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Improving Biometric Authentication Performance from the User Quality

Ajay Kumar, *David Zhang*

Abstract

The effectiveness of a biometric measurement and sensing system is directly related to the performance generated from the sensed data. This paper investigates a new approach to quantify the quality of sensed data from the user templates. The objective is to incorporate quality of sensed data to generate reliable estimate on the matching scores. The proposed method of extracting user quality is based on the confidence of generating reliable matching scores from the user templates. We simultaneously extract the palmprint and hand-shape images from the single hand image and ascertain the performance improvement for the individual trait. The experimental results from the proposed approach are also presented when the biometric measurements from the finger knuckles are employed. The experimental results presented in this paper show significant improvement in the performance while incorporating the proposed method of user quality in the matching stages. The proposed user quality based fusion of the two biometric modalities also achieves promising improvement in the performance.

I. Introduction

Biometric measurement is key component of several personal authentication systems that render services to only legitimately enrolled users. The performance and user-acceptance are the two primary criterions for the selection of such biometric measurement systems for real deployment. The biometric measurement systems that employ hand image data have high user-acceptance and have invited lot of attention in the literature [1]-[8]. The peg-free hand imaging is more user-friendly, as compared to the imaging setup employing pegs to constrain the hand pose, but generates high variations in the acquired images. Therefore the performance of hand-based biometric measurement system using peg-free imaging is quite low and requires further efforts to make such systems ready for real deployment. The acquisition of hand images that can deliver palmprint and hand shape information is easy and has also been demonstrated in our earlier work [5], [8]. In the context of recent work on the quality-based fusion in [9]-[14] and the current popularity of hand-based biometrics system, the quality based analysis for hand based system deserves careful evaluation and is the focus of this paper.

1.1 Prior Work

The hand-based biometric measurement systems have attracted lot of attention in the literature. The matching of palmprint measurements derived from Gabor phase features [2], ordinal filters [4], and minutiae features [1] have shown to offer promising results for civilian and forensic applications. The extraction of hand-geometry requires low-resolution imaging and has attracted several studies in the literature [3], [5]-[6], [8]. There has been recent trend to investigate the usage of peg-free imaging for the hand-authentication, primarily due to the high user convenience in civilian applications, and shown to offer promising results. The quality dependent fusion can offer significant improvement in the performance over the fusion without quality and has been extensively investigated for iris [14], face [13] and fingerprint [10] modalities. Recently, there have also been interesting efforts [18] to achieve promising improvement in the performance using quality-based normalization of matching scores. However, there has not been any effort to exploit the quality-based performance improvement for the palmprint or the hand-geometry based biometric systems. It may be noted that, unlike the textured gray-level patterns for fingerprint, iris or face images, it is very difficult to ascertain the quality of a shape, *i.e.* binary (hand-geometry) images. Therefore one has to develop new approaches to ascertain the quality of such images, possibly from the nature of the extracted features or the response of employed matcher to the extracted features.

II. User Quality

The quality of a biometric sample is not only associated with the images but also with the interaction of biometric with the employed feature extractor and the matching criteria used for the decision. The *user quality* in this work is defined from the associated biometric sample and quantified as a measure of confidence of user biometric sample with its own templates. Therefore the *user quality* is computed from the user templates (acquired during the registration). The researchers in the prior work have presented promising efforts on the quantification of image quality. However, in our approach instead of estimating the quality of the query images from various integral transforms individually, a single quality measure for each user is estimated from its genuine training matching scores. The estimated quality of the biometric samples in such a way can be efficiently employed to achieve the performance improvement. This type of quality is the quality for the biometric of the user, rather than quality of an image, and hence it is termed as *user quality*. The *user quality* is defined as follows:

$$Q_p = \min\{S_i^p\}\,,\ \forall\ i = 1,\ldots\ {}^{z}C_2 \tag{1}$$

where Q_p is the *user quality* of p^{th} user, S_i^p are the genuine matching scores and z represents the number of templates available for the p^{th} user.

The user quality score estimated during the training phase is used in matching the test and training images. The matching of two images uses the maximum of the two quality scores, corresponding to the class the images belong to, as the weight (equation 2). In case of genuine user the class remains the same and so the maximum is the same as the quality score for that user. After computing the usual matching score from test and training image that score is multiplied by the weight obtained for that pair of images. This essentially means that if a user is more probable to be near any other class then its quality score would be high and multiplying by that value will put that user away from the other classes.

$$S' = S * \max(Q_a, Q_b) \qquad (2)$$

where S' is the new or quality-weighted score, Q_a is the *user quality* of the claimed class and Q_b is the *user quality* of imposter class. The smaller is the genuine matching score Q_p, better is the *user quality* as this offers high confidence on the generated matching scores or larger separation of user from the imposters.

III. Feature Extraction

The performance improvement using hand-based biometric measurement systems is the focus our efforts in this paper. We firstly employed hand images as samples of typical biometric measurement. The acquired hand images are firstly subjected to the image normalization for the reliable segmentation of region of interest, *i.e.* palmprint and hand-geometry images. The employed steps for the image normalization and feature extraction are the same as detailed in [5]. As detailed in [5], the hand binarized shape images are firstly obtained for the extraction of effective features based on geometrical information or geometry plus interior content. The 17 features that can characterize every hand-shape images; *i.e.* perimeter, 4 finger length, 8 finger width, palm width, palm length, hand area, and hand length, are extracted The distance between feature vector from an unknown hand shape f_x and that from the known class x is computed from the Euclidean norm ($\|.\|$);

$$h(f, f_x) = \sum_i \left| f^i - f_x^i \right| \qquad (3)$$

The simultaneously extracted fixed size palmprint images are subjected to the Discrete Cosine Transform (DCT) decomposition for the characterization of palmprint texture. DCT is highly computationally efficient[1] and therefore suitable for any online hand identification system. Each of the 300 × 300 pixels segmented palmprint images are divided into 24 × 24 pixels overlapping blocks. The extent of this overlapping has been empirically selected as 6 pixels [5]. Thus we obtain 144 separate blocks from each palmprint image. The DCT coefficients from the decomposition of each of these L square block pixels, *i.e.* $f(j,k)$, is obtained as follows:

$$C(u,v) = \varepsilon(u) * \varepsilon(v) * \sum_{j=o}^{L-1}\sum_{k=0}^{L-1} f(j,k)\cos\left[\frac{\pi.u}{2.L}(2j+1)\right]\cos\left[\frac{\pi.v}{2.L}(2k+1)\right] \qquad (4)$$

where u, v = 0,1, .. L - 1, $\varepsilon(u) = \varepsilon(v) = \sqrt{\frac{2}{L}}$ for $u \neq 0$ and

$\varepsilon(u) = \varepsilon(v) = \sqrt{\frac{1}{L}}$ for $u = 0$.

The standard deviation of DCT coefficients in each of the blocks, *i.e.* $C(u,v)$ forms the 1 × 144 feature set from each of the extracted palmprint images. The high degree of intra-class variability in palmprint features, mainly resulting from the peg-free imaging, is reduced using Z score normalization.

IV. Experiments and Results

In order to study the relative merits of employing the *user quality*, we performed several experiments on the hand image database from 100 subjects which has been employed in [5] earlier. This database has 5 left hand images acquired in one session and rest five images acquired in the second session. The estimation of *user quality* is performed during the training phase and the estimated *user quality* is used to evaluate the performance from the test images (second session). The typical hand geometry and palmprint image samples resulting from the automated segmentation of acquired hand images is shown in figure 1. The distribution of *user quality* from the palmprint and hand geometry images is shown in figure 2. The comparative receiver operating characteristics (ROC) from the test data, with and without the usage of user quality, is illustrated in figure 3 and 4. These ROCs illustrate that the integration of the user quality has significantly improved the individual performance using palmprint (figure 3) and hand-geometry (figure 4) matching. The equal error rate for palmprint is reduced from 5.6% to 3.6% while it decreases from 6.4% to 5.8% for the hand-geometry. Therefore, the achieved performance improvement is higher for the palmprint images than from the hand-geometry images and more pronounced at lower values of false acceptance rate (FAR). The palmprint and hand

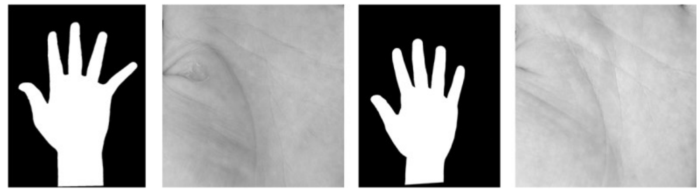
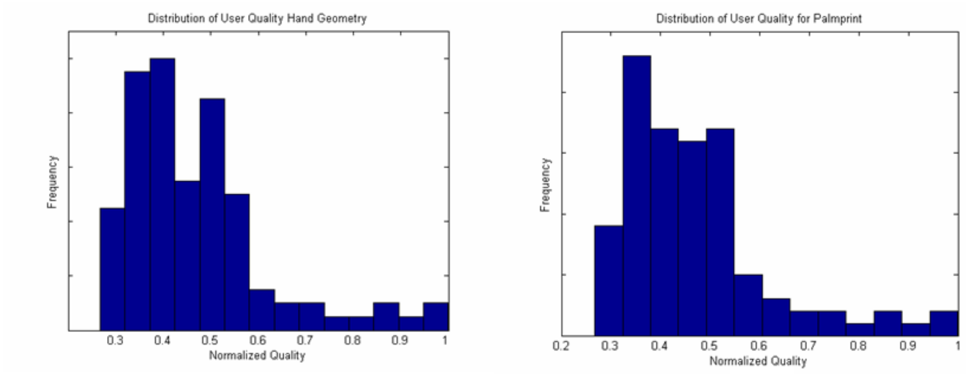


Figure 1: The hand-geometry and palmprint image samples from two subjects employed in experiments.

[1] DCT is basis of JPEG and several other standards (MPEG-1, MPEG-2 for TV/video, and H.263 for video-phones).

Table 1: Improvement in Equal Error Rate using User Quality

	Palmprint	Hand Geometry	Palmprint + Hand Geometry
Without Quality	5.6 %	6.4%	2.6%
With Quality	3.6%	5.8%	2.2%



(a) (b)

Figure 2: Distribution of estimated *user quality* for the palmprint in (a) and hand-geometry in (b)

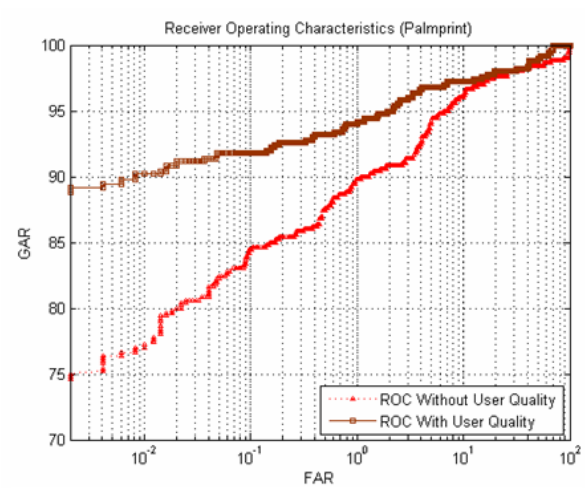


Figure 3: Comparative Receiver Operating Characteristics from the palmprint.

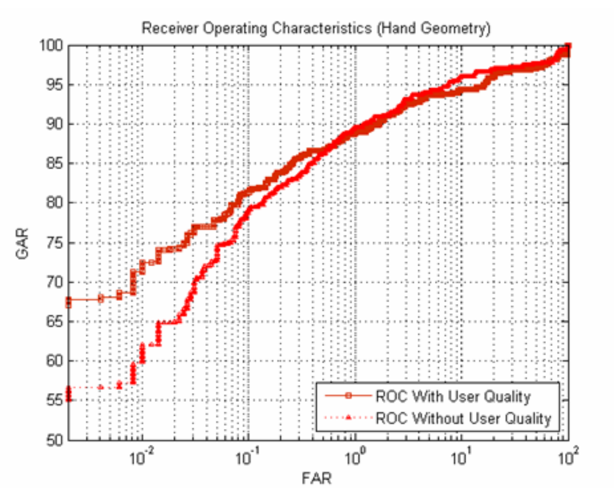


Figure 4: Comparative Receiver Operating Characteristics from the hand-geometry.

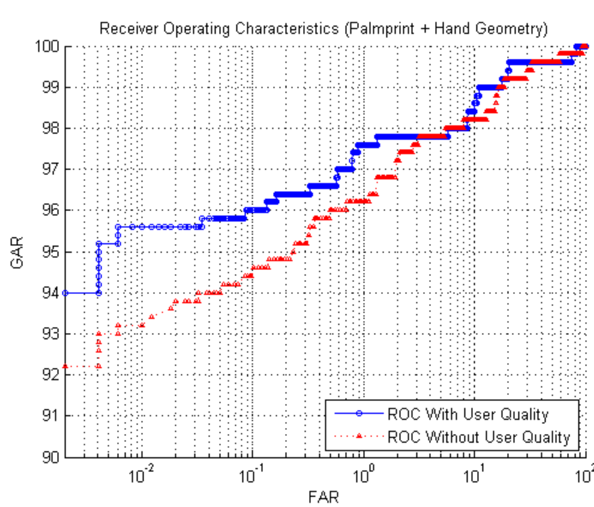
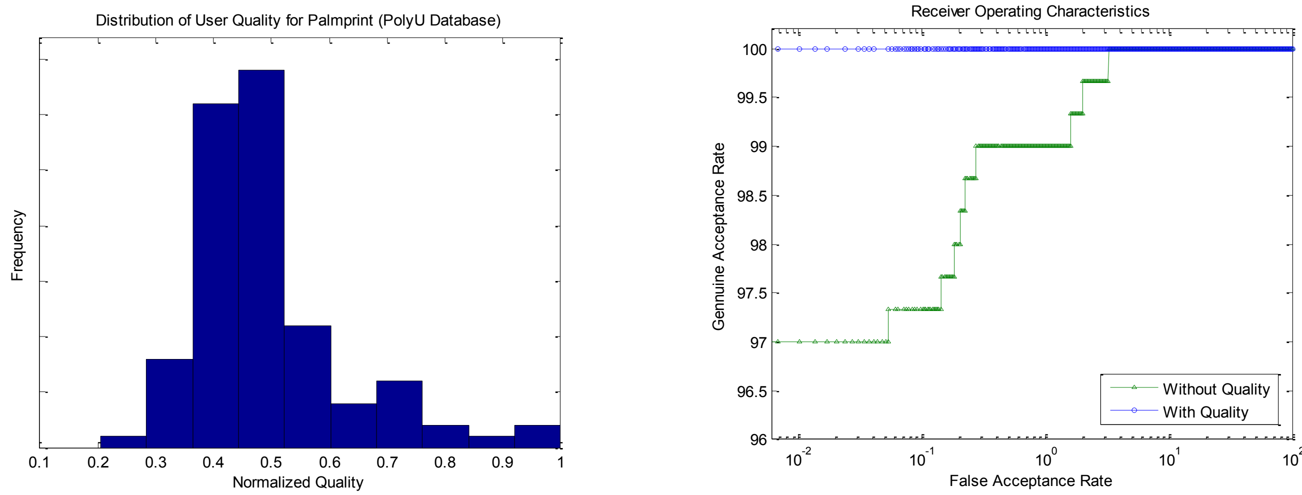


Figure 5: Comparative Receiver Operating Characteristics for the score-level combination.



(a) (b) (a)

Figure 6: The distribution of User Quality for the PolyU Palmprint database in (a), and the comparative Receiver Operating Characteristics in (b).

geometry matching scores were combined using hyperbolic product combination to ascertain the performance from the combination of two modalities. The hyperbolic product combination generates the combined score from $\tanh(s_p * s_h)$, where the s_p is the normalized palmprint score and s_h is the normalized hand-geometry score. This combination was empirically evaluated against the sum, product, weighted sum and found to generate better performance. The comparative performance, with and without the usage of user quality based matching scores, from this nonlinear combination is

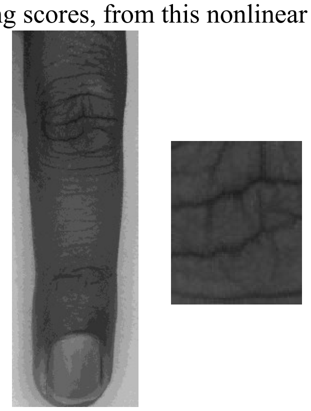


Figure 7: Sample image of a middle finger and automatically extracted knuckle region.

illustrated in figure 5. The table 1 summarizes the comparative equal error rate (EER) obtained from each of the experiments.

We also performed the experiments on the PolyU palmprint v1 database [15] from 108 users to ascertain the quality-based performance improvement. However, the ordinal representation, as detailed in [4], was employed for the extraction of the reliable features since this representation has shown to offer better performance than those from Gabor phase features employed in [2]. The feature extraction using ordinal representations employed the same parameters as used in [4]. We employed first four images for the training, *i.e.*, generation of *user quality*, and the rest of the images were used to ascertain the performance. The distribution of *user quality* from this palmprint dataset is illustrated in figure 6(a) and the corresponding comparative performance can be ascertained from the ROCs displayed in figure 6(b). The performance improvement from the *user quality* based matching is significant, especially at lower FAR which is a preferred operating point for majority of applications.

Another set of experiments were performed using the finger knuckle biometric image samples. Automatically extracted finger knuckle images of size 80 × 100 pixels, from the left hand middle fingers, were employed to ascertain the performance improvement

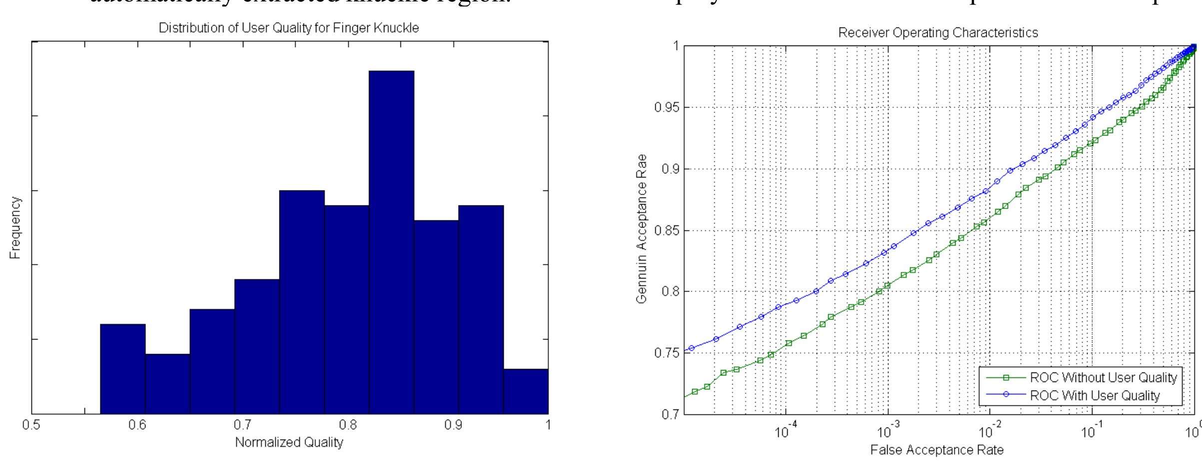


Figure 8: The distribution of User Quality for the middle finger knuckles in (a), and the comparative Receiver Operating Characteristics in (b).

using *user quality*. Figure 7 shows a sample image from the middle finger and the automatically extracted knuckle region employed for the biometric measurement. The method of extracting finger knuckle is same as detailed in reference [16]. The database from 105 subjects was employed for the performance evaluation and the three enrolment images are used for the training, *i.e.* to ascertain *user quality*, and rest two images were employed for the testing phase. The ordinal representation was employed for the representation of knuckle features and matching scores were generated using the steps detailed in reference [4]. The distribution of *user quality* for the finger knuckle biometric image samples is illustrated in figure 8(a). The receiver operating characteristics for the test data, with and without the usage of *user quality*, is illustrated in figure 8(b). The equal error rate of 5.8 % was achieved from the test samples which reduced to 4.22 % when the *user quality* was employed in the authentication. The experimental results shown in figure 8(b) suggest significant improvement in the performance for finger knuckle biometric measurement system when the u*ser quality* is incorporated in the decision making process.

V. Conclusions

This paper has investigated a new approach to achieve the performance improvement for the hand-based biometric measurement systems by incorporating *user quality* during the matching stage. The estimation of *user quality* is based on the confidence of generating reliable matching score from the user templates. The experimental results illustrated in figure 3, 4, 6 and 8 consistently suggest significant improvement in the performance from the usage of quality-based matching. In addition, the experimental results in figure 5 suggest that the quality-based fusion of palmprint and hand geometry scores achieves promising improvement in the performance. In this work five user templates were employed for the palmprint and hand geometry experiments (table 1) since these samples were acquired during the registration stage. The number of user templates acquired during the registration is usually smaller. In worst case when only one user template is available, the *user quality* scores can be generated by the matching scores ascertained from the scaled and rotated templates with itself.

The quality of biometric measurement also depends on image quality, which is often linked to imaging resolution. In case of palmprints, the civilian applications typically use 100 dpi imaging while about 400 dpi is typically needed to acquire palmer ridge or minutiae features. The quantification of *user quality* introduced in this paper can also be generalized for high resolution palmprint images [1] and can be useful for forensic applications. It should be noted that increase in imaging resolution not necessarily results in higher *user quality* since the quality and background of palmer ridge structure is user specific. The future efforts should be focused in evaluating the *user quality* based personal recognition on the large biometric databases, *i.e.* samples from more than 500 subjects. Recently, reference [17] has illustrated the utility of multi-spectral palmprint images for the personal identification. The comparison and combination of the integrated palmprint image quality with the *user quality* measure suggested in this paper would be highly useful and suggested for the further work.

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