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Research Report

Fingerprint Image Quality Estimation

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ABSTRACT

Fingerprints have been used for manual personal identification for centuries. Recent advances in ink less image capture devices for fingerprint image acquisition, coupled with the availability of more processing power on affordable computing systems, have generated significant interest in using fingerprints for several civil applications including authentication. In an automatic fingerprint identification system, it is desirable to estimate the image quality of the fingerprint image before it is processed for feature extraction. This helps in deciding on the type of image enhancements that are needed and in deciding on thresholds for the matcher in the case that dynamic thresholds are used. Several techniques for fingerprint image quality estimation in the spatial domain are described in the literature. In this paper, we propose a method for image quality estimation from a wavelet compressed fingerprint image. The results are compared with an existing model of quality estimation in the spatial domain. Our analysis shows that the results are very accurate estimations of the image quality. It further has the advantage that the image need not be fully decompressed if the quality measure does not exceed the threshold for acceptable image quality.

1. Introduction

For many applications such as bank ATM access, credit card transaction authorization, building access control and secure user authentication on computer systems, authentication or identification of the user is a fundamental task. Many tools and techniques are used to automatically identify a person. Fingerprints in particular have addressed the issue of manual personal identification for centuries. For automatic identification, it is one of the oldest and most reliable methods because of invariance of the fingerprint features over the age of the subject. A generic automatic fingerprint identification system (AFIS) consists of three subsystems: (i) image acquisition, (ii) feature extraction and (iii) matching. Often, a preprocessing stage before the feature extraction stage handles the image enhancements needed for the input image. In image acquisition, a digital image of the fingerprint is captured either from the live person's fingers or from an existing paper record. An old method of acquiring a fingerprint involved applying ink on the finger and then rolling or dabbing the finger on a paper. More recent methods involve using ink less methods. Currently, there are four different technologies available, namely (i) optical, (ii) ultrasound, (iii) electric field and (iv) thermal. After the image is acquired, the feature extraction stage involves representing the fingerprint for the purpose of matching. In matching, a decision is made about the confirmation of the fingerprint's "closeness" to the fingerprints in the database after taking into account affine transformations and elastic deformations. The latter stages, such as feature extraction and matching, are highly compute intensive. Moreover, many parameters in feature extraction and matching can be tuned for better results if a proper estimate of the image quality is available.

An ideal sensed or scanned fingerprint image is characterized by clear and distinct ridges and valleys. Often imaging limitations as well as skin characteristics cause the sensed image to be far from ideal fingerprints as shown in Figure 1. For example, if the ink applied is uneven, or the finger is wet, we get patches of dark areas in the fingerprint. In many cases, the image can be enhanced significantly for the subsequent stages by assuming a reasonable model for fingerprint images.

Several image enhancement techniques have been described in the literature that operate either in spatial domain or in the frequency domain. Kamei and Mizoguchi [5] describe an image enhancement algorithm for fingerprint which manipulates the images in the frequency domain. Sherlock et al. [6] describe an image enhancement technique to improve fingerprint ridges based on Gabor filters. Hong et al. [4] also describe an image enhancement technique based on Gabor filters and additionally describe a method to evaluate enhancement achieved. Most of the

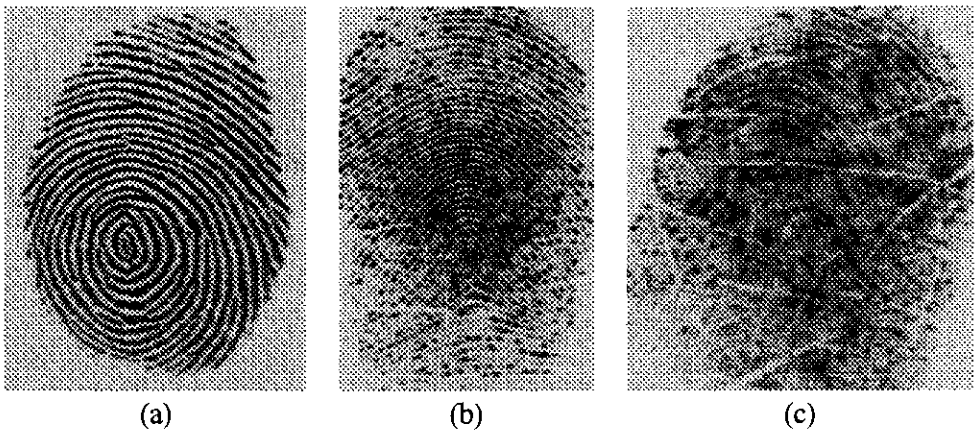


Figure 1. Fingerprint images of varying quality. (a) good; (b) average; (c) poor.

image enhancement algorithms run on the full image and detect poor quality regions in the image before applying the enhancements. To use these spatial domain methods, the compressed image needs to be decompressed. The decompression, a compute intensive process, would only be useful if the image can be handled by the later stages of the system.

Rather than estimating the quality of the fingerprint image in spatial domain, the domain of a transformation may be advantageous. The transform domains usually attempt to concentrate the signal energy in a small number transform coefficients. Often, the image may be acquired remotely as in many e-commerce applications and remote unattended authentication applications without operators for supervision. After compression, the images are transmitted from the remote site. Typically, a compression process consists of a transform stage followed by quantization stage where several low signal-to-noise ratio coefficients are dropped to accomplish compression. If the coefficients in the compressed domain can be used to estimate the image quality, we get two advantages: (i) we deal with a smaller set of transform coefficients and (ii) we do not have the extra step of compression/decompression to estimate the image quality.

Many domain specific compression techniques have been proposed for fingerprint image compression. General purpose compression techniques tend to blur the high frequency-based structural ridge features in fingerprint images. Recently, the FBI has proposed a standard for image compression using wavelets known as Wavelet Scalar Quantization (WSQ). This has been widely accepted in the industry as the *de facto* standard.

In this paper, we propose an elegant method for computing image quality in the WSQ compressed domain. The proposed technique can be used either on already WSQ compressed image databases or on newly acquired images and applying the first two stages of WSQ algorithm. The wavelet transform has an edge over Fourier transform-based approaches as the image representation is obtained using basis functions localized in both space and frequency. That is, for noise estimation (perhaps better, image dirt estimation), a compact signal representation is very useful. Hence, the two advantages of this method are (i) from a partially decompressed image, we can decide the image quality and proceed only if the image can be processed by later stages; (ii) the wavelets provide a compact representation scheme. The signal characteristics are better understood in the wavelet domain than in the spatial domain.

The paper is organized as follows. The details of the WSQ algorithm is briefly reviewed in Section 2. In Section 3, the proposed quality estimation algorithm method is presented. The results based on the proposed algorithm is discussed in Section 4 and conclusions describe in Section 5.

2. WSQ Fingerprint Compression

To understand the quality estimation algorithm proposed in this paper, a short review of the FBI standard WSQ fingerprint compression is presented. More details of the FBI standard WSQ are available in [3, 1]. The WSQ compression algorithm consists of three steps: a discrete wavelet transform (DWT) computation of the normalized input fingerprint image, scalar quantization of the DWT coefficients, and lossless entropy coding of the quantized indices. The standard specifies a source image normalization step before applying the DWT as per the following equation.

$$I'(m,n) = \frac{I(m,n) - M}{R} \qquad (1)$$

where M is the image mean and

$$R = \frac{max(I_{max} - M, M - I_{min}}{128}. \quad (2)$$

I_{max} and I_{min} are the maximum and minimum pixel values in the image $I(m,n)$.

The block diagram of the WSQ encoder and decoder are shown in Figure 2.

In the first step of DWT computation, the input image is decomposed into 64 spatial frequency subbands using perfect reconstruction multirate filter banks. The filters are implemented as a pair of separable 1-D filters. The two filters specified for Encoder 1 of the FBI standard are plotted in Figure 2. The subbands are the filter outputs obtained after a desired level of cascading of the filters described in the standard. For example, the subband 25 is obtained by the filter bank cascading path of '00,10,00,11', where 0 implies low pass filtering on row (column) and 1 implies highpass filtered on the row (column). The first index as it is read from the left represents the row operation index. An interesting aspect of the WSQ algorithm is the way it handles the image at the boundary. Instead of simply periodizing the image at the boundaries in both the dimensions, the standard specifies symmetric extension transforms (SET) which essentially mirrors the image across the boundaries. By extrapolating the signal this way, the discrete wavelet transform results in the same number of coefficients as the image size. The details of the SET are available in [3].

The second stage of WSQ encoding is the quantization process where the discrete wavelet transform (DWT) coefficients are transformed to integers with a small number of discrete values. This is accomplished by uniform scalar quantization for each subband. There are two characteristics for each band: width of the bins (Q_k) and zero of the band (Z_k). Both Z_k and Q_k for each band are transmitted to the decoder.

The final stage in the WSQ encoding process is Huffman coding of the integer indices. For this purpose the bands are grouped into three blocks. In each block, the integer coefficients are remapped to numbers between 0-255 as per a translation table described in the standard. This translation table encodes run lengths of zeros and large values. The negative numbers are also translated similarly.

The decompression process is similar to the compression process steps in the reverse order and has three steps. The compressed bit stream is decomposed using the Huffman tables available in the compressed image to obtain the quantized indices. Using the quantization tables, the quantized indices are converted to dequantized indices. Using the inverse discrete wavelet filters available in the tables in the decompressed image the reconstructed image is computed.

For the quality estimation purpose, we are using the quantized indices available either during the encoder or decoder process.

3. Image quality estimation

Good quality fingerprint images are characterized by clear, well-separated and good contrast ridges. In the wavelet domain, the following observations can be made: (i) the zero-th band is equivalent of the DC component in the signal. Hence, this band contains no valuable information about image quality. (ii) for the quality estimation to be rotation invariant, we have to consider bands symmetrical in row and column filtering operations. (iii) a poor quality fingerprint image is characterized by blurred ridges and unclear separation. We observe that in a good quality fingerprint the normalized cumulative energy in the initial few subbands fingerprint is significantly higher than a poor quality fingerprint. For this purpose we have chosen a good quality area of a fingerprint and added different levels of noise patches in the image. Note that the noise patch can be black or white. The sample images are shown in Figure 4. The normalized cumulative energy over the subbands plotted in Figure 5 demonstrates this point. The rate of growth of cumulative energy is significantly different for good quality fingerprints from the poor quality fingerprints. That is, for poor quality images, the energy distribution in the low order subbands is more or less the same, while for good quality images the energy is concentrated in few selected subbands. With these two observations, our quality estimation algorithm can be stated as follows:

- From the compressed bit stream, construct the Huffman tables and decode the quantized indices.
- Translate the values back to real quantized coefficients. Note that the stored indices are always mapped to numbers between 0-255 with run length and larger numbers represented by special sequences. These two operations are fairly lightweight operations.
- Compute the energy in the subbands 1-18.
- Compute the cumulative total energy (CTE) in the subbands 1-18.

$$CTE_k = \sum_{i=1}^{k} energy_i. \quad (3)$$

- Overall quality of the image is given by:

$$Quality = \frac{CTE_{18} - CTE_4}{CTE_{18}} \quad (4)$$

Note that the we have a normalized index for quality in [0-1].

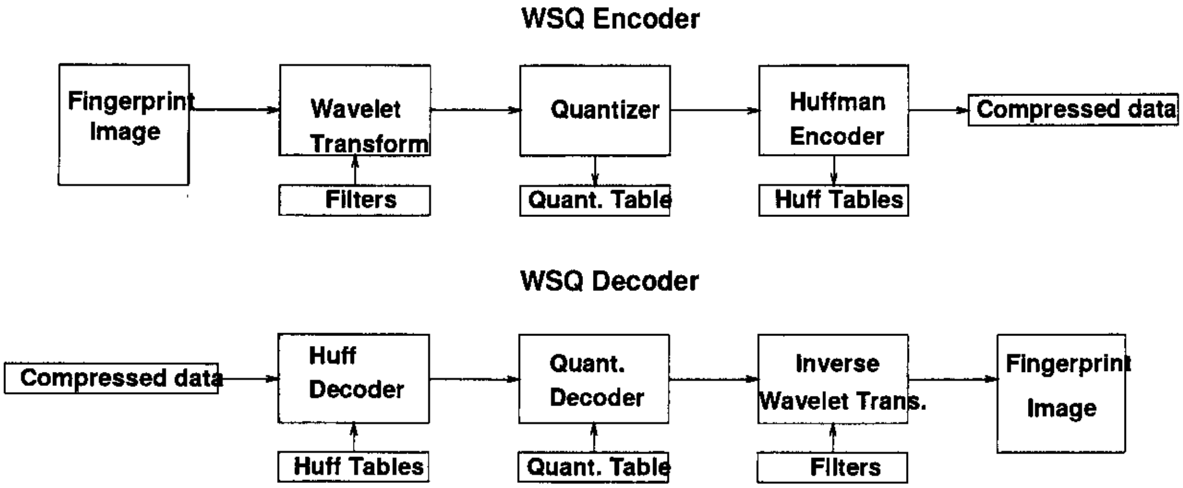


Figure 2. Stages in the WSQ algorithm.

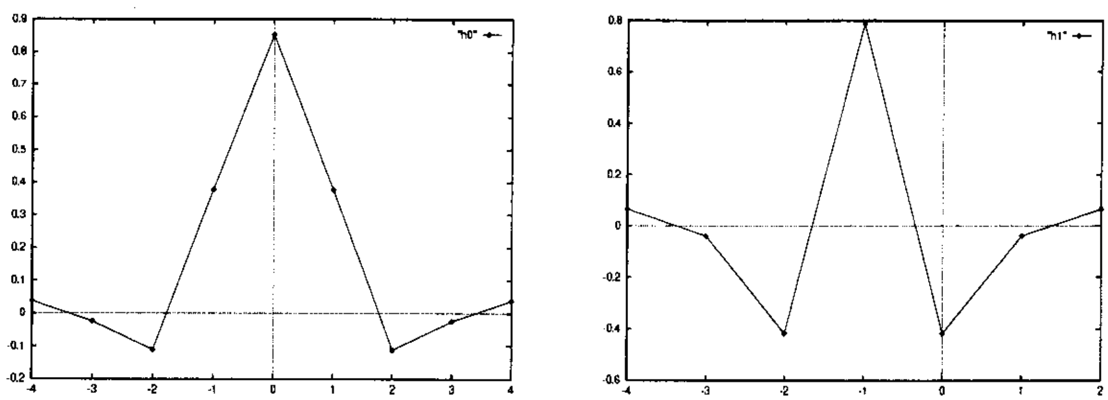
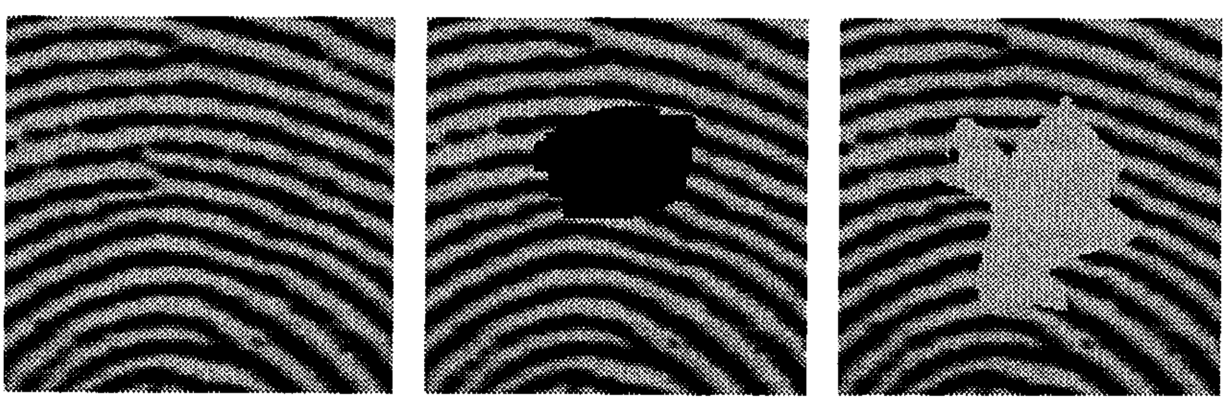


Figure 3. Filters in WSQ encoder.



(a) (b) (c)

Figure 4. Fingerprint images with synthetic noise. (a) good image; (b)-(c) noisy versions.

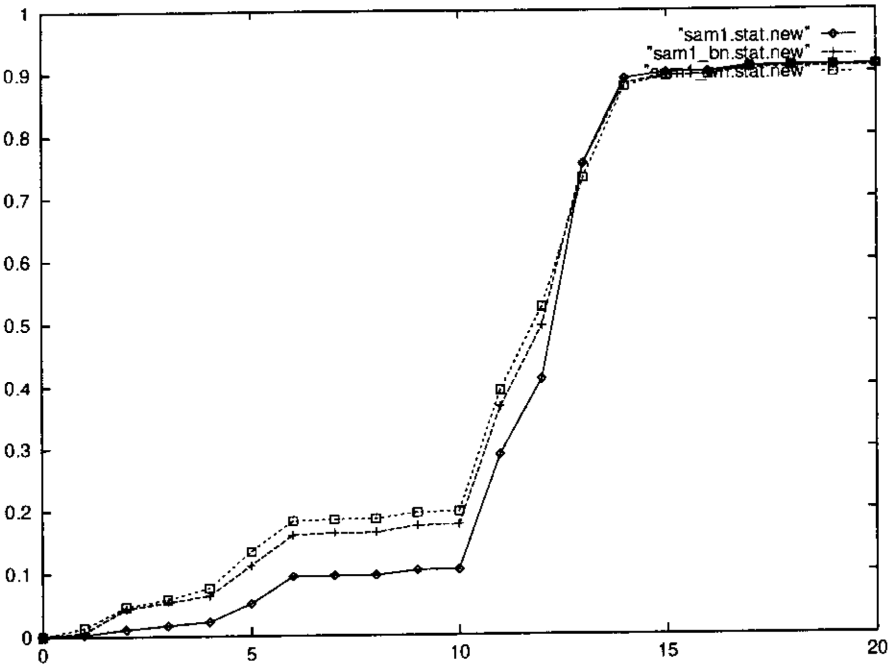


Figure 5. Energy in the subbands of the images shown earlier.

4. Results

Using the above algorithm, the quality indices for images shown in Figure 1 are 0.83, 0.58 and 0.34 respectively. We also ran the proposed algorithm on a database of 100 livescan images using a spatial domain quality measure described in [2] and the proposed measure. The plot shown in Figure 6 demonstrates that the quality indices are similar in nature. Evaluating the quality measures, of course, is a subjective matter.

5. Conclusions

We proposed a robust quality estimation algorithm in the wavelet compressed domain for fingerprint images. While the algorithm has been tested with fingerprint images, the model can be easily extended to other image domains such as medical images, satellite images, and other classes of biometrics images such as faces. Currently, we are examining the possibility of image enhancements in the wavelet compressed domain based on the image quality estimation and we are exploring generic descriptions of image quality in other domains.

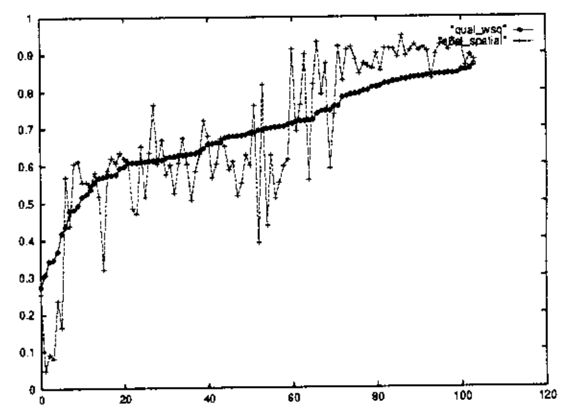


Figure 6. Quality indices of 100 fingerprint images.

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