International Journal of Electrical and Computer Engineering (IJECE)
Vol. 3, No. 6, December 2013, pp. 863~874
ISSN: 2088-8708

Facial Image Verification and Quality Assessment System - FaceIVQA

Omidiora E. O.[1], Olabiyisi S. O.[1], Ojo J. A.[2], Abayomi-Alli A.[3], Abayomi-Alli O.[3] and Erameh K. B.[4]
1Department of Computer Science and Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria
[2]Department of Electronic and Electrical Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria
[3]Department of Computer Science, Federal University of Agriculture, Abeokuta, Nigeria
[4]Department of Electrical and Electronic Engineering, University of Benin, Benin, Nigeria

Article Info

Article history:

Received Oct 3, 2013
Revised Nov 2, 2013
Accepted Nov 12, 2013

Keyword:

Algorithms
Authentication
Facial
Image
Quality
Recognition
Verification

ABSTRACT

Although several techniques have been proposed for predicting biometric system performance using quality values, many of the research works were based on no-reference assessment technique using a single quality attribute measured directly from the data. These techniques have proved to be inappropriate for facial verification scenarios and inefficient because no single quality attribute can sufficient measure the quality of a facial image. In this research work, a facial image verification and quality assessment framework (FaceIVQA) was developed. Different algorithms and methods were implemented in FaceIVQA to extract the faceness, pose, illumination, contrast and similarity quality attributes using an objective full-reference image quality assessment approach. Structured image verification experiments were conducted on the surveillance camera (SCface) database to collect individual quality scores and algorithm matching scores from FaceIVQA using three recognition algorithms namely principal component analysis (PCA), linear discriminant analysis (LDA) and a commercial recognition SDK. FaceIVQA produced accurate and consistent facial image assessment data. The Result shows that it accurately assigns quality scores to probe image samples. The resulting quality score can be assigned to images captured for enrolment or recognition and can be used as an input to quality-driven biometric fusion systems.

Corresponding Author:

Abayomi-Alli A.
Department of Computer Science,
Federal University of Agriculture,
Abeokuta, Ogun State, Nigeria
Email: abayomiallia@unaab.edu.ng

1. INTRODUCTION

Image quality is a characteristic of an image that measures the perceived image degradation; typically, compared to an ideal or perfect image [1]. Imaging systems may introduce some amounts of distortion or artifacts in the signal, so the quality assessment is an important problem. The primary goal of image quality assessment is to supply the quality metrics that can predict perceived image quality automatically. By defining image quality in terms of a deviation from the ideal situation, quality measures become technical in the sense that they can be objectively determined in terms of deviations from the ideal models. Image quality can, however, also be related to the subjective perception of an image, e.g., a human looking at a photograph. Examples are how colors are represented in a black-and-white image, as well as in color images, or that the reduction of image quality from noise depends on how the noise correlates with the information the viewer seeks in the image rather than its overall strength.

Image quality values can be used in different stages of biometric applications, some of these include: enrollment-phase quality assessment, verification/identification quality assessment, prediction of algorithm failure, quality-based adaptation of the processing phase and multimodal biometric fusion [2]-[6].

While steady progress is registered each year in face recognition research, real world deployment of biometric verification systems perform far less than the results obtained in the laboratory. The reason is simple biometric system performance is directly affected by the quality of the images captured in real world and those present in the database. That is, if the quality of the biometric images is poor, the recognition system's performance is certain to be reduced [7].

Variations due to low quality images plaque all biometric systems, such variability is due to a long list of factors which includes facial expressions, illumination conditions, pose, presence or absence of eye glasses and facial hairs, occlusion, aging, e.t.c. [8]. These variations in image quality vary significantly depending on where and when the system operates. [3] Posit that the quality of biometric data is operationally important because it directly influences recognition performance while [9] concluded that a major research area is the study of face recognition over a wide range of quality factors. Although there has been a significant improvement in face recognition performance during the past decade, it is still below acceptable levels for use in many applications [10] [11]. This is because different face recognition algorithms are designed to be robust to particular subsets of these factors. Hence, a high quality image for one algorithm is not necessarily of the same quality for another. Therefore, quality should be learned for a specific face matching algorithm [12]. The performance of a facial recognition algorithm is directly affected by the quality of the facial images captured by the sensor (probe) and the one present in the database (gallery). Although principled quality measures have been developed for fingerprint samples like the NIST Fingerprint image quality (NFIQ), the facial image quality problem still remains open [12]. The knowledge of such biometric image quality prior to recognition can be used to improve the operation and performance of the system.

Several researchers have made attempts to measure biometric system performance using image quality assessment and prediction but many of these research works were based on no-reference quality assessment techniques and the assessment evaluation is usually focused on the biometric samples themselves, thereby using quality measures directly calculated from the data, such as denoising techniques [13], the signal-to-noise-ratio [14], similarity surface analysis [15], modelling recognition similarity scores [6], high frequency components of discrete cosine transformation [16], difference in image intensity [17] and image activity estimation in both horizontal and vertical direction [18]. Contrary to [19] which conclude that no single quality metric can reliably measure performance, all these techniques used only one property of the biometric image to assess quality and measure performance. Secondly, these techniques have proved to be inappropriate for verification scenarios where the performance of a recognition algorithm is a function of the probe image's quality when compared with the gallery image [20].

This paper focuses on developing an image quality feature extraction system for full-reference objective image quality assessment using statistical and geometric features of the facial image. Hence, a facial image verification and quality assessment system (FaceIVQA) was developed to extract selected image quality features that will correlate with the variations in the probe image and the algorithm recognition scores.

2. RESEARCH METHOD

The approach for developing FaceIVQA was based on [20], which concludes that for a verification task, when a probe image i_p is compared against the gallery image i_g of the claimed identity i using recognition algorithm **Ă**, if the probe samples are of uniformly high quality then the probe sample's quality is sufficient to predict algorithm **Ă**'s performance. The matching algorithm **Ă** will produce a recognition score for a given pair of images:

$$\boldsymbol{s_{i_p i_g}} = \breve{A}(\boldsymbol{i_p}, \boldsymbol{i_g}) \tag{1}$$

If the recognition score $s_{i_p i_g}$ is above a predefined threshold, the verification task is considered to be successful. FaceIVQA was developed to combine feature extraction techniques for five quality measures of the face images through an integration of their geometric and statistical information. This approach was aimed at extracting image quality values that is effective and will highly correlate with the recognition matching scores. The concept of similarity as measure of facial quality was introduced because this research study believes that without a suitable conceptualization and measure of true similarity between facial images, a true measure of quality disparity between a probe and gallery image cannot be done in verification scenario.

2.1. FaceIVQA Image Quality Features

The complete FaceIVQA architecture is shown on figure 1. The system will assess the quality of the facial images using five features namely: faceness, pose, contrast, illumination, and similarity. The methods and algorithm for each quality feature is discussed below:

Faceness measure

The faceness measure is a combination of occlusion and distance between the eyes (DBE). The amount of the face region available for recognition is determined by the occlusion from non-cooperative subjects due to objects or accessories (e.g sunglasses, scarf, masks, etc) and the size of the face due to face-to-camera distance (measured as distance between eyes). Thus, this research set out to combine the two qualities as the faceness feature since both is dependent on the amount of the face area that is detected by the algorithm.

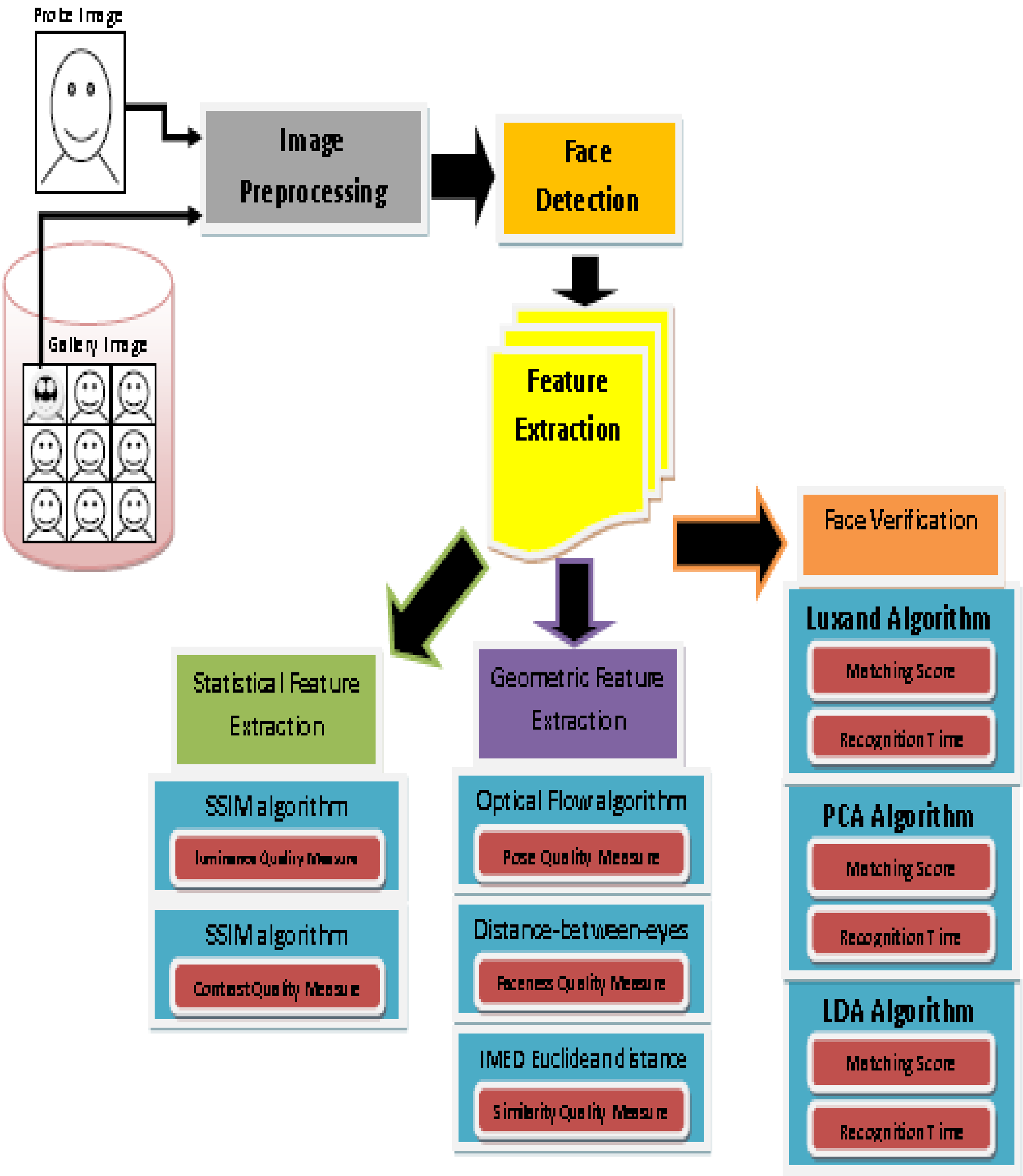

Figure 1. Complete FaceIVQA architecture

The face-to-camera distance is recommended by [21] to be between 1.2–2.5m in a typical photo studio and distance-between-eyes (DBE) to be 120 pixels. DBE is inversely related to the size of the face in an image, thus it can be used as a quality estimate for the subject's distance from the camera [22]. To measure the faceness quality, the face in the probe image is tracked. If a face is not detected then there is no faceness measure and an error message is given. However, if a face is detected then the distance between the eyes (DBE) is obtained with equation 2.

To find the distance between the two eyes (points) whose pixel coordinates are given. Let $LE\ (x_1, y_1)$ and $RE\ (x_2, y_2)$ be the points representing the left and right eyes respectively. From the right angled triangle, the distance between the points LE and RE is given by:

$$DBE = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)}^2 \quad (2)$$

The faceness quality (M_F) in this research is measured as percentage of the distance between the eyes (DBE) of the probe image (i_p) with respect to the standard gallery image (i_g) of that subject in the database.

$$M_F = \frac{DTE_p}{DTE_g}\ x\ 100 \quad (3)$$

Pose measure

Pose is a major covariate that determines the usability of the face image in recognition [23]. The amount of face region available for recognition is directly affected by the subject's pose. A good quality face image may not be useful during recognition due to severe pose variations.

In this research, the optical flow technique proposed by Lucas and Kanade in [24] was adapted with slight modifications from [25] and [26]. The Lucas–Kanade method assumes that the displacement of the image contents between two nearby instants (frames) is small and approximately constant within a neighborhood of the point *p* under consideration.

The local image flow (velocity) vector (V_x, V_y) must satisfy

$$\begin{aligned} I_x(q_1)V_x + I_y(q_1)V_y &= -I_t(q_1) \\ I_x(q_2)V_x + I_y(q_2)V_y &= -I_t(q_2) \\ &\vdots \\ I_x(q_n)V_x + I_y(q_n)V_y &= -I_t(q_n) \end{aligned} \quad (4)$$

Where $q_1, q_2, \ldots, q_n$ are the pixels inside the window, and $I_x(q_i), I_y(q_i), I_t(q_i)$ are the partial derivatives of the image I with respect to position *x*, *y* and time *t*, evaluated at the point q_i and at the current time. These equations can be written in matrix form $Av = b$, where

$$A = \begin{bmatrix} I_x(q_1) & I_y(q_1) \\ I_x(q_2) & I_y(q_2) \\ \vdots & \vdots \\ I_x(q_n) & I_y(q_n) \end{bmatrix}, \quad v = \begin{bmatrix} V_x \\ V_y \end{bmatrix}, \quad \text{and} \quad b = \begin{bmatrix} -I_t(q_1) \\ -I_t(q_2) \\ \vdots \\ -I_t(q_n) \end{bmatrix} \quad (5)$$

Thus the optical flow equation can be assumed to hold for all pixels within a window centered at *p*. In order to track the face, well-textured facial features within the target region which is the standard gallery image is first identified and then the corresponding optical flow in each subject probe image is calculated using a two-frame gradient-based method developed by [24]. The task of matching a face in the standard gallery image (i_g) to a target (probe) image (i_p) in the past frame $i-1$ is generally referred to as a registration problem. Optical flow is a registration method that provides a measure of the apparent motion within sequence of images. Based on the position of the feature points in each image and the position of the feature points (after the tracking process) in the standard image, optical flow vectors were calculated. This measure is referred to in this research approach as the pose measure(M_P).

Modification in this research study to Lucas and Kanade 1981 algorithm were in terms of:

(a) Area of application to image pose measurement
(b) Use of Gaussian error distribution rather than the least squared approach.

(c) Incorporation of textured facial feature extraction for face detection.

Table 1 summarizes the procedure to obtain optical flow vectors for each subject and their corresponding varying probe face images as adapted from [26].

Table 1. Algorithm for obtaining optical the flow vectors.

Input: *face images.*

Let $\boldsymbol{x_{ji}} \in \boldsymbol{R^{m*n}}$ $(\boldsymbol{i = 1, 2, \ldots, M, j = 1, 2, \ldots, N})$ *denote face images.*

M represents the number of images for each person, N represents the number of persons.

Output: *face optical flow* $\boldsymbol{D_{ji}}$ $(\boldsymbol{i = 1, 2, \ldots, M, j = 1, 2, \ldots, N})$.

1: face images are averaged by

$$\boldsymbol{\bar{x}} = \frac{\boldsymbol{1}}{\boldsymbol{MN}} \sum_{\boldsymbol{j=1}}^{\boldsymbol{N}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{M}} \boldsymbol{x_{ji}} \quad (6)$$

2: face images are normalized by subtracting average frame $\boldsymbol{\bar{x}}$.

3: for Each face image $\boldsymbol{x_{ji}}$ *and* $\boldsymbol{x_{jk}}$ *, optical flow do*

4: calculate the optical flow

$$\boldsymbol{D_{ji}} \ (\boldsymbol{i = 1, 2, \ldots, M, j = 1, 2, \ldots, N}).$$

5: end

6: end.

Source: [26]

Where, D_{ji} denote optical flow between face image x_{ji} $(j = 1,2, \ldots, N, i = 1,2, \ldots, M)$ and x_{jk}.

$$M_P = \frac{\|D_{j(k,i)}\|_2}{\|\sum_{i=1}^{M} D_{j(k,i)}\|_2} X \ 100\% \quad (7)$$

Contrast and illumination measure

Structural Similarity index (SSIM) is an image quality metric. SSIM is computed for the image with respect to the reference image. The reference image usually needs to be of perfect quality. This is consistent with the approach of this study hence the SSIM index was used to obtain a quantitative value for two parameters namely uneven illumination (luminance) and contrast quality measure between the standard gallery image (i_g) and the target (probe) image(i_p). SSIM can be used as a benchmark to check the performance of other image processing algorithms [18] and it is an improvement to Universal Image Quality Index (UIQI) proposed by [27]. The SSIM algorithm separates out the similarity measurements into three different components between the two non-negative image signals: Luminance *L(g,p)*, Contrast *C(g,p)* and Structural *S(g,p)* but the structural value is outside the interest of this research.

A useful measure of face image quality is the contrast of the skin area of the face. SSIM determines contrast by the standard deviation of the signal from the two images.

$$C(i_g, i_p) = \frac{(2\sigma_g\sigma_p + C_2)}{(2\sigma_g{}^2 + 2\sigma_p{}^2 + C_2)} \quad (8)$$

Hence, the contrast quality measurement between the standard gallery image i_g and the probe image i_p of the subject in the database is denoted by M_C which is equivalent to $C(i_g, i_p)$ in equation 8.

Variation in illumination conditions poses a significant problem for the face recognition task [28] [29]. Factors such as illumination direction and intensity of the light source can severely alter the appearance of an individual's face and subsequently weaken genuine match scores.

The SSIM index determines the luminance between two images by the mean intensity of their signals.

$$L(i_g, i_p) = \frac{(2\mu_g\mu_p + C_1)}{(2\mu_g{}^2 + 2\mu_p{}^2 + C_1)} \quad (9)$$

Subsequently, uneven illumination quality measure between the standard gallery image (i_g) and the probe image(i_p) of any of the subject in the database is denoted by M_L which is equivalent to $L(i_g, i_p)$ in equation 9.

Similarity measure

Similarity in facial recognition is defined as the Euclidean distance between two face images when represented in a principal component (PCA) feature vector space [30]. This approach is capable of providing a set of generating dimensions that can accurately represent faces. There exist several methods for measuring the distance between images and/or faces; they include tangent distance, generalized Hausdorff distance and Euclidean distance. Among all the image metrics, Euclidean distance is the most commonly used due to its simplicity. However, the traditional Euclidean distance metric suffers from a high sensitivity to small deformation between images and does not take into account the spatial relationship between pixels. Hence, [31] presented the Image Euclidean Distance (IMED) metric which was adopted and incorporated into FaceIVQA for facial similarity measure. The choice of IMED for the similarity measure is based it:

(a) Robustness to small changes between images;
(b) Simplicity of computation;
(c) Ease of incorporation into most of the image recognition techniques such as Radial Basis Function Support Vector Machines (RBF-SVMs), Principal Component Analysis (PCA) and Bayesian similarity.

For an *M* by *N* image in an *MN* dimensional Euclidean space (image space), $e_1, e_2, \ldots, e_{MN}$ will form a coordinate system of the image space, where e_{kN+l} corresponds to an ideal point source with unit intensity at location(k, l). If Image $x = (x^1, x^2, \cdots, x^{MN})$, where x^{kN+l} is the coordinate with respect to e_{kN+l} and the metric coefficients g_{ij}; $i, j = 1,2, \cdots, MN$, are defined as:

$$g_{ij} =< e_i, e_j >= \sqrt{< e_i, e_j >} \sqrt{< e_j, e_i >} \cdot \cos\theta_{ij} \tag{10}$$

Where <,> is the scalar product and θ_{ij} is the angle between e_i and e_j. The Euclidean distance of two images x, y is written by:

$$d_E^2(x, y) = \sum_{i,j=1}^{MN} g_{ij}(x^i - y^i)(x^j - y^j) = (x - y)^T G(x - y) \tag{11}$$

The symmetric matrix $G = (g_{ij})_{MNxMN}$ will be referred to as metric matrix. For images of fixed size *M* by *N*, every *MN*th order symmetric and positive definite matrix G induces a Euclidean distance. If the metric coefficients depend properly on the pixel distances, the obtained Euclidean distance is insensitive to small deformation. The appealing properties are based on its satisfying three conditions [31], which states that:

(a) The metric coefficient g_{ij} depends on the distance between pixels P_i and P_j. Let *f* represent this dependency;
(b) *f* is continuous, and g_{ij} decreases monotonically as $|P_i - P_j|$ increases;
(c) The functional dependency *f* is a universal function. That is, it is not for images of a particular size or resolution.

Finally, the similarity measure (M_S) is defined as a facial image quality measure in terms of the similarity between the standard gallery image (i_g) and the probe image (i_p) of a particular subject in the database.

$$\text{Ms}(g, p) = [(g - p)^T\ G(g - p)]^{1/2}, \text{ and } G = (g_{ij})_{MNxMN} \tag{12}$$

2.2. Overall Quality Score Fusion

An overall-normalized score is obtained by the fusion of the normalized quality scores (Q') using the Sum rule which is simply the sum of all normalized quality measure scores. Thus a composite score known as the overall quality score(OQS) is derived as:

$$OQS = \sum_{i=1}^{N} Q' \tag{13}$$

This overall quality score (OQS) is expected to be predictive of the contribution of the probe image to the performance of the recognition algorithms used.

2.3. FaceIVQA Recognition Algorithms

FaceIVQA combines three recognition algorithms and returns their recognition scores simultaneously. The face recognition algorithms used in FaceIVQA are PCA [30], LDA [32] and a commercial recognition engine [33] luxand.

2.4. Facial Verification Experiement

A facial image verification experiment was conducted on FaceIVQA and the face authentication protocol proposed by [34] was adopted. Following the day-time and night-time test scenarios 2,990 images from all 130 subjects in the Scface surveillance camera database [29] was utilized. Frontal mug shots of each subject (130) will represent the gallery of known high quality images while the probe database for verification trials will include the 130 high quality images of each subject and their other (22x130) images with considerable session and quality variations. Each subject was enrolled with a single high quality mug shot image for the gallery database, probe images were taken from the 8 surveillance cameras at 3 different distances: close, medium and far. Each subject's gallery image was compared (verification) with the 23 probe images of varying quality.

3. RESULTS AND ANALYSIS

FaceIVQA was successfully implemented. When tested and used for the experiment it was observed to perform the following tasks accurately:

(a) Accept a probe or gallery image from a file or folder directory;
(b) Take live images from the computer webcam;
(c) Detect face in images and carry out recognition;
(d) Extract selected quality features from the probe image and save the data on a table in database;
(e) Output recognition results or error messages.

Table 2 summaries the result of the verification experiment with FaceIVQA through the performance of the three recognition algorithms. The result was generally poor across the three recognition algorithms. This is consistent with the results reported by [29] and [35] whose evaluations were based on PCA and Mace correlation filter algorithm respectively. It proved that the low quality of probe images from the Scface database provided a very difficult test to the recognition algorithms implemented in FaceIVQA also. Luxand SDK had 2,718 false reject (FR) while PCA and LDA had 2,850 respectively. Although PCA and LDA seems to have the same performance, PCA had slightly higher mean recognition score (MRS) than LDA. Fifty-four (54) images failed-to-acquire (FTA) because the face detection algorithm could not detect the face in the images due to extremely low quality.

Table 2. Summary of verification experiment with recognition algorithm's performance

Algorithm	SR	FTA	TA	FR	FA	TR	MRS
Luxand SDK	2,936	54	217	2,718	0	0	0.083
PCA	2,936	54	130	2,805	0	0	0.072
LDA	2,936	54	130	2,805	0	0	0.067

** Decision threshold = 0.4 SR = Successful Recognition
TA = True Accept FTA = Failure to Acquire (failure to detect face in image)
FR = False Reject FA = False Accept
TR = True Reject MRS = Mean Recognition Score

Figures 2- 4 shows other experimental results such as the effect of varying camera quality on algorithm performance, the effect of face-to-camera distance on algorithm performance and the effect of face-to-camera distance on average recognition time. In order to reduce the number of false rejects (FR), the recognition threshold was set at 0.4 due to the very low quality of the probe images.

Figure 2 shows that camera 7 had the highest number of failure-to-acquire (FTA) followed by camera 6 while cameras 3, 5 and 9 (frontal day) had none. It was observed on figure 3 that Face-to-camera distance had a significant effect on performance especially at distance 1 (4.2m) but at distance 2 (2.6m) the performance improved. This is consistent with the recommendations for face image data on conditions for taking pictures in [21]. In addition to this, camera 7 and camera 1 frontal-day returns the highest and lowest average recognition time of 5.05 and 1.82 seconds respectively as shown on figure 4. All these result are consistent with those reported by [29] [35].

Table 3 shows that pose image quality (QP) had the highest correlation coefficient of R= 0.936 with Overall Quality Scores (OQS) while on table 4 similarity quality (QS) had the highest correlation coefficient of R=0.855 with Algorithm Matching Scores (AMS). The luminance quality (QL) and contrast quality (QC) had the least correlation coefficient for OQS and AMS.

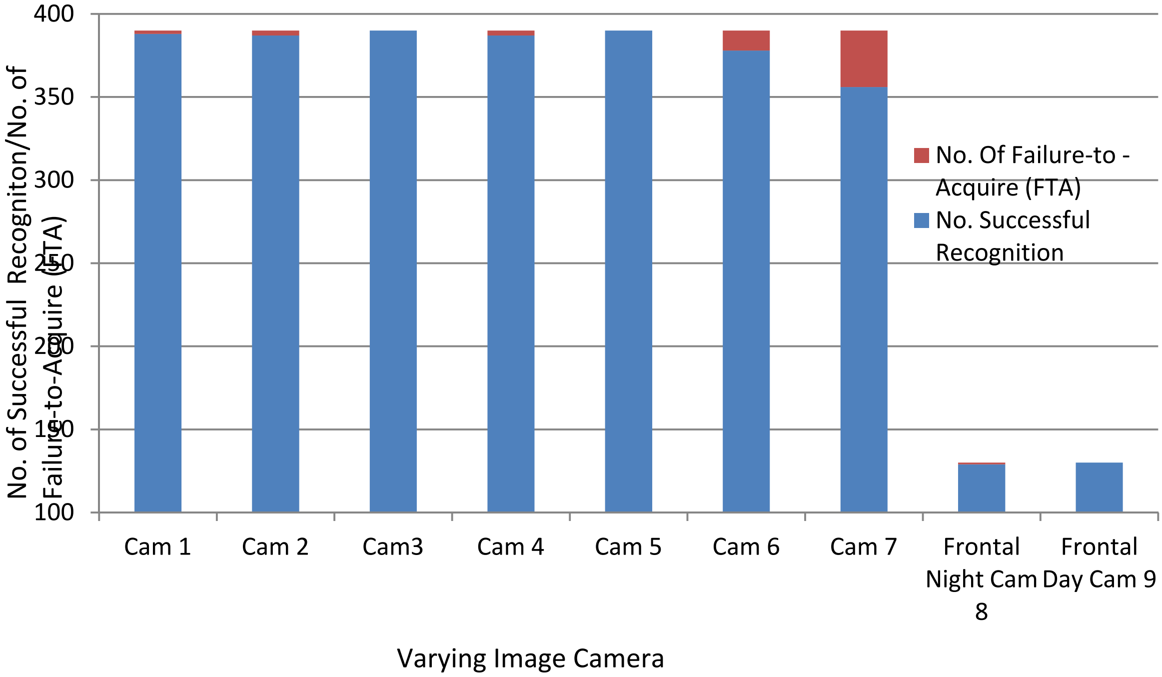

Figure 2. Graph showing the effect of varying camera quality on algorithm performance

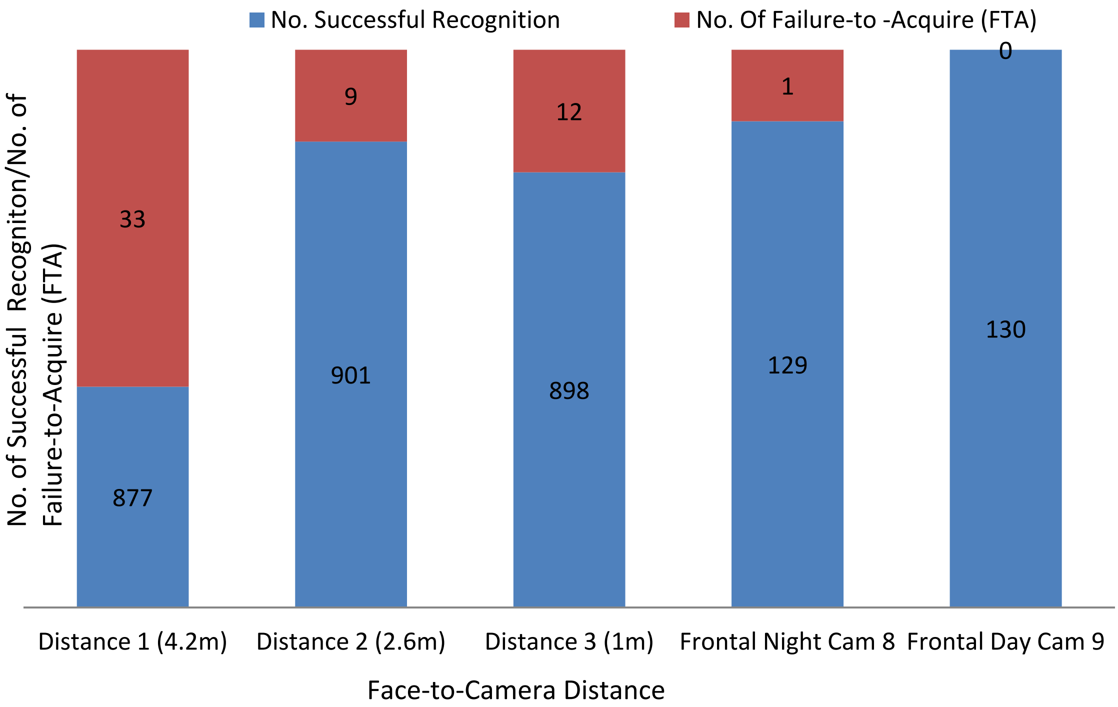

Figure 3. Graph showing the effect of face-to-camera distance on algorithm performance

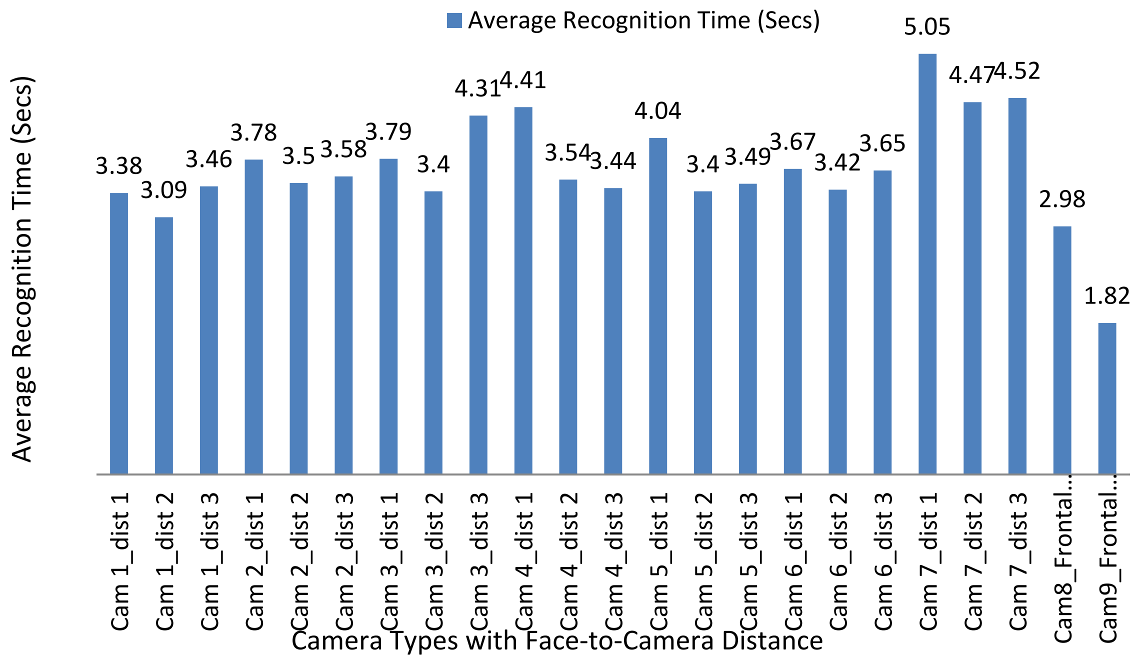

Figure 4. Graph showing the effect of face-to-camera distance on average recognition time

Table 3. Correlation of overall quality scores (OQS) with individual image quality scores

		QP	QF	QL	QC	QS
OQS	Pearson Correlation	0.936**	0.840**	0.266**	0.262**	0.670**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000
	N	2936	2936	2936	2936	2936

** Correlation is significant at the 0.01 level (2-tailed)

Table 4. Correlation of algorithm matching scores (AMS) with individual image quality scores

		QP	QF	QL	QC	QS
AMS	Pearson Correlation	0.599**	0.379**	0.168**	0.048**	0.855**
	Sig. (2-tailed)	0.000	0.000	0.000	0.009	0.000
	N	2936	2936	2936	2936	2936

** Correlation is significant at the 0.01 level (2-tailed)

The overall image quality scores (OQS) was categorized into five quality classes as shown on table 5 and each image verification and quality assessment (IVQA) number is a prediction of the recognition algorithm's performance and the contribution of the probe image to the overall performance of the biometric facial recognition system. The implication of this categorization is that 1,718 and 1,020 images within the "unacceptable" and "poor" category was discarded from the experimental database. That is 93.3% (2,738) of the images was removed and only 6.7% (198) was left to form a new database.

Table 5. Categorization of database probe images across quality scales

Overall quality Score range	IVQA number	Description
0.9 - 1.0	5	Excellent
0.80 – 0.89	4	Good
0.60 – 0.79	3	Acceptable
0.40- 0.59	2	Poor
0 – 0.39	1	Unacceptable

The new database now contains images of acceptable (55), good (13) or excellent quality (130). Hence, the performance of the biometric recognition system was greatly improved on the new database with 100% accuracy of 198 true accept (TA), zero false reject (FR) and a mean recognition score (MRS) of 0.76 across the three recognition algorithm as shown on table 6.

Table 6. Summary of recognition algorithm's performance on the new database.

Algorithm	SR	FTA	TA	FR	FA	TR	MRS
Luxand SDK	198	0	198	0	0	0	0.88
PCA	198	0	198	0	0	0	0.72
LDA	198	0	198	0	0	0	0.67

** Decision threshold = 0.6

4. CONCLUSION

This paper describes the development and implementation of different methods to measure the quality of facial images using the geometric and statistical features of the face through a proposed facial image verification and quality assessment system (FaceIVQA). The quality of the facial image is expressed by implementing measures and algorithms for five image quality attributes such as faceness, pose, illumination, contrast, and similarity. The full-reference objective quality measurement technique for was employed in FaceIVQA. The distance between the eyes (DBE) and the amount of face area detected by the algorithm was used to measure the faceness quality, a modified and adapted optical flow technique was used for the pose quality, structural similarity index (SSIM) was used for uneven illumination and contrast quality measure while the image Euclidean distance (IMED) metric was used for the similarity quality measure.

The Results of evaluating FaceIVQA shows that it accurately assigns quality scores to probe image samples. These individual quality scores have shown both to be highly correlated with each other and also predictive of the algorithm's matching scores (AMS). They disclosed a correlation between different quality metrics and face recognition performance leading to the possible incorporation of quality measures in a face performance prediction scheme to reduce the negative effect of poor quality samples in face databases. A means of quantifying match performance was developed, the result shows that normalized disparate quality attribute scores predicts match performance, and combines multiple quality measures into a single score (OQS). The resulting quality score can be assigned to images captured for enrollment or recognition and can be used as an input to quality-driven biometric fusion systems.

ACKNOWLEDGEMENTS

The authors wish to thank Professors Mislav Grgic, Kresimir Delac and Sonja Grgic for the release of the SCFace -surveillance cameras face database. Special thanks to the Luxand incorporation for releasing the evaluation version of the Luxand SDK 4.0 library.

REFERENCES

[1] DP D'Amato. "Best practices for taking face photographs and face image quality Metrics". *NIST Biometric Quality Workshop*. 2006.
[2] WJ Scheirer, et al., "*Predicting biometric facial recognition failure with similarity surfaces and support vector machines*". in Proc. of IEEE Computer Society Workshop on Biometrics, in association with CVPR. 2008.
[3] P Grother and E Tabassi. "Performance of Biometric Quality Measures". *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2007; 29(4): 531-543.
[4] MT Chan, et al. "*Incorporating quality metrics in multimodal biometric fusion*". in Proc. of IEEE Computer Society Workshop on Biometrics, in association with CVPR. 2006: 67-79.
[5] K Nandakumar, et al. "Quality-based score level fusion in multibiometric systems". *In International Conference on Pattern Recognition*. 2006.
[6] P Wang, et al. "*Modeling and predicting face recognition system performance based on analysis of similarity scores*". in Proc. of IEEE Transactions on Pattern Analysis and Machine Intelligence. 2007; 29(4): 665–670.
[7] E Tabassi. "NIST Fingerprint image quality and relation to PIV". *NIST Image Group Technical report*. 2005.
[8] F Perronnin. "A Probabilistic Model of Face Mapping Applied to Person Recognition". *An Unpublished Ph.D Thesis submitted to the Department of Multi-Media Communications*, École Polytechnique Federale Lausanne (EPFL), France. 2004.
[9] F Hua, et al. "Impact of Out-of-Focus Blur on Face Recognition Performance Based on Modular Transfer Function". *International Conference on Biometrics'12*. 2012 256-272.
[10] PJ Phillips, et al. "Face Recognition Vendor Test 2002". *Evaluation Report, Tech. Report NISTIR 6965*. 2003.

[11] SZ Li and AK Jain (Eds.). "Handbook of Face Recognition". Springer-Verlag, Secaucus, New York, USA.
[12] N Ozay, et al. "*Improving face recognition with a quality-based probabilistic framework*". in Proc. Computer Vision and Pattern Recognition (CVPR) conference 2009.
[13] S Bharadwaj, et al. "*Quality assessment based denoising to improve face recognition performance*". Proc. of IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). 2011: 140-145.
[14] Y Du, et al. "Feature correlation evaluation approach for iris feature quality measure". *Signal Processing*. 2010; 90: 1176-1187.
[15] WJ Scheirer, et al. "*Predicting biometric facial recognition failure with similarity surfaces and support vector machines*". in Proc. of IEEE Computer Society Workshop on Biometrics, in association with CVPR, 2008.
[16] X Wang and X Tang. "A unified framework for subspace face recognition". *IEEE Trans. Pattern Anal. Mach. Intell*. 2004; 26(9): 1222–1232.
[17] P Marziliano. "A no-reference perceptual blur metric". *ICIP*. 2004: 57–60.
[18] Z Wang, et al. "Image quality assessment: from error visibility to structural similarity". *IEEE Transactions on Image Processing*. 2004; 13(4): 600–612.
[19] JS Doyle. "Quality Metrics for Biometrics". MSc. Thesis, Department of Computer Science and Engineering, University of Notre Dame, USA, 2011.
[20] E Tabassi, et al. "Fingerprint Image Quality". *Technical Report NISTIR 7151*. 2004.
[21] ISO/IEC. "Proposed Draft Amendment to ISO/IEC 19794-5 Face Image Data on Conditions for Taking Pictures". *ISO/IEC JTC 1/SC 37 N 1511*, 2006.
[22] X Gao, et al. "Standardization of Face Image Quality". in: SW Lee and SZ Li (Eds.), *ICB' 200*7, Springer, Heidelberg, LNCS 4642. 2007: 242-251.
[23] G Givens, et al. "How features of the human face affect recognition: a statistical comparison of three face recognition algorithms". *CVPR*. 2004; 2(2): 76-89.
[24] B Lucas, and T Kanade. "*An Iterative Image Registration Technique with an Application to Stereo Vision*". Proc. of 7th International Joint Conference on Artificial Intelligence (IJCAI). 1981: 674-679.
[25] A Besinger, et al. "Optical flow based analyses to detect emotion from human facial image data". *Expert Systems with Applications'2010*. 2010; 5(63): 1-6.
[26] XH Chen and CZ Li. "*Image quality assessment model based on features and applications in face recognition*". in Proc. IEEE ICSPCC. 2011: 1-4.
[27] Z Wang and AC Bovik. "*A universal image quality index*". in Proc. of IEEE Signal Proc. Letters. 2002; 9: 81-84.
[28] Y Adini, et al. "Face Recognition: The problem of Compensating for Changes in Illumination Direction". *IEEE Trans. on PAMI*. 1997; 19: 721-732.
[29] M Grgic, et al., "SCface-Surveillance Cameras Face Database". *Multimed Tools Application*. 2011; 51: 863–879.
[30] M Kirby and L Sirovich. "Application of the Karhunen-loeve procedure for the characterization of human faces". *IEEE Transactions on PAMI*. 1990; 12(1): 103-108.
[31] L Wang. "On the Euclidean Distance of Images". *IEEE Transactions on PAMI*. 2005; 27(8): 1334-1339.
[32] RA Fisher. "The statistical utilization of multiple measurements". *Annals of Eugenics*. 1938; 8: 376-386.
[33] Luxand. "Detect and Recognize Faces with Luxand FaceSDK". *Luxand Incorporation,* USA, Available online at http://www.luxand.com/facesdk/, Accessed on 23rd August, 2013.
[34] R Wallace, et al. "*Inter-session Variability Modelling and Joint Factor Analysis for Face Authentication*". in Proc. International Joint Conference on Biometrics (IJCB), 2011.
[35] EO Omidiora, et al. "MACE Correlation Filter Algorithm for Face Verification in Surveillance Scenario". *IJCSE*, USA. 2013; 13(1): 6-15.

BIOGRAPHIES OF AUTHORS

Omidiora, E. O. received the B.Eng degree in Computer Engineering, Obafemi Awolowo University, Ile-Ife in 1992, M.Sc. Computer Science, University of Lagos, Lagos in 1998 and Ph.D Computer Science, Ladoke Akintola University of Technology, Ogbomoso, Nigeria in 2006. He is currently a Professor of Computer Engineering at the Department of Computer Science and Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria. He has published in reputable journals and learned conferences. Professor Omidiora is a full member of Computer Professional (Registration) Council of Nigeria (CPN) and a registered engineer by COREN. His research interests are in biometric algorithm and application, image processing and microprocessor based system.

Olabiyisi, S. O. received his B. Tech., M. Tech and Ph.D degrees in Mathematics from Ladoke Akintola University of Technology, Ogbomoso, Nigeria, in 1999, 2002 and 2006 respectively. He also received M.Sc. degree in Computer Science from University of Ibadan, Ibadan, Nigeria in 2003. He is currently an Associate Professor in the Department of Computer Science and Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria. He has published in reputable journals and learned conferences. Dr Olabiyisi is a full member of Computer Professional (Registration) Council of Nigeria (CPN). His research interests are in computational mathematics, theoretical computer science, information systems and performance modelling and simulation.

OJO, J. A. received a B.Tech degree in Electronic and Electrical Engineering from Ladoke Akintola University of Technology (LAUTECH), Ogbomoso, Nigeria in 1998, M.Sc. in the same field from University of Lagos, Nigeria in 2003 and Ph.D from LAUTECH in 2011. He is presently a senior Lecturer in the Department of Electronic and Electrical Engineering in the same institution; he is a member of the Nigerian Society of Engineers (NSE) and a registered engineer by COREN. His research interest includes biometrics, security and surveillance systems, e-health and mobile-health biomedical engineering and image pre-processing techniques.

Abayomi-Alli, A. obtained his B.Tech Degree in Computer Engineering from Ladoke Akintola University of Technology (LAUTECH), Ogbomoso in 2005, M.Sc. Computer Science from the University of Ibadan, Nigeria in the 2009. He is a registered engineer by COREN and a chartered information technology practitioneer by the Computer Professional Registration Council of Nigeria (CPN). His current research interests include biometrics, image quality assessment and machine learning. He is currently working towards completing his Ph.D. degree in Computer Science.

Abayomi-Alli, **O**. obtained a B.Sc. degree in Electronics and Computer Engineering from the Lagos State University (LASU), Lagos State, Nigeria in 2008. She is presently working towards her M.Sc. Degree in Comptuer Science from the Federal University of Agricultrue, Abeokuta, Nigeria. Her research interest includes information security, image processing and e-learning system.

Erameh, **K. B**. graduated with a first class Degree in Computer Engineering from the Department of Electrical and Computer Engineering at Igbinedion University Okada, Nigeria in 2011. She is presently a graduate assistant on post graduate studies at the University of Benin, Nigeria. Her research interest includes telecommunication systems and image/signal processing.