FINGERPRINT IMAGE QUALITY ANALYSIS

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ABSTRACT

This paper discusses methods in evaluating fingerprint image quality on a local level. Feature vectors covering directional strength, sinusoidal local ridge/valley pattern, ridge/valley uniformity and core occurrences are first extracted from fingerprint image sub-blocks. Each sub-block is then assigned a quality level through pattern classification. Three different classifiers are employed to compare each of its different effectiveness. Positive results have been obtained based on our database.

1. INTRODUCTION

An automatic fingerprint identification system (AFIS) is an integrated system that can handle fingerprint registration as well as identification with minimum human attention. However, the identification performance of such system is very sensitive to the quality of the captured fingerprint image. Since AFIS is expected to work independently, exposed to potentially large number of users, the fingerprint sensor that is attached to the system is possibly subjected to impropriate use. This includes the applying of one's finger that is dry, wet or dirty on the sensor. In addition, some CMOS type of sensors has problems of residue and background noise.

In the general model of biometric system proposed by *Mansfield* et. al. from National Physical Laboratory [1], Quality control is an important component of a biometric system prior to the pattern matching stage. The quality control block is functioning to act as a filter prior to the pattern matching, as well as contributes to the matching acceptance criteria. It is thus the objective of this work to implement a quality analysis module, which can improve the accuracy of an AFIS.

In [2] Bolle et. al. divides a fingerprint image into blocks of pixels. Each block is marked as directional or non-directional by searching for sufficiently large image gradient in some pre-defined directions. The image quality measure is given by the area ratio of the selected contiguous to the total foreground area. Shen et al [3] applied Gabor filter to image sub-blocks, and concluded that a good quality block with clear repetition of ridge and valley pattern can be identified by the outputs of a Gabor filter bank. Kang et al [4] applied direction contrast method in their image quality measure. It is obvious that local directional strength alone is not sufficient to

The methods above make use of the local orientation information of the fingerprint image. However, the local directional strength alone is not sufficient to describe the ridge and valley structure of a fingerprint image. Hong et al [5] classifies a sub-block in an input fingerprint image as recoverable or unrecoverable region based on the amplitude, frequency as well as variance that characterized the sinusoidal-shaped wave formed by local ridge and valley patterns. However, as fingerprint sub-blocks are more than just simple sin wave, a sub-block that contains minutiae or core will cause the modeling to fail and the sub-block will be reported as unrecoverable or bad block.

Ratha and Bolle [6] proposed a method for image quality estimation from a wavelet compressed fingerprint image. This is beneficial if the image to be processed is in WSQ compressed format. However, it is not the case for an automatic fingerprint identification system.

This work is an extension of [7]. New methods are implemented while a more systematical study is made. We can use the following blocks representation to recap on the features used for fingerprint quality analysis.

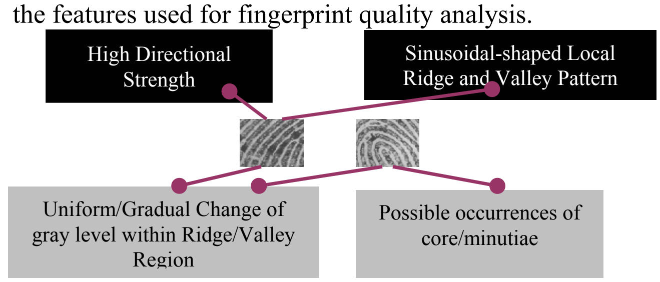

Figure 1: Features used in quality evaluation

As shown in the Figure 1 above, most researchers looked into the high directional strength or the sinusoidal-shaped local ridge and valley pattern of a fingerprint image sub-block. In this paper, we are also looking at the gray level uniformity as well as cases involving core points.

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2. PROPOSED METHOD

2.1. Database

Database of fingerprint images were constructed through fingerprint images collection and synthetic fingerprint image generation to allow for a more complete coverage of database samples.

2.1.1 Fingerprint images collection

We collect 500 fingerprint image sub-blocks for each of the following quality levels:

1. *Very Good* and *Good* groups contain images with acceptable quality, where ridges and valleys are clearly differentiated from one another such that a minutiae extraction algorithm is able to operate reasonably well.
2. *Very Good* images are “perfect” intuitively while *Good* images suffer from either one of the following: noisy ridge, noisy valley, or background with residue.
3. *Bad* images suffer from serious blurring or residue. The minutiae information cannot be identified for this group of image due to the excessive corruption.
4. *Very Bad* images are so heavily corrupted that even basic ridge or valley information can hardly be identified. They can also be captures of unwanted residue or wet patches in sensor daily operation.

For each of the image groups, 500 images were collected, building up a database of 2000.

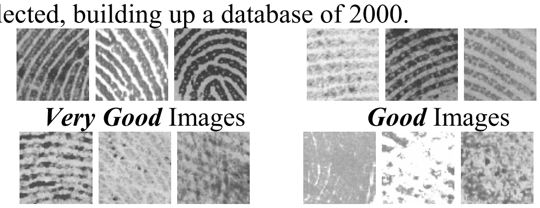


Figure 2: Fingerprint Image Sub-blocks of Different Qualities

Out of the 500 image sub-blocks for each group, we assign 400 as training samples while 100 as query samples.

2.1.2 Synthetic Fingerprint Image Generation

Other than the fingerprint images collected, we also synthesize 48 fingerprint image sub-blocks with different degree of curvature to be included in our training sets. For each of this synthesized image, we add different degree of “pepper and salt” noise to simulate sub-blocks of different qualities. Some samples of the synthetic fingerprint images are shown in Figure 3 below:

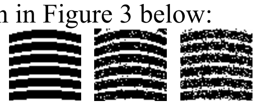


Figure 3: Synthetic fingerprint image sub-blocks of different qualities

2.2. Feature Extraction

2.2.1 Orientation certainty

A fingerprint image sub-block generally consists of dark ridgelines separated by white valley lines along a same orientation. The consistent ridge orientation is therefore the one of the distinguishable local characteristics of the fingerprint image.

As described in [7], the covariance matrix C of the gradient vector for an N points image block is given by

$$C = E\left\{\begin{bmatrix} dx \\ dy \end{bmatrix}\begin{bmatrix} dx & dy \end{bmatrix}\right\} = \begin{bmatrix} a & c \\ c & b \end{bmatrix}.$$

where $E\{\bullet\} \equiv \frac{1}{N}\sum_{N} \bullet$ and

$$ocl = \frac{(a+b) - \sqrt{(a-b)^2 + 4c^2}}{(a+b) + \sqrt{(a-b)^2 + 4c^2}}$$

gives an indication of how strong the energy is concentrated along the ridge-valley orientation. The lower the value the stronger it is. It is obvious that ocl is between 0 and 1 as a,b>0.

The principal component analysis approach described above can effectively indicates the directional strength possessed by an image sub-block. However, it does not guarantee any periodic layout of ridges and valleys.

2.2.2 Image quality measure

For each sub-blocks, we can compute a signature along the ridge-valley (x) direction, centered at the center of each sub-block as shown below. The signature will pass through the centre of the image sub-block in the direction of x as shown.

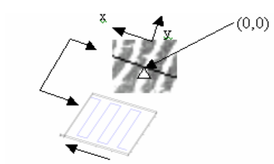


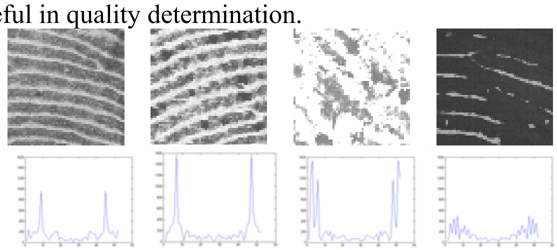
Figure 4: Signature along x direction

In the coordinate system of (x, y) as shown above, the signature is computed as below:

$$T(x) = \frac{1}{2r+1}\sum_{k=-r}^{r} D(x,k)$$

where D(x, y) being the gray level at point (x, y)

The signature of a high quality image is a periodic signal, which can be approximated either by a square wave or a sinusoidal wave. In frequency domain, an ideal square wave should exhibit a dominant frequency with sideband frequency components (sinc function). Sinusoidal wave consists of one dominant frequency and minimum component at other non-dominant frequencies. Thus, we are able to make use of such information in identifying good or bad quality blocks. The existences of one dominant frequency as well as the frequency of such dominant component are two main elements that are useful in quality determination.



(a) High SNR (b) High SNR (c) Low SNR (d) Low SNR

Figure 5: Image sub-blocks with DFT of the signatures along x

Figure 5 above shows four fingerprint image sub-blocks with varying quality. Bad quality image from (c) can be easily identified by the existence of dominant frequency at very low frequency (<5), which is out of the normal ridge frequency range. On the other hand, figure (d) does not possess obvious dominant frequency, which suggests that the image is highly contaminated.

Two outputs were computed from this analysis and included as part of the feature vector's component for training. The first output is the frequency index F_{max} corresponds to maximum amplitude in frequency domain. The second output being image quality measure computed by:

$$IQM = \frac{\{A(F_{\max}) + 0.3[A(F_{\max} - 1) + A(F_{\max} + 1)]]\}}{\sum_{F=1}^{26} A(F)}$$

Where *A (x)* is the amplitude at frequency index x. *F* is the DFT frequency index ranging from 1 to 26 (A 52 point DFT is employed).

The IQM study above computes the one-dimensional signatures by performing averaging along the ridge flow direction. The averaging process filters off noises along the ridges and valleys flow and provides a better modeling of smooth changing signal in a direction perpendicular to ridge flow. However, the effect of pixel level noise along the ridges and valleys would also be neglected due to the averaging process. Random variations in ridges or valleys gray level is another symptoms of low quality image, which is not taken cared by both methods above.

2.2.3 Uniformity

Uniformity is the consistency in ridge and valley's gray level. Four samples of fingerprint sub-blocks with good to bad uniformity are listed below:

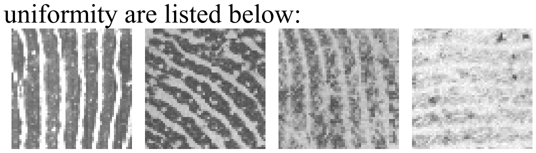


Figure 6: Four Fingerprint Sub-blocks. Uniformity ranged from highest (Leftmost) to Lowest (Rightmost)

Figure 6 shows fingerprint image sub-blocks of different uniformity. The first image sub-block on the left carries a fairly constant gray level for ridges/valleys region while the rightmost has no obvious ridge/valley darkness.

Clustering Factor is defined as the degree to which similar (gray level) pixels clustering in the nearby region. The fundamental background supporting the use of such measure in our analysis of a binary system is that: The more the clustering "black" or "white" pixels, the higher the confidence level of such structure to be useful signal, and hence higher image quality.

To produce a binary image before clustering factor is computed, Otsu method [8] is first applied to obtain optimum threshold values to binarize the image sub-block.

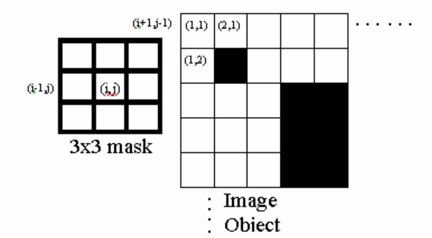


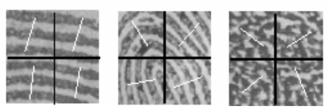
Figure 6: Uniformity computation

Figure 6 shows the Image Object (for our case 60x60 fingerprint image sub-block) as well as a 3x3 mask used for clustering factor computation. The mask is centered at (i,j) and overlaid on the image object. The center of the mask moves from (2,2) to (59,59), computing accumulative results for clustering factor. The clustering factors for both black and white pixels were computed. For the mask centered at a black pixel, the region covered under the masking area is examined for its pixel value. If more than 4 out of 9 carry black pixel, a 1 is returned. If less than 4 pixels carry black pixel, a prorated value is returned (n*0.2, where n is the number of pixels carrying the same pixel value). The returned value is accumulated for the whole mask-shifting process with the mask centered at black pixels. The higher the clustering factors indicates a higher the confidence level of the structure. A lower value indicates a randomly organized structured and hence lower quality.

2.2.4 Curvature

The curvature information within each fingerprint image sub-blocks is included as part of the feature vector to be used for training. Although curvature has no direct relationship with fingerprint image quality at the first sight, it will greatly affect the quality determination process through orientation certainty and image quality measure above. For an acutely curved ridge-valley structure (around core point, for example), orientation certainty determination will give a low confidence value. It is also unlikely for the signature of such structure to exhibit a periodic sinusoidal or square wave pattern. On the other hand, the curvature within a fingerprint image sub-block should follow a particular trend. Thus, it is useful to include the curvature information in the training process, not just to identify core point region, but also to identify invalid curvature.

The curvature information of an image sub-block is captured by orientations of four quadrants, together with each of their certainty level. Figure 7 below shows orientations information for four quadrants of a fingerprint image sub-block. While orientation is useful to distinguish between (a) and (b), (c). Orientation certainty level certainly helps to separate (b) from (c).



(a) Normal (b) Core Region (c) Bad Quality

Figure 7: Image sub-blocks with orientation information

4. EVALUATION RESULTS

To combine the features above and classify them into each of the four quality levels accordingly, we employ three different classifiers to study each of its effectiveness.

100 test samples from each of the four quality levels were fed into the trained network for performance evaluation while others used for training. The results were tabulated as below. The results for two quality groups and four quality groups were presented.

		Classified by SOM as			
		Very Good	Good	Bad	Very Bad
Subjective Quality	Very Good	**69**	22	7	2
	Good	35	**43**	19	3
	Bad	6	11	**52**	31
	Very Bad	1	2	14	**83**

		Classified by SOM as	
		Good	Bad
Subjective Quality	Good	**169**(84.5%)	31(15.5%)
	Bad	20(10%)	**180**(90%)

		Classified by RBFNN as			
		Very Good	Good	Bad	Very Bad
Subjective Quality	Very Good	**69**	30	1	0
	Good	19	**70**	11	0
	Bad	0	10	**72**	18
	Very Bad	0	0	46	**54**

		Classified by RBNN as	
		Good	Bad
Subjective Quality	Good	**188**(94%)	12(6%)
	Bad	10(5%)	**190**(95%)

		Classified by Naïve Bayes as			
		Very Good	Good	Bad	Very Bad
Subjective Quality	Very Good	**88**	9	0	3
	Good	19	**72**	9	0
	Bad	1	15	**61**	23
	Very Bad	0	1	20	**79**

		Classified by Naïve Bayes as	
		Good	Bad
Subjective Quality	Good	**188**(94%)	12(6%)
	Bad	17(8.5%)	**183**(91.5%)

Due to the complex nature of quality analysis, it appears for the first sight that none of the three classifiers provides a high accuracy classification, with a targeted accuracy higher than 90% for all quality levels. However, an insight view of the results reveals that the classification of the feature vectors that we defined are able to function reasonably well in classifying a generalized Good (which includes previous entries from Good and Very Good quality levels) and generalized Bad (which includes previous entries from Bad and Very Bad quality levels). All three classification algorithms presented are capable of performing classification at accuracy higher than 84% for both good and bad quality levels. We will look into decision fusion to further improve the results above.

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