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BLACKFACE SURVEILLANCE CAMERA DATABASE FOR EVALUATING FACE RECOGNITION IN LOW QUALITY SCENARIOS

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ABSTRACT

Many face recognition algorithms perform poorly in real life surveillance scenarios because they were tested with datasets that are already biased with high quality images and certain ethnic or racial types. In this paper a black face surveillance camera (BFSC) database was described, which was collected from four low quality cameras and a professional camera. There were fifty (50) random volunteers and 2,850 images were collected for the frontal mugshot, surveillance (visible light), surveillance (IR night vision), and pose variations datasets, respectively. Images were taken at distance 3.4, 2.4, and 1.4 metres from the camera, while the pose variation images were taken at nine distinct pose angles with an increment of 22.5 degrees to the left and right of the subject. Three Face Recognition Algorithms (FRA), a commercially available Luxand SDK, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) were evaluated for performance comparison in low quality scenarios. Results obtained show that camera quality (resolution), face-to-camera distance, average recognition time, lighting conditions and pose variations all affect the performance of FRAs. Luxand SDK, PCA and LDA returned an overall accuracy of 97.5%, 93.8% and 92.9% after categorizing the BFSC images into excellent, good and acceptable quality scales.

Keywords: Algorithm, Databases, Face-recognition, Performance, Pose, Quality and Surveillance.

INTRODUCTION

Face recognition is an important research problem spanning various fields and disciplines (Abayomi-Alli *et al.*, 2015) with numerous practical applications such as ATM card identification, access control, Mug shots verification, security monitoring, and surveillance systems (Amir, 2008). It is the identification of humans by the unique characteristics of their faces (Draper *et al.*, 2003) and can automatically identify or verify an individual in a digital image by analyzing and comparing patterns (Face-rechomepage, 2013). Facial recognition is an active area of research due to its clandestine or covert capability (Jain, 2008) as a camera from some distance away can capture a person's face and the subject will not necessarily know he has been observed. Thus, there is a departure from the easy scenario leading to real world scenario of low quality images, this makes the face recognition system to experience severe problems (Omidiora *et al*., 2013b) such as pose variation, illumination conditions, scale variability, aging, glasses, moustaches, beards, low quality image acquisition, occluded faces etc.

Although there have been significant improvement in face recognition performance in the past decade, it is still below acceptable levels for use in many applications (Abayomi-Alli, 2015; Grgic, Delac and Grgic, 2011) as a face recognition system (FRS) must cope with real world, uncontrolled and dynamic environments (Poh, Kittler, Marcel, Matrouf, and Bonastre, 2010; Park, 2009). These intrinsic and extrinsic variations plague the FRS and directly affect its performance. Most face recognition systems are usually not tested in the surveillance conditions in which they are usually deployed (Abayomi-Alli *et al*., 2015). Thus, when performing recognition, one or more combinations of these variations come into play, thereby making recognition more difficult with attendant low performance from the FRS (Abayomi-Alli, 2015). It is therefore important to put in place a framework for the performance evaluation of a FRS implementing a particular algorithm before deployment to have a clue regarding what its eventual performance will be like and to determine if it will be acceptable for its intended purpose (Omidiora *et al*., 2013).

LITERATURE REVIEW

For a facial recognition system to be complete, a facial database is required. Several databases have been used in the evaluation of facial recognition algorithms to enable performance comparison between biometric systems. For effective, performance measurement of FRS it is necessary to test the recognition algorithms on well-known and widely available databases. Different researchers have collected a comparatively large number of face databases (FaceRecHomePage, 2012). Many of these databases are tailored to the specific needs of the algorithm under development or investigation.

In order to assert claim that any face recognition system is efficient, robust, and reliable, it must undergo rigorous testing and verification, preferably on real-world datasets. Also for researchers to appropriately measure the performance of an algorithm and directly compare the results, it is recommendable to use a standard test data (Omidiora *et al*., 2013a). While there are many databases in use currently, the choice of an appropriate database to use should be made based on the task and/or research direction. Another method is to choose the dataset specific to the property being tested for example the performance of an algorithm on images with different facial expressions and varying lighting conditions.

Table 1: Summary of some existing face recognition databases

Name and Description of Database with Date	Number of Subjects	Conditions		Image Resolution	Number of Images
FERET (August, 1993 – July, 1996) (Phillips *et al*., 2000)	1199	Facial expression Illumination Pose Time	2 2 9-20 2	256 x 384 pixels (8 bit grey scale)	14,051
AT &T (1992 -1994) (Samaria and Harter, 1994)	40	Varying lighting Facial expression Facial details	 4 2	92 x 112 pixels (PGM, grey scale)	400
AR (PURDUE) (1998) (Martine and Benavente, 1998)	116	Facial expression Illumination Occlusion Time	4 4 2 2	768 x 578 pixels	41,368
CMU- PIE (October –December, 2003) (Sim, Baker and Bsat, 2003)	68	Pose Illumination Facial expression	13 43 3	640 x 480 pixels	41,368
CAS-PEAL (August, 2002 –April, 2003) (Gao *et al*., 2004)	1040 377 438 233 297 296 66	Pose Facial expression Accessory Illumination Background Distance-from-camera Time	21 6 6 9-15 2-4 12 2	360 x 480 (Cropped grey scale images)	30,900
Indian Face (February, 2002) (Jain and Mukherjee, 2002)		Pose Facial Expression	7 4	640 x 480 pixels (JPEG, 256-grey levels)	440
VT_AAST (2007) (Abdallah, El-Nasr and Abbott, 2007)		Pose Orientation Race Structural Components	3 2 4 3	300 x 225 (JPEG & GIF)	1,027
SCFace 5 days (Grgic *et al*., 2011)	130	Camera quality IR frontal mug shot Visible light mug shot Distance-from-camera Different pose	7 1 1 3 9	100 x 75, 144 x 108 224 x 168 pixels 1,600 x 1,200 pixels 426 x 320 pixels 3,072 x 2,048 pixels	4,160

Source : (Abayomi-Alli, 2015)

Owing to the large body of literatures, an exhaustive review of publicly available databases that are of demonstrated use in the facial recognition community will be out of scope. However, details and descriptions of existing face databases used by researchers are updated on the FaceRecHomePage (2012). Table 1 summaries the features of some of the existing face databases. Although there are many databases in use currently, the choice of an appropriate database to use should be based on the face recognition task at hand (Face-rec homepage, 2013). Some of these databases include the Yale Face Database, PIE Database, AT&T, MIT-CBCL Face Recognition Database, NIST Mugshot Identification Database, and Surveillance Camera Face Database (SCface) (Gross *et al.,* 2005). Using still images from low-resolution surveillance cameras in controlled conditions as input, it is reasonable to omit the face normalization stage. However, when locating and segmenting a face in complex scenes under unconstraint environments, such as in a video scene, it is necessary to define and design a standardized face database.

The FERET database contains monochrome images taken in different frontal views and in left and right profiles. Only the upper torso of an individual (mostly head and neck) appears in an image on a uniform and uncluttered background (Philip *et al*., 2000). Turk and Pentland created a face database of 16 people. The face database from AT&T Cambridge Laboratories, formerly known as the Olivetti database and also known as the ORL-AT&T database, consists of 10 different images for 40 persons. The images were taken at different times, varying the lighting, facial expressions, and facial details (ORL, 2013).

The Harvard database consists of cropped, masked frontal face images taken from a wide variety of light sources. There are images of 16 individuals in the Yale face database, which contains 10 frontal images per person, each with different facial expressions, with and without glasses, and under different lighting conditions (Belhumeur *et al*., 1997). The XM2VTS multimodal database contains sequences of face images of 37 people. The five sequences for each person were taken over one week. Each image sequence contains images from right profile (-90 degree) to left profile (90 degree) while the subjects count from 0 to 9 in their native languages. The UMIST database consists of 564 images of 20 people with varying poses. The images of each subject cover a range of poses from right profile to frontal views.

The Purdue AR database contains over 3,276 color images of 126 people (70 males and 56 females) in frontal view (Martine and Benavente, 1998). This database is designed for face recognition experiments under several mixing factors such as facial expressions, illumination conditions, and occlusions. All the faces appear with different facial expressions (neutral, smile, anger, and scream), illumination (left light source, right light source, and sources from both sides), and occlusion (wearing sunglasses or scarf). The images were taken during two sessions separated by two weeks. All the images were taken by the same camera setup under tightly controlled conditions of illumination and pose. This face database has been applied to image and video indexing as well as retrieval. Zhao *et al.* (2003) can be referred to for the details of preparation of face databases.

RESEARCH METHODOLOGY

The methodology for this study involves the collection of the Black Face Surveillance Camera database (BFSC) and the evaluation of three face recognition algorithms in low quality scenarios. The BFSC database was collected primarily to mimic real life surveillance scenarios just like the SCface database. Only black faces were used to populate the database. Each participant is required to fill a consent form and a brief orientation is done before capturing. The database consists of fifty (50) subjects, collected over a period of four weeks. Variations in the database include pose, face distance to camera, resolution, contrast and illumination. The capturing of image took place in computer science laboratory at the Computer Science Department, Federal University of Agriculture, Abeokuta. The capturing equipment includes four surveillance cameras, high quality digital professional photo camera, and a computer. For many shots image acquisition and pose image acquisition we use a quality video camera, for surveillance camera image acquisition we make use of four surveillance cameras of different models and functions, which include one IR digital video camera.

BFSC Database Description

The surveillance images were taken in controlled lighting environment using two head lamps tilted at angle 45° on both sides of the surveillance cameras. All the cameras were installed and kept in a fixed position at a height of 2.25m from the ground as shown on Figure 1. The images were then captured using the Multiviewer software for windows XP that has 4 channels (see Figure 3). The resulting images were first cropped out and later resized using the following dimensions: 76 x 111, 58 x 82, 46 x 58 and 51 x 72 for the first, second, third and fourth images from the four cameras respectively.

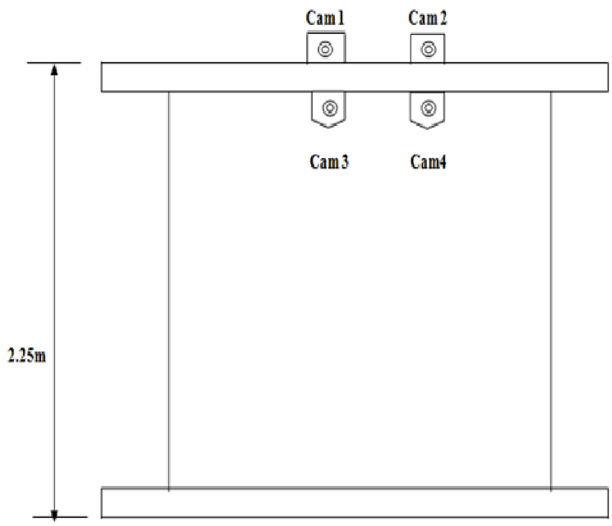

Figure 1: Heights and positions of the surveillance cameras

Figure 2: Four surveillance cameras used for the BFSC database

Subjects' images were taken at three distinct distances with their heads looking straight. Subjects were captured at 1.4 m, 2.4 m and 3.4 m face to camera distances as shown on Figures 2 and 3. The headlamps had all of these states- left light on (LL), right light on (RL), both lights on (BL) and no light on (NL), this was done using two switches. For each distance, the headlamps had a constant intensity throughout the process. The pose variation dataset was collected with a 12-mega pixel professional digital camera mounted on a tripod stand at a fixed position to capture nine different pose angles. The angles ranged from 0° to 180° with an increment of approximately 22.5°.

Protocol for Capturing Images

In order to ensure consistency, all volunteers (subjects) must pass through and adhere strictly to the database collection protocol as described in sub-section Phase I (surveillance image dataset) and sub-section Phase II (pose variation dataset), respectively.

Phase I

Participant should walk in front of the surveillance cameras. See Figures 3 and 4.

Subject stand at distance 1.4 m from the camera:

1. Right light on (RLN) image captured;
2. Left light on (LLN) image captured;
3. Both lights on (BLN) image captured;
4. Both lights off (BLO) image captured;

Subject stand at distance 2.4m from the camera:

5. Right light on (RLN) image captured;
6. Left light on (LLN) image captured;
7. Both lights on (BLN) image captured;
8. Both lights off (BLO) image captured;

Subject stand at distance 3.4m from the camera:

9. Right light on (RLN) image captured;
10. Left light on (LLN) image captured;
11. Both lights on (BLN) image captured;
12. Both lights off (BLO) image captured.

Figure 3: Image acquisition using multiviewer software

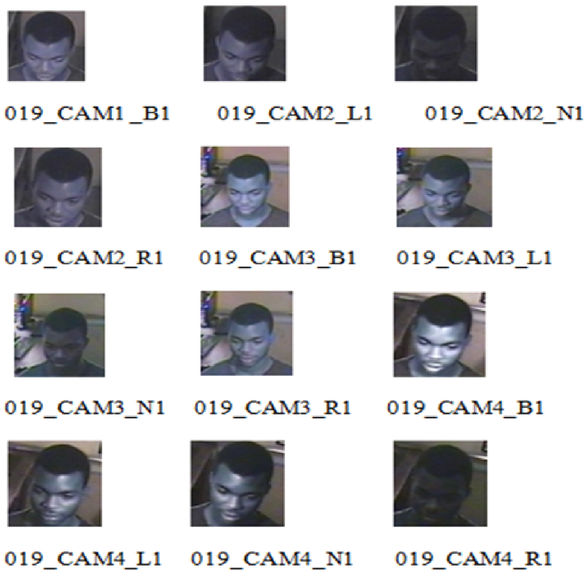

Figure 4: Surveillance camera Images for subject 19 in the database

Phase II

Participant post is taken at 9 different angles in between 22.5 degree from +90 to -90 degree from left to right and one frontal mug shot. The labeling includes FF (frontal), R1, R2, R3, R4, L1, L2, L3, and L4. See Table 2, figure 5 and figure 6.

The protocol for phase II includes:

Subject stand in between FF and face forward and image taken;

1. Subject stand in between R1 and face forward image taken;
2. Subject stand in between R2 and face forward image taken;
3. Subject stand in between R3 and face forward image taken;
4. Subject stand in between R4 and face forward image taken;

5. Subject stand in between L1 and face forward image taken;
6. Subject stand in between L2 and face forward image taken;
7. Subject stand in between L3 and face forward image taken;
8. Subject stand in between L4 and face forward image taken.

Naming Convention

For the surveillance camera images the naming of the subjects, camera, light label and distance is as follows: Sub Number_CamNumber_Light Label_ Distance. See Figures 4 and 6. The naming convention for the images obtained from the digital camera is as follows: Subject ID_angle Label.

Figure 5: Frontal mug shot Image for subject 19 in the database

The angles are labeled as shown on Table 2 while Figure 6 shows an example of pose variation images. Using this naming convention every image in the database gained a unique name, carrying information both about a subject's unique ordinal and at what distance and surveillance conditions was the subject's picture taken. Distance labels 1, 2 and 3 represent distances of 1.4m, 2.4m and 3.4m, respectively from the surveillance cameras. For example, the filename 001_cam1_L1.jpg means that this image shows subject 001 captured with surveillance camera 1 when left light is on at a distance of 1.4 m to the cameras, e.g. 001_cam1_L1, 001_cam2_L1, 001_cam3_L1, 001_cam4_L1, 001_cam1_R1. The same protocol is repeated for distance two and distance three.

Table 2: Pose variation label and angles

Label	IVQA number
F	Frontal mug shot
R1	22.50
R2	450
R3	67.50
R4	900
L1	22.50
L2	450
L3	67.50
L4	900

Naming different pose images: SubjectID_angleLabeled.jpg. For example the file name 001_F means that the subject identity 001 taken at angle 90 degree which is the frontal mug and there is a different of 22.5 degree interval both to the right labeled R1, R2, R3, R4, and to the left L1, L2, L3, L4, of which 9 different poses where captured per subject. See Table 2. Example for subject 001: 001_F, 001_R1, 001_R2, 001_R3, 001_R4, 001_L1, 001_L2, 001_L3, 001_L4.

Table 3: shows a summary image sets and description of the BFSC database

Image gallery	Camera	Description	Images per Subject	Total number of images
Frontal facial Mug shot images	1 Frontal mug shot camera	Facial mug shots of high quality static colour images.	1	50
Surveillance Cameras images (Visible light)	Cameras 1, 2 and 3	Images taken with cameras of different qualities at three discrete distances (3.40, 2.40 and 1.40m). Four illumination levels (indoor light only, left control light only, right control light only and both control lights on).	36	1800
Surveillance cameras images (IR night vision).	Camera 4	Images are in gray scale at three discrete distances (3.40, 2.40 and 1.40m). Four illumination levels (indoor light only, left control light only, right control light only and both control lights on).	12	600
Pose variation images	Professional digital camera	Images taken at different pose angles with an increment of 22.5^{o}.	8	400

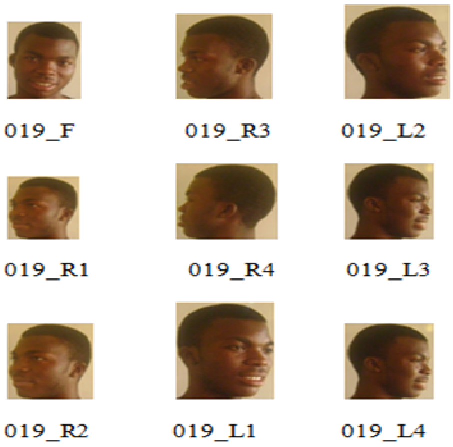

Figure 6: Pose Variation Image of Subject 19 in the database

From Table 3, frontal mug shot images per subject will give fifty (50) mug shot images, surveillance cameras 1, 2 and 3 will give 1800 images with 36 images per subject, while camera 4 has 600 night vision images with 12 images per subject in gray scale. The pose variation dataset contains 400 images with 8 images of per subject. Finally, the total number of images in the BFSC is 2,850 images (50-frontal, 2400-surveillance and 400-pose variation).

Equipment used in Database Collection

1. A personal computer;
   a) Intel(R) Core i3@2.10GHz (4 CPUs),
   b) 4096MB RAM,
   c) 500 GB HDD;
   d) 1366*768 (32 bit) (60Hz) current display mode
2. 4 Low resolution surveillance cameras;
3. Professional digital camera;
   a) 12.1-megapixel Super HAD CCD image sensor.
   b) 5x optical zoom, 28mm wide-angle Carl Zeiss Vario-Tessar lens;
   c) Optical Steady Shot image stabilization;
   d) 720p high-definition movie capture; BIONZ image processor
   e) 3.0-inch (230K pixels) Clear Photo LCD.
4. Camera tripod stand;
5. RealTime Color Quad Processor RT-404 QD (4 Channel Digital Multiplexer);
6. EasyCAPture (4 channel USB 2.0 DVR surveillance system);
7. AV Cables and other connection wires;
8. Electrical Switches and Extension box;
9. 2 Head lamps.

Software Requirements

a) Windows XP/Vista/7 operating system;
b) Multiviewer application for XP;
c) Microsoft picture manager 2010;
d) Picasa software - version 3.9 for Windows XP/Vista/7.

BFSC Database Testing

Three facial recognition algorithms were evaluated on the BFSC database to test their strength in low quality surveillance scenario.

The performance comparison of the recognition algorithms was done through structured face verification experiments carried out based on the face authentication protocol proposed by Wallace et al. (2011). The recognition threshold was set at 0.4 in order to reduce the number of returned false reject (FR) due the low quality of the BFSC images. The face recognition images evaluated with BFSC are Luxand face SDK (Luxand, 2013), Principal Component Analysis (PCA) (Turk and Pentland, 1991) and Linear Discriminant Analysis (LDA) (Cai, He and Han, 2007).

Each frontal mug shot images of the fifty database subjects was compared (Verification) with the low quality surveillance and pose variation images across the three recognition algorithms. These resulted in 2,850 verification trails. For each algorithm $\check{A}$, if the probe samples are of uniformly high quality then the probe sample's quality is sufficient to predict algorithm $\check{A}$'s performance. The matching algorithm $\check{A}$ will produce a recognition score for a given pair of images, $s_{i_p i_g} = \check{A}(i_p, i_g)$. If the recognition score $s_{i_p i_g}$ is above a predefined threshold, the verification task is considered successful and the result is returned.

Other metrics that affect and measure the accuracy and performance of face recognition systems include algorithm recognition time, true accept (TA), false reject (FR), false accept (FA), true reject (TR), failure-to-acquire rate (FTA) (Mansfield and Wayman, 2002; Du and Chang, 2007, Wayman, 2010). The mean recognition score (MRS) and the number of successful recognition (SR) also was used to measure the performance of a facial recognition algorithms on the BFSC database.

RESULTS AND DISCUSSION

Results from the verification experiments of the BFSC database on Luxand SDK, PCA and LDA recognition algorithms shows that the Mean Recognition Score (MRS) was quite low across the three algorithms, Failure -To-Acquire (FTA) was the same at 87 (See table 4). The low MRS was due to the low quality and resolution of the BFSC images, which informed the choice of 0.4 as the decision threshold for the Face Recognition Algorithms (FRAs).

Table 4: Summary of verification experiment with recognition algorithm's performance

Algorithm	SR	FTA	TA	FR	FA	TR	MRS
Luxand SDK	2713	87	879	1834	0	0	3.433
PCA	2713	87	742	1971	0	0	2.976
LDA	2713	87	723	1990	0	0	2.904

** Decision threshold = 0.4

Figure 7 shows the effect of varying camera qualities on the FRA's performance. Camera 5 represents the frontal mugshot dataset of 50 images. Camera 5, 4 and 3 returned 0, 1 and 11 FTA, respectively.

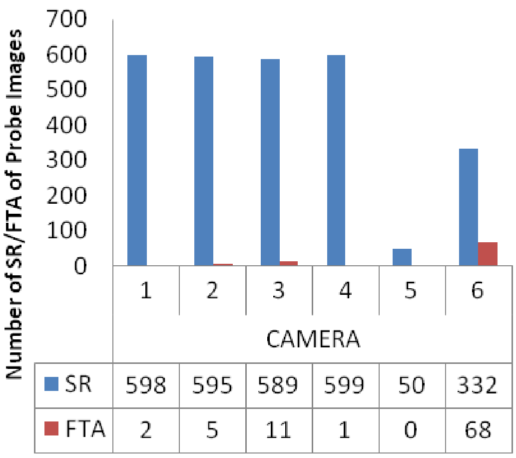

Figure 7: Graph showing the effect of varying camera qualities on the algorithms performance

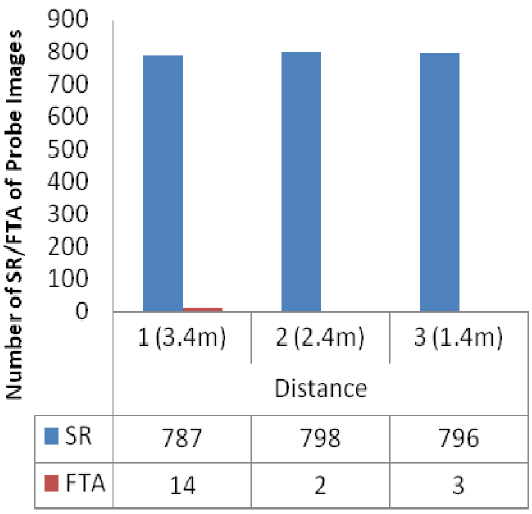

Figure 8: Graph showing the effect of subject's face to camera distance on algorithms performance

Figure 8, shows the effect of subject's face to Camera distance with distance 1 (3.4m) having the 14 FTAs. This is consistent with the recommendations for face image data on conditions for taking pictures in (ISO/ IEC, 2006). Figure 9 shows that camera 5 (Pose variation images) returned the lowest average recognition time (Secs) of 1.64 seconds while camera 3 at distance 3.4m had 4.27 seconds. This proves that the lower the quality or resolution of an image the more time the FRA will take to detect facial features and carry out recognition.

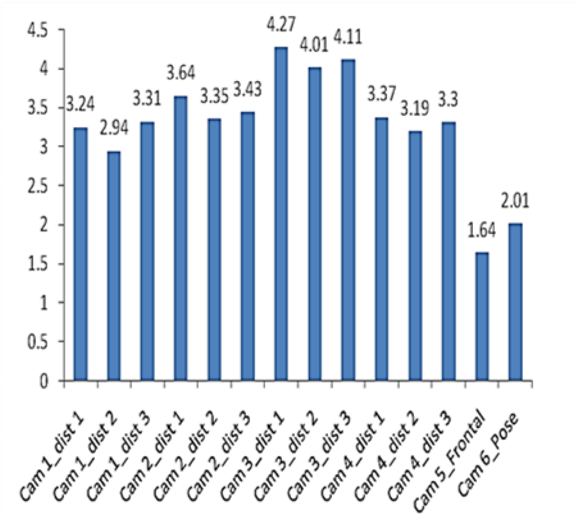

Figure 9: Graph showing the effect of varying camera qualities and face to camera distances on average recognition time

From Table 5, results showed that pose variation images at extreme angles of 90 degrees returned the highest number of FTA. The variations in the lighting condition under which the images were taken was of no significant difference to the performance of the FRA's as seen from Table 6.

Table 5: Effect of Pose variation/angles on Algorithm Performance

Label	Pose Angle	SR	FTA
F	Frontal mug shot	50	0
R1	22.50	50	0
R2	450	50	0
R3	67.50	50	0
R4	900	22	28
L1	22.50	50	0
L2	450	50	0
L3	67.50	50	0
L4	900	10	40

Table 6: Effect of lighting variation on algorithm performance

Lighting Condition	SR	FTA
Indoor light only	594	6
Left control light only	595	5
Right control light only	596	4
Both control light on	596	4

Table 7 shows the categorization of the BFSC database images into different quality scales using the Image Verification and Quality Assessment (IVQA) number proposed by Abayomi-Alli (2015). The database images was classified based on the returned algorithm matching scores (AMS) of range zero to one as against the Overall Quality Scores (OQS) as originally proposed by (Abayomi-Alli, 2015).

Table 7: Categorization of BFSC database images across IVQA quality scales

Overall quality Score range	IVQA number	Description	Number of images
0.9 - 1.0	5	Excellent	64
0.80 – 0.89	4	Good	246
0.60 – 0.79	3	Acceptable	1047
0.40- 0.59	2	Poor	1406
0 – 0.39	1	Unacceptable	87

With the IVQA classification, a new BFSC dataset was obtained containing only the images with an AMS of equal or greater than 0.6. Thus, 1,493 images was discarded as having poor or unacceptable quality while 1,357 images was recorded as either acceptable, good or excellent quality. The new BFSC database was applied on Luxand SDK, PCA and LDA for another set of verification trials, and the result obtained is summaries on Table 8 with zero FTAs and an increased MRS of 0.92, 0.90 and 0.89, respectively. Table 9 shows other statistical analysis results obtained from the verification experiment with Luxand SDK having the lowest standard error of 0.8% and the highest accuracy of 97.5%.

Table 8: Summary of Luxand SDK, PCA and LDA's performance on the BFSC high quality images

Algorithm	SD	FTA	TA	FR	FA	TR	MRS
Luxand SDK	1,357	0	1,357	0	0	0	0.92
PCA	1,357	0	1,357	0	0	0	0.90
LDA	1,357	0	1,357	0	0	0	0.89

** Decision threshold = 0.6

Table 9: Other Performance Results of Luxand SDK, PCA and LDA on the new BFSC dataset

FRA	Accuracy (%)	Std. Error a (%)	Asymptotic Confidence Interval (95%)		Total verification trials
			Lower bound	Upper bound	
Luxand SDK	97.5	0.8	0.964	1.0	1,357
PCA	93.8	1.7	0.914	0.978	1,357
LDA	92.9	2.2	0.909	0.953	1,357

The classification accuracy of Luxand SDK, PCA and LDA using the Receiver Operating Characteristics (ROC) and the Area Under the Curve (AUC) was obtained as shown in Figures 10, 11 and 12. The AUC of Luxand SDK, PCA and LDA represent the Accuracy of the FRA in the verification experiment as 97.5, 93.8 and 92.9, respectively.

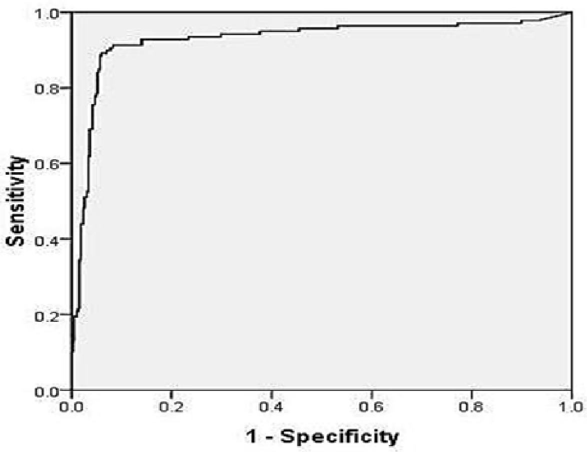

Figure 10: ROC curve of LDA classification Performance on the new BFSC dataset

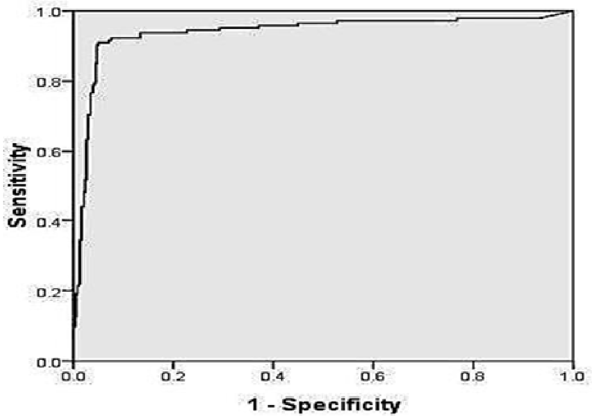

Figure 11: ROC curve of PCA classification Performance on the new BFSC dataset

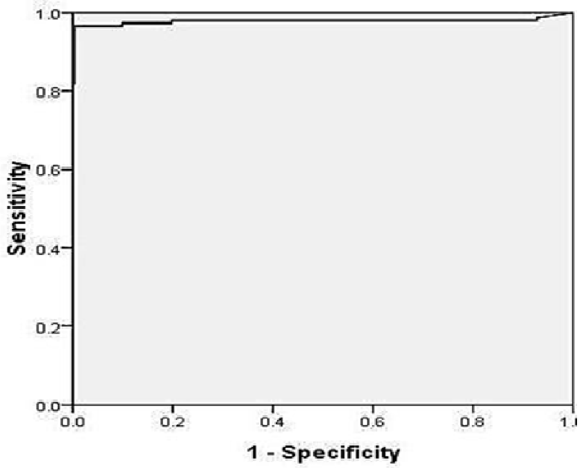

Figure 12: ROC curve of Luxand SDK classification Performance on the new BFSC dataset

CONCLUSION

A Black Face Surveillance Camera database (BFSC) was populated with 50 volunteer subjects and 2850 images was collected. The BFSC was tested on a commercially available Luxand SDk, PCA, and LDA for performance evaluation. Results obtained were consistent with those obtained by Abayomi-Alli (2015), Omidiora *et al.* (2013a), Omidiora *et al.* (2013b), Omojola (2012); Grgic, Delac & Grgic (2011) and Chen, Flynn & Bowyer (2005). It was observed that pose variations is the major cause of low performance of FRA's in detecting and recognition facial images in real life or low quality surveillance scenarios as compared to lighting, expression, aging or resolution. The height of surveillance cameras may contribute to the difficulty of FRA's in recognizing or detecting faces in extreme pose angles. 3D zoom cameras may be recommended to tackle this. Finally, Luxand SDK was observed to consistently outperforms PCA and LDA.

REFERENCES

Abayomi-Alli, A. 2015. Image Verification and Quality Assessment Models for Predicting Facial Recognition System Performance, PhD Computer Science and Engineering Thesis, Ladoke Akintola University of Technology, Nigeria.

Abayomi-Alli, A., Omidiora E. O., Olabiyisi S. O., Ojo J. A. 2015. Adaptive Regression Splines Models for Predicting Facial Image Verification and Quality Assessment Scores, *Balkan Journal of Electrical and Computer Engineering* (BAJECE). 3(1): 17-26.

Abdallah, A. S., El-Nasr, M. A., Abbott, A. C. 2007. "A New Colour Image Database for Benchmarking of Automatic Face Detection and Human Skin Segmentation Techniques". Proceedings of World Academy of Science, Engineering and Technology, 20: 353-357.

Amir, F. 2008. Robust Face Detection Using Template Matching Algorithm. Masters of Applied Science thesis, University of Toronto, Canada.

Belhumeur, P. N., Hespanha, J. P. and Kriegman, D. J. 1997. Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection, IEEE Trans. on PAMI, (7):711-720.

Cai, D., He, X., Han, J. 2007. Semi-supervised discriminant analysis, Proc. IEEE 11th International Conference on Computer Vision, 14:1–7.

Chen, X., Flynn, P. J., and Bowyer, K. W. 2005. IR and visible light face recognition. *Computer Vs Image Understanding*, 99 (3):332–358.

Draper, B., Kyungim, B., Marian, S. B., Ross, J. B. 2003. Computer Vision and Image Understanding: Recognizing faces with PCA and ICA. Retrieved from http://www.elsevier.com/locate/cviu

Du, Y., Chang, C. I. 2007. Rethinking the effective assessment of biometric Systems, SPIE Newsroom, Available online at http://spie.org/x2412.xml, accessed on 13th November, 2014.

FaceRecHomePage 2012. Facial Recognition Homepage, Available online at http://www.face-rec.org/algorithms/new-papers/databases, accessed on 11/05/2013.

Gao, W., Cao, B., Shans, S., Zhou, D., Zhang, X., Zhao, D. 2004. CASP-PEAL Large Scale Chinese Face Database and Evaluation Protocols Technical Report. JDL-TR-04FR-001, Joint research Development laboratory. Available at: http://www.jdl.ac.cn/peal/index.html

Grgic, M., Delac, K., Grgic, S. 2011. SCface-Surveillance Cameras Face Database, Multimed Tools Application, 51:863–879.

Gross, R. 2005.Face database, handbook of face recognition, Eds. Stanz li and Arilk. Jan, Springer–verlag February, 2005.

ISO/IEC 2006. Proposed Draft Amendment to ISO/IEC 19794-5 Face Image Data on Conditions for Taking Pictures, ISO/IEC JTC 1/SC 37 N 1511.

Jain, A. 2008. Biometrics, Microsoft Encarta 2008, Microsoft Corporation, Redmond, WA, 2008.

Jain, V., Mukherjee, A. 2002. The Indian Face Database, Available at http://

viswww.is.umass.edu/~vidit/IndianFaceDatabase2002

Luxand 2013. Detect and Recognize Faces with Luxand FaceSDK, Luxand Incorporation, USA, Available online at http://www.luxand.com/facesdk/, Accessed on 23rd August, 2013.

Mansfield, A. J., Wayman, J. L. 2002. Best Practices in Testing and Reporting Performance of Biometric Devices, Centre for Mathematics and Scientific Computing, National Physical Laboratory, Middlesex, TW110LW. Version 2.01 NPL Report CMSC 14/02.

Martine A. M., Benavente, R. 2002. The AR Face Database, CVC Technical Report #24, June 1998.

Omidiora, E. O., Olabiyisi, S. O., Ojo, J. A., Abayomi-Alli, A., Abayomi-Alli, O. , Erameh, K. B. 2013(a). Facial Image Verification and Quality Assessment System FaceIVQA. *International Journal of Electrical and Computer Engineering* (IJECE), 3(6), 863-874.

Omidiora, E. O., Olabiyisi, S. O., Ojo, J. A., Abayomi-Alli, A.; Izilein, F., Ezomo, P. I. 2013(b). Mace correlation filter algorithm for face verification in surveillance scenario, IJCSE, UK, 18(1):6-15

Omidiora, E. O., Olabiyisi, S. O., Ojo, J. A., Ganiyu, R. A., Abayomi-Alli, A. 2014. Enhanced Face Verification and Image Quality Assessment Scheme Using Modified Optical Flow Technique, Lecture Notes in Engineering and Computer Science: In: Proceedings of the International Conference on Signal Processing and Imaging Engineering (ICSPIE), University of California, Berkeley, San Francisco, USA, 22nd - 24th October, 2014.

Omojola, S. O. 2012. Performance evaluation of facial recognition algorithm in surveillance scenario: a case study of correlation filter, Computer Science B.Sc. Thesis, Federal University of Agriculture, Abeokuta, Nigeria.

ORL 2013. ORL face database, Available online at http://www.uk.research.att.com/facedatabase.html, accessed on 13/09/2013.

Park, U. 2009. Face recognition: face in video, age invariance, and facial marks, Ph.D. Dissertation, Department of Computer Science, Michigan State University, U.S.A.

Phillips, P. J., Moon, H., Rizvi, S. A., Rauss, P. J. 2000. The FERET Evaluation Methodology for Face-Recognition Algorithms. *IEEE Transaction on Pattern Analysis and Machine Intelligence*. 22(10):1090-1104.

Poh, N., kittler, J., Marcel, S., Matrouf, D., Bonastre, J. 2010. Model and score adaptation for biometric systems: coping with device interoperability and changing acquisition conditions, In Proc. international Conference on Pattern Recognition, IEEE Computer Society, 23rd - 26th, Istanbul, Turkey, pp. 1229-1232.

Samaria, F., Harter, A. 1994. Parameterization of a Stochastic Model for Human face Identification, 2nd IEEE Workshop on Applications of Computer Vision, 5th-7th December, Saratosa, Florida, pp. 138-142.

Sim, T., Baker, S., Bsat, M. 2003. The CMU Pose, Illumination and Expression Database. *IEEE Transactions on Pattern Analysis and Machine Intelligence.* 25(12): 1615-1618

2003.

Turk, M., Pentland, A. 1991. Eigenfaces for recognition. *J. CognNeurosci* 3(1):71–86.

Wallace, R., McLaren, M., McCool, C., Marcel, S. 2011. Inter-session variability modeling and Joint Factor Analysis for Face Authentication, In Proc. International Joint Conference on Biometrics (IJCB), 11th-13th October, Arlington, Virginia, USA, pp. 1-8.

Zhao, W.; Chellappa, R., Rosenfeld, A., Phillips, P. J. 2003. Face recognition: A literature survey. *ACM Computing Surveys.* 35(4): 399-458.

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