fig 3). A block is defined as wet block if the product of its mean(m) and standard deviation(σ) is less than a threshold. A block is defined as dry block if its mean greater than a threshold, its average contrast is between 20 and 50, the ratio of its mean and average contrast is greater than 5, and the ratio of its uniformity(U) and smoothness(R) is greater than 20.

- If the percentage of the blocks with very low directional contrast is above 30%, the image is classified as level 5. The margin of background can be excluded for consideration because the average gray level of blocks in the background is higher.
- If the limited ring-wedge spectral energy is below threshold S_l, and the percentage of the good blocks, which are classified using *Inhomogeneity* and directional contrast, is below 30%, the image is classified as level 4, if the percentage of dry blocks is above 30% and it is level 3 if the percentage of wet blocks is above 30%;
- The images of level 1 possess high limited ring-wedge spectral energy and more than 75% good blocks, the images of level 2 have medium limited ring-wedge spectral energy and less than 75% good blocks.



(a) (b) (c)

Fig. 3. *Inhomogeneity*(inH)values for different quality fingerprint blocks, (a)good block sample with inH of 0.1769 and standard deviation(σ) of 71.4442, (b) wet block sample with inH of 2.0275 and standard deviation(σ) of 29.0199, and (c) dry block sample with inH of 47.1083 and standard deviation(σ) of 49.8631.

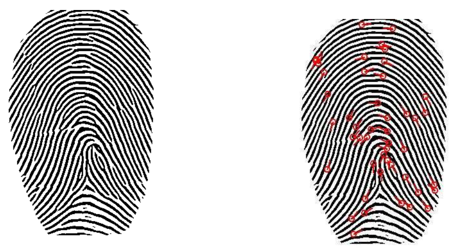
Based on our experiment, the exponential distribution is used as the desired histogram shape (see equation (8)). Assume that f and g are input and output variables, respectively, g_{min} is minimum pixel value, $P_f(f)$ is the cumulative probability distribution, and $H_f(m)$ represents the histogram for the m level.

$$g = g_{min} - \frac{1}{\alpha} \ln(1 - P_f(f)) \tag{8}$$

$$P_f(f) = \sum_{m=0}^{f} H_f(m) \tag{9}$$

4 Experiments

Our methodology has been tested on FVC2002 DB1, which consists of 800 fingerprint images (100 distinct fingers, 8 impressions each). Image size is 374×388 and the resolution is 500dpi. To evaluate the methodology of correlating preprocessing parameter selections to the fingerprint image characteristic features, we modified the Gabor-based fingerprint enhancement algorithm [6] with adaptive enhancement of high-curvature regions. Minutiae are detected using chaincode-based contour tracing. In Figure 4, enhanced image of low quality image shown in Figure 1(b) shows that the proposed method can enhance fingerprint ridges and reduce block and boundary artifacts simultaneously.



(a) (b)

Fig. 4. Enhancement and feature detection for the fingerprint of Figure 1(c)

Figure 5 shows results of utilizing the selective method of image enhancement on the fingerprint verification. We used the fingerprint matcher developed at the Center for Unified Biometrics and Sensors(CUBS)[10]. The automatic method selects clip limit in CLAHE algorithm depending on the image quality level in section 3. The non-automatic method uses same clip limit for all images. The minimum total error rate (TER) of 2.29%(with FAR at 0.79% and FRR at 1.5%) and the equal error rate(EER) of 1.22% are achieved for automatic method, compared with TER of 3.23%(with FAR at 1.05% and FRR at 2.18%) and ERR of 1.82% in the non-automatic enhancement parameter selection system. Note that the improvement is caused by only applying 5 different clip limit parameters to predetermined 5 image quality classes, and achieved results confirm that such image quality classification is indeed useful.

5 Conclusions

We have presented a novel methodology of fingerprint image quality classification for automatic parameter selection in fingerprint image preprocessing. We propose the limited ring-wedge spectral measure to estimate global fingerprint image features, and inhomogeneity with directional contrast to estimate local fingerprint image features.

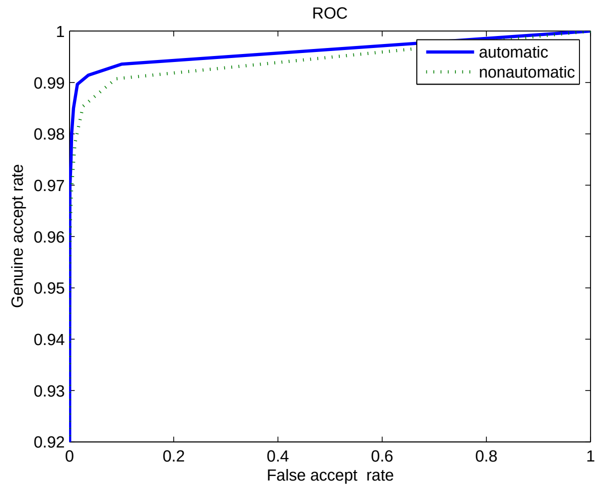


Fig. 5. A comparison of ROC curves for system testings on DB1 of FVC2002.

Experiment results demonstrate that the proposed feature extraction methods are accurate, and the methodology of automatic parameter selection (clip level in CLAHE for contrast enhancement) for fingerprint enhancement is effective.

References

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