Enhanced Face Verification and Image Quality Assessment Scheme Using Modified Optical Flow Technique

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***Abstract*—Biometric applications are faced with enormous performance challenges due to submission of low quality facial images. Previous research studies used only one property of the face or one feature within the recognition process to assess facial image quality, others employed expensive and cumbersome partial or no-reference subjective quality assessment protocols. In this work, an enhanced face verification and image quality assessment (FVIQA) scheme for predicting images in low quality surveillance scenarios was developed. Pose, faceness, illumination, contrast and similarity quality attributes were extracted using an objective full-reference quality assessment protocol but emphasis was placed on the modified Lucas and Kanade's algorithm for measuring pose displacement between a pair of probe and gallery image from same subject. Structured image verification experiments were conducted on the surveillance camera (SCface) database to collect individual quality scores and algorithm matching scores from FVIQA using three recognition algorithms namely principal component analysis (PCA), linear discriminant analysis (LDA) and a commercial recognition SDK. Results from the experiments were improved and shows consistency with previous studies. FVIQA accurately assigns quality scores to probe image samples and the quality scores highly correlate with the algorithms matching scores. The pose quality scores (QP) was significantly improved with a correlation coefficient (R) of 0.982 and 0.839 with OQS and AMS respectively. In future FVIQA could be extended to a larger set of assessment and enhancement techniques such as age, color neutrality, exposure, out-of-focus and blur.**

***Index Terms*—Algorithm, Authentication, Biometric, Facial image, Quality-assessment, Recognition, Verification.**

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I. INTRODUCTION

Facial recognition is the identification of humans by the unique characteristics of their faces [1]. It is a vividly researched area of computer vision, pattern recognition and biometrics [2] [3] [4] [5]. It is a very important part of our daily lives and its research interest is currently on the rise [6]. Biometric systems have to deal with real world uncontrolled and dynamic conditions [7] [8]. Thus they are plagued with several intrinsic and extrinsic variations that directly affect their recognition performance. Variations due to low quality images plaque all biometric systems [9].

Image quality is a characteristic of an image that measures the perceived image degradation; typically, compared to an ideal or perfect image [10]. Imaging systems usually introduce certain amounts of distortion or artifacts in the signals, this makes quality assessment is an important problem. Image quality assessment is primarily to supply the quality metrics that can predict perceived image quality automatically. Thus, 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. Hence, variations in image quality vary significantly depending on where and when the system operates. There has been a significant improvement in face recognition performance during the past years but it is still below acceptable levels for use in many applications [11].

A lot of researchers have proposed and reported results claiming to solve the biometric system performance prediction problem using facial image quality but none has been able to solve the problem efficiently and completely in all settings. The reason is a lot of the proposed techniques in literature used only one property of the face or one feature within the recognition process to assess facial image quality. This is contrary to [12] which concluded that no single quality metric can reliably measure biometric system 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 [13].

Multiple facial features has been considered by some researchers like [14] that proposed the first overall quality assessment scheme for facial images based on statistical learning. The results from the research were significantly more consistent with the human perception when compared to previous studies. However, the subjective quality assessment protocol used has been reported as cumbersome and expensive to implement by several researchers including [15]. Thus obtaining objective quality scores is a preferred option that will eliminate the need for expensive subjective studies [16].

This study propose a facial image verification and quality assessment scheme that measures five image quality attributes such as faceness, pose, illumination, contrast, and similarity for predicting facial recognition and image quality scores.

II. LITERATURE REVIEW

A. Problems of face recognition

In biometrics, the distortion of biometric template data comes from two main sources: intra-user variability and the changes in acquisition conditions. Face recognition also faces some issues inherent to these problem definitions such as hardware constraints, acquisition and environmental conditions. Human face appearance has potentially very large intra-subject variation due to 3-D head pose, facial expression, occlusion due to other objects or accessories, facial hair, aging, etc. Although there is also a problem of inter-user variability but the variations are small due to the similarity of individual appearances. [17] Showed that the difference in face images of the same person due to severe lighting variation could be more significant than the difference in face images of different persons. Pose variation is one of the major sources of performance degradation in face recognition [4]. The face is a 3D object that appears differently whenever the direction of the face image changes. Thus, images taken at two different viewpoints of the same subject (intra-user variation) may appear more different from two images taken from the same viewpoint for two different subjects (inter-user variation) [7].

The accuracy of facial recognition systems (FRS) drops significantly under certain enrollment, verification, and identification conditions. FRS is especially ineffective when the environmental condition of the database image is different from that of the test image. On the other hand, when users are enrolled in one location and verified in another. Factors such as shadows and glare, face -to-camera distance, direct and ambient lighting, angle of acquisition, camera quality and background composition can significantly reduce performance accuracy. Reduction in accuracy is strongly reflected when terrorists or fraudsters beat identification systems due to different acquisition conditions of probe and gallery image pair. Alternatively, authorized users are being incorrectly rejected by the authentication systems [7].

B. Pose variation

Images of a face vary due to the relative camera-face pose (frontal, 45 degree, profile, upside down), and some facial features such as an eye or the nose may become partially or wholly occluded. One method that has been widely used for pose measurement between images is the optical flow technique proposed by [18]. It has been modified by several researchers over time such as [19] and [20]. [18] Assumed that the displacement of the image contents between two nearby instants (frames) is small and approximately constant within a neighborhood of point p under consideration. Thus the optical flow equation is 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 also developed by [18]. 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. Chen and Liadopted the Lucas and Kanade's technique to measure pose displacement between several images in a database by generating noisy image scores. The algorithm is given below [20]:

Where, D_{ji}denote optical flow between face image $x_{ji}(j = 1,2,\dots,N, i = 1,2,\dots,M)$and x_{jk}.
Input: face images
Let $x_{ji} \epsilon R^{m*n}(i = 1,2,,M, j = 1,2,,N)$denote face images
M = images for each person, N =Number of persons
Output: face optical flow $D_{ji}(i = 1,2,\dots,M , j = 1,2,\dots,N)$.

1. Face images are averaged by
$$\bar{x} = \frac{1}{MN}\sum_{j=1}^{N}\sum_{i=1}^{M} x_{ji} \quad (1)$$
2. images are normalized by subtracting average frame$\bar{x}$.
3. ***for*** *Each face image $x_{ji}$and x_{jk}, optical flow* ***do***
4. Calculate the optical flow
$$D_{ji}(i = 1,2,\dots,M , j = 1,2,\dots,N) \quad (2)$$
5. ***end***

End.

Other significant variations that affect recognition system are lighting variation, occlusion, expression, age variation, contrast, blur, color, etc.

III. RESEARCH METHODOLOGY

A. Research Approach

In this research work, an enhanced face verification and image quality assessment (FVIQA) scheme was proposed and developed. The scheme is an improved modification to the FaceIVQA framework in [21]. FVIQA employs an objective full-reference feature extraction of facial images in database for image quality assessment. The developed scheme was designed to extract the faceness, pose, illumination, contrast, and similarity measures of facial images with reference to their high quality gallery pair.

B. Data Acquisition

The primary data used in this work was collected from the verification experiments using the developed FVIQA scheme; other secondary data sources include the SCface database (training and testing dataset) and a black face surveillance camera (BFSC) database (target dataset) which was collected partly for this work.

The face authentication protocol proposed by [22] was adopted for this research because it models true surveillance scenarios. The day-time and night-time test scenarios were followed strictly resulting in the use of 2,990 images from the surveillance camera (SCface) database by [11]. Frontal mug shots of each one hundred and thirty (130) subjects represent the gallery of known high quality images while the probe database for verification trials include the high quality images of each subject and their twenty-two (22) images with considerable session and quality variations. The database was divided into two subsets namely training and testing datasets. Images of ninety-one subjects (1–91) were allocated to the training dataset while thirty-nine (92–130) were allocated to the test dataset. These represents the general 70:30% data split for training and testing data. Each subject was enrolled with a single high quality mug shot image for the gallery database, probe images were taken from the eight surveillance cameras at three different distances: 1m, 2.6m and 4.2m respectively. Each subject's gallery image was compared (verification) with twenty-three images of varying qualities including the twenty-two probe images and the subject's high quality gallery image. At the end 2,093 training and 897 testing verification trials were conducted.

C. Face Verification and Image Quality Assessment Scheme

The approach for developing FaceIVQA framework in [21] was based on the conclusion in [13] 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 algorithmĂ, if the probe samples are of uniformly high quality then the probe sample's quality is sufficient to predict algorithmĂ's performance.

The scheme was developed to combine feature extraction techniques for five facial quality measures such as pose, faceness, illumination, contrast and similarity. This approach was aimed at extracting image quality values that are effective and will highly correlate with the recognition matching scores. The concept of similarity as a measure of facial quality was introduced because this study believes that a true measure of quality disparity between a probe and gallery image cannot be done in verification scenario without a suitable conceptualization and measure of true similarity between facial images.

FVIQA accepts a low quality probe image from the file, folder or computer's webcam. It compares the probe image with the high quality gallery image and continues with the face recognition steps such as image pre-processing, face detection, feature extraction before entering the face verification and quality assessment part. The scheme consists of two modules namely Face verification and Quality assessment. The algorithm FVIQA is shown below:

Input: face images (gallery and probe).
1. Image Pre-processing
2. Face Detection
   If *face area is detected* ***Then*** *proceed to 4*
   Else *Print error message "Face not detected, re-submit image"*
3. Feature Extraction
4. Face Verification
   Generate templates
   Compare templates
   Output AMS (%)
   Output Recognition Time (seconds)
   If *algorithm matching score (AMS) ≥ Threshold* ***Then***
   Declare match "image is verified"
   Else *"image is not verified"*
5. Quality Assessment
   Extract facial quality scores (Q_F, Q_P, Q_C, Q_L, Q_S)
   Geometric {Similarity, Pose and Faceness}
   Statistical {Luminance and Contrast}
   Data Pre-processing (Q_F, Q_P, Q_C, Q_L, Q_S)
6. Score normalization
   Decimal Scaling: $Q' = \frac{Q}{10^n}$, n $=\log_{10} Max$ (Q_K) (3)
7. Fusion of normalized scores
   sum rule: $OQS = \sum_{i=1}^{N} Q'$ (4)
   If *algorithm matching score (OQS) ≥ Threshold* ***Then***
   Accept image "acceptable image quality"
   Else *"submit image of higher IVQA number"*

Output: IVQA number

The methods for extracting the faceness, illumination, contrast and similarity quality features were the same as in [21] except for pose.

D. Pose measure

At the feature extraction stage of the scheme, the geometric values of some feature points on the faces from the standard and probe images were extracted. The values for these feature points are their equivalent x and y pixel coordinates.

These feature points includes centre of left eye (LE), centre of right eye (RE), nose tip (NT), centre of mouth (CM) and chin tip (CT). Based on the position of the feature points in the probe image and the position of the feature points (after the tracking process) in the standard image, optical flow vectors were calculated and a pose score allocated.

[20]Developed an algorithm for measuring pose displacement between several images in a database using modified [18] optical flow vectors. The algorithm was further modified to meet this study objective which is to generate pose measure between a standard gallery image and a low quality probe image of the same subject in database. The modified algorithm for obtaining optical flow vectors between a standard image and probe image of same subject is shown on below:

Input: face images (gallery and probe).
Let $x_i \epsilon X_1^m (i = 1,2,\dots,M)$ denote probe images.
M represents the number of images for the subject in the probe dataset.
G represents the subject's gallery image.
Begin
1. Acquire the detected facial image region
2. Extract the location of the feature points on template G (gallery) and P (probe)
3. ***for*** (every frame F) in template G and P ***do***
   a) get rectified image using the pose parameters of G
   b) face images are averaged by
   $$\bar{x} = \frac{1}{PG}\sum_{j=1}^{P}\sum_{i=1}^{G} x_{ji} \quad (5)$$
Face images are normalized by subtracting average frame $\bar{x}$ from G.
Calculate similarity map of image G and P
end
4. Calculate the optical flow D_{ji}
   $$D_{ji}(pi = 1,2,\dots,M\ , gj = 1,2,\dots,N) \quad (6)$$
5. Find the best match in the similarity map

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6. Calculate template displacement and generate normalized pose score (Mp)

End.

Where, D_{ji}denote optical flow between face image x_{pi}andx_{gj}.

$$M_P = \frac{\|D_{j(g,P)}\|_2}{\|\sum_{i=1}^{M} D_{j(g,p)}\|_2} X\ 100\% \qquad (7)$$

E. Overall quality score fusion

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

$$OQS = \sum_{i=1}^{N} Q' \qquad (8)$$

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.

F. Recognition algorithms and Experiment

A statistical comparison of three facial recognition algorithms was conducted. The evaluated algorithms are Luxand FaceSDK [23], Principal component analysis (PCA) [24] [25] and Linear discriminant analysis (LDA) [26]. In order to reduce the number of false rejects (FR), 0.4 was used as the recognition threshold due to the low quality of the probe images. A facial image verification experiment was conducted on the image datasets using FVIQA and the authentication protocol was based [22].

IV. RESULTS AND DISCUSSIONS

Table I summaries the result of the verification experiment with FVIQA through the performance of the three recognition algorithms. The result was consistently low across the three recognition algorithms. This is consistent with the results reported by [11] and [27] whose evaluations were based on PCA and Mace correlation filter algorithm respectively. This proved that the low quality of SCface probe images provided a very difficult test to the recognition algorithms implemented in FVIQA, [11] [21] and [27].

TABLE I
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	0.091
PCA	2,936	54	130	2,805	0	0	0.088
LDA	2,936	54	130	2,805	0	0	0.075

** Decision threshold = 0.4

Key:
FTA = Failure to Acquire (failure to detect a face in image)
SR = Successful Recognition   TA = True Accept
FR = False Reject   FA = False Accept
TR = True Reject   MRS = Mean Recognition Score

Luxand SDK had 2,718 false reject (FR) while PCA and LDA had 2,850 respectively. Although PCA and LDA seems to have close performance their mean recognition score (MRS) is slightly different. Fifty-four (54) images failed-to-acquire (FTA) because the face detection algorithm could not detect the face in the images due to extreme low quality.

Figures 1-3 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.

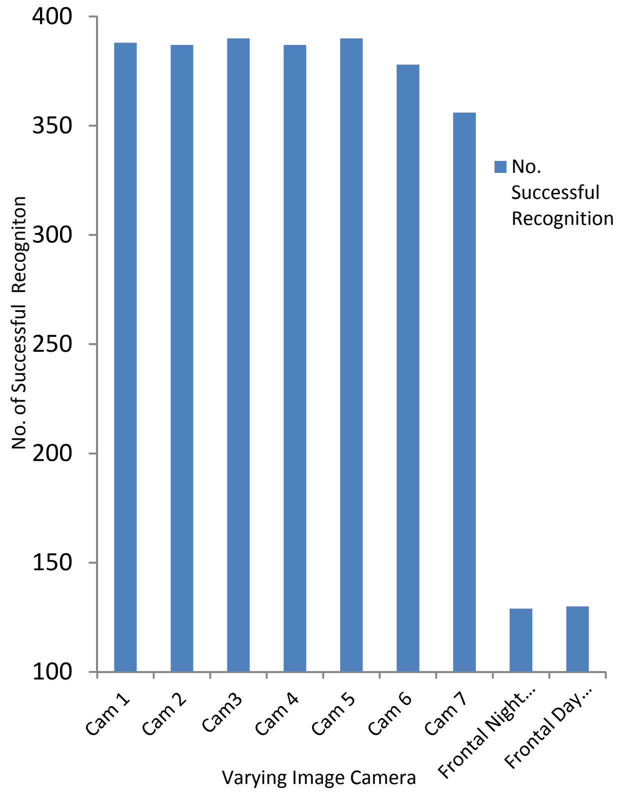

Fig. 1. Graph showing the effect of varying camera quality on algorithm performance

Figure 1 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 2 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 was seen to improve. These observations were consistent with the recommendations in [28] that stated the conditions for taking pictures and image data.

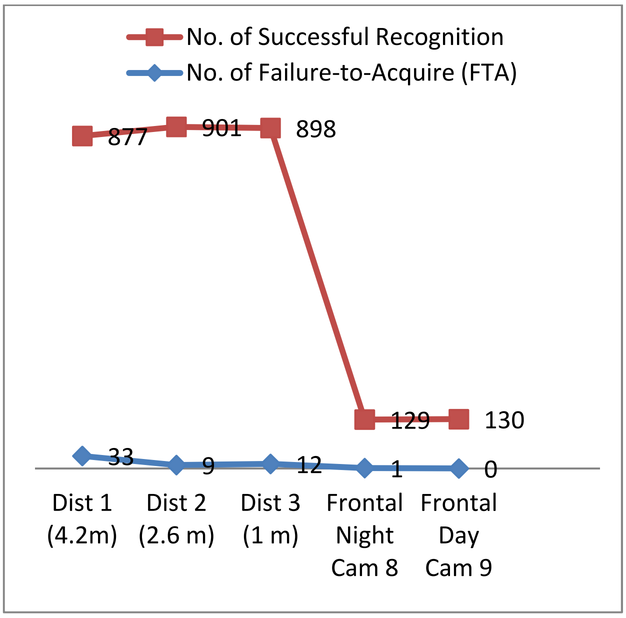

Fig.2. Graph showing the effect of face-to-camera distance on algorithm performance

Additionally, frontal daylight camera 9 and camera 7 returned the lowest and highest average recognition time of 1.82 and 5.05 seconds respectively as shown on figure 3. All these result are consistent with those reported by [11] [21] [27].

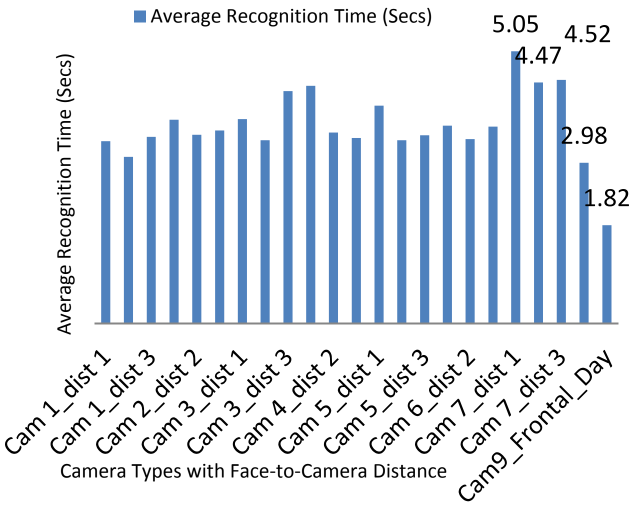

Fig. 3. Graph showing the effect of face-to-camera distance on average recognition time

Table II shows that pose image quality (QP) had the highest correlation coefficient of R=0.982 which is a significant improvement when compared with R=0.936 in [21].

TABLE II. CORRELATION OF OVERALL QUALITY SCORES (OQS) WITH INDIVIDUAL IMAGE QUALITY SCORES

		QP	QF	QL	QC	QS
OQS	Pearson Correlation	0.982**	0.852**	0.269**	0.261**	0.750**
	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)

Overall Quality Scores (OQS) on table III shows similarity quality (QS) had the highest correlation coefficient of R=0.857 with Algorithm Matching Scores (AMS). The table also shows a more improved correlation of QP with AMS (0.839).The luminance quality (QL) and contrast quality (QC) had the least correlation coefficient for OQS and AMS as it was in [21].

TABLE III. CORRELATION OF ALGORITHM MATCHING SCORES (AMS) WITH INDIVIDUAL IMAGE QUALITY SCORES.

		QP	QF	QL	QC	QS
AMS	Pearson Correlation	0.839**	0.379**	0.168**	0.048**	0.857**
	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)

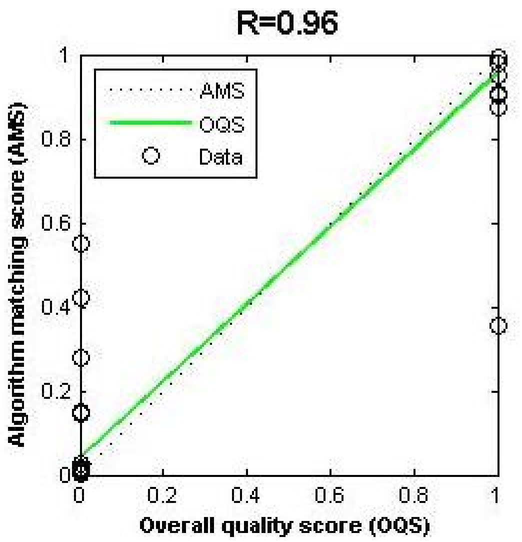

Fig. 4. Graph showing the correlation between algorithm matching score (AMS) and overall quality score (OQS)

Figure 4 shows the correlation between algorithm matching score (AMS) and the overall quality score (OQS). The result shows that both share a correlation coefficient of R=0.96.

V. CONCLUSION

A face verification and image quality assessment (FVIQA) scheme has been proposed and implemented in this research study. FVIQA image quality is expressed by implementing measures and algorithms for five image quality attributes such as similarity, contrast, illumination faceness and pose. The full-reference objective quality measurement technique for faces was employed. The image Euclidean distance (IMED) metric was used for similarity quality measure, structural similarity index (SSIM) was used for contrast and uneven illumination quality measure, distance between the eyes (DBE) and the amount of face area detected by the algorithm was used to measure the faceness quality while a modified optical flow technique was used for the pose quality.

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Results obtained shows that FVIQA 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 algorithm matching score was developed, the result shows that normalized disparate quality attribute scores can predictrecognition match performance, when combined into a single overall quality 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.

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