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Optimised Fisher Discriminant Analysis for Recognition of Faces Having Black Features

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Abstract: A face recognition system is one of the most desirable biometric identification such as computerized access control, document control and database retrieval. Although, several researches have been done on face recognition, most (if not all) have made use of non-black faces or very few numbers of black faces in their experiments. This study presents results of experiments based on black African faces (with and without tribal marks) using the optimized Fisher Discriminant Analysis. In the experiment, different sizes of gray scale images were used for recognition performance accuracy of between 88 and 99% were obtained. Also, taking into consideration was the rate of identifying an image using the same number of images to test the face recognition system. While, a completely robust real-time face recognition system is still under heavy investigation and development, the implemented system serves as an extendable foundation for future research.

Key words: Face, optimised fisher discriminant analysis, principal component analysis, linear discriminant analysis

INTRODUCTION

Face recognition has aroused the interest of researchers from security, psychology and image processing to computer vision fields. It is one of the biometric techniques that allows or would grant access by who we are and not by conventional methods that allow access by what we have such as ID cards keys, passwords, PIN nos. Biometric systems are systems that identify or verify human beings. Also, it has the merits of both high accuracy and low intrusiveness. Different biometrics being investigated include fingerprints (Bottou *et al.*, 1994), speech (Qi and Hunt, 1994), signature dynamics (Ilker, 1996) and face recognition (Man Kwok Ming, 2003) etc. Among the various biometric, ID methods enumerated above, the physiological methods (face, DNA and fingerprint) are more stable than the behavioral methods (signature dynamics and speech). The reasons being the non-alterable nature (except by injury) of the physiological features but the behavioral methods have the advantage of being non-intrusive (Lin, 2000). As a result of these good attributes, biometric system is very difficult to forge since they exhibit biological characteristics to identify.

Face recognition is useful in finding a person within a large database of faces e.g., in a police, school or library database. These systems usually return a list of the most likely people in the database.

- It is also useful in identifying particular people in real-time for example a security monitoring system, location tracking system etc.
- It is used in allowing access to a group of people and denying access to all others for example access to a building, computer etc.
- It creates an easier way of making information access faster in a large database.

Review of related works: Faces represent complex, multidimensional, meaningful visual stimuli and developing a computer model for face recognition is difficult (Lawrence, 2000). Psychologists and neuroscientists have studied issues such as uniqueness of face, how infants perceive faces and organization of memory of faces, while engineering scientists have designed and developed face recognition algorithms (Ilker, 1996).

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 2 groups: dynamic (video) and static matching (Chellapa *et al.*, 1995). *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 1 face present in the picture. On the other hand, *static matching* uses image

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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.

Starovoitov *et al.* (2002) categorises main tasks of face recognition into 3 namely: document control, access control and database retrieval. The term document control means the verification of a human by comparing his/her actual camera image with a document photo. Access control, being the most investigated field, compares the portrait of a test person with photos of people who have access permissions to jointly used object. The last task arises when it is necessary to determine name and other information about a person just based on his/her one casual photo.

The method proposed by Brunelli and Poggio (1993) used a set of templates to detect the eye positions in a new image, by looking for the maximum absolute values of the normalized correlation of these templates at each point in the test image. Template matching is also a common technique. By using correlation, input images can be compared to a set of known faces, with the largest correlation resembling the closest match. Turk and Pentland 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 between different faces. Every pixel in the image would contribute into 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 Sirovich and Kirby 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.

Man Kwok Ming (2003) studied and implemented the Eigenface and Fisherface algorithms in face recognition carrying out various experiments to evaluate and compare them. He tested the Yale and ORL database using various brightness variations with different error rates.

Carlos and Duncan (1998) proposed a new LDA-based method. He based it on a straightforward stabilisation approach for the within-class scatter matrix and performed experiments on face recognition to compare his approach with other LDA-based methods. The results indicate, that his method improved the LDA classification performance when the within-class scatter matrix is and poorly estimated.

Although, several researches have been done on face recognition, most (if not all) have made use of non-black faces in their experiments or few numbers of black faces. Aliu (1999) developed an automatic knowledge-based face recognition system for faces having African features by employing PCA. This research presents results of experiments based on black African faces (with and without tribal marks) using the Optimized Fisher Discriminant Analysis.

MATERIALS AND METHODS

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 8×8 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 Fisher Discriminant Analysis, also called the Linear Discriminant Analysis (LDA), has been used successfully as a statistical feature extraction technique in several classification problems. 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 (Johnson and Wichern, 1998).

The Optimised Fisher Discriminant Analysis (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) (Turk and Pentland, 1991) and then Linear Discriminant Analysis (LDA) is applied next to find the best linear discriminant features on that PCA subspace.

The Principal Component Analysis algorithm can be stated as follows:

Center 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.

Create data matrix: Once the training images are centred, they are combined into a data matrix; A of size N × M, where M is the number of training images and each column is a single image.

Create covariance matrix: The data matrix is multiplied by its transpose to create a covariance matrix.

$$\Omega = AA^T$$

Compute the eigenvalues and eigenvectors: The eigenvalues and corresponding eigenvectors are computed for the covariance matrix.

$$\Omega V = \Lambda V$$

Where, V is the set of eigenvectors associated with the eigenvalues Λ.

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.

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 method outlined above 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) (Horn and Johnson, 1985). 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 (Horn and Johnson, 1985; Kirby, 2000; Trucco and Verri, 1998; Wendy Yambor, 2000). Using this theorem, the optimised method can be used to create the eigenspace from an M×*M* matrix rather than an N×N covariance matrix. The following steps show the optimised PCA:

- **Center data:** (Same as original method).
- **Create data matrix:** (Same as original method).
- **Create covariance matrix:** The data matrix's transpose is multiplied by the data matrix to create a covariance matrix.

$$\Omega' = A^TA$$

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

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

- **Compute the eigenvectors of AA^T:** Multiply the data matrix by the eigenvectors. Then, divide the eigenvectors by their norm.
- **Order eigenvectors:** (Same as original method).

The Linear Discriminant Analysis (LDA) algorithm can be stated as follows:

Calculate the within class scatter matrix: The within class scatter matrix measures the amount of scatter between items in the same class. For the ith class, a scatter matrix (S_i) is calculated as the sum of the covariance matrices of the centred images in that class.

$$S_i = \sum_{z \in x_i} (x - m_i)(x - m_i)^T \quad (1)$$

where, m_i is the mean of the images in the class. The within class scatter matrix (S_w) is the sum of all the scatter matrices.

$$S_w = \sum_{i=1}^{C} S_i \quad (2)$$

where, C is the number of classes.

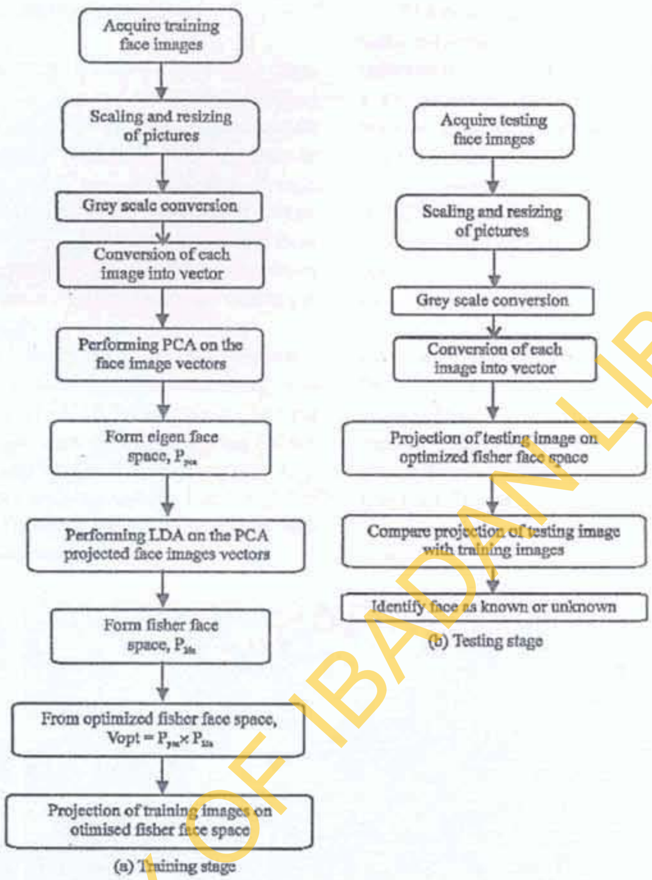

Fig. 1: Block diagram showing the processes involved in the training and testing stage of a face recognition system using optimised FDA

Calculate the between class scatter matrix: The between class scatter matrix (S_B) measures the amount of scatter between classes. It is calculated as the sum of the covariance matrices of the difference between the total mean and the mean of each class.

$$S_B = \sum_{i=1}^{C} n_i (m_i - m)(m_i - m)^T \tag{3}$$

where, n_i is the number of images in the class, m_i is the mean of the images in the class and m is the mean of all the images.

Solve the generalized eigenvalue problem: Solve for the generalized eigenvectors (V) and eigenvalues (Λ) of the within class and between class scatter matrices.

$$S_B V = \Lambda S_W V$$

Keep first C-1 eigenvectors: Sort the eigenvectors by their associated eigenvalues from high to low and keep the first C-1 eigenvectors. These eigenvectors form the Fisher basis vectors.

Project images onto Fisher basis vectors: Project all original (i.e., not centred) images onto the Fisher basis vectors by calculating the dot product of the image with each of the Fisher basis vectors. The original images are projected onto this line because these are the points that the line has been created to discriminate, not the centred images. This is the standard LDA procedure.

The Optimised Fisherface Algorithm can be summarised by the flowchart Fig. 1.

RESULTS AND DISCUSSION

Face images of 46 black African individuals were taken with a Finepix zoom digital camera. Each individual has 10 images from different face views, expressions and lighting; the best six frontal face images with very little or no rotation were selected per person. The size of each image was originally 480×640 pixels. Microsoft Office Picture Manager 2003 was used to crop out the face images and they were resized to have dimensions 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 2 classes; training class containing 4 images per individual and testing class having a total of 92 images with 2 images per individual. The images were named using the format A_B, where 1< A < 46 and 1< B < 6. Images A_1 to A_4 (A = 1.46) were used for training and A_5 and A_6 for testing face databases. Figure 2 shows some of the face images used in the experiment.

The coloured images (3-dimensional) in the database were converted into grayscale images with pixel values between 0 (black) and 255 (white). The coloured images were converted to gray images because most of the present face recognition algorithms (FDA inclusive) require 2-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. Figure 3 shows some of the cropped greyscale images. Figure 4 shows one of the tribal-marked faces at the different cropping levels including the original grayscale face image.

The code implementing the face recognition system was tested on an AMD Duron system board with

Fig. 2: Some of the faces acquired for training the face database

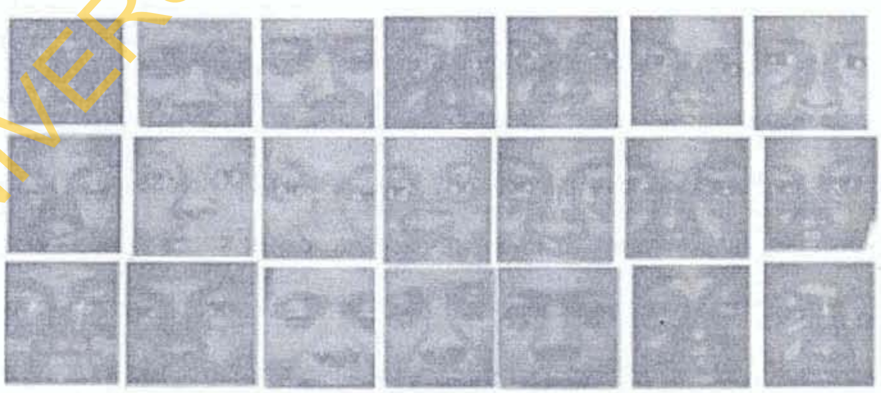

Fig. 3: Some of the cropped grayscale images

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

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 (sec)	Time to identify an image as known or Unknown (sec)
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

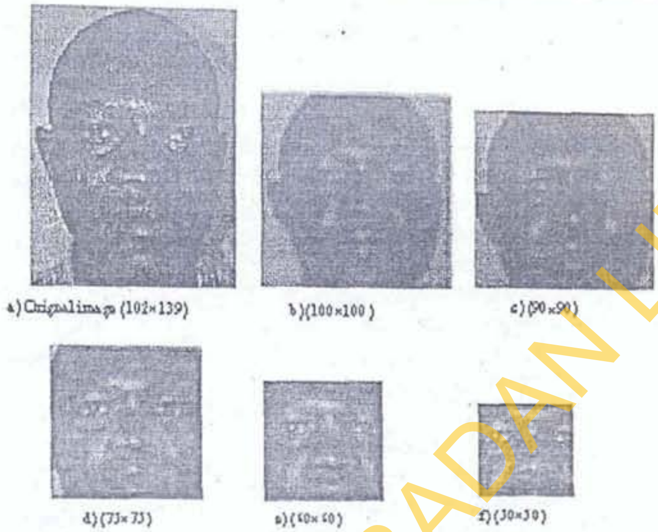

Fig. 4: One of the faces at different levels of cropping

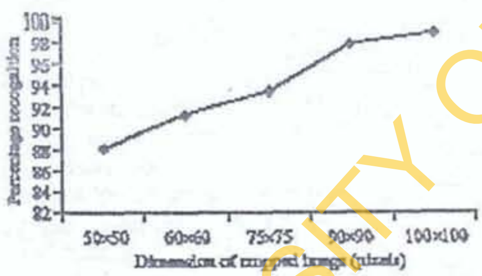

Fig. 5: Graph of percentage recognition performance at different cropped image resolution

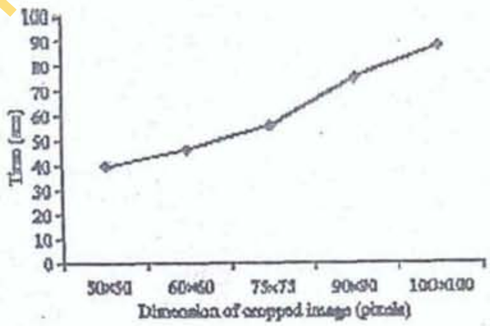

Fig. 6: Graph of time used in training face database at different cropped image resolution

1.16 Ghz processor speed. The face recognition system was experimented with a total of 276 images, out of which 184 images were used in training the database and 92 images were used for testing the created database. This represents 6 images (4 training and 2 testing) for 46 individuals representing a class each.

A recognition performance of between 88 and 99% was obtained when testing with images under the same constrained environment but with different facial expressions in the order of between 50×50 and 100×100 pixels resolution, respectively. The unidentified images were found not to be properly centred frontally, therefore the cropping could not remove the background efficiently.

Table 1 and Fig. 5-8 shows 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 graphs showing these comparisons are as shown in between Fig. 4 and 7.

The results show that, the more the facial features that are included in the training and testing images, the better the recognition performance. Many of the

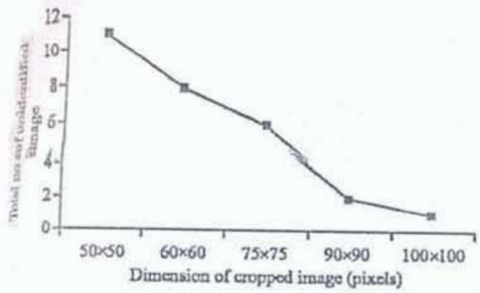

Fig. 7: Graph of total number of unidentified images vs. Dimensions of cropped images

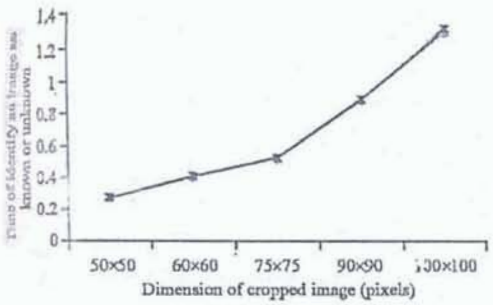

Fig. 8: Graph of time to identify an image as known or unknown vs dimensions of cropped images

recognition uncertainties can be explained by slight differences in orientations and scaling of the test faces compared to the database.

It should also be noted that the recognition system is, to some extent, invariant to facial expressions. In one of the testings, the recognition system was even able to correctly identify an individual with and without glasses (Image 10_5 and 10_6).

Many errors in recognition can similarly be attributed to poor normalisation, emphasizing the importance of strictly standardised databases. Comparing with the database shows that it is due to the face being improperly scaled, such that a complete picture of the face was not provided to the recognition stage.

CONCLUSION

An overview of the design and development of a real-time face recognition system has been presented in this research work. Although, some aspects of the system are still under experimental development especially the normalisation procedures, the research has resulted in an overall success, being able to perform reliable recognition in a constrained environment using Black African faces. Under static mode, where recognition is performed on single scaled images without rotation, a recognition accuracy of between 88-99% has been achieved at different level of cropping.

The design of the face recognition system is based upon Fisherfaces and has been separated into 3 major studies-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 Optimised Fisher face Algorithm.

The application of fisher faces 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 of the faces to be able to really take place in the face recognition system.

RECOMMENDATIONS

While, the problem of recognising faces under gross variations remains largely unsolved, a thorough analysis of the strengths and weaknesses of recognising black faces using fisher faces has been successfully experimented.

The following methods are recommended as part of research work to be embarked upon for an expanded face recognition system to be developed:

- Analysis and implementation of a PCA-Euclidean based face recognition system.
- Analysis and implementation of a PCA-Artificial Neural Networks based face recognition system.
- Analysis and implementation of an OFDA- Artificial Neural Networks based face recognition system.
- Comparative analysis of all the algorithms (including the present one) developed by us will also be carried out with our face database.

REFERENCES

Aliu, S.A., 1999. Development of an automatic knowledge based face recognition system for faces having African features. Unpublished Ph.D. Thesis, University of Ilorin, Nigeria.

Bottou, L., C. Cortes, J. Denker, H. Drucker, I. Guyon, L. Jackel, Y. Le Cun, U. Muller, E. Sackinger, P. Simard and V. Vapnik, 1994. Comparison of classifier methods: A case study in handwritten digit recognition. Proceedings of the International Conference on Pattern Recognition. IEEE Computer Society Press, Los Alamitos, CA.

Brunelli, R. and T. Poggio, 1993. Face Recognition: Features versus Templates. IEEE Trans. Pattern Anal. Machine Intell., 15: 1042-1052.

Carlos E. Thomaz and Duncan F. Gillies, 1998. A maximum uncertainty LDA-based approach for limited sample size problems-with application to face recognition. Imperial College London, London, UK.

Chellapa, R., C.L. Wilson and S. Sirohey, 1996. Human and Machine recognition of faces: A Survey. Proc. IEEE., 83 (5): 705-740.

Horn, R. and C. Johnson, 1985. Matrix Analysis. New York: Cambridge University Press.

Ilker Atalay, 1996. Face Recognition Using Eigenfaces. Unpublished M.Sc. Thesis, Institute of Science and Technology, pp: 24-40.

Johnson, R.A. and D.W. Wichern, 1998. Applied Multivariate Statistical Analysis. 4th Edn. New Jersey: Prentice Hall, pp: 41-836.

Kirby, M., 2000. Dimensionality of Reduction and Pattern Analysis: An empirical approach. Wiley.

Lawrence, S., L.C. Giles, T.A. Chung and D.B. Andrew, 1997. Face Recognition: A Convolutional Neural Network Approach. IEEE Trans. Neural Network, 8 (1): 98-113.

Lin, S.H., 2000. An Introduction to face Recognition Technologies-Part, 2 (3): 1.

Man Kwok Ming, 2003. Face Recognition. Unpublished B.Sc Thesis, University of Hong Kong.

Qi, Y. and B. Hunt, 1994. Signature verification using global and grid features. Pattern Recog., 27 (12): 1621-1629.

Starovoitov, V.V., D.I. Samal and D.V. Briliuk, 2002. Three Approaches for Face Recognition. 6th Int. Conf. Pattern Recognition and Image Analysis, Velikiy Novgorod, Russia, pp: 707-711.

Trucco, E. and A. Verri, 1998. Introductory techniques for 3-D computer vision. New Jersey: Prentice-Hall, Inc.

Turk, M. and A. Pentland, 1991. Eigenfaces for recognition. J. Cognitive Neurosci., 3 (1): 71-86.

Wendy S. Yambor, 2000. Analysis of PCA-Based and Fisher Discriminant-Based Image Recognition Algorithms. Unpublished M.S. Thesis, Colorado State University, Fort Collins, Colorado.