# Palmprint Image Quality Measurement Algorithm

**Fares Guerrache and Hamid Haddadou**

**Abstract** Biometric systems proposed in the literature have reached a correct performance level when the acquired samples are of good quality. However, the performances fall when these samples are of poor quality. In order to face up to this problem, integration of modules for measuring sample quality in the process of biometric recognition is necessary. In this paper, we propose a new approach for measuring palmprint image quality in terms of illumination, and integrate it in the biometric system to reject the palmprint of poor illumination and to make new session of acquisition. The proposed approach has been evaluated on PolyU Palmprint database. The achieved results are very encouraging.

**Keywords** Biometric · Palmprint · Image quality · Quality measurement · Quality evaluation · Quality assessment

## 1 Introduction

The automatic personal identification is an important service for the physical and logical resources security in many areas such as access control to buildings, border control and e-commerce. Traditionally, there are two categories of automatic personal identification: knowledge-based, such as a password and a PIN, and token-based such as a physical key and an ID card. However, these methods have some limitations. In the knowledge-based approach, the "knowledge" can be guessed or forgotten. In the

F. Guerrache (✉)
STIC Doctoral School, High National School of Computer Science (ESI),
BP 68 M Oued Smar, 16309 El Harrach, Algiers, Algeria
e-mail: f_guerrache@esi.dz

H. Haddadou (✉)
LCSI Laboratory, High National School of Computer Science (ESI),
BP 68 M Oued Smar, 16309 El Harrach, Algiers, Algeria
e-mail: h_haddadou@esi.dz



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token-based approach, the "token" can be easily stolen or lost. As a result, biometric personal identification is a best alternative. Biometrics is an automatic technique for recognizing humans based on physiological characteristics such as fingerprint, palmprint, face, iris pattern and retina, or behavior characteristics such as voice, signature and gait [1]. Unlike the token and the knowledge of the traditional identification approaches, biometric characteristics cannot be lost, stolen, or easily forged, they are also considered to be persistent and unique.

Palmprint recognition is one of the most important newly developing biometric technologies. Palmprint recognition uses the person's palm as a biometric for identifying or verifying person's identity. Palmprint personal authentication employs two types of images: high resolution and low resolution images [2]. A wide variety of features can be extracted at different image resolutions. In low resolution images features such as principal lines, wrinkles and textures can be extracted with less than 100 dpi (dots per inch) [3]. However, features like minutiae points, ridges and singular points can be obtained from high resolution images with at least 400 dpi [3]. In general, high resolution images are suitable for forensic applications such as criminal detection, while low resolution images essential for civil and commercial applications such as access control. Initially palmprint research focused on high-resolution images but now almost all research is on low resolution images for civil and commercial applications [4–6]. Palmprint recognition approaches are categorized mainly based on structural features, statistical features or the hybrid of these two types of features [7].

All biometric systems stages (enrolment, identification and verification), based on physiological characteristics, need a step of image acquisition. The biometric image acquired from this step may undergo a number of distortions such as poor illumination on a face, cuts on a fingerprint and reflections in an iris. This may significantly decrease the performances of the biometric systems. In order to face up to this problem, researchers have recently defined the concept of the biometric image quality measurement. It is useful in different settings (enrolment, identification and verification) as well as in different processing phases (pre-processing, matching and decision) of a biometric system [8]. The image quality measurement constitutes a full-fledged module in biometric processes and follows the image acquisition module. The image quality measurement module takes a biometric image $I$ as input, and returns a value $Q$ called quality score. The quality score can be used to generate feedback on image acquisition, to guard the enrollment process, to estimate the failure-to-enroll rate (FTE), to improve the matching performance, to enhance the classification performance and to evaluate the sensor state [7, 9–11].

During the past decades, several approaches have been proposed for the biometric image quality measurement and the most of them are addressed to evaluate the image quality of fingerprint [12–16], face [17–20] and iris [21–23]. However, few researchers attempted to measure the quality of low-resolution palmprint image owing to the complex nature of its features. To the best of our knowledge, only Prasad et al. [11] have proposed an approach for measuring the low-resolution palmprint image quality in terms of illumination. This approach divides the palmprint image into non-overlapped square blocks and computed a local quality score for each block using the root mean square contrast. Based on this local score and a threshold $K$th, each non-overlapping block is classified either as good or bad. The global quality score is then computed based on the number of good and bad blocks in the palmprint. To apply this global quality score in the palmprint recognition system, this work propose to fusion it with the score match for the recognition performance enhancement. The analysis of experimental results of this work shows that the proposed fusion improves the recognition performance only when the palmprint image is of good and intermediate illumination. However, when the palmprint is of poor illumination, the performance remains the same that without fusion.

To deal with this problem, we propose in this paper a new low resolution palmprint quality measurement approach and we apply it in the palmprint recognition system to reject the image of poor illumination and generate feedback on image acquisition.

The rest of the paper is organized as follows. Section 2 presents the quality measure (illumination) proposed in our approach. We indicate the details of the proposed palmprint image algorithm in Sect. 3. Section 4 describes the application of our quality measurement image algorithm in the palmprint recognition system. Section 5 provides the experimental results of our work. We conclude this work in Sect. 6.

## 2 Proposed Quality Measure

The acquisition process of the low resolution palmprint image begins generally with the palm lighting using light source of biometric capture. The non-frontal exposure of the palm to the capture light source, its overexposure or underexposure to the light source and the imperfect lighting conditions of the room acquisition can cause bright spots and/or dark spots in captured palmprint image as shown in Fig. 1. This incorrect illumination affects greatly the palmprint biometric features, and thus severely degrades the performance of a recognition system. Preprocessing methods are among the most extended and easiest to use of all methods proposed to deal with illumination problems. However, its complete elimination or correction using these preprocessing methods is a complicated and difficult task. This is why we propose the illumination as a quality measure in our new approach for measuring low resolution palmprint image quality.

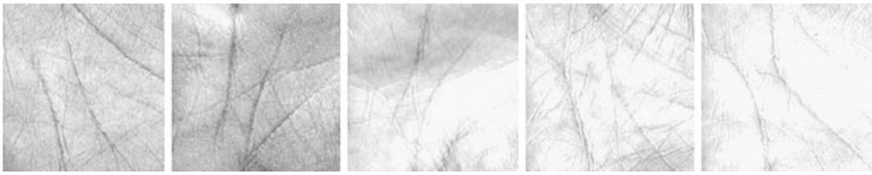


**Fig. 1** Palmprints of different illumination quality from PloyU Palmprint Database [25]

# 3 Proposed Palmprint Image Quality Measurement Algorithm

The main aim of our work is to propose a new palmprint image quality measurement algorithm that allows determining if the palmprint image is acquired under good illumination conditions or not. Our quality measurement algorithm is based on the assessment of the palmprint image area correctly illuminated by the exclusion of the very bright spots and the very dark spots. To deal the palmprint illumination problem, we adopt here a local approach that takes the palmprint region of interest as input, and returns a scalar value which represents its quality. The following sections present the four main steps of our palmprint image quality measurement algorithm:

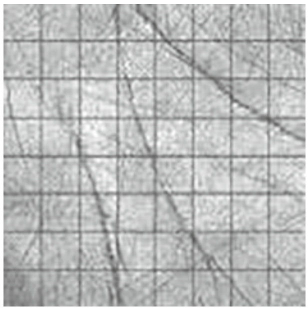
## *3.1 Palmprint Region of Interest Dividing*

In the first step of our algorithm, the $128 \times 128$ pixel ROI (Region Of interest) of gray level palmprint image is divided into $N$ non-overlapped square blocks of $8 \times 8$ pixel everyone as shown in Fig. 2.

## *3.2 Reference Bloc Determining*

According to Zhang et al. [24], the structural information of images (high-frequency components) is invariant to illumination. Since the principal lines of low resolution palmprint are biometric structural information, we can therefore justify the existence of at least one good quality illumination block located above these lines, even if the palmprint image is of poor illumination. Based on this heuristics, we choose among the $N$ blocks of the ROI the one that has the best illumination and to designate it as reference block ($B_R$). This choice is based on the gray level histograms of the palmprint image blocks. As shown in Fig. 3, the distribution of the

**Fig. 2** Palmprint image dividing



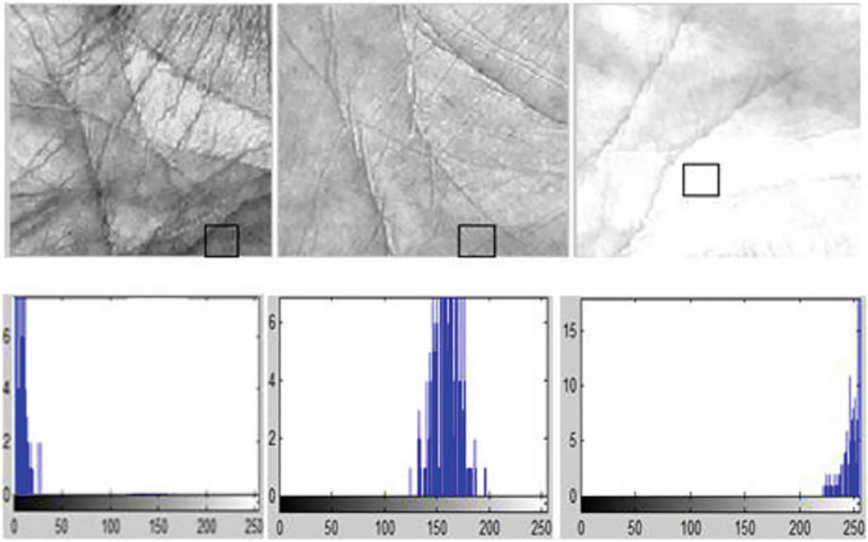


**Fig. 3** Gray level distribution of different quality blocs

gray level values of a block of a normal illumination is concentrated generally in the middle of the histogram, while the distribution of the gray level values of a block of very dark or very bright illumination is concentrated respectively in the lower or higher end of the histogram [10]. To determine the concentration of the gray level distribution of the histogram $h_B$ of each block, we compute its center of mass $mc(h_B)$ as follow:

$$\mathrm{mc}(\mathrm{h_B}) = \left(\sum_{\mathrm{i}=0}^{255} \mathrm{i.h_B(i)}\right) \Big/ \left(\sum_{\mathrm{i}=0}^{255} \mathrm{h_B(i)}\right) \quad (1)$$

where $i$ and $h_B(i)$ are the gray level and the value of histogram at this level respectively.

After having computed the centers of mass of the histograms of $N$ blocks, we select the one that has the closest center of mass of the value 127.5 as a reference bloc $B_R$.

## 3.3 Local Quality Score Computing

Once the reference block $B_R$ is located on the ROI of palmprint image, we proceed in this step to calculate the degree of similarity between each block of the ROI (called test bloc $B_T$) and the reference block $B_R$. This degree of similarity is called local quality score *LQS*. To compute the *LQS*, we propose to calculate the similarity between the gray level histogram $h_T$ of the test block and the gray level histogram of the reference block $h_R$ using the following formula:

$$\mathrm{LQS} = \mathrm{d}(\mathrm{h_T}, \mathrm{h_R}) = \sum_{\mathrm{i}=0}^{255} \min[\mathrm{h_T}(\mathrm{i}), \mathrm{h_R}(\mathrm{i})] \tag{2}$$

where $h_T(i)$ and $h_R(i)$ are the values of the test and reference block histograms at the gray level $i$.

The *LQS* takes its value in the interval [0, L] where $L = \sum_{i=0}^{255} h_R(i)$, 0 means a poor quality block, while $L$ means good quality block.

However, since we are interested in values in the interval [0, 1], we compute the normalized local score quality *NLQS* using the following function:

$$\mathrm{NLQS} = \frac{\mathrm{SQL}}{\mathrm{L}} \tag{3}$$

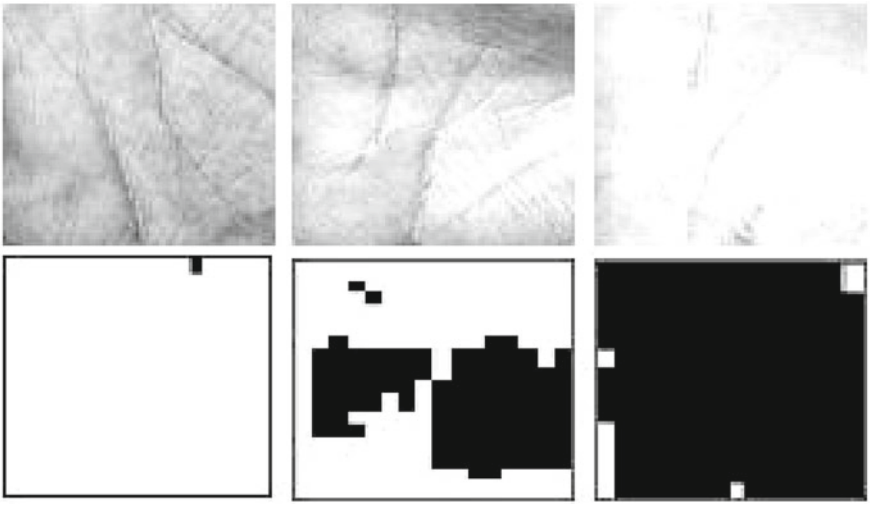
where $L = \sum_{i=0}^{255} h_R(i)$, 0 means poor quality block and 1 means good quality block.

## *3.4 Global Quality Score Computing*

In order to compute the global quality score *GQS* of the whole palmprint image, we propose to mark each block of the ROI palmprint image either as good or poor based on its normalized local sore quality *NLQS* and a threshold α experimentally determined. In fact, the blocks that have the normalized local quality score greater than or equal the threshold $\alpha$ ($NLQS \geq \alpha$) are marked as good, while those having the normalized local quality score less than the threshold $\alpha$ ($NLQS < \alpha$) are marked as poor. Hence, the global quality score GQS is computed by the percentage of blocks marked as good as follows (see Fig. 4):

$$\mathrm{GQS} = \frac{\mathrm{N_B}}{\mathrm{N}} \tag{4}$$

with $N_B$ and $N$ are the number of good blocks and the overall blocks number respectively.



*GQS=0.9961* *GSQ=0.6172* *GSQ=0.0352*

**Fig. 4** The global score quality computation (Blocks with *white color* indicate higher quality and Blocks with *black color* indicate poor quality)

## 4 Application in Palmprint Recognition

In our work, we propose to apply the proposed quality measurement algorithm in palmprint system recognition (enrolment, identification and verification) in order to generate feedback on image acquisition as shown in the framework of Fig. 5. In

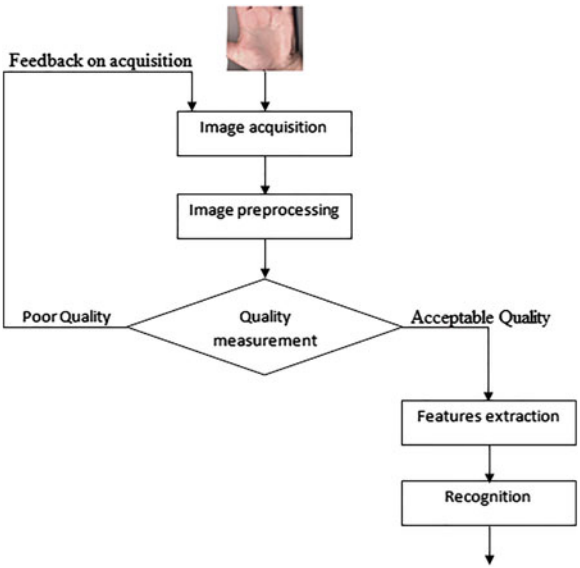



**Fig. 5** Framework using our palmprint image quality measurement algorithm

fact, once palmprint images are preprocessed and their quality is evaluated, only images with acceptable quality are received for recognition; others (images with Poor Quality) are discarded and reacquired. To determine the quality of a given palmprint image *I*, we propose to divide it into two classes: *C1* for Acceptable Quality and *C2* for Poor Quality. Then, the palmprint image *I* is assigned to its class using its global quality score computed by the proposed palmprint quality measurement algorithm and a threshold β experimentally determined, as follow:

$$I \in \begin{cases} C_1 \text{ if} & GQS \geq \beta \\ C_2 & \text{otherwise} \end{cases} \tag{5}$$

## 5 Experimental Results

The presented palmprint image quality measurement approach has been tested on the Hong Kong Polytechnic University (PolyU) palmprint database [25] using MATLAB 7.14.0 (R2012a). The PolyU database has 7752 gray scale low-resolution (75 dpi) palmprint images corresponding to 386 classes. Each class has 18 to 20 images taken in two sessions. The PolyU database palmprint images are captured using CCD-based camera under different illumination conditions. The palmprint images of the first session are acquired under good and intermediate illumination, while those of the second session are acquired under poor illumination. This makes PolyU palmprint as a good choice to test our palmprint image quality measurement approach. We have carried out two experiments in our work. The first is performed to determine the thresholds α and β of our proposed quality measurement approach. The second experiment aims to validate and directly test the performance of our approach.

### *5.1 Experiment for Determining the Thresholds α and β*

To determine the optimum values of the thresholds α and β, we have selected randomly a set of 100 poor quality palmprint images of different classes from the images of the second session of PolyU palmprint database. Then, we have evaluated the quality illumination of this image set using our quality measurement approach at different values of α and β. We have registered for each pair of values (α, β) the number of images judged of poor quality by our approach compared to those randomly selected (see Table 1). The results of this experiment show that the number of the poor quality palmprint images obtained by our approach reaches the number of the poor quality images randomly selected where the values of the thresholds α and β are respectively 0.3 and 0.6. Thus, the optimum values of the thresholds α and β are respectively 0.3 and 0.6.

**Table 1** Experiment results for determining the thresholds α and β

| α | B | Number of poor quality images obtained/randomly set |
|---|---|---|
| $\alpha = 0.2$ | $\beta = 0.2$ | 23 |
| | $\beta = 0.3$ | 42 |
| | $\beta = 0.4$ | 58 |
| | $\beta = 0.5$ | 68 |
| | $\beta = 0.6$ | 70 |
| | $\beta = 0.7$ | 82 |
| | $\beta = 0.8$ | 96 |
| $\alpha = 0.3$ | $\beta = 0.2$ | 63 |
| | $\beta = 0.3$ | 69 |
| | $\beta = 0.4$ | 72 |
| | $\beta = 0.5$ | 89 |
| | $\beta = 0.6$ | 100 |
| | $\beta = 0.7$ | 100 |
| | $\beta = 0.8$ | 100 |
| $\alpha = 0.4$ | $\beta = 0.2$ | 100 |
| | $\beta = 0.3$ | 100 |
| | $\beta = 0.4$ | 100 |
| | $\beta = 0.5$ | 100 |
| | $\beta = 0.6$ | 100 |
| | $\beta = 0.7$ | 100 |
| | $\beta = 0.8$ | 100 |
| $\alpha = 0.5$ | $\beta = 0.2$ | 100 |
| | $\beta = 0.3$ | 100 |
| | $\beta = 0.4$ | 100 |
| | $\beta = 0.5$ | 100 |
| | $\beta = 0.6$ | 100 |
| | $\beta = 0.7$ | 100 |
| | $\beta = 0.8$ | 100 |
| $\alpha = 0.6$ | $\beta = 0.2$ | 100 |
| | $\beta = 0.3$ | 100 |
| | $\beta = 0.4$ | 100 |
| | $\beta = 0.5$ | 100 |
| | $\beta = 0.6$ | 100 |
| | $\beta = 0.7$ | 100 |
| | $\beta = 0.8$ | 100 |

## 5.2 *Experiment to Validate and to Test the Performance*

In order to validate our image quality measurement approach and to determine its accuracy to assign a given palmprint image at its real quality class: acceptable

**Table 2** Experiment results for testing the performance

| Classified quality | Assigned quality | |
|---|---|---|
| | Acceptable | Poor |
| Acceptable | 100 | 5 |
| Poor | 0 | 95 |
| Accuracy | 100 % | 95 % |

(Good and Intermediate) or poor, we have exploited the separating of the image quality in terms of illumination viewed in the database PolyU where the images of acceptable (good and intermediate) are acquired in the first session and those of poor quality are acquired in the second session. In fact, we have selected randomly two sets of 100 palmprint images of different classes from PolyU palmprint database. The first set (SET 1) contains palmprint images of the first session of PolyU (palmprint of acceptable quality); while the second set (SET 2) contains palmprint images of the second session of PolyU (palmprint of poor quality). Then, we have applied our palmprint image quality measurement algorithm on the two sets (SET 1 and SET 2) to determine the number of palmprint images correctly assigned at its real quality classes compared to the quality classification viewed in the database PolyU. Comparing results are shown in Table 2. This results show that our palmprint image quality measurement approach has a very high level accuracy.

## 6 Conclusions

This paper proposes a new approach for measuring low-resolution palmprint image quality in terms of illumination. It is a local-based method that divides the region of interest of the palmprint image into non-overlapped square blocks. A local quality score is then computed for each bloc using the center of mass of the gray level histogram and the best bloc of image. The global score is computed from the local scores. This approach is integrated in the palmprint recognition system to reject the image of poor illumination and generate feedback on image acquisition. The acceptable palmprint images are received for recognition. The experimental results on PolyU palmprint database confirm the effectiveness of our approach and its usefulness in the low-resolution palmprint recognition system.

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