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Quantitative Evaluation of Principal Component Analysis and Fisher Discriminant Analysis Techniques in Face Images

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ABSTRACT

Face recognition is an attractive field in enhancing both the security and the image retrieval activities in the multimedia world. Its natural basis in verification or identification purposes is a major factor of its wide acceptance in this evolving world of information technology.

In this paper, experiments based on black African faces using Principal Component Analysis (OPCA) and Fisher Discriminant Analysis (OFDA) techniques were carried out. The design of the face recognition system was separated into three major sections – image acquisition and standardisation, dimensionality reduction, training and testing for recognition.

Under static mode, experiments were performed on single scaled images without rotation, OPCA and OFDA both give recognition accuracies of between 89% and 97%; and, 88% and 98% respectively.

These have been achieved at different levels of cropping. Despite the constraint created by the resources available, different results got showed that standard face recognition system could be developed using both algorithms.

Keywords: *Face Recognition, Principal Component Analysis, Fisher Discriminant Analysis, Eigenface and Fisherface.*

1.0 INTRODUCTION

Face is the only natural member of the body that has been the only primary focus of social intercourse. This normal way of identification and recognition is easily observed among animals, among human beings and between human beings and animals [16]. It communicates identity, emotion, face, age, and is also useful for judging gender, size and perhaps even character.

Face recognition has aroused the interest of researchers from security, psychology and image processing to computer vision fields. Its use is based on identification by the characteristics of a person [12]. Also, other biometric types: fingerprint, handwriting style, retina etc are the metrics being used as a result of their uniqueness and its difficulty to forge. A person involved does not need to remember anything and ones mode of authentication is always carried with the individual.

Furthermore, face stands out as the only method with high accuracy and low intrusiveness, hence its main focus in the paper. It is widely applied in surveillance purposes; to perform one-to-one or one-to-many searches through a database of faces [9]; also, its deployment as an index for search engine is fast growing in multimedia and Internet technology etc [1, 3]. In this paper, our main objective is to involve the use of the following parameters, such as, percentage recognition rate; time involved to train a face database; time to identify an image as known or unknown; total number of unidentified image; resolution of cropped face images and; total number of images used in testing, to evaluate the performances of both PCA and FDA techniques in the recognition of faces.

The paper is organised as follows: review of related works and methodology are described in sections 2 and 3 respectively. The experiments performed are explained in section 4. And, section 5 makes up the analysis of results and discussion; and section 6 concludes the write-up.

2.0 REVIEW OF RELATED WORKS

Face recognition is a natural phenomenon and the easiest activity being continually performed in every human being. But this has become challenging task for scientists, engineers and researchers in the field of computer vision. Developing a system that recognizes, analyses, compares and stores images, precisely facial images has become a daily task which gets broader and wider each and everyday with every attempt to such development [4].

Techniques for face recognition began as early as 1888 by Francis Galton. He proposed a recognition system based on the detection and comparison of the relative distances between key facial features such as eyes corners and mouths. Research into how human perceive and recognizes faces, however has shown that adult do not identify human faces based on immediate relationship between individual facial features. Recognition through feature distance, moreover, is quite fragile and thus extremely sensitive to changes. However, recognition techniques based on detecting individual features are still popular and used in conjunction with other techniques to improve performance.

The solution to the problem of face recognition involves segmentation of face from cluttered scenes, extraction of features from face region, identification and matching. Face Recognition problems and techniques can be separated into two groups: dynamic (video) and static matching [14, 6, 8]. *Dynamic matching* is used when a Video sequence is available. The video images tend to be of low quality; the background is cluttered and often is more than one face present in the picture. On the other hand, *static matching* uses image with typically reasonably controlled illumination, background, resolution and distance between camera and the person. Some of the images that arise in this group can be acquired from a video camera.

Yan et al [19] developed an automatic face recognition system by using a database with only small number of samples for each individual by using the shape localization problem formulated in the Bayesian framework. The results of their research work demonstrated that their proposed shape localisation approach significantly improved the shape localization accuracy, robustness and face recognition.

Turk and Pentland [17] proposed a different technique that scales and normalises the facial features based on their relative importance. This method analyses each facial image into a set of eigenvector components, essentially capturing the variations in a collection of face images independent of any judgement of particular facial features. With each component representing a certain dimension and description of the face, the whole set of eigenvectors characterises the variations among different faces. Every pixel in the image would contribute to the formation of the eigenvectors. Thus, each eigenvector is essentially an image of the face with a certain deviation from the average face depending on the local and global facial features. Each of these eigenvectors of the faces, are called eigenfaces, hence this technique is termed the "eigenface approach".

The eigenface approach uses a technique developed by Kirby and Sirovich [11] called Principal Component Analysis (PCA). PCA is a technique that effectively and efficiently represents pictures of faces into its eigenface components. With a given set of weights for each face image and a set of standard pictures, they argue that any face image can be approximately reconstructed by combining the entire standard faces according to their relative weights. This idea of linear combination is the backbone of the eigenface technique, and has been proven extremely successful.

Carlos and Duncan [5] proposed a new LDA-based method. The new method is based on a straightforward stabilisation approach for the within-class scatter matrix and performed experiments on face recognition to compare their approach with other LDA-based methods. The results indicate that their method improved the LDA classification performance when the within-class scatter matrix is poorly estimated.

Although, several researches have been done on face recognition, majority have made use of non-black faces in their experiments or few numbers of black faces. Aliu [2] developed an automatic knowledge-based face recognition system for faces having African features by developing a driver program by partitioning a face into nine sub-matrices of sizes 85*85 pixels. This research presents results of experiments based on black African faces using the Principal Component Analysis (OPCA) and Fisher Discriminant Analysis (OFDA) based algorithms. Actually, two algorithms are proposed as stated, and experimented with, taking into consideration several variations in determining the recognition performance of the face recognition system.

3.0 METHODOLOGY

3.1 Background Theory

An image can be viewed as a vector of pixels where the value of each entry in the vector is the grayscale value (0-255) of the corresponding pixel. For example, an 8x8 image may be unwrapped and treated as a vector of length 64. The image is said to sit in N-dimensional space, where N is the number of pixels (and the length of the vector). This vector representation of the image is considered to be the original space of the image.

The Principal Component Analysis (PCA) is a multivariable procedure that rotates the data such that maximum variabilities are projected onto the axes. Essentially, a set of correlated variables is transformed into a set of uncorrelated variable which are ordered by reducing variability. The uncorrelated variables in these variables can be removed with minimum loss of data. PCA is to reduce the dimensionality of a data set while retaining as much information as is possible.

The Fisher Discriminant Analysis, also called the Linear Discriminant Analysis (LDA), has been used successfully as a statistical feature extraction technique in several classification problems [7, 20-22]. The primary purpose of the Linear Discriminant Analysis is to separate samples of distinct groups by maximising their between-class separability while minimising their within-class variability. Although LDA does not assume that the populations of the distinct groups are normally distributed, it assumes implicitly that the true covariance matrices of each class are equal because the same within-class scatter matrix is used for all the classes considered [10].

The OFDA (Fisherfaces) method is essentially a two-stage dimensionality reduction technique. First the face images from the original vector space are projected to a lower dimensional space using Principal Component Analysis (PCA) [17] and then Linear Discriminant Analysis (LDA) is applied next to find the best linear discriminant features on that PCA subspace.

3.2 Principal Component Analysis

The standard PCA algorithm is as outlined in flowchart (figure 1). This method can lead to extremely large covariance matrices. For example, images of size 64*64 combine to create a data matrix of size 4096*M (M is the number of images) and a covariance matrix of size 4096*4096. This is a problem because calculating the covariance matrix and the eigenvectors/eigenvalues of the covariance is computationally demanding. It is known that for a N*M matrix the maximum number of non-zero eigenvectors the matrix can have is minimum (N-1, M-1). Since the number of training images (M) is usually less than the number of pixels (N), the most eigenvectors/eigenvalues that can be found are M-1.

A common theorem in linear algebra states that the eigenvalues of XX^T and X^TX are the same. Furthermore, the eigenvectors of XX^T are the same as the eigenvectors of X^TX multiplied by the matrix X and normalized [10, 15, and 18]. Using this theorem, the method can be used to create the eigenspace from an $M*M$ matrix rather than an $N*N$ covariance matrix. The following steps and flowchart in figure 1 show the PCA:

1. Centre data: Each of the training images must be centred. Subtracting the mean image from each of the training images centres the training images. The mean image is a column vector such that each entry is the mean of all corresponding pixels of the training images.
2. Create data matrix: Once the training images are centred, they are combined into a data matrix; A of size NxM, where M is the number of training images and each column is a single image.

3. Create covariance matrix: The data matrix's transpose is multiplied by the data matrix to create a covariance matrix.

$$\Omega' = A^T A$$

4. Compute the eigenvalues and eigenvectors of Ω': The eigenvalues and corresponding eigenvectors are computed for Ω'.

$$\Omega' V' = \Lambda' V'$$

5. Compute the eigenvectors of AA^T: Multiply the data matrix by the eigenvectors. Then, divide the eigenvectors by their norm.

6. Order eigenvectors: Order the eigenvectors according to their corresponding eigenvalues from high to low. Keep only the eigenvectors associated with non-zero eigenvalues. This matrix of eigenvectors is the eigenspace P_{pca}, also known as the projection matrix.

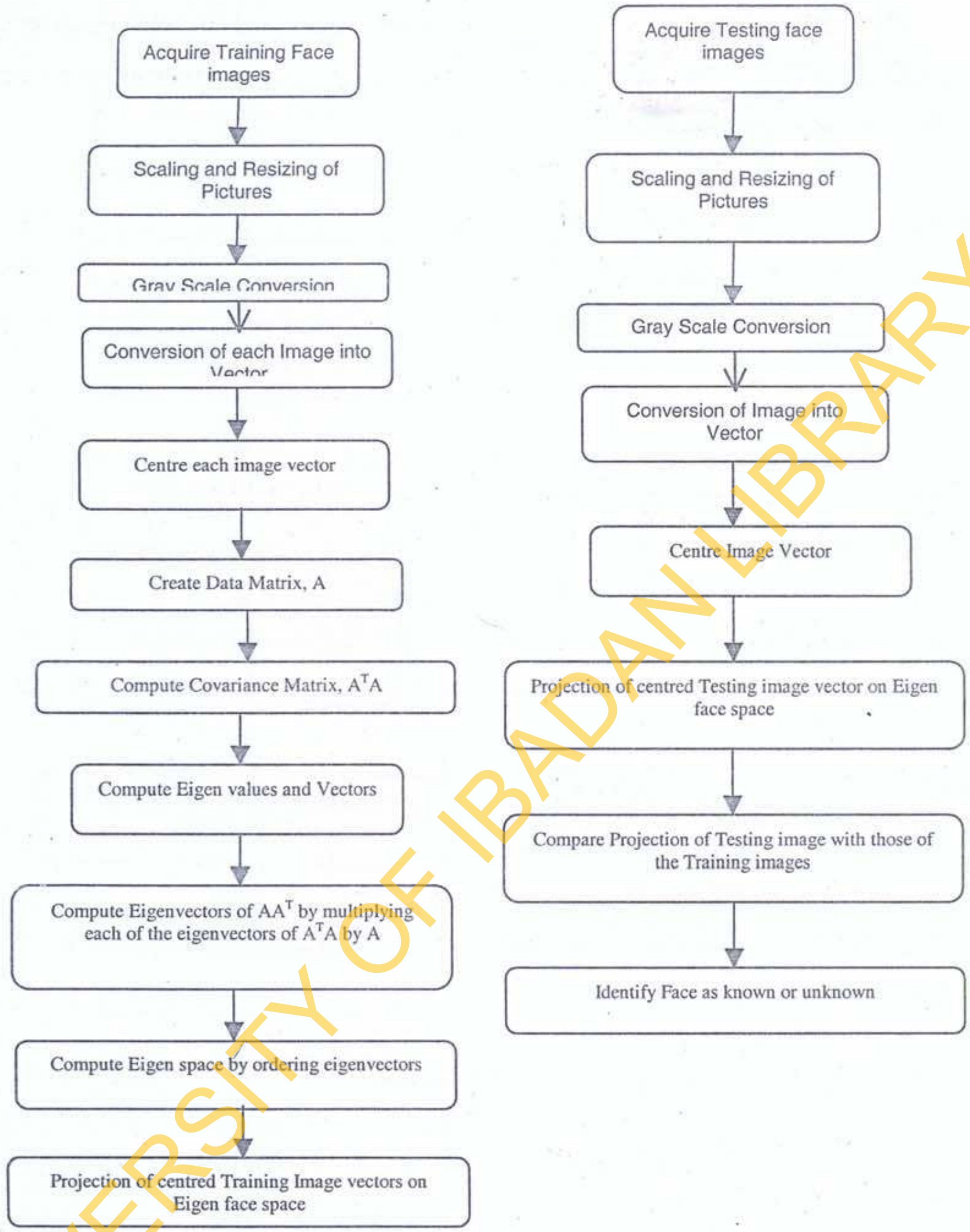
7. Project training images: Each of the centred training images is projected into the eigenspace. To project an image into the eigenspace, the dot product of the image with each of the ordered eigenvectors (projection matrix) is calculated. Therefore, the dot product of the image and the first eigenvector will be the first value in the new vector. The new vector of the projected image will contain as many values as eigenvectors.

The same procedure applies for testing face images. Flowchart depicting the processes involved in the training and testing stage of the system is as shown in figure 1.

3.3 Fisher Discriminant Analysis

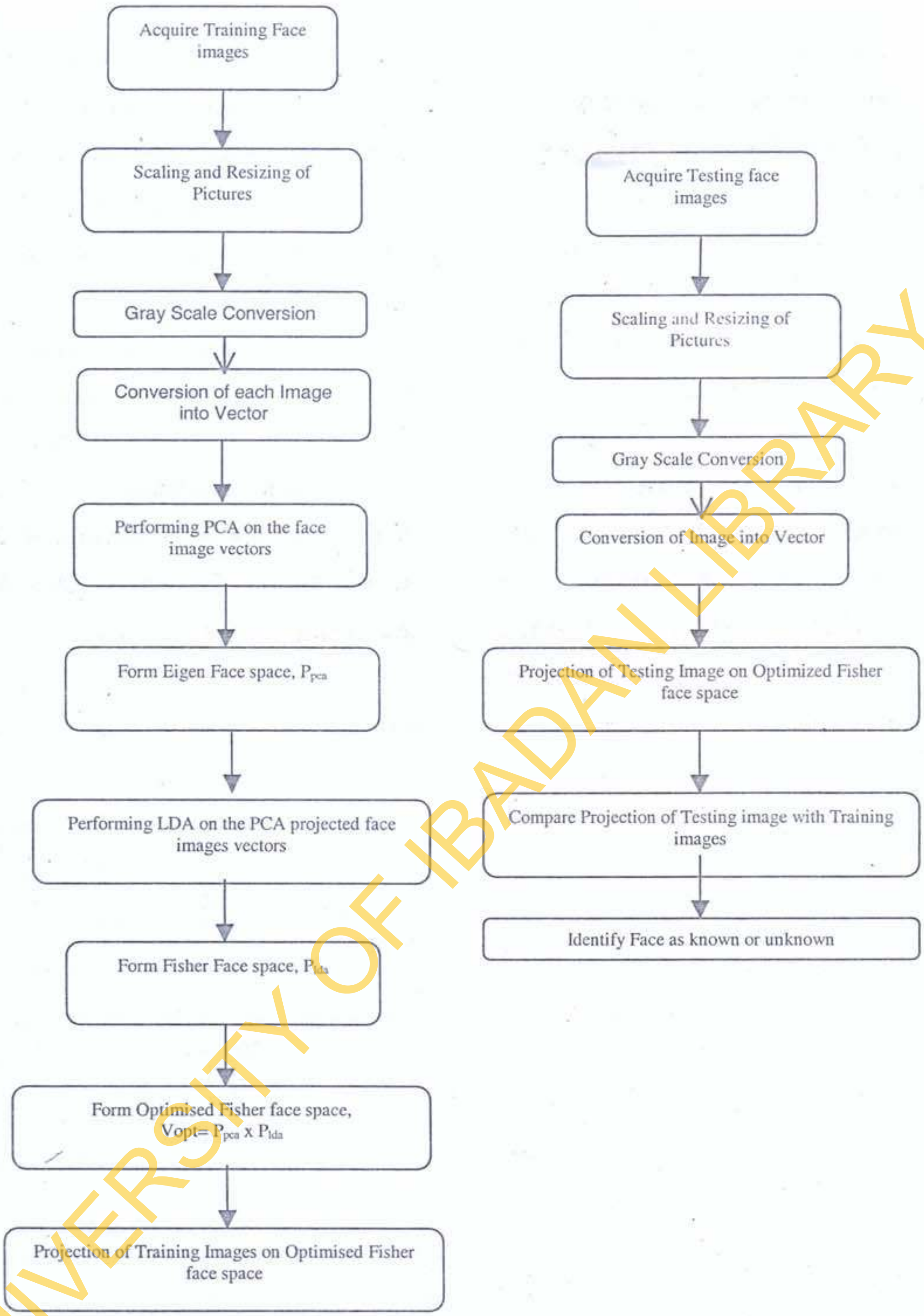
The Fisherface Algorithm can be divided into the following steps and is easily shown in figure 2:

1. Acquire a set of face images (the training set).
2. Find the principal components of the distribution of faces
3. Form the "Eigen face space"
4. Project the faces in the training set onto the "Eigen face space"
5. The projected faces form the training set to the Linear Discriminant stage.
6. Find the between-class scatter matrix and within-class scatter matrix S_B and S_W of the eigen projected faces.
7. Find the set of generalized eigenvectors of S_B and S_W
8. Form the "fisher face space"
9. Form the "fisher face space"
10. Project a testing image onto the "fisher face space"
11. Determine whether the testing image is a known face or not using Euclidean distance. A threshold is set to separate faces in the created database from others that are not.



(a) Training Stage (b) Testing stage

Figure 1: Block diagram showing the processes involved in the training and testing stage of a Face Recognition System using PCA



(a) Training Stage (b) Testing stage

Figure 2: Block diagram showing the processes involved in the training and testing stage of a Face Recognition System using FDA

4.0 EXPERIMENTS

Face images of forty-six black African individuals were taken with a Finepix zoom digital camera. Six frontal face images with very little or no rotation were selected per person for forty-six (46) individuals. Each individual image was taken from different face views, expressions and lighting. The size of each image was originally 480*640 pixels. The face images were cropped out and they were resized to have dimensions of between 102*127 and 104*167 pixels without distortion due to the different distances at which the images were taken.

The resized images were then grouped into two classes; training class containing four images per individual and testing class with two images per individual (184 training and 92 testing images respectively). The colored images (three-dimensional) in the database were converted into grayscale images with pixel values between 0 (black) and 255 (white). Conversion to gray images was necessary because most of the present face recognition algorithms require two-dimensional arrays in their analysis.

The grayscale images were cropped to sizes of 50*50, 60*60, 75*75, 90*90, 100*100 (N*N) pixels from the centre of the image by the program in order to remove the background of the pictures and to extract features like eyes, nose, eye lids and the upper part of the lips whose appearance do not change easily over time. The different pixel sizes indicate varying numbers of essential face features and were used at both the training and testing stages.

Also, further experiments were performed in determining the error rate and the number of unidentified testing images using different number of eigenvectors for both OPCA and OFDA as illustrated in Tables 3 and 4 and graphically in figures 6 and 7.

5.0 ANALYSIS OF RESULTS AND DISCUSSION

OPCA and OFDA algorithms were experimented by implementing both with different facial expressions in the order of between 50*50 and 100*100 pixels resolutions. With both algorithms, the following parameters were taking into consideration namely:

- The recognition rate (%)
- Time involved to train a face database
- Time to identify an image as known or unknown (sees)
- Total number of unidentified image
- Resolution of cropped face images and;
- Total number of images used in testing.

Results got were stated below in Tables 1-4 below.

Table 1: Recognition rate, time to train a face database and time before an image could be identified for different levels of cropping of the original image for OFD.

Resolution of Cropped Face Image	Total Number of Images used in Testing	Total Number of Unidentified Images	Percentage Recognition rate (%)	Time to train face database (seconds)	Time to identify an image as known or Unknown (seconds)
50*50	92	11	88.04	39.887	0.271
60*60	92	8	91.3	46.417	0.411
75*75	92	6	93.48	56.191	0.531
90*90	92	2	97.83	74.827	0.892
100*100	92	1	98.91	87.306	1.322

Table 2: Recognition rate, time to train a face database and time before an image could be identified for different levels of cropping of the original image for OPC

Resolution of Cropped Face Image	Tot Number of Images used in Testing	Total Number of Unidentified Images	Percentage Recognition rate (%)	Time to train face database (seconds)	Time to identify an image as known or Unknown (seconds)
50*50	92	10	89.13	26.468	0.321
60*60	92	9	90.22	30.424	0.361
75*75	92	5	94.57	32.006	0.370
90*90	92	2	96.74	35.952	0.421
100*100	92	4	95.65	39.276	0.420

Table 3: Error rate of a face recognition system using different Eigenvectors in OPCA

No of Eigenvector	No of Unidentified Testing Images	% Error rate
20	7	7.61
40	5	5.44
60	3	3.26
80	4	3.45
100	4	3.45

Table 4: Error rate of a face recognition system using different Eigenvectors in OFDA

No of Eigenvector	No of Unidentified Testing Images	% Error rate
10	13	14.13
20	7	7.61
30	6	6.52
40	6	6.52

Figures 3-5 show the bar charts comparisons of the results obtained with both OPCA and OFDA. These are further clarity in terms of the parameters considered for both algorithms. OPCA has the higher percentage recognition and in close range with OFDA algorithms (94.54% and 93.48% respectively). OPCA algorithm performs better when all parameters considered are taken into consideration. The unidentified images were found not to be properly centred frontally, thus cropping could not remove the background efficiently.

Phillips et al [13] and other literatures consulted strongly emphasized that OPCA and OFDA could also be used as face recognition systems since they all have recognition accuracies of more than 80%. The results got were basically limited by the medium level state of the computer system used, resolution of the digital camera, different environmental conditions like illumination and different distances between the camera and every face. The face database under consideration was developed entirely from the scratch and the facilities for proper face alignment used were the ones at our disposal.

Tables 1 and 2 show the recognition rate, time to train a face database and time before an image could be identified for different levels of cropping of the original image. The results show that the more the facial features that are included in the training and testing images, the better the recognition performance. Also, the system developed is, to some extent, invariant to facial expressions. In some tests, the recognition system was able to correctly identify an individual with and without glasses and to correctly distinguish a set of very identical twins.

With 75*75 pixel resolution, the results obtained (in Tables 3 and 4) showed that both the percentage error rate and number of unidentified testing images reduce with increase in the number of eigenvectors employed in determining the face space.

Many of the recognition uncertainties can be explained by slight differences in orientations and scaling of the test faces compared to the database; poor normalisation, emphasizing the importance of strictly standardised databases.

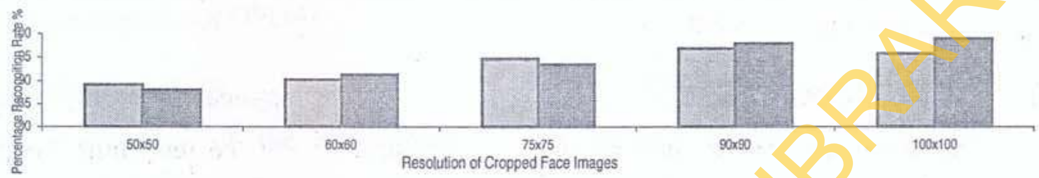


Fig 3: Comparison of Percentage Recognition Rate for different resolutions of Cropped face images

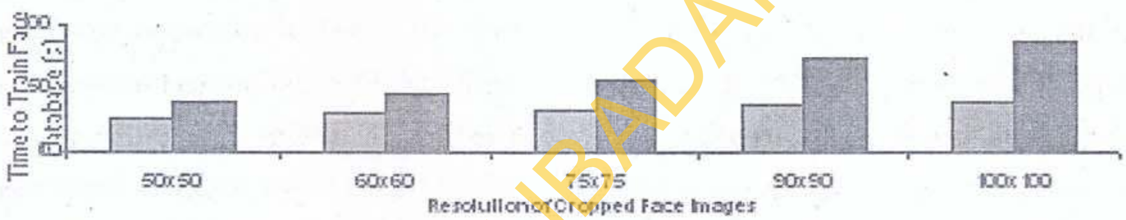


Fig 4: Comparison of Time to Train face database for different resolutions of cropped images

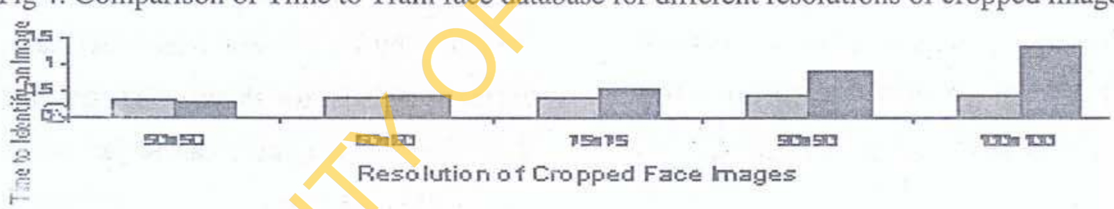


Fig 5: Comparison of Time to identify a face for different resolutions of cropped images

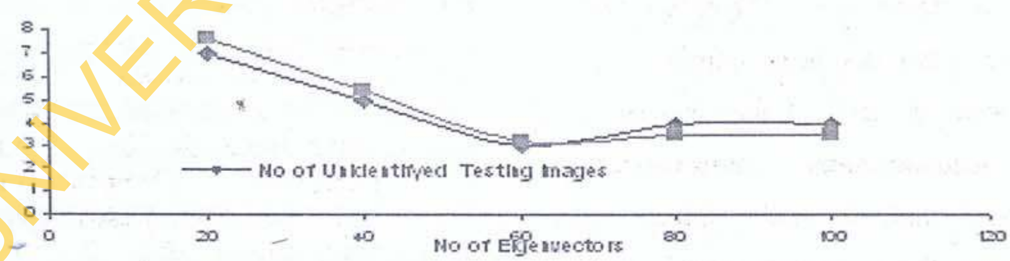


Fig 6: Graph of Unidentified Testing Images and Percentage Error Rate vs No of Eigenvectors for OPCA

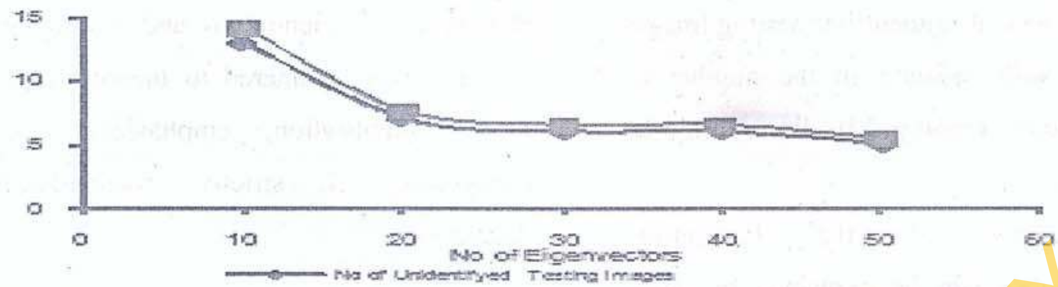


Fig 7: Graph of Unidentified Testing Images and Percentage Error Rate vs No of Eigenvectors for OFDA

6.0 CONCLUSION

An overview of the design and development of a real-time face recognition system has been presented in this research work. This work presents results of experiments based on black African faces using the OPCA, OFDA, Under static mode, where recognition is performed on single scaled images without rotation, OPCA, OFDA both give recognition accuracies of between 89-97% and between 88-98% respectively. These have been achieved at different levels of cropping.

The design of the face recognition system is based upon Eigenfaces and Fisherfaces and has been separated into three major sections – image acquisition and standardisation, dimensionality reduction, training and testing for recognition. Static images were acquired by taking photos of people using a digital camera. The dimensionality reduction was done by the Eigenface and the Fisher face based Algorithms.

The application of the algorithms to the task of face recognition requires a perfectly standardised and aligned database of faces; face cropping and image resizing were done before the dimensionality reduction stages to account for background removal and uniformity in sizes of the images for the training and testing to be performed in the face recognition system. Despite the constraint created by the resources available, different results got showed that standard face recognition system can be developed using both algorithms.

7.0 REFERENCES

1. Adeyanju, I. (2004). *"Face Recognition Using Optimized Fisher Discriminant Analysis"*, Unpublished B. Tech. Project, Department of Computer Science and Engineering, Ladoke Akintola University of Technology, Ogbomoso.
2. Aliu S.A. (1999) *"Development of an automatic knowledge based face recognition system for faces having African features"*, Unpublished Ph. D. Thesis, Department of Engineering, University of Ilorin, Nigeria.

3. Bryliuk D. and Starovoitov V. (2000), *"Access Control by Face Recognition Using Neural Networks"*, http://neuroface.narod.ru.
4. Carey S. and Diamond R. (1977), *"From piecemeal to configuration representation of faces"*, Science, Vol. 195, pp 312 – 313.
5. Carlos E. Thomaz and Duncan F. Gillies (1998), *"A Maximum Uncertainty LDA-based approach for Limited Sample Size problems – with application to Face Recognition"*, Department of Computing, Imperial College London, London, UK.
6. Chellapa R.,Wilson, C. L. and Sirohey, S. (1995), *"Human and Machine recognition of faces: A Survey"*, Proceeding of the IEEE,Vol 83, No 5, pp 705-740.
7. Chen L., Liao H., Ko M., Lin J., and Yu G. (2000), *"A new LDA-based face recognition system which can solve the small sample size problem"*, Pattern Recognition, 33 (10), pp. 1713-1726.
8. Etemad K and Chellappa R. (1997), *"Discriminant analysis for recognition of human face images"*, Journal of the Optical Society of America A: Optics Image Science and Vision; 14(8): 1724-1733.
9. Guevin, L. (2002) *"Facial – Recognition Solutions Roundup"*, http://www.biometritech.com/features/roundup051502
10. Johnson R. A. and Wichern D. W. (1998), *"Applied Multivariate Statistical Analysis"*, fourth edition. New Jersey: Prentice Hall. pp 41-836.
11. Kirby M and Sirovich L. (1990), *"Application of the Karhunen-Loève procedure for the characterization of human faces"*, IEEE Transactions on Pattern Analysis and Machine Intelligence; 12(1): 103-108.
12. Lin Shang-Hung (2000), *"An Introduction to Face Recognition Technology"*, Informing Science: Special Issue on Multimedia Informing Technologies, Vol. 3 No.2, p 1-5.
13. Phillips P J, Wechsler H, Huang J, Rauss P J. (1998), *"The FERET database and evaluation procedure for face recognition algorithms"*, Image and Vision Computing", 16(5): 295-306.
14. Samal A. and Iyengar P. (1992), *"Automatic Recognition and Analysis of Human Faces and Facial Expressions: A Survey"*, Pattern Recognition, 25 (1), pp. 65-77.
15. Trucco E. and Verri A. (1998), *"Introductory Techniques for 3-D Computer Vision"*, New Jersey: Prentice-Hall, Inc.
16. Turk M. (2001), *"A Random walk Through Eigenspace"*, IEEE transaction in Information and System, Vol E84-D, No 12, pp 1585 – 1593
17. Turk M and Pentland A. (1991), *"Eigenfaces for recognition"*, Journal of Cognitive Neuroscience: 3(1): 71-86.
18. Wendy S. Yambor (2000), *"Analysis of PCA-Based and Fisher Discriminant-Based Image Recognition Algorithms"*, Department of Computer Science, Unpublished Master of Science Thesis, Colorado State University, Fort Collins, Colorado.
19. Yan S., He X., Hu Y., Zhang H., Li M. and Cheng Q. (2004), *"Bayesian Shape Localization for Face Recognition Using Global and Local Texture"*, IEEE Transactions on circuits and systems for Video Technology, Vol. 14, No1, pp 102-113.

20. Yang J. and Yang J. (2003), *"Why can LDA be performed in PCA transformed space?"*, Pattern Recognition, vol. 36, pp. 563-566.

21. Yang J. and Yang J. (2001), *"Optimal FLD algorithm for facial feature extraction"*, SPIE Proceedings of the Intelligent Robots and Computer Vision XX: Algorithms, Techniques, and Active Vision, vol. 4572, pp. 438-444.

22. Yu H. and Yang J. (2001), *"A direct LDA algorithm for high dimensional data – with application to face recognition"*, Pattern Recognition, vol. 34, pp. 2067-2070.

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