

APPEARANCE-BASED FEATURE EXTRACTION TECHNIQUES FOR FACIAL RECOGNITION: COMPARATIVE STUDY

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Abstract: One of the important steps that must be considered in developing a robust facial recognition is feature extraction. The rate of recognition in the face-based biometric system can be determined by the amount of measurable and relevant features extracted from the face image. Several feature extraction algorithms in appearance-based technique such as Linear Discriminant Analysis (LDA), Independent Analysis (LDA) and Principal Component Analysis (PCA) have been used in face recognition. This paper applied Contrast Limited Adaptive Histogram Equalization (CLAHE) before three appearance-based feature extraction algorithms: PCA, LDA and combined PCA/LDA for face recognition system. A comparative analysis was conducted on the three techniques, experimental results showed that the PCA technique recorded the best recognition accuracy (RA) of 95.65% for ORL database, the best False Rejection Rate (FRR) of 0.1250 in LDA for FERET database and the best False Acceptance Rate (FAR) of 0.5000 in PCA / LDA for FERET database.

Keywords: Appearance-based technique, Face recognition, Feature extraction, Image processing.

1. INTRODUCTION

Face recognition is a physiological approach of a biometric system that identifies or verifies individual based on feature vectors derived from face image [1]. The extraction of features can be referred to as a representation of the original image in a measurable form to simplify decision making such classification and pattern detection [2]. The process of finding reliable and discriminative features is seen to be an essential phase in image processing and computer vision task [3]. One of the most significant steps in pattern recognition is the extraction of feature, which major purpose is to obtain reduced features accurately for classification [4].

The extraction of facial feature is one of the principal components and attempted problems in computer vision [5], it performs two vital functions: converts input vector into a feature vector and also reduces its dimensionality [6] [7]. In complex data analysis or pattern recognition such as face image data, part of the key problems encountered is the amount of features involved. It is very important to extract a well-defined feature just to make the process of recognition more effective and accurate. The face representation is a predominant phase that should be correctly observed before classification [8].

Faces not properly represented can affect classifier efficiency. Analyzing a huge volume of features normally involve a large memory usage and computation power. The major task of feature extraction is to select only the essential features from the input features to accomplish the desired function based on the representation of a reduced form of the complete features input [9]. The techniques developed for the extraction of feature is divided into two main types: geometrical and appearance-based approaches [10].

The techniques of geometric normally involve distinct features which include nose, eyes, mouth and a head structure to be employed in developing a recognition system by the dimension and point of these characteristics. The appearance-based approach applies statistical values for extraction, in which a high number of face images are to be detected using statistical or machine learning techniques [11]. This technique considers a face image as patterns of two dimensions; theory of feature in this method is unlike the general features of the face such as eyes and mouth.

Appearance-based techniques have been considered for its efficiency in dimensionality reduction ability in computer vision applications like face recognition system [4]. Several feature extraction techniques under appearance-based approach have been applied such as Fisher LDA, PCA, ICA, Locality Preserving Projections (LPP) and Discrete Wavelet Transform (DWT) [12]. Appearance method is identified to be an efficient facial feature extraction approach due to its ability to reject the redundant information and also retain significant information of image [13].

The paper considered the appearance-based feature extraction for facial recognition system using PCA and LDA and the combined features of the individual techniques.

2. RELATED WORK

Authors in [11] conducted a comparative survey on some feature extraction techniques available in face detection. The study considered different feature extraction algorithms like DWT, Scale Invariant Fourier Transform (SIFT), LDA, PCA. It was recommended that better results would be produced if the DWT has been hybridized with other mentioned techniques.

Authors in [14] presented a comparative study on various extraction of feature methods; Singular Value Decomposition (SVD), PCA for facial expressions and emotion recognition. The result revealed that the

recognition accuracy of combined PCA with SVD outperformed PCA approach. It was demonstrated that when edge projection analysis, SUSAN edge detector, and geometry distance measure were combined. The combination produced an effective system for location of grayscale images in constrained environments. The feed-forward back propagation neural network. propagation neural network was applied to detect the facial expression. 100% accuracy was obtained for the training phase and 95.26% accuracy was obtained for the testing phase using the JAFFE database. Authors in [15] performed a study to reveal the efficiency of the combination of Independent Component Analysis (ICA) with Gabor algorithm (I-Gabor) as feature extraction. The features were obtained from the eye and nose of known faces using Gabor and I-Gabor. The Support Vector Machine was used for local characteristics classification of facial features regions. The performance of classification algorithms was tested using FAR, FRR and RA. The experimental results recorded 4.4 % of FAR, 5.3 % of FRR, 87.7 % of accuracy for Gabor feature extraction method and 2.8 % of FAR, 3.9 % of FRR, 94.9 % of accuracy for Gabor-Independent Component Analysis method

Authors in [16] applied several linear subspace techniques to perform two significant tasks; reduction of dimensionality and loss of performance in classification due to facial appearance variations. The design of experiments was carried out which specifically investigated the gain invariant to lighting and changes in expression on the face. The reduction of dimensionality techniques was used to choose relevant features and also find the region that is less variant to basic deformations due to expression or lighting. Support Vector Machine (SVM) was used for classification. The proposed algorithm was evaluated with ORL face image database under different expressions or illumination conditions. More significant and comparative results were discovered.

3. METHODOLOGY

The study performed a comparative analysis of three selected appearance-based techniques: LDA, PCA and combined PCA/LDA. Three face image datasets: ORL, FERET and Black database were employed to carry out the system evaluation. The face images normalization was performed geometrically and photometrically to produce a standard image for analysis. Contrast Limited Histogram Equalization (CLAHE) was applied to reduce lighting variations in face images. Classification of the face image into matched and mismatched was achieved using Neural Network (NN). The framework of the developed system is shown in Figure 1.

3.1 Image Acquisition

The study used three image datasets, two of the image database: FERET and YALE face image database are publicly available online as the samples are shown in

Figure 2 and 3. The BLACK face image database, which contains face images from students of University of Ilorin, Ilorin as shown in Figure 4.

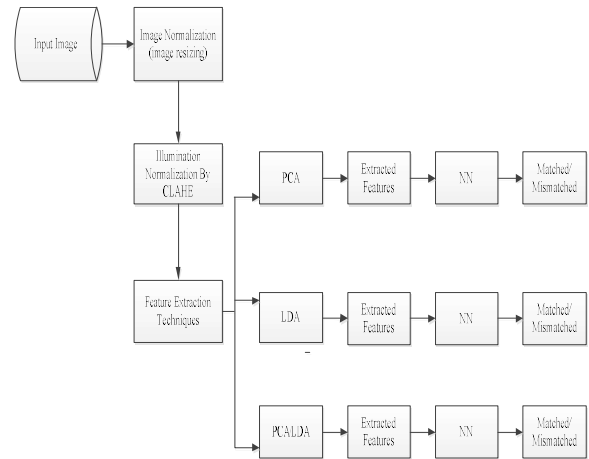


Figure 1: Framework of the Appearance-Based Feature Extraction Techniques



Figure 2: Sample of Face Images (FERET Database)



Figure 3: Sample of Face Images (YALE Database)



Figure 4: Sample of Face Images (BLACK Database)

3.2 Feature Extraction

After the illumination normalization process, face images were passed into two techniques extraction of the feature: PCA and LDA. The individual resultant features were combined. The feature extraction algorithms are shown in Figure 5 and Figure 6.

Step 1: Obtain original set of face images (training sets)
 Step 2: Calculate the Average Mean of testing face

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$$

 Step 3: Normalize each input face image by subtracting from face
 Step 4: Compute the covariance matrix

$$C = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})(x_i - \bar{x})^T$$

 Step 5: Calculate the Eigenvalues of covariance matrix, keep only K largest Eigenvalues
 Step 6: Compute the Eigenvectors of the covariance matrix corresponding to the largest Eigenvalues

$$CV = \lambda V$$

 Where v and λ are Eigenvector / Eigenvalue respectively
 Step 7: Compute Eigen faces containing highest information of face image
 Step 8: Compute the projected face image
 Step 9: End

Figure 5: PCA Algorithm

Step 1: Given a set of N image samples, each of which is represented as a row of length M.
 Step 2: Compute the mean of each class

$$\mu_i (1 \times M)$$

 Step 3: Compute the total mean of all image data

$$\mu_t (1 \times M)$$

 Step 4: Calculate between class matrix

$$S_B (M \times M)$$

 Step 5: For all class i, i = 1, 2, ..., c do
 Step 6: Compute within class matrix of each class

$$S_{W_i} (M \times M)$$

$$S_{W_i} = \sum_{x_i \in \omega_i} (x_i - \mu_j)(x_i - \mu_j)^T$$

 Step 7: Construct a transformation matrix for each class

$$W_i = S_{W_i}^{-1} S_B$$

 Step 8: Calculate eigenvalues (λ^i) and eigenvectors (V^i) of each transformation matrix (W_j)
 Step 9: Sort the eigenvector in descending order according to their corresponding eigenvalues.
 Step 10: Project the image samples of each class (ω_j) onto their lower dimensional space (V_k^i)

$$\Omega_j = X_i V_k^j, \quad x_i \in \omega_j$$

 Step 11: End

Figure 6: LDA Algorithm

3.3 Image Classification

The classification phase involves the testing of the developed appearance-based feature extraction techniques. In the study, A Neural Network (NN) was employed to classify an image into either matched or mismatched. Images used for the evaluation were gathered from the BLACK, FERET and ORL datasets. The Some images were used as impostors (images not trained and also not contained in the databases) to test the proposed system for true negative (images that were not seen in the databases) as well as true positive. For the false positive (mismatched images), 5 images were considered as impostors to test system. For false negative (mismatched), 40 images were used to test the system, where the mismatched images were obtained. The simple architecture of ANN is shown in Figure 7.

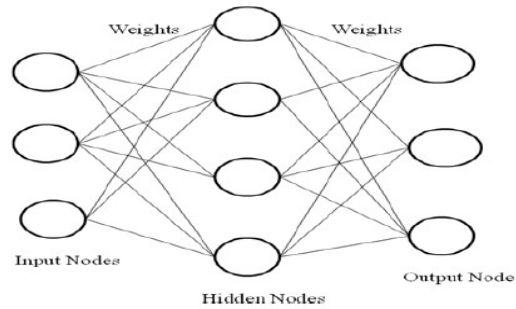


Figure 7: Architecture of Neural Network [17]

4. RESULTS AND DISCUSSION

4.1 Experimental Results of Developed Appearance-Based Face Recognition System

The experimental results of the developed appearance based system were conducted using FAR, FRR and RA. The definition of each evaluation metric is as follows:

- (i) FAR: It is a measure of the possibility that face recognition system as a biometric system will wrongly accept an access attempt by an unauthorized user. FAR is stated as the ratio of the number of false acceptance divided by the number of identification attempts as shown in Equation (1).

$$FAR = \frac{\text{number of false acceptance}}{\text{number of identification attempts}} = \frac{FP}{FP+TN} \dots\dots(1)$$

(ii) FRR: This is the measure of the likelihood that face biometric system will wrongly reject an access attempt by authorized user. A system of FRR can be defined as the ratio of the number of false rejection divided by the number of identification attempts as shown in Equation (2).

$$FRR = \frac{\text{False rejection}}{\text{number of identification attempts}} = \frac{FN}{TP+FN} \dots\dots\dots(2)$$

(iii) RA: The recognition accuracy can be measured according to the percentage of the recognition of faces per total number of tested faces of the same person as shown in Equation (3)

$$RA (\%) = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \dots\dots\dots(3)$$

Where FP represents the false positive (number of impostor images not classified in the database) and TN represents the true negative (number of impostor images wrongly classified in the database). Where FN denotes the false negative (number of images wrongly mismatched during classification); and TP denotes the true positive (number of images correctly matched during classification).

4.1.1 False Acceptance Rate (FAR)

The FAR was conducted on the appearance-based feature extraction techniques using ORL, FERET and BLACK face image datasets as shown in Table 1

Table 1: False Acceptance Rate (FAR)

Technique	ORL	FERET	BLACK
PCA	0.1667	0.4000	0.3333
LDA	0.3333	0.3333	0.2500
PCA/LDA	0.2500	0.5000	0.2000

From Table 1, the highest FAR of 0.5000 was recorded in PCA / LDA for FERET database, while the lowest FAR of 0.1667 was obtained in PCA for ORL database.

4.1.2 False Rejection Rate (FRR)

The FRR was conducted on the appearance-based feature extraction techniques using ORL, FERET and BLACK face image datasets as shown in Table 2.

Table 2: False Rejection Rate (FRR)

Technique	ORL	FERET	BLACK
PCA	0.0250	0.0750	0.0714
LDA	0.0750	0.1250	0.1081
PCA/LDA	0.0500	0.1000	0.0976

From Table 2, the highest FAR of 0.1250 was recorded in LDA for FERET database, while the lowest FAR of 0.0250 was obtained in PCA for ORL database.

4.1.3 Recognition Accuracy (RA)

The results of the recognition accuracy of appearance-based feature extraction methods are given for the three datasets; ORL, FERET and BLACK face image datasets. Results are represented in Table 3.

Table 3: Recognition Accuracy (RA) (%)

Technique	ORL	FERET	BLACK
PCA	95.65	88.89	91.11
LDA	89.13	84.78	85.71
PCA/LDA	93.18	89.13	89.13

From Table 3, the highest RA of 95.65% was recorded in PCA for the ORL database, while the RA of 84.78% was obtained in LDA for FERET database.

4.2 Comparative Analysis of Feature Extraction Techniques

This section provides a complete comparative analysis of appearance-based feature extraction techniques for three face image datasets. The result of the comparison is shown in Table 4, Table 5 and Table 6 respectively.

Table 4: Comparative Analysis of the Feature Extraction Techniques (ORL Database)

Technique	FAR	FRR	RA
PCA	0.1667	0.0250	95.65%
LDA	0.3333	0.0750	89.13%
PCA/LDA	0.2500	0.0500	93.18%

From Table 4, the ORL Database has the best FAR of 0.3333 in LDA and the best FRR of 0.0750 was obtained in LDA. The best recognition accuracy of 95.65% was achieved in PCA

Table 5: Comparative Analysis of Feature Extraction Techniques (FERET Database)

Technique	FAR	FRR	RA
PCA	0.4000	0.0750	88.89%
LDA	0.3333	0.1250	84.78%
PCA/LDA	0.5000	0.1000	89.13%

From Table 5, the FERET Database has the best FAR of 0.5000 in PCA / LDA technique and also the best FRR of 0.1250 was achieved in LDA. The best recognition accuracy of 89.13% was achieved in the PCA / LDA technique.

From Table 6, the Blackface has the best FAR of 0.3333 in PCA technique and also the best FRR of 0.1081 is obtained in LDA. The highest RA of 91.11% was achieved in the PCA technique.

Table 6: Comparative Analysis of Feature Extraction Techniques (BLACK Database)

Technique	FAR	FRR	RA
PCA	0.3333	0.0714	91.11%
LDA	0.2500	0.1081	85.71%
PCA/LDA	0.2000	0.0976	89.13%

5. CONCLUSION

Feature extraction technique remains a significant phase of any facial recognition algorithm. The feature extraction technique is classified into two parts the feature-based and appearance-based method. Among these methods, the appearance-based technique has gained much attention of researchers in pattern recognition because the method represents the whole face image during recognition. One of the main challenges of appearance-based is illumination (variation in lighting conditions), thus this may influence the face recognition performance. To investigate the effect of illumination normalization method on appearance-based approach, this paper carried out a comparative study on three selected appearance-based feature extraction approaches PCA, LDA and PCA/LDA. The experimental results showed that the best recognition accuracy of 95.65% was achieved in PCA for ORL database, the best FAR of 0.5000 was obtained in PCA / LDA for FERET database and the best FRR of 0.1250 was achieved in LDA for FERET database.

REFERENCES

- [1] A. S. Joshi, A. G. & Deshpande, "Review of Face Recognition Techniques," *Int. J. Adv. Res. Comput. Sci. Softw. Engineering*, vol. 5, no. 1, pp. 71–75, 2015.
- [2] A. Chadha and N. Carolina, "Comparative Study and Optimization of Feature- Extraction Techniques for Content-based Image Retrieval," *Int. J. Comput. Appl.*, vol. 52, no. 20, pp. 35–42, 2012.
- [3] Riyanka, "Face Recognition Based on Principal Component Analysis and Linear Discriminant Analysis," *Int. J. Adv. Res. Electr. Electron. Instrumentation Engineering*, vol. 4, no. 8, pp. 7266–7274, 2015.
- [4] P. K. Kumar, G., & Bhatia, "A Detailed Review of Feature Extraction in Image Processing Systems," in *International Conference on Advanced Computing & Communication*, 2014, pp. 5–12.
- [5] A. G. Akintola, A. T. Oniyangi, and M. B. Jibrin, "Comparative Analysis of Appearance-Based Feature Extraction Techniques in Face Recognition: Proposed Study," *Univ. Pitești Sci. Bull. Comput. Sci.*, vol. 18, no. 2, pp. 1–8, 2018.
- [6] U. Bakshi and R. Singhal, "A Survey on Face Detection Methods and Feature Extraction Techniques of Face Recognition," *Int. J. Emerg. Trends Technol. Comput. Sci.*, vol. 3, no. 3, pp. 233–237, 2014.
- [7] M. L. Raymer, W. F. Punch, E. D. Goodman, L. A. Kuhn, and A. K. Jain, "Dimensionality reduction using genetic algorithms," *IEEE Trans. Evol. Comput.*, vol. 4, no. 2, pp. 164–171, 2000.
- [8] B. Rouhi, R., Amiri, M. & Irannejad, "A Review on Feature Extraction Techniques in Face Recognition," *Signal Image Process.*, vol. 3, no. 6, pp. 1–15, 2012.
- [9] P. Flynn, "A survey of approaches and challenges in 3D and multi-modal 3D + 2D face recognition," *Comput. Vis. Image Underst.*, vol. 101, no. 1, pp. 1–15, 2006.
- [10] H. Makwana and T. Singh, "Comparison of Different Algorithm for Face Recognition," *Glob. J. Comput. Sci. Technol. Graph. Vis.*, vol. 13, no. 9, pp. 17–20, 2013.
- [11] K. Kaur, M. & Jasjit, "Review of Face Recognition Techniques," *Int. J. Comput. Appl.*, vol. 164, no. 6, pp. 31–35, 2017.
- [12] N. Struc, V., Gajsek, R., & Pavesic, "Principal Gabor filters for Face Recognition," in *IEEE 3rd International Conference on Biometric: Theory, Application, and Systems, 2009. BTAS '09.*, 2009, pp. 11–16.
- [13] A. Kaur, S. Singh, and T. Dir, "Face Recognition Using PCA (Principal Component Analysis) and LDA (Linear Discriminant Analysis) Techniques," *Int. J. Adv. Res. Comput. Commun. Eng.*, vol. 4, no. 3, pp. 308–310, 2015.
- [14] P. P. Shinde, A. R. & Agnihotric, "Comparative Study of Facial Feature Extraction, Expressions and Emotion Recognition Shinde A.R. 1 and Agnihotri P.P. 2 1," *J. Manag. Res.*, vol. 3, no. 2, pp. 66–69, 2014.
- [15] W. O. Ismaila, A. B. Adetunji, and A. S. Falohun, "A Study of Features Extraction Algorithms for Human Face Recognition," *Transnatl. J. Sci. Technol.*, vol. 2, no. 6, pp. 14–22, 2012.
- [16] R. Sakthivel, S. & Lakshmi pathi, "Enhancing Face Recognition Using Improved Dimensionality Reduction and Feature Extraction Algorithms – an Evaluation with ORL Database," *Int. J. Eng. Sci. Technol.*, vol. 2, no. 6, pp. 2288–2295, 2010.
- [17] M. M. Kasar, D. Bhattacharyya, and T. Kim, "Face Recognition Using Neural Network: A Review," *Int. J. Secur. Its Appl.*, vol. 10, no. 3, pp. 81–100, 2016.