QUALITY ASSESSMENT OF KNUCKLEPRINT BIOMETRIC IMAGES

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ABSTRACT

Image quality can play key role in the system performance. The recently introduced knuckleprint biometric has shown promising results, but its quality assessment is difficult because it lacks well defined and structured features as in the case of face or fingerprint. To our knowledge this is the first attempt to automatically assess the quality of knuckleprint images. The quality of knuckleprint images mainly depends upon the vertical line like features, focus, contrast and reflections produced by the camera flash. In this paper an effort has been made to identify, estimate and quantify some of these quality attributes and fuse them to obtain an overall quality score for any knuckleprint image. The largest publicly available PolyU knuckleprint database is used for testing, containing 7920 images. Extensive study is being carried out in order to establish a relationship between image quality and matching performance in order to demonstrate the proposed framework's utility.

***Index Terms*—** Knuckleprint, Quality, Focus, Reflection, Entropy, Biometrics, Score level Fusion.

1. INTRODUCTION

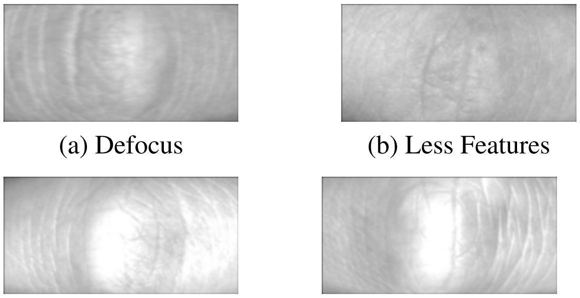
Biometric based authentication is extensively applied in law enforcement, computer security *etc.* Behavioral as well as physiological biometrics based characteristics (such as face [1, 2, 3], fingerprint [4], iris [5, 6], palmprint [7, 8], knuckleprint [9, 10], gait, voice,vein patterns *etc.*) are used to develop robust, accurate and highly efficient personal authentication systems. Recently introduced biometric trait knuckleprint has attracted the research community because of its inexpensive acquisition, good performance and user friendliness. However the images acquired from the sensors have inevitably wide distribution of quality. Hence quality assessment should be done during early phases such as data acquisition so that one can discard the bad quality images and recapture the better one. Also quality parameters can revel the type of deficiency which can be used to apply the suitable enhancement technique to reduce its effect. The biometric data quality facilitates the benchmarking and fine tuning of various parameters to improve the system performance. Multi-instance and multi-trait systems can choose best samples or assign lower weights to the poor quality samples.

Not much amount of work is reported in knuckleprint recognition. In [11, 12] local features such as robust line orientation code (RLOC) and modified finite radon transform (MFRAT) are used to extract local orientation and stored it in *knucklecode*. In [13, 14, 15, 16] knuckleprint ROI's are extracted using convex coding scheme and local as well as global features are extracted using set of gabor filters and band limited phase only correlation (BLPOC) respectively. Later they fused both local and global features for performance boost-up.

The knuckleprint image quality is degraded mostly because of fewer or blurred line like features, defocus, poor contrast and high or low illumination and reflections produced by the camera flash as shown in Fig.1. In this paper we have proposed a comprehensive scheme for knuckleprint quality assessment which is the first attempt as per our knowledge. Six quality parameters are proposed along with the methods to quantify and fuse them in order to obtain a single quality score for each image. Fusion of the parameters is done using likelihood ratio based fusion method [17]. The proposed system is tested on PolyU [18] knuckleprint database. Finally the assessed quality is critically tested using a knuckleprint recognition algorithm [9] to establish a correlation between the quality scores and the recognition performance. The rest of the paper is organized as follows: Section 2 presents the proposed quality parameters and the methods to compute them. Section 3 discusses the detailed experimental setup and the results. Conclusion are presented in the last section.

2. PROPOSED QUALITY PARAMETERS

The comprehensive knuckleprint quality assessment is a complex problem because several factors should have to addressed simultaneously. Also there does not exist a well structured and formalized quality assessment benchmark as it does in the case of fingerprint [19], which is primarily because fingerprint have well formulated and structured minutia features and organized ridges. The knuckleprint image quality is obtained by computing the amount of well focus edges $\boldsymbol{F}$, amount of clutter $\boldsymbol{C}$, distribution of focused edges $\boldsymbol{S}$, block-wise entropy of



(a) Defocus (b) Less Features

(c) High Reflection (d) Poor Uniformity

Fig. 1. Poor Quality Knuckleprint ROI Samples

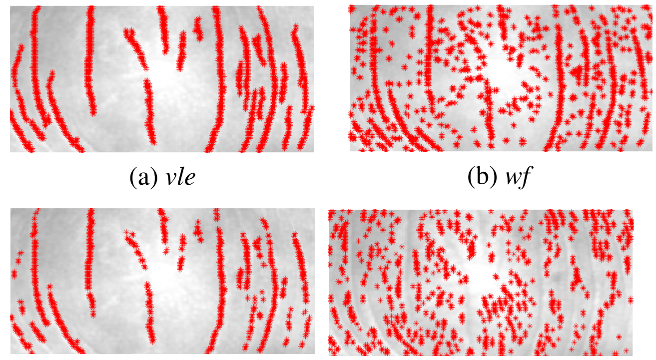
focused edges ***E***, reflection caused by light source and camera flash ***Re*** and the amount of contrast ***Con*** which are discussed below.

The most important and vital features in knuckleprint images are vertical long edges (***vle***) as shown in Fig. 2(a), hence most of the quality parameters listed above tend to analyses *vle* for quality assessment first. Pixel set that corresponds to only vertical strong edge pixels is computed using sobel kernel over the input image (I) and then the connected components are computed. Finally out of all the connected components only long enough (more than an empirically selected threshold t_{cc}) components are retained that constitute the pixel set ***vle***.

[1] Focus (*F*): The defocus blurring effect occurs when the focal point of the sensor's lens is not at the reference object during image acquisition as shown in Fig. 1(a). The frequency analysis of defocus images have reveled that their 2D Fourier spectrum is usually dense towards lower frequencies while well focused image posses almost uniform spectrum. The amount of well focused knuckleprint area is considered for quality assessment. It is computed by convolving the sample image by the proposed 6×6 kernel K as defined in Eq (1) that can well approximate the 2D Fourier spectrum high frequency band pass filter. Then only those pixels are retained that are well focused (*i.e* having convolved value more than an empirically selected threshold t_f) constituting the pixel set *wf* as shown in Fig. 2(b).

$$K = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & -8 & -8 & 1 & 1 \\ 1 & 1 & -8 & -8 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \quad (1)$$

The size and the coefficients of the filter is customized for knuckleprint images using some domain knowledge and statistical hints. A focus map F_{map} is obtained by $anding$ pixel set *vle* and *wf* as shown in Fig. 2(c) which is later used as most significant region. Finally focus quality parameter F is defined as the number of well focused vertically aligned long edge pixels and its value is computed by counting number of pixels in F_{map}.



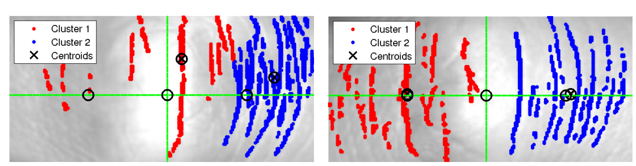
(a) *vle* (b) *wf*

(c) F_{map} (anding *vle,wf*) (d) Clutter (Short Edges)

Fig. 2. Defocus based Quality Attribute F and C

[2] Clutter (*C*):The short vertical edge pixels that are well focused can be considered as clutter as shown in Fig. 2(d), that can degrade the quality of the image. They are usually present due to abrupt discontinuity in the edge structure because of several possible extrinsic factors. Clutter create false features that can confuse any recognition algorithm. The quality parameter clutter (C) is defined as the ratio of long vertically aligned strong edge pixels and the shorter ones. It is inversely proportional to the image quality.

[3] Uniformity based Quality Attribute (*S*): In any good quality image the texture should have to be distributed uniformly through out the whole image. There are several images having well focused left or right half only as shown in Fig. 1(d). The focus parameter F may produce high scores even though half of the image is of very poor quality. Hence uniformity in texture distribution should have to be given some importance. The quality attribute (S) is proposed which is directly proportional to the uniformity in texture distribution as shown in Fig. 3. The pixel set F_{map} as defined in focus parameter is clustered using K-Means algorithm using $K = 2$, because knuckleprint images have some symmetry *w.r.t* Y axis. Then some statistical and geometrical parameters of the two clusters are used to obtain the value of S as described in Algorithm 1.



(a) Non Uniform Texture(0.221)(b) Uniform Texture(0.622)

Fig. 3. Uniformity based Quality Attribute (S)

[4] Entropy based Quality Attribute (*E*): The most common statistical measure that is used to quantify the

Algorithm 1 Uniformity based Quality Attribute (S)

Require: The vle and wf pixel set for the input image (I) of size $m \times n$.

Ensure: Return the value S for the input image (I).

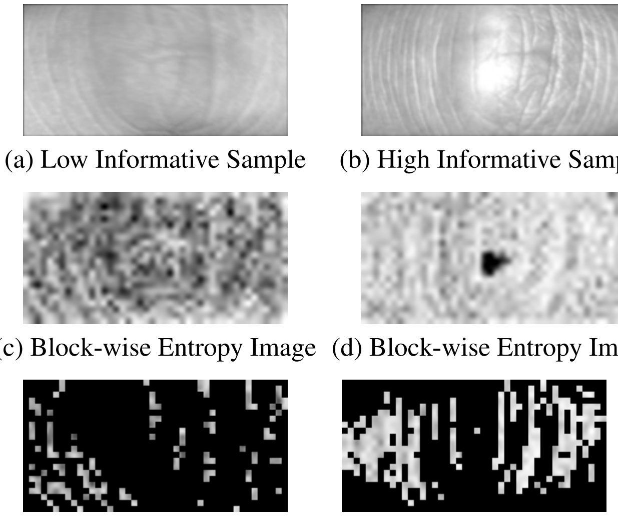
1. $F_{map} = and(wf, vle)$; $[focus\ mask]$
2. M_1, M_2=Mid-point of Left half $(\frac{n}{2}, \frac{n}{2})$ and Right half $(\frac{m+n}{2}, \frac{n}{2})$ of the input image (I);
3. Apply 2-Mean Clustering over pixel set F_{map};
4. $C_1, C_2, nc_1, nc_2, std_1, std_2$=Mean loc., Number of pixels and Standard dev. of Left and Right cluster respectively;
5. d_1, d_2= Euclidean Distance between point C_1 and M_1 and that of between C_2 and M_2 respectively;
6. $d = 0.7 * max(d_1, d_2) + 0.3 * min(d_1, d_2)$;
7. $p_r = \frac{max(nc_1, nc_2)}{min(nc_1, nc_2)}$;[Cluster Point Ratio]
8. $std_r = \frac{max(std_1, std_2)}{min(std_1, std_2)}$;[Cluster Standard Dev. Ratio]
9. $comb_r = 0.8 * p_r + 0.2 * std_r$;
10. $D_{std} = 1 - \frac{d}{\sqrt{std_1^2 + std_2^2}}$;
11. $D_{nc} = 1 - \frac{d}{\sqrt{nc_1^2 + nc_2^2}}$;
12. $S = 0.5 * d + 0.2 * comb_r + 0.15 * D_{std} + 0.15 * D_{nc}$

amount of information in any gray scale image (I) is the entropy value defined as:

$$e = -\sum_{i=0}^{255} hist[i] * \log(2 * hist[i]) \qquad (2)$$

where $hist[i]$ is the i^{th} element of 256 valued gray level histogram $hist$ of the input image I. The input image is divided into blocks of size 5×5 and block-wise entropy is calculated using the Eq (2) (as shown in Fig. 4(c,d)). All the blocks does not carrying the same amount of importance therefore only blocks that are having well focused long vertically aligned edge pixels (using F_{map} as defined in focus parameter) more than a predefined empirically selected threshold t_{fm} are considered as significant blocks. Finally the entropy based quality attribute (E) is obtained by summing up the entropy values of all the significant blocks as shown in Fig. 4(e,f).

[5] Reflection based Quality Attribute (*Re*): High reflection can be caused by light source or camera flash and will create a patch of very high intensity gray values. The unique line based information with-in this patch is completely ruined leading to severe quality degradation. This reflection patch is identified by using adaptive thresholding and later can be ignored while matching. The sample knuckleprint image is repeatedly thresholded in order to estimate the most accurate reflection patch intensity level starting from a high gray level and gradually reducing it. After each thresholding step number of pixels are calculated. This count keeps on changing significantly as some of the nearby area around the reflection patch may not be captured by the previous threshold. This thresholding procedure got terminated when this count got saturated (*i.e* when the difference in the count before and after thresholding is less than an empirically selected value t_r). After termination the full reflection patch is identified as shown in Fig. 5(b). The reflection based quality attribute (*Re*) is defined as the fraction of pixels belonging to the reflection patch hence it is inversely proportional to the image quality.

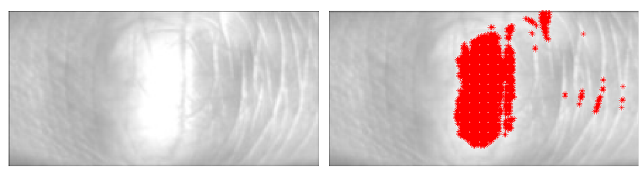


(a) Low Informative Sample (b) High Informative Sample

(c) Block-wise Entropy Image (d) Block-wise Entropy Image

(e) Significant Blocks Entropy (f) Significant Blocks Entropy

Fig. 4. Entropy based Quality Attribute *E*



(a) Original Image (b) Computed Reflection patch

Fig. 5. Reflection based Quality Attribute *Re*

[6] Contrast based Quality Attribute (*Con*): Often the knuckleprint image quality got severely affected by very poor or heavy lighting condition. Large illumination variation can reduce the discriminative line based features and hence degrading the overall uniqueness of biometric images. The contrast of the input image (I) can give some information about the dynamic gray level range present in the image. Hence, it can be used to infer that image is either too dark or light. Basically, we can use it to estimate the uniformity in illumination through-out the image. Maximum and minimum gray levels are ignored for its estimation. The whole gray level range is divided into three groups $(0, 75), (76, 235), (236, 255)$. The contrast based quality attribute (*Con*) is defined as the fraction of pixels belonging to the mid gray level range (*i.e* $(76, 235)$) because it indicate the moderated intensity range.

3. EXPERIMENTAL RESULTS

The testing of the proposed system is done over publicly available largest FKP database from the Hong Kong Polytechnic University (PolyU) [18]. It containing 7920 images collected from 660 distinct knuckles taken in 2 sessions with 6 images per session.

Fusing Quality Attributes: The proposed parameters are computed and normalized using $maxmin$ normalization. All the six proposed quality parameters should have to fused in order to predict the overall quality of the input image. All parameters computes a variety of local attributes and each of them can directly affect the overall fused quality. The likelihood ratio based fusion is [17] done to fuse the obtained individual quality attributes for any input image I as defined below.

$$Quality_{fused}(I) = \prod_{\forall q \in F,C,S,E,Re,Con} \frac{PD(I_q|G_q)}{PD(I_q|B_q)} \quad (3)$$

where $PD(I_q)$ denotes the probability distribution of quality parameter $\forall q \in F, C, S, E, Re, Con$ and G_q, B_q are the good and bad quality samples $w.r.t$ quality q. This fusion strategy requires the images to be classified only in two class ($i.e$ Good and Bad) which is a huge advantage. Also product rule prevent attenuation of small values in the fusion. In order to estimate the prior probability distributions, a training set consisting of only first 100 subjects is considered. Each image in the training set is classified as good or bad with respect to a particular quality attribute (say Q) in order to estimate the probability distribution with respect to quality attribute Q.

Quality based Recognition Analysis: A good quality assessment framework must improves the matching performance of any biometric system. Hence the fused quality score for each image in the database is computed. The recognition algorithm used for testing [9] make use of consistent corner optical flow algorithm for matching two knuckleprint images. As knuckleprint images are collected in two sessions hence first session images are used as gallery while second session images are used as query as suggested in [16, 9]. The total number of matching performed are 15681600 with 23760 genuine (when both images are from same subject) and 15657840 imposter (when images are from different subjects) matching. The quality of a match between two images I_1 and I_2 is defined as $min(Quality_{fused}(I_1), Quality_{fused}(I_2))$. The minimum quality value is considered because matching score is dependent mostly on the poor quality images. Finally the quality of a match obtained is divided into 7 quality levels $q_i \forall i \in 1 \ldots 7$ with q_7 as the best quality. The thresholds for these levels are chosen empirically by inspecting the match quality based histogram. Finally each match is having some quality level associated with it. The number of matching having quality level at-least up-to $q_1, q_2, q_3, q_4, q_5, q_6$ and q_7 are $15681600, 12545280, 10193040, 7056720, 4390848, 3136320$ and 78408 respectively.

Performance of the recognition system is measured using ROC curves ($i.e$ a plot between FAR and FRR) and equal error rate (EER) as defined below. At a given recognition score threshold, the probability of accepting the impostor, known as false acceptance rate (FAR) and probability of rejecting the genuine user known as false rejection rate (FRR) are obtained. Equal error rate (EER) is the value of FAR for which FAR and FRR are equal.

$$EER = \{FAR|FAR = FRR\} \quad (4)$$

The seven ROC curves are plotted by considering matchings that are having match quality level (ql) at-least up-to $q_i \forall i \in 1 \ldots 7$ with q_7 as the best quality. An ideal ROC curve would include a point at $FRR = FAR = 0$. Hence lower ROC curve nearer to the axis is better. It can be seen clearly that the matching performance is increasing with match quality and EER is monotonically decreasing with increasing match quality as shown in Fig. 6.

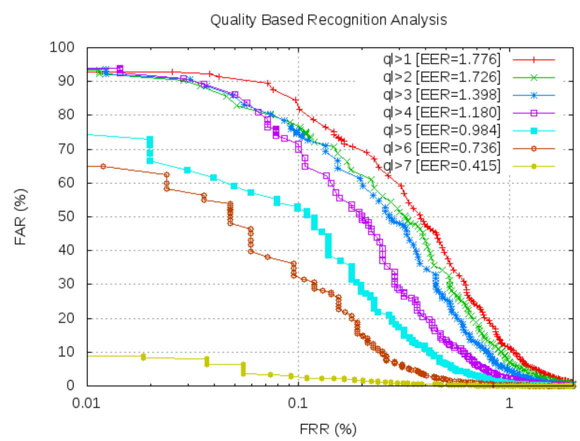


Fig. 6. Quality based Recognition Analysis

4. CONCLUSION

Image quality is a vital parameter and must be evaluated during data acquisition. Recently introduced knuckleprint based recognition systems have shown promising results although no work on its quality assessment is reported yet. This is the first attempt to compute knuckleprint image quality. Six quality attributes are identified and methods to compute them are proposed in this paper. Also they are fused using likelihood ratio based fusion [17] method. The proposed quality assessment system is tested over PolyU knuckleprint database [18] using recognition algorithm proposed in [9]. Comprehensive testing is done in order to establish a relationship between image quality and matching performance. The proposed quality assessment system have shown significant recognition performance boost-up while considering better quality matching.

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