Face Recognition Using PCA and Eigen Face Approach

Abhishek Singh(108CS061)
Saurabh Kumar(108CS034)

Department of Computer Science and Engineering
National Institute of Technology Rourkela
Rourkela – 769008, India

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Abhishek Singh

(Roll 108CS061)

Saurabh Kumar

(Roll 108CS034)

under the supervision of

Prof. Pankaj Kumar Sa

Department of Computer Science and Engineering

National Institute of Technology Rourkela

Rourkela – 769008, India

Computer Science and Engineering
National Institute of Technology Rourkela
Rourkela-769008, India. www.nitrkl.ac.in

Dr. Pankaj Kumar Sa

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Certificate

This is to certify that the work in the Project entitled *Face Recognition using PCA and Eigen Face approach* by *Abhishek Singh* and *Saurabh Kumar*, is a record of an original research work carried out by him under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of *Bachelor of Technology* in *Computer Science and Engineering.* Neither this thesis nor any part of it has been submitted for any degree or academic award elsewhere.

Pankaj Kumar Sa

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Abhishek Singh

Saurabh Kumar

Abstract

Face is a complex multidimensional structure and needs a good computing techniques for recognition. Our approach treats face recognition as a two-dimensional recognition problem. In this scheme face recognition is done by *Principal Component Analysis (PCA)*. Face images are projected onto a face space that encodes best variation among known face images. The face space is defined by eigenface which are eigenvectors of the set of faces, which may not correspond to general facial features such as eyes, nose, lips. The eigenface approach uses the PCA for recognition of the images. The system performs by projecting pre extracted face image onto a set of face space that represent significant variations among known face images. Face will be categorized as known or unknown face after matching with the present database. If the user is new to the face recognition system then his/her template will be stored in the database else matched against the templates stored in the database. The variable reducing theory of PCA accounts for the smaller face space than the training set of face.

Contents

List of Figures

List of Tables

Chapter 1
Introduction

Chapter 1

Introduction

1.1 Biometrics

Biometrics is used in the process of authentication of a person by verifying or identifying that a user requesting a network resource is who he, she, or it claims to be, and vice versa. It uses the property that a human trait associated with a person itself like structure of finger, face details etc. By comparing the existing data with the incoming data we can verify the identity of a particular person [1].

There are many types of biometric system like fingerprint recognition, face detection and recognition, iris recognition etc., these traits are used for human identification in surveillance system, criminal identification. Advantages of using these traits for identification are that they cannot be forgotten or lost. These are unique features of a human being which is being used widely [2].

1.2 Face Recognition

Face is a complex multidimensional structure and needs good computing techniques for recognition. The face is our primary and first focus of attention in social life playing an important role in identity of individual. We can recognize a number of faces learned throughout our lifespan and identify that faces at a glance even after years. There may be variations in faces due to aging and distractions like beard, glasses or change of hairstyles.

Face recognition is an integral part of biometrics. In biometrics basic traits of human is matched to the existing data and depending on result of matching identification of a human being is traced. Facial features are extracted and implemented through algorithms which are efficient and some modifications are done to improve the existing algorithm models.

Computers that detect and recognize faces could be applied to a wide variety of practical applications including criminal identification, security systems, identity verification etc. Face detection and recognition is used in many places nowadays, in websites hosting images and social networking sites. Face recognition and detection can be achieved using technologies related to computer science.

Features extracted from a face are processed and compared with similarly processed faces present in the database. If a face is recognized it is known or the system may show a similar face existing in database else it is unknown. In surveillance system if a unknown face appears more than one time then it is stored in database for further recognition. These steps are very useful in criminal identification. In general, face recognition techniques can be divided into two groups based on the face representation they use appearance-based, which uses holistic texture features and is applied to either whole-face or specific regions in a face image and feature-based, which uses geometric facial features (mouth, eyes, brows, cheeks etc), and geometric relationships between them.

Chapter 2

Literature Survey

Chapter 2

Literature Survey

2.1 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 the 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 ar 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.

2.2 Eigen Face Approach

It is adequate and efficient 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. 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 measurement were 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.

2.2.1 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.

$AX = \lambda X$, where A is a vector function.

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

$Det(A - \lambda I) = 0$, where det 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.

$AX_i = \lambda_i X_i$, where i = 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.

2.2.2 Face Image Representation

Training set of m images of size NxN are represented by vectors of size N^2.

Each face is represented by $\Gamma_1, \Gamma_2, \Gamma_3, , \Gamma_M$.

Feature vector of a face is stored in a $N \times N$ matrix. Now, this two dimensional vector is changed to one dimensional vector.

For Example- $\begin{bmatrix} 1 & 2 \\ 2 & 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 2 \\ 1 \end{bmatrix}$

Each face image is represented by the vector Γ_i.

$$\Gamma 1 = \begin{bmatrix} 1 \\ -2 \\ 1 \\ -3 \end{bmatrix} \ \Gamma 2 = \begin{bmatrix} 1 \\ 3 \\ -1 \\ 2 \end{bmatrix} \ \Gamma 2 = \begin{bmatrix} 2 \\ 1 \\ -2 \\ 3 \end{bmatrix} \ ....\Gamma M \begin{bmatrix} 1 \\ 2 \\ 2 \\ 1 \end{bmatrix}$$

2.2.3 Mean and Mean Centered Images

Average face image is calculated by

$\Psi = (1/M) \sum_{i=1}^{M} \Gamma_i$

$$\begin{bmatrix} 1 \\ -2 \\ 1 \\ -3 \end{bmatrix} + \begin{bmatrix} 1 \\ 3 \\ -1 \\ 2 \end{bmatrix} + \begin{bmatrix} 2 \\ 1 \\ -2 \\ 3 \end{bmatrix} +................+ \begin{bmatrix} 1 \\ 2 \\ 2 \\ 1 \end{bmatrix} \rightarrow \begin{bmatrix} -1 \\ -1 \\ 2 \\ -3 \end{bmatrix}$$

$\Psi = (\Gamma_1 + \Gamma_2 + \Gamma_3 + ... + \Gamma_M)/M$

Each face differs from the average by $\Phi_i = \Gamma_i - \Psi$ which is called mean centered image.

$$\Phi_1 = \begin{bmatrix} 2 \\ -1 \\ -1 \\ 0 \end{bmatrix} \ \Phi_2 = \begin{bmatrix} 2 \\ 4 \\ -3 \\ 5 \end{bmatrix} \ \Phi_3 = \begin{bmatrix} 3 \\ 2 \\ -4 \\ 6 \end{bmatrix} \ ....\Phi_M = \begin{bmatrix} 2 \\ 3 \\ 0 \\ 4 \end{bmatrix}$$

2.2.4 Covariance Matrix

A covariance matrix is constructed as:

$C = AA^T$, where $A = [\Phi_1, \Phi_2, , \Phi_M]$ of size $N^2 \times N^2$.

$$A = \begin{bmatrix} 2 & 3 \\ -1 & -2 \\ -1 & 1 \\ 0 & 2 \end{bmatrix} \quad A^T = \begin{bmatrix} 2 & -1 & -1 & 0 \\ 3 & -2 & 1 & 2 \end{bmatrix}$$

Size of covariance matrix will be $N^2 \times N^2$ (4x 4 in this case).

Eigen vectors corresponding to this covariance matrix is needed to be calculated, but that will be a tedious task therefore,

For simplicity we calculate $A^T A$ which would be a 2×2 matrix in this case.

$A^T A = \begin{bmatrix} 6 & 7 \\ 7 & 18 \end{bmatrix}$ size of this matrix is MxM.

Consider the eigenvectors $v_i$of A^T A such that

$A^T A X_i = \lambda_i X_i$

The eigenvectors v_i of $A^T A$ are X_1 and X_2 which are 2×1. Now multiplying the above equation with A both sides we get-

$A A^T A X_i = A \lambda_i X_i$

$A A^T (A X_i) = \lambda_i (A X_i)$

Eigen vectors corresponding to AA^T can now be easily calculated now with reduced dimensionality where AX_i is the Eigen vector and λ_i is the Eigen value.

2.2.5 Eigen Face Space

The Eigen vectors of the covariance matrix AA^T are AX^i which is denoted by U^i. U^i resembles facial images which look ghostly and are called Eigen faces. Eigen vectors correspond to each Eigen face in the face space and discard the faces for which Eigen values are zero thus reducing the Eigen face space to an extent. The Eigen faces are ranked according to their usefulness in characterizing the variation among the images.

A face image can be projected into this face space by

$\Omega_k = U^T(\Gamma_k - \Psi)$; k=1,....,M, where $(\Gamma_k \Psi)$ is the mean centered image.

Hence projection of each image can be obtained as Ω_1 for projection of $image_1$ and Ω_2 for projection of $image_2$ and hence forth.

2.3 Recognition Step

The test image, Γ, is projected into the face space to obtain a vector, Ω as

$\Omega = U^T(\Gamma - \Psi)$

The distance of Ω to each face is called Euclidean distance and defined by

$\epsilon_k^2 = ||\Omega - \Omega_k||^2$; k = 1,,M where Ω_k is a vector describing the k^th face class. A face is classified as belonging to class k when the minimum ϵ_k is below some chosen threshold Θ_c. otherwise the face is classified as unknown.

Θ_c, is half the largest distance between any two face images:

$\Theta_c = (1/2)max_{j,k} ||\Omega_j - \Omega_k||$; j,k = 1,.....,M

We have to find the distance ϵ between the original test image Γ and its reconstructed image from the Eigen face Γ_f

$\epsilon^2 = ||\Gamma - \Gamma^f||^2$, where $\Gamma^f = U * \Omega + \Psi$

If $\epsilon \geq \Theta_c$ then input image is not even a face image and not recognized.

If $\epsilon < \Theta_c$ and $\epsilon_k \geq \Theta$ for all k then input image is a face image but it is recognized as unknown face.

If $\epsilon < \Theta_c$ and $\epsilon_k < \Theta$ for all k then input images are the individual face image associated with the class vector Ω_k.

Chapter 3

Implementation

Chapter 3

Implementation

3.1 Testing Parameters

Matlab 2011a is used for coding. A colored face image is converted to grey scale image as grey scale images are easier for applying computational techniques in image processing.

Figure 3.1: A colored face image

A grey scale face image is scaled for a particular pixel size as 250x250 because many input images can be of different size whenever we take a input face for recognition.

Figure 3.2: Grey scale face image

3.1.1 Training Set

Database for different set of conditions is maintained. Ten different expressions for ten different people thus creating a 10x10 that is equal to 100 different set of face images. Rotated images in left and right direction and different illumination conditions are also considered while making the training set. Size variations in a input face image can also change the output therefore input images by varying their size are also taken for recognition.

Figure 3.3: A single face image for ten different expressions

3.1.2 Testing Conditions

Figure 3.4: Image in reduced light intensity

Expression- When a expression of a person is changed the orientation of face organs are changed according to it thus changing the feature vectos accordingly. Therefore changed expressions alters the recognition procedure.

Illumination- Different intensity of light on face may change the recognition just as bright light causes image saturation.

Size variation- If the size of image is varied the recognition may alter accordingly.

3.2 Face Recognition Using Eigen Faces

3.2.1 Face Image Testing

A test image for recognition is tested by comparing to the stored data set.

Figure 3.5: 200×200 image as input

Figure 3.6: 5×5 training set

3.2.2 Mean Face

Mean face is obtained by $\Psi = (1/M)\sum_{i=1}^{M}\Gamma_i$ where $\Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_n$ are training set images and hence mean centered images are also evaluated by $\Phi_i = \Gamma_i - \Psi$ for further computations.

Figure 3.7: Mean face

3.2.3 Eigen Face

The eigenvectors corresponding to the covariance matrix define the Eigen face which has a ghostly face like appearance and a match is found if new face is close to these images.

Figure 3.8: Eigenface ranked according to usefulness

Chapter 4

Result

Chapter 4

Result

4.1 Result and Analysis

Threshold value of the test face image to Eigen face space which is Euclidean distance is taken as 5.9 which classifies the face as known or unknown.

Table 4.1: Comparison between different conditions

.	Normal	Smiling	Angry	Sad	Illumination	Size Variation
Image1	Y	Y	N	Y	Y	Y
Image2	Y	Y	Y	Y	Y	Y
Image3	Y	Y	Y	N	N	N
Image4	N	Y	Y	Y	Similar	Y
Image5	Y	Y	Y	Similar	N	N
Image6	Y	Similar	Y	Y	Y	Similar
Image7	Y	Y	N	Y	N	N
Image8	Y	Y	Y	Similar	Y	Y
Image9	Y	Y	Similar	Y	Y	Y
Image10	Y	Y	Y	Y	Similar	Y

Six different images for each mentioned condition were taken to test for ten different people. Light intensity is tried to keep low. Size variation of a test image is not altered to much extent. We can observe that normal expressions are recognized as face efficiently because facial features are not changed much in that case and in other cases where facial features are changed efficiency is reduced in recognition.

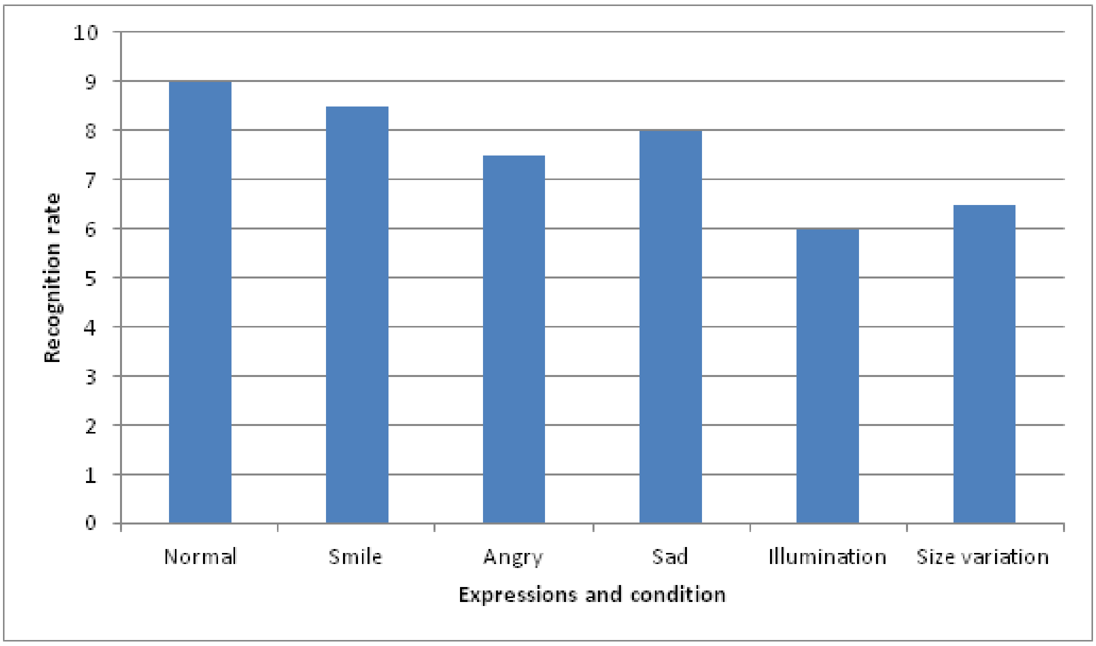

Figure 4.1: Output for different expressions and conditions

4.1.1 Efficiency

$(9 + 8.5 + 7.5 + 8 + 6 + 6.5)/6 = 7.583$

Therefore $7.583 \times 10 = 75.83\%$

However this efficiency cannot be generalized as it is performed on less number of test of images and conditions under which tested may be changed on other time.

Chapter 5

Conclusion

Chapter 5

Conclusion

5.1 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.

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