MEDOID BASED MODEL FOR FACE RECOGNITION USING EIGEN AND FISHER FACES

Aruna Bhat¹

¹Department of Electrical Engineering, IIT Delhi, Hauz Khas, New Delhi, India
minu_aru@yahoo.co.in

ABSTRACT

Biometric technologies have gained a remarkable impetus in high security applications. Various biometric modalities are widely being used these days. The need for unobtrusive biometric recognition can be fulfilled through Face recognition which is the most natural and non intrusive authentication system. However the vulnerability to changes owing to variations in face due to various factors like pose, illumination, ageing, emotions, expressions etc make it necessary to have robust face recognition systems. Various statistical models have been developed so far with varying degree of accuracy and efficiency. This paper discusses a new approach to utilize Eigen face and Fisher face methodology by using medoid instead of mean as a statistic in calculating the Eigen faces and Fisher faces. The method not only requires lesser training but also demonstrates better time efficiency and performance compared to the conventional method of using mean.

KEYWORDS

Eigen Face, Fisher Face, PCA, LDA, medoid

1. INTRODUCTION

A biometric system automatically recognizes individuals based on certain physiological or behavioral traits. Face which is naturally used by humans for recognizing people can be also be utilized as a biometric trait. In fact it is the most unobtrusive biometric authentication modality [1]. Humans have the capability of accurately recognizing people using their facial information both in static and dynamic context. They possess the ability to precisely recognize individuals even in presence of variations due pose, expression, emotion, illumination, ageing, facial distraction like hair growth, makeup etc. These observations lead us towards the development of face recognition systems which could have performance as high as humans deliver [2]. Such a system needs to be swift and accurate at the same time and possess reasonable resilience too.

Various computational models for face recognition have been designed in the past [3]. Different approaches have been developed to provide input to the face recognition systems. The entire face could be used as the input or one may use only the local features like eyes, nose and mouth. Several techniques for feature extraction have been composed [4] [5]. One of the most significant achievements in the area of face recognition was the Eigen Face methodology, proposed by M.A.Turk & A.P.Pentland [6] [7]. It utilizes Principal Component Analysis to extract the features from the facial images [8]. Utilisation of Karhunen-Loève procedure for the characterization of human faces was proposed by M. Kirby & L. Sirovich [9]. PCA (Principal Component Analysis) is a well known technique for performing dimensionality reduction [10]. A D-dimension space is transformed into C-dimensional space, such that $D > C$. Through PCA the face image is

transformed into Eigen Face images which contain the principal components of the face image. The principal components are represented through the eigen vectors. For every facial image, the eigenvectors with largest eigen values can be used to represent the face.

This methodology was successful in providing a reasonable face recognition system. Many developments have followed and various alterations to the procedure have been proposed to further augment the efficiency of the system. One such method was application of Linear Discriminant Analysis [11] [12] in place of PCA for face recognition. It yielded better results and was more robust too. The use of FLDA gave rise to the name Fisher faces [12] which are analogous to eigen faces produced by the PCA method. Many other methodologies on similar lines have been proposed. Independent Component Analysis [13] and Probabilistic LDA have also been used for face biometrics and are reasonably efficient. Apart from these one may find various other approaches which are based on different methods of feature extraction and classification like using Neural networks [14], SVMs [15], HMM etc. The method discussed in this paper provides a different approach to calculate the Eigen and Fisher faces. The conventional statistic of mean has been replaced by Medoid and the method is observed to perform better in terms of time and efficiency with lesser training effort.

The rest of this paper is organized as follows: Section 2 discusses the details about the Eigen Face and Fisher Face methods for face recognition. The proposed methodology of using Medoid instead of mean in the Eigen Face and Fisher Face is discussed in Section 3. It also elaborates on the concepts of Medoid as a statistic. Experimental results are provided in Section 4. Section 5 discusses the conclusion and future scope.

2. OVERVIEW OF EIGEN FACES AND FISHER FACES METHODOLOGY

Eigen faces are generated using PCA. The technique is capable of identifying a face with reasonable precision. However its performance is improved by using LDA instead of PCA which generates Fisher faces that are analogous to Eigen faces generated by PCA method. The mechanism of both the techniques is detailed below:

2.1. Eigen Faces using PCA

The system follows a supervised learning approach. The system is trained first and then evaluated for the test data.

2.6.1. Training the system

The steps for training the recognition system are as follows:

1. The input training set consists of n facial images of size $M \times M$.

Figure 1. Sample from Training data

2. The images are represented by vectors of size M^2 , $x_1, x_2, x_3, \dots, x_m$.
3. Find the average image from training set:

$$\mu = (1/m) \sum_{i=1}^m x_i$$

Figure 2. Mean Image

4. Find the difference of each face differs from the mean image:

$$r_i = x_i - \mu$$

5. Derive the covariance matrix:

$$C = AA^T \text{ where } A = [r_1, \dots, r_m]$$

6. Derive the eigenvectors for the matrix $A^T A$ of size $m \times m$.
7. If v is a nonzero vector and λ is a number such that $Av = \lambda v$, then v is said to be an eigenvector of A with eigenvalue λ .
8. Consider the eigenvectors v_i of $A^T A$:

$$A^T A v_i = \mu_i v_i$$

9. Pre-multiplying both sides by A such that,

$$AA^T (A v_i) = \mu_i (A v_i)$$

10. The eigenvectors of covariance matrix are $u_i = A v_i$
11. u_i represent the Eigen faces.

Figure 3. Eigen Faces

12. A face image can be projected into this face space by:

$$d_k = U^T (x_k - \mu) \text{ where } k=1, \dots, m$$

2.6.2. Testing

The steps for testing the recognition system are as follows:

1. The image x to be tested is projected into the face space U to obtain a vector d :

$$d = U^T(x - \mu)$$
2. The distance of d to each face class is calculated as:

$$d_k^2 = \|d - d_k\|^2, \text{ where } k = 1, \dots, m$$
3. ϵ is the distance threshold which is calculated as:

$$\epsilon = \frac{1}{2} \max_{j,k} \{\|p_j - p_k\|\} \text{ where } j, k = 1, \dots, m$$
4. Calculate the distance between the original image x and its reconstructed image x_f from the eigenface space:

$$d^2 = \|x - x_f\|^2, \text{ where } x_f = U * x + \mu$$
5. Decision regarding the test face image is taken as per the below mentioned three cases:
 case1: $d_k^2 > \epsilon$
 output: the input image is not a face
 case2: for all values of k , $d_k^2 < \epsilon$ & $k \neq k^*$
 output: the input image is a face unknown to the database
 case3: $d_{k^*}^2 < \epsilon$ & $k^* = \min_k \{d_k^2\} < \epsilon$
 output: the input image is recognized as the face of individual k^*

2.2. Fisher Faces using LDA

Linear Discriminant Analysis is an enhancement over PCA. It creates a discriminant subspace which minimizes the scatter S_W between images of same class and maximizes the scatter S_B between different class images. The below procedure is used to find the Fisher faces and classification is done on similar lines of Eigen face approach.

1. $X_1, X_2, \dots, X_c$ represent the c classes of face in the database. Each face class is represented by vector X_i , $i = 1, 2, \dots, c$ has k facial images x_j , $j=1, 2, \dots, k$.
2. Find the mean image μ_i of each class X_i as:

$$\mu_i = \frac{1}{k} \sum_{j=1}^k x_j$$

3. Mean image μ of all the face classes in the database can be calculated as:

$$\mu = \frac{1}{c} \sum_{i=1}^c \mu_i$$

3. Calculate the within-class scatter matrix:

$$S_W = \sum_{i=1}^c \sum_{x_k \in X_i} (x_k - \mu_i)(x_k - \mu_i)^T$$

5. Calculate the between-class scatter matrix:

$$S_B = \sum_{i=1}^c N_i (\mu_i - \mu)(\mu_i - \mu)^T$$

6. We find the projection directions as the matrix W that maximizes

$$= \operatorname{argmax} J(Z) = |Z^T S_B Z| / |Z^T S_W Z|$$

7. We can observe that it represents a generalized eigenvalue problem where the columns of Z are given by the vectors Z_i such that,

$$S_B Z_i = \lambda_i S_W Z_i$$

8. Find the product of S_W^{-1} and S_B and calculate its eigenvectors after reducing the dimension of the feature space.
9. Compose a matrix Z that represents all eigenvectors of $S_W^{-1} * S_B$ by placing each eigenvector Z_i as a column in Z.

Figure 4. Fisher Faces

10. Each face image $x_j \in X_i$ can be projected into this face space as:

$$p_i = Z^T (x_j - \mu)$$

4. PROPOSED CHANGES IN THE CONVENTIONAL METHOD

3.1. Medoid vs Mean

Medoid is a statistic which is based on the degree of dissimilarity of an object to all the other objects in the cluster/data set. It represents the data instance whose average dissimilarity to all the other data items in the data set is minimal.

$$m_d(S) = \operatorname{argmin}_{x \in M} \sum_{y \in S} d^2(x, y)$$

This suggests that one may end up having more than a single medoid in a data set. Another important aspect of medoids is that they are always a member of a data set unlike mean which may or may not be a component of the data set. Mean or centroid value simply represents the average of a data. It need not be a data member itself. However medoid being an instance of the data immediately gives rise to the modelling of the inter-dependence of the data items. Partitioning Around Medoids and K-Medoid Clustering techniques have come up due to this property of medoids and are known to produce reasonable results.

3.2. Preprocessing

For analyzing the proposed technique, open source data sources were used. JAFFE database [16] was used to train and thereafter test the system. The preliminary steps of face detection, segmentation and facial image processing are crucial to the end results that are obtained by any face recognition system. The feature extraction using both eigen and fisher faces was preceded by these vital components of pattern recognition. The images were segmented so that the entire image consists only of the face of a person. The segmented image containing only the facial information was converted to grayscale and filtered to remove any noise. Post quality enhancement of face image, the appropriate ROI for the same was calculated. The facial image is then ready for feature extraction. Instead of finding the average image, we find the Medoid image for the training database.

3.3. Feature extraction and Classification

Both the methods of Eigen faces and Fisher faces based on Medoid are explained below:

3.3.1. Eigen Faces using medoids

1. Training the system
 - a. Convert all the face images (size $M \times M$) present in the training data set to Vectors of size M^2 , $x_1, x_2, x_3, \dots, x_m$.
 - b. Find the Medoid image from training set:

$$Y = \underset{i,j}{\operatorname{argmin}} d^2(x_i, x_j)$$

- c. Find the difference of each face differs from the Medoid image:

$$r_i = x_i - Y$$

- d. Derive the covariance matrix

$$C = AA^T \text{ where } A = [r_1, \dots, r_m]$$

- e. Derive the eigenvectors for the matrix $A^T A$ of size $m \times m$.

$$A^T A v_i = Y_i v_i$$

- f. Pre-multiplying both sides by A such that,

$$AA^T(Av_i) = Y_i(Av_i)$$

- g. The eigenvectors are given by $u_i = Av_i$, which represent the Eigen faces.

- h. A face image can be projected into this face space by:

$$d_k = U^T(x_k - Y) \text{ where } k=1, \dots, m$$

2. Testing the system

- a. The test face image x is transformed to vector d :

$$d = U^T(x - Y)$$

- b. Calculate the Euclidean distance d_k of d to each face class:

- c. ϵ is the distance threshold which is calculated as:

$$c = \frac{1}{2} \max_{j,k} \{ \|p_j - p_k\| \} \text{ where } j,k = 1, \dots, m$$

- d. Calculate the distance between the original image x and its reconstructed image x_f from the eigenface space:

$$^2 = \|x - x_f\|^2, \text{ where } x^f = U * x + Y$$

- e. Decision regarding the test face image is taken as per the below mentioned three cases:

case1: c

output: input image is not a face

case2: for all values of k , $c < c_k$ & $k < c$

output: input image is a face unknown to the database

case3: $c < c_k$ & $k^* = \min_k \{ c_k \} < c$

output: input image is recognized as the face of individual k^*

3.3.2. Fisher Faces using medoids

1. The C face classes in the database are represented by vector X_i , $i = 1, 2, \dots, c$ and each has k facial images x_j , $j=1, 2, \dots, k$.
2. Find the Medoid image Y of each class X_i as:

$$Y_i = \operatorname{argmin}_{i,j} \sum_{j=1}^k d^2(x_i, x_j)$$

3. Medoid image Y of all the face classes in the database can be calculated as:

$$Y = \operatorname{argmin}_{i,j} \sum_{i,j=1}^c d^2(Y_i, Y_j)$$

4. Calculate the within-class scatter matrix S_W and between-class scatter matrix S_B using Medoid values Y_i and Y .
5. Derive the Fisher faces by composing a matrix Z that represents all eigenvectors of the product $S_W^{-1} * S_B$ by placing each eigenvector Z_i as a column in Z .
6. Each face image $x_j \in X_i$ can be projected into this face space as:

$$p_i = Z^T(x_j - Y)$$

4. EXPERIMENTAL RESULTS

The method was evaluated using the JAFFE database [16] which contains the facial images with different expressions (sad, angry, happy etc).

Table 1. Comparison of results Mean vs Medoid based Eigen Faces

Method	Training			
	1 image per subject	2 images per subject	3 images per subject	5 images per subject
Mean based Eigen Faces	61	63	65	68
Medoid based Eigen Faces	67	67	66	66

Figure 5. Comparison of results Mean vs Medoid based Eigen Faces

Table 2. Comparison of results Mean vs Medoid based Fisher Faces

Method	Training			
	1 image per subject	2 images per subject	3 images per subject	5 images per subject
Mean based Fisher Faces	68	72	78	80
Medoid based Fisher Faces	78	80	80	77

Figure 6. Comparison of results Mean vs Medoid based Fisher Faces

Figure 7. Sample from Results

5. CONCLUSIONS

The use of medoid instead of mean in calculating the Eigen faces was observed to yield comparable performance to the conventional method. It requires lesser training of the system and yet performs with reasonable success rate at higher time efficiency. The system was tested for expression invariance using open source data sets and reasonable results were achieved for the same.

The novel idea of using medoid as a statistic directs us towards the concept of PAM (Partitioning Around Medoids) and unsupervised face recognition using K-Medoid Clustering. We may also use medoids in developing new statistical models for 3D face recognition applications. Medoids can also be used to find which images are likely to cause mismatch in the recognition system due to their less dissimilarity to the other images in the database. This information can be useful to assess and address the potential issues in a face database. We may also test Eigen face and Fisher face method using medoids for different distance classifiers apart from Euclidean Distance like Manhattan distance, Minkowski distance etc. The approach may be evaluated for Pose and Illumination invariance and further enhanced to increase the robustness against expression and other variances present individually or collectively.

ACKNOWLEDGEMENTS

The author would like to thank the faculty and staff at the Department of Electrical Engineering, IIT Delhi for the immense guidance and help they have graciously provided.

REFERENCES

- [1] R. Baron, (1981) "Mechanisms of Human Facial Recognition," International Journal of Man-Machine Studies, Vol. 15, pp. 137—178.
- [2] R. Chellappa, C. Wilson & S. Sirohey, (1995) "Human and Machine Recognition of Faces: A Survey," Proc. IEEE, vol. 83, no. 5, pp. 705-740.
- [3] W. Zhao, R. Chellappa, A. Rosenfeld, P.J. Phillips, "Face Recognition: A Literature Survey".
- [4] E.Saber & A.Tekalp, (1998) "Frontal-View Face Detection and Facial Feature Extraction using Colour, Shape and Symmetry based Cost Functions", Pattern Recognition Letters, pages 669-680.
- [5] R. Brunelli and T. Poggio, (1993) "Face recognition: Features versus templates", IEEE Transactions on Pattern Analysis and Machine Intelligence, 15:1042-1052.
- [6] M.Turk & A.Pentland, (1991) "Eigenfaces for Recognition", Journal of Cognitive Neuroscience, vol.3, no.1, pp. 71-86, 1991a.
- [7] M. Turk & A. Pentland, (1991) "Face Recognition Using Eigenfaces", Proc. IEEE Conf. on Computer Vision and Pattern Recognition, pp. 586-591.
- [8] P.J.B. Hancock, A.M. Burton & V. Bruce, (1996) "Face processing: Human perception and principal components analysis", Memory and Cognition, 24(1):26-40
- [9] M. Kirby & L. Sirovich, (1990) "Application of the Karhunen-Lo`eve procedure for the characterization of human faces", IEEE Transactions on Pattern Analysis and Machine Intelligence, 12, N1:103-108.
- [10] I.T. Jolliffe, (1986) "Principal Component Analysis (Springer-Verlag, New York).
- [11] P.N. Belhumeur, J.P. Hespanha & D.J. Kriegman, (July 1997) "Eigenfaces vs. Fisherfaces: Recognition Using Class-Specific Linear Projection", PAMI(19), No. 7, pp. 711-720.
- [12] W.Zhao, R. Chellappa & A. Krishnaswamy, (1998) "Discriminant Analysis of Principal Components for face Recognition", Proc. Third Int'l Conf. Automatic Face and Gesture Recognition, pp. 336-341.
- [13] Marian Stewart Bartlett, Javier R. Movellan & Ferrence J. Sejnowski, (Nov'2002) "Face Recognition by Independent Component Analysis", IEEE Trans. on Neural Networks, vol.13, no. 6.
- [14] Henry A. Rowley, Shumeet Baluja & Takeo Kanade , (1998) "Neural Network-Based Face Detection". IEEE Trans. on Patt. Analysis and Machine Intelligence, 20(1):23-28.
- [15] E. Osuna, R. Freund & F. Girosi, (1997) "Training support vector machines: An application to face detection", Proceedings of CVPR'97, Puerto Rico.
- [16] Coding Facial Expressions with Gabor Wavelets Michael J. Lyons, Shigeru Akamatsu, Miyuki Kamachi & Jiro Gyoba Proceedings, Third IEEE International Conference on Automatic Face and Gesture Recognition, April 14-16 1998, Nara Japan, IEEE Computer Society, pp. 200-205

AUTHORS

The author is a research scholar at Indian Institute of Technology, Delhi.