IJREAT International Journal of Research in Engineering & Advanced Technology, Volume 1, Issue 2, April-May, 2013
ISSN: 2320 - 8791
www.ijreat.org

FACE RECOGNITION USING PRINCIPLE COMPONENT ANALYSIS (PCA) ALGORITHM

P.Priyanka[1], Dorairaj Sukanya[2] and V.Sumathy[3]

[1,2,3] Department of Computer Science and Engineering, Kingston Engineering College, Vellore, Tamil Nadu.

Abstract

Face recognition refers to an automated or semi-automated process of matching facial images.Face recognition can be applied for a wide variety of problems like image and film processing, human-computer interaction, criminal identification etc. This has motivated researchers to develop computational models to identify the faces, which are relatively simple and easy to implement. One of the methods that have proved to be among the best is Principle Component Analysis (PCA).PCA is a way of identifying patterns in data and expressing the data in such a way to highlight their similarities and differences.

The goal is to implement the system (model) for a particular face and distinguish it from a large number of stored faces with some real-time variations as well. The Eigenface approach uses PCA algorithm for the recognition of the images.

Principle Component Analysis PCA is a classical feature extraction and data representation technique widely used in pattern recognition. It is one of the most successful techniques in face recognition.This paper conducts a study to optimize the time complexity of PCA (EigenFaces) that does not affects the recognition performance. A comparison is done to compare the differences between the recognition time in the original algorithm and in the enhanced algorithm.The algorithm models the real-time varying lighting conditions as well.

KeyWords:*Eigen faces, Eigen Vectors, PrincipalComponent Analysis (PCA), Face recognition, pattern recognition.*

I. INTRODUCTION

For the detection of facial regions in color images, several techniques have been proposed so far, using texture, shape and color information. Due to the fact that color is the most discriminating feature of a facial region, the first step of many face detection algorithms is a pixel-based color segmentation to detect skin-colored regions. The performance of such a hierarchical system is highly dependent on the result of this initial segmentation. The subsequent classification based on shape may fail if only parts of the face are detected or the face region is merged with skin colored background.Principle Component Analysis(PCA) is used for incorporating color information into a face detection scheme. Instead of performing a pixel-based color segmentation, we create a new image which indicates the probability of each image pixel belonging to a skin regionusing the fact that the original luminance image and the probability image have similar grey level distributions in facial regions, PCA detects facial regions in the probability image. This color informationresults in a robust face detection even in the presence of complex and skin colored background.

The jobs which PCA can do are prediction, redundancy removal, feature extraction, data compression, etc.Face recognition has many applicable areas. The most useful applications contain crowd surveillance, video content indexing, personal identification, mug shots matching, entrance security, etc.

The main idea of using PCA for face recognition is to express the large 1-D vector of pixels constructed from 2-D facial image into the compact principal components of the feature space. This can be called Eigenspace projection. Eigenspace is calculated by identifying the eigenvectors of the covariance matrix derived from a set of facial images (vectors).

II. PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal component analysis (PCA) was invented in 1901 by Karl Pearson. PCA is a variable reduction procedure and useful when obtained data have some redundancy. This will result into reduction of variables into smaller number of variables which are called Principal Components which will account for the most of e variance in the observed variable. Problems arise when we wish to perform recognition in a high-dimensional space.

Goal of PCA is to reduce the dimensionality of the data by retaining as much as variation possible in our original data set. On the other hand dimensionality reduction implies information loss. The best low-dimensional space can be determined by best principal components. The major advantage of PCA is using it in Eigenface approach which helps in reducing the size of the database for recognition of a test images. The images are stored as their feature vectors in the database which are found out projecting each and every trained image to the set of Eigen faces obtained. PCA is applied on Eigen face approach to reduce the dimensionality of a large data set.

The central idea of PCA is to find a low dimensional subspace(the feature space)which captures most of the variation within the dataset and therefore allows the best least-square approximation.

Goals of PCA

The goals of pca are to

(a) Extract the most important information from the data table.
(b) Compress the size of the data set by keeping only this important information.
(c) Simplify the description of the data set.
(d) Analyze the structure of the observations and the variables.

In order to achieve these goals, pca computes new variables called *principal components* which are obtained as linear combinations of the original variables.The first principal component is required to have the largest possible variance.

The second component is computed under the constraint of being orthogonal to the first component and to have the largest possible inertia.

The other components are computed likewise. The values of these new variables for the observations are called *factor scores*, these factors scores can be interpreted geometrically as the *projections* of the observations onto the principal components.

Procedure

To identify an input image we proceed as follows

1. Evaluate the components of input image along the selected k Eigen vectors.
2. Reconstruct the image from the components.
3. If the distance between the reconstructed image and the original image is above a threshold, then the input image is not a face image.
4. Now compute the distance of the input image from the training images in the space spanned by the k Eigen vectors.If the minimum distance is above threshold then the input image is not a face from the training database else report the training image with the minimum distance asthe recognized image.

Observations

Broadly we can divide the input into three types

1. Face of a person whose training image has been provided in the training database
2. Face of new person
3. An arbitrary image(not a face)

For each of the three classes for inputs we can monitor two types of distances

1. Distance between the reconstructed image and the original image.
2. Distance to the nearest image in the training database.

Characteristics of principal components

The first component extracted in a principal component analysis accounts for a maximal amount of total variance in the observed variables.Under typical conditions, this means that the first component will be correlated with at least some of the observed variables. It may be correlated with many.

The second component extracted will have two important characteristics. First, this componentwill account for a maximal amount of variance in the data set that was not accounted for by thefirst component. Again under typical conditions, this means that the second component will be*Principal Component Analysis* correlated with some of the observed variables that did not display strong correlations with component 1.

The second characteristic of the second component is that it will be *uncorrelated* with the first component. Literally, if you were to compute the correlation between components 1 and 2, that correlation would be zero.

The remaining components that are extracted in the analysis display the same two characteristics: each component accounts for a maximal amount of variance in the observed variables that was not accounted for by the preceding components, and is uncorrelated with all of the preceding components. A principal component analysis proceeds in this fashion, with each new component accounting for progressively smaller and smaller amounts of variance (this is why only the first few components are usually retained and interpreted).

When the analysis is complete, the resulting components will display varying degrees of correlation with the observed variables, but are completely uncorrelated with one another.

ALGORITHM

Principle Component Analysis

1. It tries to detect a face pattern as a whole unit.
2. Each image pattern of dimension I and J can be considered as a vector x in a N=IJ dimensional space.
3. The central idea of PCA is to find a low dimensional subspace(the feature space)which captures most of the variation within the dataset and therefore allows the best least-square approximation.

Advantages of PCA

1. Smaller representation of database because we only store the training images in the form of their projectionson the reduced basis.
2. Noise is reduced because we choose the maximum variation basis and hence features likebackground with small variation are automatically ignored.

III. EIGEN FACE APPROACH

It is adequate method to be used in face recognition due to its simplicity, speed and learning capability. Eigen faces are a set of Eigen vectors used in the Computer Vision problem of human face recognition. EigenFaces assume ghastly appearance. They refer to an appearance based approach to face recognition that seeks to capture the variation in a collection of face images and use this information to encode and compare images of individual faces in a holistic manner.

The Eigen faces are Principal Components of a distribution of faces, or equivalently, the Eigen vectors of the covariance matrix of the set of the face images, where an image with N by N pixels is considered a point in N 2 dimensional space. Previous work on face recognition ignored the issue of face stimulus, assuming that predefined measurementwere relevant and sufficient.

This suggests that coding and decoding of face images may give information of face images emphasizing the significance of features. These features may or may not be related to facial features such as eyes, nose, lips and hairs. We want to extract the relevant information in a face image, encode it efficiently and compare one face encoding with a database of faces encoded similarly.

A simple approach to extracting the information content in an image of a face is to somehow capture the variation in a collection of face images. We wish to find Principal Components of the distribution of faces, or the Eigen vectors of the covariance matrix of the set of face images. Each image location contributes to each Eigen vector, so that we can display the

Eigen vector as a sort of face. Each face image can be represented exactly in terms of linear combination of the Eigen faces. The number of possible Eigen faces is equal to the number of face image in the training set. The faces can also be approximated by using best Eigen face, those that have the largest Eigen values, and which therefore account for most variance between the set of face images. The primary reason for using fewer Eigen faces is computational efficiency.

Eigen Values and Eigen Vectors

In linear algebra, the eigenvectors of a linear operator are non-zero vectors which, when operated by the operator, result in a scalar multiple of them. Scalar is then called Eigen value (λ) associated with the eigenvector (X). Eigen vector is a vector that is scaled by linear transformation. It is a property of matrix. When a matrix acts on it, only the vector magnitude is changed not the direction.

$$AX = \lambda X, \quad (1)$$

where A is a vector function.

$$(A - \lambda I)X = 0, \quad (2)$$

where I is the identity matrix.

This is a homogeneous system of equations and form fundamental linear algebra. We know a non-trivial solution exists if and only if-

$$\mathrm{Det}(A - \lambda I) = 0, \quad (3)$$

wheredet denotes determinant.

When evaluated becomes a polynomial of degree n. This is called characteristic polynomial of A. If A is N by N then there are n solutions or n roots of the characteristic polynomial.Thus there are n Eigen values of A satisfying the equation.

$$AX_i = \lambda_i X_i, \quad (4)$$

Wherei = 1,2,3,.....n

If the Eigen values are all distinct, there are n associated linearly independent eigenvectors, whose directions are unique, which span an n dimensional Euclidean space.

EigenFaces are mostly used to

a. Extract the relevant facial information, which may or may not be directly related to human

ISSN: 2320 - 8791
www.ijreat.org

intuition of face features such as the eyes, nose, and lips. One way to do so is to capture the statistical variation between face images.

b. Represent face images efficiently. To reduce the computation and space complexity, each face image can be represented using a small number of dimensions.

Manhattan And Euclidean Distance:

If ***A*** and ***B*** are two vectors of length ***D***, the distance between them is determined as follows

1. Manhattan Distance :

$$\mathbf{d\ (A,\ B)} = \sum_{i=1}^{D} |a_i - b_i|$$

2. Euclidean Distance :

$$\mathbf{d\ (A,\ B)} = \sqrt{\sum_{i=1}^{D} (a_i - b_i)^2} = \| \mathbf{A} - \mathbf{B} \|$$

Some observations may be made

1. Distance to the reconstructed image decreases with no of eigenvectors considered. This is expected because we project onto a higher dimensional space and hence the residual error is reduced. Similar argument also explains the increase in distance to the nearest training image.

2. New Face Vs Trained Face

If we consider the distances to the reconstructed image , there is not much distinction to be made. But these two types of images may be distinguished by comparing the distances to the nearest image in the training image database. Hence we can use a suitable threshold to distinguish between the two.

3. Face image Vs Arbitrary Image

These two types of images may be distinguished by comparing the distances to the reconstructed image. The Eigen space for face image will not be a proper representation for an arbitrary image and hence distance will be larger.

IV.PRACTICAL IMPLEMENTATION

Prepare a training set of face images. The pictures constituting the training set should have been taken under the same lighting conditions, and must be normalized to have the eyes and mouths aligned across all images. They must also be all resample to the same pixel resolution. For this implementation, it is assumed that all images of the training set are stored in a single matrix T, where each row of the matrix is an image.

Fig 4.1 Pictures from the training base

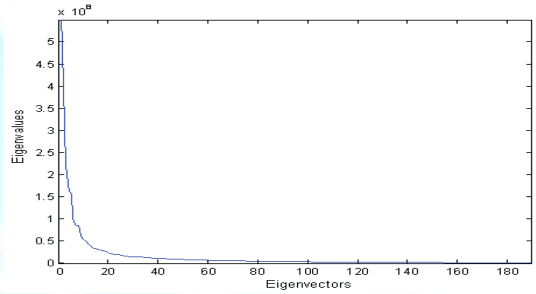

Fig 4.2 Eigen Values

Subtract the mean. The average image a has to be calculated and then subtracted from each original image in T.

Fig 4.3 Mean Image

Calculate the eigenvectors and Eigen values of the covariance matrix S. Each eigenvector has the same dimensionality as the original images, and thus can itself be seen as an image. The eigenvectors of this covariance matrix are therefore called Eigen Faces. They are the directions in which the images differ from the mean image.

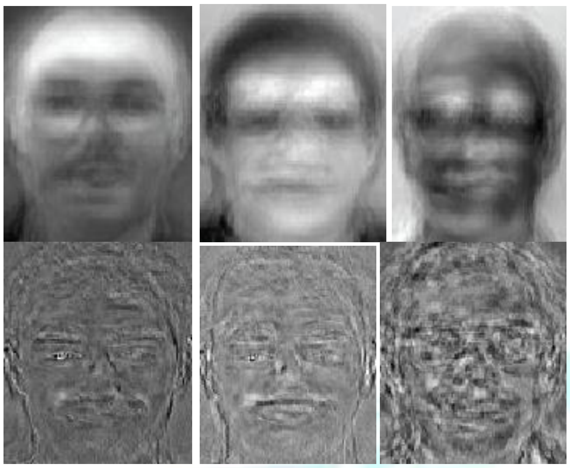

Fig 4.4 Eigen Faces for Training Base

Table 1 shows that the proposed algorithm gives the same results regardless of whether we used only the first 20 or all 190 eigenvectors. Recognition rate is higher for Manhattan than for Euclidean distance if we use 5 or 10 eigenvectors, while for 20 eigenvectors it is the same in both cases.

In practice, only a few images per person are available for the training base, so it is important to note the effect of a number of images per subject on the rate of recognition. The corresponding recognition rates for different number of training images per subject. For comparison, we selected the first 20 principal components in each case.

Table 1

The result of face recognition using Eigen Face

Number of Principal Components	**RECOGNITION RATE**	
	Euclidean Distance	**Manhattan Distance**
5	77.5%	80%
10	92.5%	95%
20	97.5%	97.5%
190	97.5%	97.5%

Table 2

Recognition rate for different number of images per person

RECOGNITION RATE					
No. of images per Person	1	2	3	4	5
Euclidean Distance	70%	87.5%	87.5%	92.5%	97.5%
Manhattan Distance	67.5%	77.5%	82.5%	92.5%	97.5%

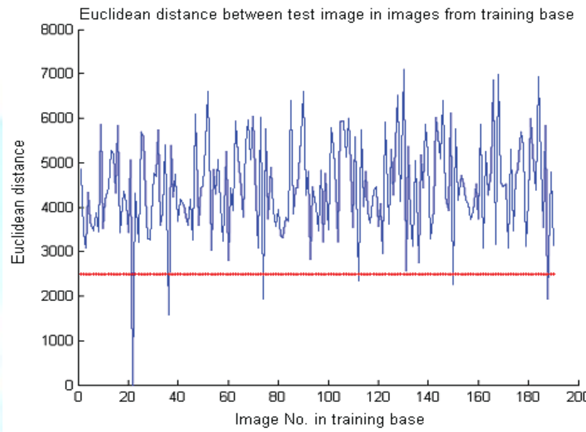

Fig 4.5 Test image and recognized image from the training base.

Face recognition method using Eigenfaces is proposed. We used database of face images which contains 190 images of 38 different persons (5 images per person). From the results, it can be concluded that, for recognition, it is sufficient to take about 10% Eigenfaces with the highest Eigenvalues.

It is alsoclear that the recognition rate increases with the number of training images per person. It is obvious that if the minimum distance between the test image and other images is zero, the test image entirely matches the image from the training base. If the distance is greater than zero but less than a certain threshold, it is a known person with other facial expression, otherwise it is an unknown person.

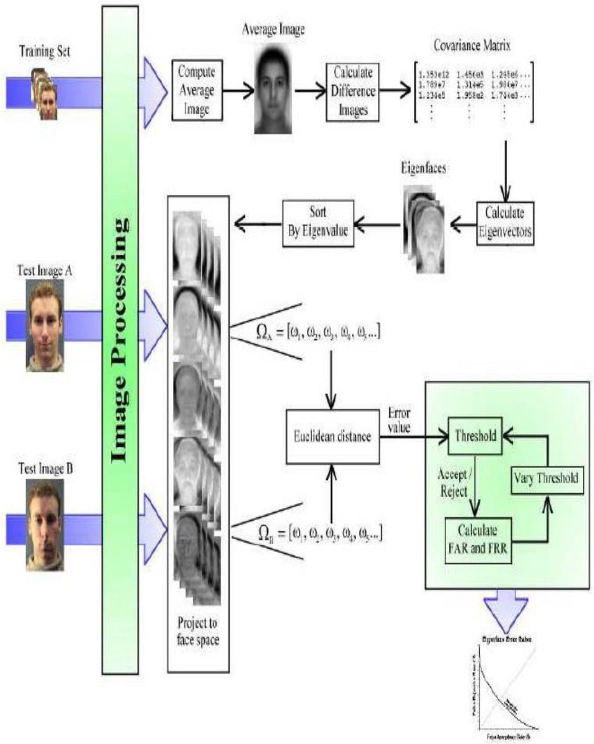

Fig 4.6 A complete process of PCA and EigenFace based Face Recognition System**.**

V. CONCLUSION AND FUTURE ENHANCEMENTS

Conclusion

In this thesis we implemented the face recognition system using Principal Component Analysis and Eigen face approach. The system successfully recognized the human faces and worked better in different conditions of face orientation.

Future enhancements

However, Face Recognition is much less reliable than Face Detection, generally 30-70% accurate. Face Recognition has been a strong field of research since the 1990s, but is still far from reliable, and more techniques are being invented each year such as the ones listed below

* 3D face recognition
* Recognition from video

VI. REFERENCE

1. Manal Abdullah, MajdaWazzan and Sahar Bo-saeed ”Optimizing Face Recognition Using Pca” Journal of Artificial Intelligence (IJALA), vol.3,No.2, March 2012.
2. “Improved PCA Algorithm for Face Recognition” World Applied Programming, Vol (2), Issue (1), January 2012. 55-59 Special section for proceeding of International e-Conference on Computer Engineering (IeCCE) 2012.
3. G. Liu, Z. Lin, and Y. Yu, “Robust subspace segmentation by low-rank representation,” in Proc. Int. Conf. Mach. Learn., 2010, pp. 1–8.
4. M. Turk and A. Pentland, “Eigenfaces for recognition,” Journal of Cognitive Neuroscience, Vol.3, 1991, pp.71-86.
5. H. Xu, C. Caramanis, and S. Sanghavi, “Robust PCA via outlier pursuit,” in Proc. Adv. Neural Inf. Process. Syst., Dec. 2010, pp. 1–30.
6. P. J. B. Hancock, V. Bruce and A. M. Burton, "Testing Principal Component Representations for Faces", Proc. of 4th Neural Computation and Psychology Workshop, 1997.
7. Taranpreet Singh Ruprah “Face Recognition Based on PCA Algorithm “IET-DAVV, Indore, India.
8. R. Vidal, “Subspace clustering,” IEEE Signal Process. Mag., vol. 28, no. 2, pp. 52–68, Mar. 2011.
9. K. Min, Z. Zhang, J. Wright, and Y. Ma, “Decomposing backgroundtopics from keywords by principal component pursuit,” in Proc. 19thInt. Conf. Inf. Knowl. Manage., 2010, pp. 269–278.
10. F. De la Torre and M. J. Black, “Robust principal component analysisfor computer vision,” in Proc. 8th Int. Conf. Comput. Vis., vol. 1. Barcelona, Spain, 2001, pp. 362–369.
11. Y. C. Eldar and M. Mishali, “Robust recovery of signals from and structured union of subspaces,” IEEE Trans. Inf. Theory, vol. 55, no. 11, pp. 5302–5316, Nov. 2009.