FINGERPRINT IMAGE QUALITY ANALYSIS

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ABSTRACT

Fingerprint image quality analysis is crucial in eliminating poor fingerprint images, which will affect the performance of the automatic fingerprint identification system. In this article, two types of new quality measures will be introduced: Ridge and valley clarity and global orientation flow to calculate the overall image quality score that can be used to quantitatively determine the quality of the fingerprint image. In order to evaluate the performance of the proposed algorithm, the quality measure is used to rank the performance of a fingerprint recognition system, and the ranking is compared with the quality measure rated manually. The result shows that the proposed scheme will return a score that ensures its reliability to indicate the quality of a given fingerprint image.

1. INTRODUCTION

Fingerprint Authentication is presently the most commonly used biometric authentication. Automatic Fingerprint Identification System (AFIS) is becoming more popular in security access and E-commerce applications. Two types of fingerprint sensor can be found: solid state sensor and optical sensor. Both types of sensor cannot avoid capturing poor quality fingerprint image due to physical problems such as dirty finger, dirty sensor surface, scar, patchy skin and other factors. Poor quality fingerprint image causes the fingerprint authentication system to have higher operation problems such as false acceptance and false rejection; resulting in the user facing difficulties when using such system for identification. Hence, in this paper, we propose a new method to justify the quality of the captured fingerprint image for the authentication system. The proposed scheme can be used to detect poor quality fingerprint image for the AFIS administrator to justify the cause of operation problems.

Previous related literatures can be found in various publications. Lim et al [1] proposed a method by using the ratio of the eigen values of the gradient vectors to estimate the local ridge orientation certainty, and using the orientation flow to determine the orientation quality. The ratio of eigen values can indicate the degree of confidence of orientation estimation, provided that the noise is not directional. However, some sensors, such as strip sensor which captures the fingerprint image by sliding the finger on the sensor, produces image with some vertical lines due to sliding. Such anisotropic noise prevents the orientation confidence level from accurately reflecting the quality of the fingerprint image. Hong et al [2] used sine wave to model the ridge and valley pattern of the fingerprint. However, it is difficult to use this method to differentiate between the valid and invalid fingerprint images as the ridge and valley pattern is not a sine wave for many real fingerprint images. Bolle et al [3] computed quality measure by using the ratio of directional area to other non-directional area. Shen et al [4] used gabor filter to every image sub-blocks with assumption that a good fingerprint with clear repetition of ridge and valley pattern can be recognized by the outputs of a gabor filter bank. Both of these methods exploited the local orientation information. However, the local directional strength is not sufficient to measure the quality of the image, if much more other information such as scar can be found in local ridge and valley structure and global smooth ridge flow in a fingerprint image. Almansa et al [5] proposed using ridgeness measure, which eliminates good area (clear ridge) from scar, fragmented ridges, blurred and over-inked area, hence giving a qualitative measure of fingerprint quality. However, this method is not effective if the area contains small quantity of noise and highly curved area. Therefore, the ridgeness measure will return a value that does not able to reflect the actual quality.

In this paper, we will introduce a method to analyze ridge and valley clarity by using overlapping regions of the distributions. Orientation quality score will be used to describe the quality of orientation flow. An overall image quality is then computed by the above indicators to describe the estimated quality of fingerprint image. The benchmarking of the proposed scheme is done by comparing the machine computed score and the human expected score from a database with 115 fingerprint images. A quantitative measure of calculating the trend error of a monotonic increasing function will be introduced to justify the reliability of the given quality engine.

2. RIDGE AND VALLEY CLARITY ANALYSIS

Ridge and valley clarity analysis indicates the ability to distinguish the ridge and valley along the ridge direction. A method of analyzing the distribution of segmented ridge and valley is introduced to describe the clarity of the given fingerprint pattern.

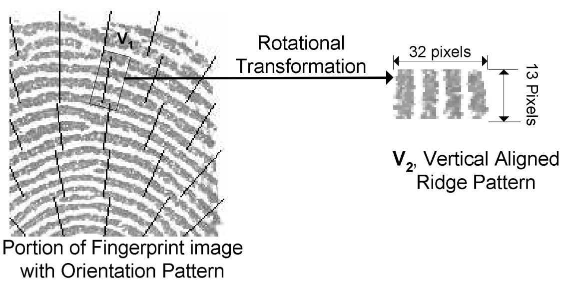

Figure 1. Extraction of a local region and transformation to vertical aligned ridge pattern

To perform local clarity analysis, the fingerprint image is quantized into blocks of size 32×32 pixels. Inside each block, an orientation line, which is perpendicular to the ridge direction, is computed. At the center of the block along the ridge direction, a 2-D vector V_1 (slanted square in Figure 1) with size 32×13 pixels can be extracted and transformed to a vertical aligned 2-D Vector V_2. By using equation (1), a 1-D Vector V_3, that is the average profile of V_2, can be calculated.

$$V_3(i) = \frac{\sum_{j=1}^{m} V_2(i,j)}{m}, \; i = 1..32 \tag{1}$$

Where m is the block height (13 pixels) and i is the horizontal index.

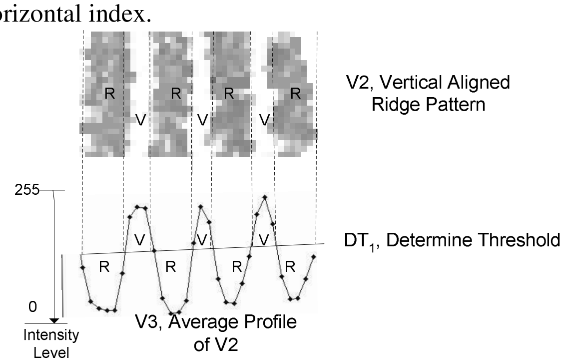

Figure 2. Region Segmentation of Vector V2

Once V_3 has been calculated by equation (1), linear regression can be applied to V_3 to find the Determine Threshold (*DT1*). Figure 2 shows the method of regional segmentation. *DT1* is the line positioned at the center of the Vector V_3, and is used to classify the ridge region and valley region. Regions lower than *DT1* are the ridges, otherwise are the valleys. Hence, the regions of ridge and valley can be separated in the 2-D vector V_2 by the 1-D average profile V_3 with the *DT1* as shown as the dotted straight line in Figure 2. As the ridge and valley have been separated, a clarity test can be performed in each segmented rectangular 2-D region. Figure 3 shows the grey level distribution of the segmented ridge and valley. The overlapping area is the region of misclassification, which is the area of failing to determine ridge or valley accurately by using *DT1*. Hence, the area of the overlapping region can be an indicator of the clarity of ridge and valley.

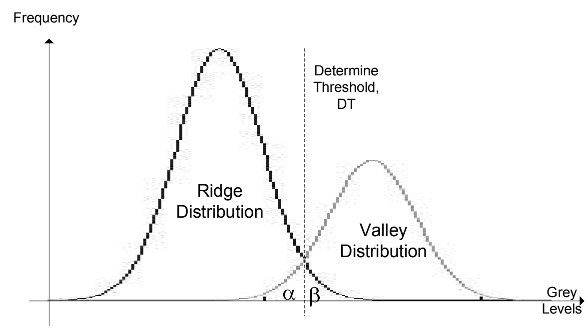

Figure 3. Distribution of Ridge and Valley

The following equations describe the calculation of the clarity score.

$$\alpha = \upsilon_B / \upsilon_T \tag{2}$$

$$\beta = \Re_B / \Re_T \tag{3}$$

$$LCS = (\alpha + \beta)/2 \tag{4}$$

Where υ_B is the number of bad pixels in the valley that the intensity is lower than the *DT1*, υ_T is the total number of pixels in the valley region, $\Re_B$ is the number of bad pixels in the ridge that the intensity is higher than the *DT1*, $\Re_T$ is the total number of pixels in the ridge region. α and β are the portion of bad pixels. Hence, the Local Clarity Score (*LCS*) is the average value of α and β.

For ridges with good clarity, both distributions should have a very small overlapping area. The following factors affect the size of Total Overlapping Area:

(1) Noise on ridge and valley
(2) Scar across the ridge pattern
(3) Water patches on the image due to wet finger
(4) Incorrect orientation angle due to the affect of directional noise
(5) Highly curved ridge
(6) Minutia, bifurcation, delta point or core.

Factors 1 to 4 are physical noise found in the image. Factors 5 and 6 are actual physical characteristics of the fingerprint. Therefore, a small window with size 32×13 is chosen to minimize the chance of encountering too many distinct features in the same location.

From our experiment of clarity score from FVC2000 [6] database, we can conclude the following classifications of the quality of the ridge pattern.

Table 1: Meaning of Clarity Score

Clarity Score, CS	Quality
$LCS < 0.15$	Good quality ridge pattern
$0.15 \le LCS < 0.35$	Intermediate quality with noise.
$0.35 \le LCS < 0.55$	Marginal quality with noise.
$LCS \ge 0.55$	Bad quality ridge pattern.

Table 1 shows the meaning of the Local Clarity Score. For the score less than 0.35, the local ridge pattern is quite clear with little noise. For *LCS* is larger than or equal to 0.35, the region is quite noisy but with visible ridge pattern. For *LCS* is larger than or equal to 0.55, the quality is bad, such that the ridges and valleys are not clear at all.

The Global Clarity Score (*GCS*) can be computed by the expected value of the Local Clarity Scores (*LCS*).

$$GCS = E(LCS(i,j)), \text{ where } E(\cdot) = \frac{\sum_{i=1}^{H}\sum_{j=1}^{V}(\cdot)}{H \cdot V} \tag{5}$$

In Equation (5), $LCS(i,j)$ is the Clarity Score that is calculated from equations (1), (2), (3) and (4) at location (i,j), where i and j are horizontal and vertical index of the image block respectively. H and V are the maximum number of horizontal and vertical block respectively. The *GCS* can be used to describe the general ridge clarity of a given fingerprint image.

3. ORIENTATION FLOW ANALYSIS

Orientation flow is another indicator to describe the quality for good fingerprint pattern because, generally speaking, the flow of the ridge direction changes gradually, except when a delta or core point is encountered. In this section, another quality indicator using the property of the orientation flow of ridges is introduced.

Figure 1 illustrates the orientation flow on the fingerprint image. A 2D array V_4 is defined to hold all orientation angles from the fingerprint. To analyze the targeted block $V_4(i,j)$, the absolute difference of orientation angle with its surrounding blocks is used. Hence, the Local Orientation Quality (*LOQ*) can be computed by Equation (6).

$$LOQ(i,j) = \frac{\sum_{m=-1}^{1}\sum_{n=-1}^{1}\left|V_4(i,j) - V_4(i-m, j-n)\right|}{8} \tag{6}$$

LOQ is the average absolute difference in orientation angles. 8° of tolerance angle are given. The average difference should not be zero because the orientation flow is constantly changing gradually. Therefore, the Local Orientation Quality Score (*LOQS*) is defined as following equation.

$$LOQS(i,j) = \begin{cases} 0, & LOQ(i,j) \le 8° \\ \dfrac{LOQ(i,j) - 8°}{90° - 8°}, & LOQ(i,j) > 8° \end{cases} \tag{7}$$

The Global Orientation Quality Score (*GOQS*) is calculated by averaging of all *LOQS* values. Therefore, *GOQS* can be computed by the following equation.

$$GOQS = E(LOQS(i,j)) \tag{8}$$

Hence, the *GOQS* can be used to provide information about the degree of smoothness of the change in orientation angles from block to block.

4. OVERALL IMAGE QUALITY

We have introduced *GCS* and *GOQS*. These scores can be used to calculate the Overall Image Quality (*OIQ*) by equation (9).

$$OIQ = \varpi_1 \cdot (1 - GCS) + \varpi_2 \cdot (1 - GOQS) \tag{9}$$

$$\varpi_1 + \varpi_2 = 1 \tag{10}$$

Where ϖ_1 and ϖ_2 are weights for *GCS* and *GOQS* respectively and the sum of all weights should be equal to 1. Those weights can be adjusted to meet specific criteria for different applications. Hence, the *OIQ* can be used to describe the quality of the given fingerprint image.

5. PERFORMANCE FOR BENCHMARKING

Two parameters are used to benchmark the quality engine: Machine Computed Score (MCS) and Human Expected Score (HES). The MCS is computed by the quality engine and the HES is estimated by human perception. It is difficult to perform direct comparison between MCS and HES, as bias may exist in the scoring of the HES. Hence, we proposed a method to test the trend of both sets of scores for the benchmarking by using a monotonic increasing trend. A fingerprint database of 115 fingerprint images was used in the benchmarking. The HES is based on visual inspection with the following criteria:

(1) Total number of false minutiae detected by the feature detection engine.
(2) Total number of undetected minutiae that is not able to be detected by features detection engine.
(3) Area of the fingerprint image.

The above criteria are inspected by human to generate a set of HES. By using the same database, the MCS is generated by using our proposed scheme. As a result, two sets of scores are generated for performance benchmarking. The principle of benchmarking is to compare the trend between MCS and HES; bad images which have poor HES should, correspondingly, have poor MCS. The same analogy should apply to good images as well. If this monotonic increasing trend can be found, the MCS is said to be consistent with our expectation. Otherwise, the MCS cannot reflect the human expectation of the image quality. Equation (11) and (12) describes the method of testing monotonic increasing trend.

$$e_{ij} = \begin{cases} 1 & \text{if } (q_{si} > q_{sj} \ \& \ q_{hi} \le q_{hj}) \ or \\ & (q_{si} \le q_{sj} \ \& \ q_{hi} > q_{hj}), \\ 0 & \text{Othewise} \end{cases} \tag{11}$$

$$E = \frac{1}{N_s} \sum_{i=1}^{Ns} \sum_{j=1}^{Ns} e(i, j) \tag{12}$$

For all fingerprint i and j with noticeable difference of *HES*, i.e, $|q_{hi} - q_{hj}| > T$. q_s and q_h are the MCS and the HES respectively, and N_S is the number of images with $|q_{hi} - q_{hj}| > T$. In this experiment, q_s is *OIQ* that is computed by the proposed algorithm from equation (9). Equation (11) is the rule to compute the expectation of monotonic increasing trend. For particular image i in the database, the score q_{si} is compared with another image score q_{sj}, and then the corresponding score q_{hi} is also compared with another corresponding q_{hj}. If both differences are not the same direction ($q_{si}>q_{sj}$ but $q_{hi}\le q_{hj}$ or $q_{si}<q_{sj}$ but $q_{hi}\ge q_{hj}$, which contradicts our expectation), one score will be given to $e(i,j)$. Otherwise, zero score will be awarded to $e(i,j)$. Hence, for a perfect monotonic increasing relationship, the trend error E, which is computed by equation (12), will be equal to 0. Otherwise, trend error E will be greater than 0. Furthermore, to account for existence of human assessment biasness, a threshold T is set so that images need not be compared if *HES* differs by only a small amount.

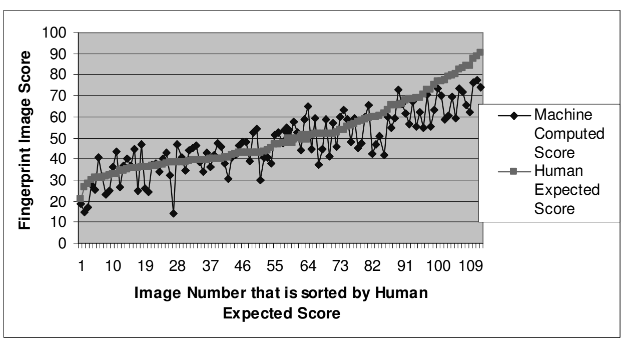

Figure 4. Score Trend of Overall Quality Score versus Sorted Quality Images by Human Expected Score

In Figure 4, the MCS versus sorted quality images is plotted. X-axis is image index that is sorted by HES. Y-axis is the MCS. In this graph, a monotonic increasing trend can be observed. By using equation (11) and (12), the trend error E of 0.1589 is found. That means the monotonic increasing error 15.89% is found in the trend. The HES also be plotted on the same graph. It is clear that the MCS has a trend similar to the HES. Hence, we can conclude that the proposed scheme is a reliable indicator of the quality of fingerprint image that is suitable for authentication used.

6. CONCLUSION

In this paper, a method of computing fingerprint image quality has been presented. Ridge and valley clarity analysis and orientation flow analysis were used as indicators to determine the quality of fingerprint image. Ridge and valley clarity analysis, which examines the overlapping region of the distribution of ridge and valley, indicates the ridge clarity. Orientation flow tests the smoothness of the orientation map of fingerprint. The overall image quality is computed by the above indicators. For performance benchmarking, the monotonic increasing trend analysis is used. 15.89% of trend error is found, compared with the human expected score. Hence, the proposed scheme is found reliable to justify the image quality for AFIS.

7. REFERENCES

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