# Standardization of Face Image Sample Quality*

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**Abstract.** Performance of biometric systems is dependent on quality of acquired biometric samples. Poor sample quality is a main reason for matching errors in biometric systems and may be the main weakness of some implementations. In this paper, we propose an approach for standardization of facial image quality, and develop facial symmetry based methods for the assessment of it by measuring facial asymmetries caused by non-frontal lighting and improper facial pose. Experimental results are provided to illustrate the concepts, definitions and effectiveness.

**Key words:** Biometric sample quality, facial symmetry, local features, methodology, standardization.

## 1 Introduction

Sample quality has significant impact on accuracy of biometric recognition. Poor sample quality is a main reason for matching errors in biometric systems and may be the main weakness of some implementations. Automatic biometric image quality assessment may help improve system performance. It can be used to monitor image quality for different applications, capture devices, enrollment and recognition algorithms. Recently, some standards on biometric sample quality have been proposed, for example, ISO/IEC JTC1/SC37 working drafts [1, 2].

Fig. 1 shows a framework of a biometric recognition system using an image sample quality assessment component. Biometric images are preprocessed and their quality is evaluated. Only images with acceptable quality are received for recognition; others are discarded. Thus some of recognition errors can be avoided and matching time expense can be saved for a large biometric database. Also, in some security situation, quality assessment can give an alert when someone does not want to be recognized on purpose, for example, a criminal hiding himself. The quality value can be sent to recognition algorithm and helps to improve its accuracy. For example, the threshold can be decreased if an image's quality is low. In this way, low false reject rate (FRR) can be achieved. A number of

* The original ideas presented in this paper belong to CBSR and the work was performed at CBSR.

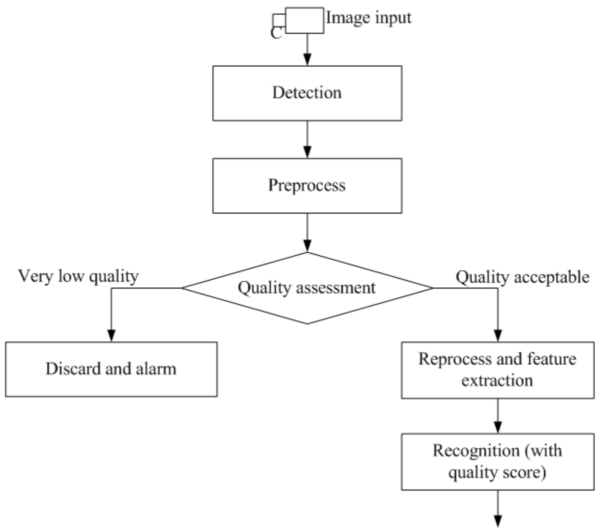


**Fig. 1.** A framework of biometric recognition using quality assessment.

biometric sample quality assessment methods have been proposed in past years. Chen [3] proposed a wavelet-based quality measure for iris image and get a performance improvement of about 20% for FRR (from 1.00% to 0.79%). For fingerprint, matching algorithms are sensitive to clarity of ridges and valleys, measures of number and quality of minutiae and size of the image [4]. Youmaran [5] introduces a definition of biometric information and proposes an algorithm to measure the changes in biometric sample quality resulting from image degradation. Most work on face image quality is based on general, face-nonspecific image properties, such as contrast, sharpness and illumination intensity etc [6]. But all these methods can not evaluate the quality degradation caused by non-frontal lighting and improper facial pose.

In this paper, we propose approaches for standardization of facial image quality. Aspects of defects are categorized. It is suggested to adopt a two-level quality score, aspect level and overall level. Then, we develop facial symmetry based methods for the assessment of facial image quality by proposing metrics measuring facial asymmetries caused by non-frontal lighting and improper facial pose. Experimental results are provided to illustrate the concepts, definitions and effectiveness. The proposed methods have been incorporated into SC37 standardization working draft [2].

The remainder of this paper is organized as follows: In Section 2, factors causing defects in face image quality are analyzed, and measures of face quality are analyzed. In Section 3, facial symmetry based face quality measures are defined. In Section 4, some other quality measures are given. Section 5 presents the methods of score normalization and experimental results are demonstrated in Section 6.

## 2 Standardization Approach

The performance of an automated face recognition system is affected by the amount of defect or the degree of imperfection present in the face image. The knowledge of quality can be used to invoke appropriate processing algorithms, for example, some image enhancement or normalization algorithms prior to feature extraction, appropriate thresholds or matchers based on quality.

The use of face image quality metrics to enhance the overall performance of the system is growing [3,4,5]. Standardization of quantitative face image quality score computation lays a basis for common interpretation of the quality scores. ISO/IEC WD 29794-1 [1] presents three approaches for calculating quantitative quality scores, namely "bottom-up", "top-down" and "combined". The presentation is based on the character, fidelity and utility concepts therein. ISO/IEC WD 29794-4 [7] emphasizes the use of annotated fingerprint corpus to standardize the score normalization. ISO-IEC WD [1, 7] suggested the use of Quality Algorithm Identification (QAID), or Quality Percentile Rank upon standardization of a Quality Score Normalization (QSN) corpus.

Reference to [1, 7], in this paper, we adopt the following approach for face sample quality standardization:

(1) Specifying possible defects of face biometric samples in four categories, namely, environment, camera, user, and user-camera interaction.
(2) Defining face quality scores (FQSs), to be calculated by face quality assessment algorithms (FQAAs), to evaluate possible defects. A FQAA analyzes a face sample locally at pixel or feature level and fuses the local analysis results over a global region. A FQS evaluates one or more defects, and provides an indicator of failing defects.
(3) Mapping the raw FQSs of each defect aspect to a normalized quality score using annotated quality score normalization dataset (QSND). The aspect-normalized FQS indicate how good the sample is for the considered aspect, and can be used as an indicator of possible failure.
(4) Mapping all the FQSs to an overall normalized quality score using annotated QSND. This provides an overall evaluation of how good the sample is for biometric recognition.

### 2.1 Categorization of Defects

A face image obtained from a static camera, video camera, or photo scanner is usually imperfect. It may contain defects caused by poor illumination, improper face positioning and imperfection of the camera. These factors can be categorized into four aspects:

(1) Application Environment.

- Deviation from the symmetric lighting.
- Uneven lighting on the face area.
- Extreme strong or weak illumination.
- Cluttered background.

(2) Camera Device.

- Low contrast.
- Geometric distortion.

(3) User Facial Condition.

- Heavy facial wears, such as thick or dark glasses.
- Exaggerated expression.
- Heavy makeup.

(4) User-camera positioning.

- Deviation from frontal pose (yaw , tilt, in-plane rotation).
- Too far (face too small) or too near (face too big).
- Out of focus (low sharpness).
- Partial occlusion of the face.

### 2.2 Face Quality Measures

Face quality can be measured at various levels [8], including using lower-level quality measures, matching score analysis, etc. It should be noted that there is no universal agreement on what should be considered as a quality problem, or what characteristics should be measured as inputs to quality measures. For quality measures that have the end goal of maximizing the correlation with matching score, factors that affect the matching score all need to be considered among the various inputs to the quality measures.

A FQAA takes a face image $I$ as its input and reports the associated quality score $Q(I)$. A quality score can be a scalar or vector.

Sample quality measures should predict performance. A matching score indicates the similarity between two samples $I_1$ and $I_2$. It may also be related to the quality scores $Q(I_1)$ and $Q(I_2)$ as $P(I_1, I_2; q_1, q_2)$.

## 3 Facial Symmetry Based Quality Measures

The illumination and pose variations are two main issues that cause serious performance degradation for most existing systems [9]. We propose to use facial symmetry to assess quality degradations caused by non-frontal lighting and improper facial pose. Fig. 2 gives intuitive illustrations. We can see how illumination and pose affect the facial symmetry.

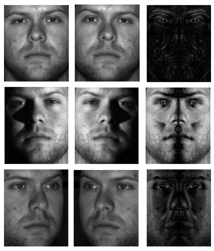

**Fig. 2.** Left: Division of a face into left and right half regions at the mid-line of the eyes. Right (columns 1-3): Original images, their mirror versions, and the corresponding left-right half difference images.

### 3.1 Facial Symmetry Analysis

The symmetry may be analyzed using some local image features, e.g., the raw image pixel values, or locally-filtered pixel values. When a local filter is chosen properly, it provides a better basis for computing facial symmetry[1]. The differences between image features at the corresponding left-right pixel locations provide local measures of asymmetry caused by non-frontal illumination or improper head pose. If the face image is strictly left-right symmetric, the differences should all be zero.

We further propose to use differences between corresponding histograms $H^L_{m\times n}$ and $H^R_{m\times n}$ of local features as local measures of asymmetry, where $m$ is the dimensionality of the feature vector, and $n$ is the number of bins in the histogram. A local feature histogram of $n$ bins can be considered as a more descriptive feature than the local feature itself. A histogram distance can be calculated as follows:

$$D_\ell = |H^L_{m\times n} - H^R_{m\times n}| \tag{1}$$

where $\ell$ indexes the $\ell$-th pair of sub-windows, $|\cdot|$ is some suitable form of histogram distance, e.g., city block distance (used in this paper), histogram intersection, cross-entropy, or Kullback-Leibler divergence. The larger the distance value is, the less the left-right symmetric of the face image is, and the lower the image quality is in some aspects.

### 3.2 Lighting and Pose Asymmetries

Lighting symmetry should be measured based on illumination sensitive image properties. For example, Local Binary Pattern (LBP) [10] code is a local feature sensitive to illumination direction, and has been used for face recognition [11–13]. In this paper, we use an Adaboost learning algorithm to select the most effective

[1] Care must be taken that the filters used for the corresponding locations in the left and right halves should be appropriately mirrored.

subset from a large pool of LBP features [12, 13], and use the local histograms of the selected LBP features as the basis for calculating facial asymmetry.

A distance is derived between the corresponding left-right LBP histograms using Equ. 1. The larger the deviation, the larger the distance value, as will be seen. The FQAA value is calculated as the sum of all the histogram distances

$$Asymmetry(I) = \sum_{\ell=1}^{N} D_\ell \qquad (2)$$

where $N$ is the number of sub-windows and $D_\ell$ is the $\ell$-th sub-window distance. The larger the $Q(I)$, the less symmetric the face image $I$ is in terms of illumination. This is used as a metric for measuring the defect in the aspect of lighting direction.

Pose symmetry evaluation can be done based on some pose-sensitive image features. In this paper, the same local LBP histogram features are used for this purpose. The histogram distance are summed up to measure the pose asymmetry in the image. The larger the sum value, the more the face is deviated from the frontal pose, and the lower the image quality is in terms of pose symmetry.

The following summarize a procedure for clculating facial symmetry based FQAAs:

1. Normalize the range of pixel values in the cropped face region using a suitable normalization or equalization algorithm;
2. Do local LBP filtering;
3. Calculate the difference between filtered values for each pixel pair of sub-windows at left-right mirror locations;
4. Calculate a suitable sum of the absolute values of the differences.

## 4 Other Face Quality Metrics

**User-Camera distance** User-camera distance is recommended to be 1.2 - 2.5m in a typical photo studio and 0.7 - 1.0m in a typical photo booth (ISO/IEC 19794-5 AMD 1 [14]); and inter-eye distance to be 120 pixels (ISO/IEC 19794-5 Annex A [15]). The distance is inversely related the size of the face. Therefore, the inter-eye distance $Dist_{eye}$ can be used to estimate the quality score for whether the user is at a proper distance from the camera

$$QS_{UC-dist} = D(Dist_{eye}, Dist_0) \qquad (3)$$

where $Dist_0$ is the average number of inter-eye pixels when the user is at the recommended distance and the image capture devise is at the recommended setting, and $D$ is some function indicating deviation of $Dist_{eye}$ from $Dist_0$.
**Illumination Intensity** This analysis calculates quality score for illumination strength. It is performed on the histogram of un-normalized image pixel values. The histogram with normal illumination generally spans a wider range. In the

case of very dark or very bright illumination, the distribution of the gray scale values is concentrated toward the lower or higher end of the histogram.

Let $H_0$ be the histogram of image under a standard illumination and $H$ is the histogram of the image being assessed. A quality score could be defined to be a distance between $H_0$ and the measured histogram $H$.

**Contrast** This analysis calculates quality score for image contrast. It is performed on the histogram of un-normalized image pixel values. It could be calculated via the following formulation:

$$C_I = L_I \cdot \sqrt{\frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [I(x,y)] - \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I(x,y)} \quad (4)$$

**Sharpness** The sharpness of a face image refers to the degree of clarity in both coarse and fine details in the face region. The quality value for sharpness can be calculated via image gradient

$$G = \sum_{x=1}^{M-2} \sum_{y=1}^{N-2} G(x,y) \quad (5)$$

where G(x,y) is the gradient value at (x,y).

## 5 Score Normalization

A raw FQS should be normalized in order to achieve interoperability . According to [1], this may be done by a quality score normalization procedure (QSNP) with a QSND. In QSND, biometric samples are annotated with normalized quality scores. Such annotation might be derived from the results of controlled performance tests. A QSNP maps native quality scores of a FQAA to normalized quality score based upon the publication of standardized QSNP.

**Aspect normalized quality scores** An aspect-normalized score is obtained for measuring the quality with respect to the concerned aspect of defects. The initial face images available will be assigned into the respective quality category using the matching score approach, with human subjective adjustment to correct some of the matching scores.

**Overall normalized quality** An overall-normalized score is obtained for measuring the overall quality. In order to obtain a single or unified output from all the quality metrics described in the earlier sections, it is necessary to combine all the scores of the quality metrics described above and produce a single quality score. There are various methods that can be used to combine all the quality scores. A simple way is to perform weighted averaging.

$$OVERALL\_QS = \sum_{i=1}^{N} \alpha_i QS_i \quad (6)$$

where $\sum_{i=1}^{N} \alpha_i = 1$, $\alpha_i$ are the weights and $QS_i$ are the normalized quality scores for the aspects that affect the quality of face images.

## 6 Experiments and Discussion

The following experiments examine on the facial asymmetry caused by non-frontal lighting and improper facial poses using the facial symmetry based methods presented in Section 3. We first test lighting symmetry and then pose symmetry. Yale face database B [16] of 10 persons are included. Images of each person are taken with 9 different poses and 65 different lighting conditions.

**Lighting Symmetry** Fig. 3 shows examples of LBP histogram distances (Equ. 1) for 3 face images of increasing deviation of lighting from the frontal direction. The differences are calculated between pairs of pixels at 2300 random locations. As can be seen, the larger the deviation, the larger the distance value.

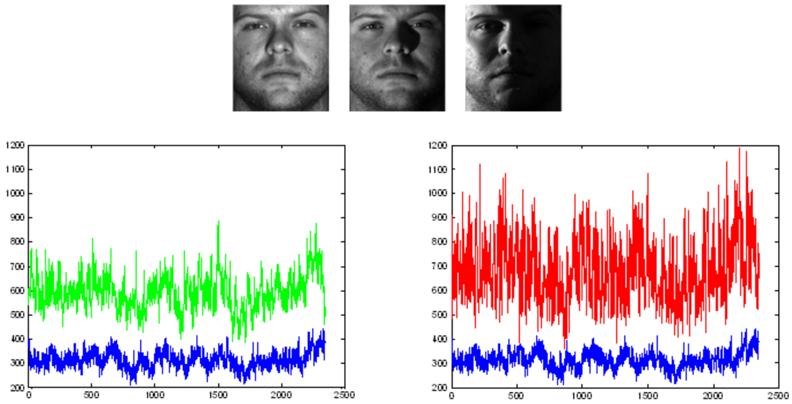

**Fig. 3.** Left-right local LBP feature differences for face images of increasing deviation of lighting from the frontal direction.

Images of 10 persons are used; 5 images are taken for each person under 5 different illumination conditions, as shown in the upper part of Fig. 4. The lower part shows the FQAA values (calculated according to Equ. 2) for the 10 persons (horizontal axis) under the 5 illumination conditions. The differences are calculated between pairs of pixels at 2300 window locations.

**Pose Symmetry** Fig. 5 gives an example of the pose asymmetric values for 4 pose categories of 10 people. Yale face database B has 9 pose categories, as shown in the left part of Fig. 5. Pose 0 is frontal, and poses 1, 2, 3, 4, and 5 are about 12 degrees from the camera optical axis (i.e., from Pose 0), while poses 6, 7, and 8 are about 24 degrees. Also it is shown that poses 1, 2, 4, 5, 6, 8 have tilt variation. We choose poses 0, 4, 8, 7 and plot differences which are calculated between pairs of pixels at 2300 random locations.

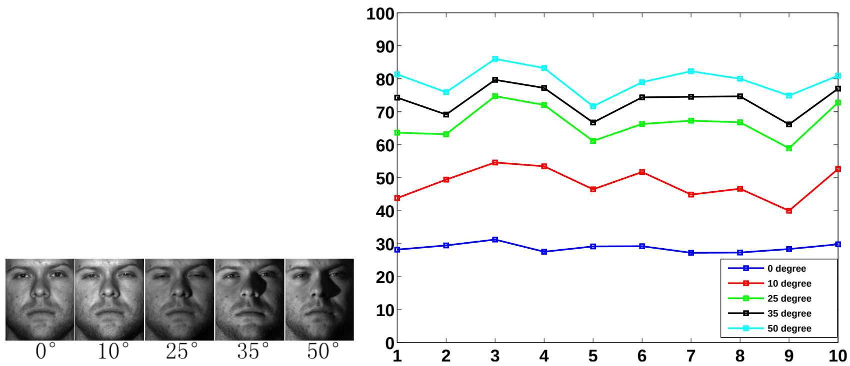


**Fig. 4.** Lighting asymmetry as defect value in the lighting aspect. The 5 curves from bottom to top correspond to the face asymmetry values for the 5 light categories in the left from left to right.

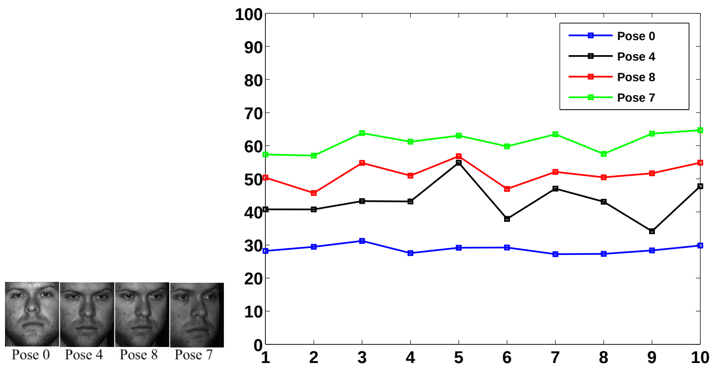


**Fig. 5.** Pose asymmetry as defect value in the pose aspect. The 4 curves from bottom to top correspond to the face asymmetry values for the pose 0, 4, 8, 7.

## 7 Conclusion

We propose approaches for standardization of facial image quality. Aspects of defects are categorized. A two-level quality score, aspect level and overall level is suggested. Then, we develop facial symmetry based methods for the assessment of facial image quality. Local analysis base on LBP histogram is adopted. It can be used to evaluation the quality degradation caused by non-frontal lighting and improper facial pose. Also other face quality metrics is concluded. Experimental results illustrate the concepts, definitions and effectiveness of facial symmetry based quality measures.

## 8 Acknowledgements

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