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PROJECTION OF EIGENFACES ONTO FACE SPACE USING PCA

A Project Report of Capstone Project - 2

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BONAFIDE CERTIFICATE

Certified that this project report "Projection Of EigenFaces Onto FaceSpace Using PCA" is the bonafide work of "AYUSH TYAGI (1613101214)" who carried out the project work under my supervision.

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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.

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LIST OF SYMBOLS

Γ	Face image
Ψ	Average face vector
Φ_I	Mean centered image
λ	Eigen value
X	Eigenvector
Θ_c	Chosen threshold

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. 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.

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 eficient 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.

Literature Survey

The visceral way to do face recognition is to look at the primary features of the face and correlate them to the equivalent features on other faces. The first attempts to do this launched in the 1960's with a semi-automated system. Stamps were made on photographs to pinpoint the major features; it used features such as eyes, ears, noses, and mouths. Then distances and ratios were computed from these stamps to a common reference point and compared to reference data. In the early 1970's Goldstein, Harmon and Lesk build a system of 21 subjective markers such as hair color and lip thickness. This proved even tough to automate due to the subjective nature of many of the measurements still made fully by hand. A more automated access to recognition began with Fisher and Elschlagerb[1] just a few years after the Goldstein paper. This approach measured the features above using templates of features of distinctive pieces of the face and them mapped them all onto a global template. After extended research it was found that these features do not contain adequate rare data to represent an adult face. Another approach is the Connectionist approach, which investigates to classify the human face using a sequence of both range of gestures and a set of identifying markers. This is usually achieved using 2-dimensional pattern recognition and neural net principles. Most of the time this approach requires a gigantic number of training faces to accomplish modest accuracy; for that reason it has yet to be carried out on a large scale. The first fully automated system to be developed exploited very general pattern recognition. It correlated faces to a generic face model of expected features and generated a series of patterns for an image relative to this model. This approach is mainly statistical and depends on histograms and the grayscale value. Kirby and Sirovich spearhead the eigenface approach in 1988 at Brown

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[1] Face Recognition using Eigenfaces

By: Marshall B. Robinson Matthew Escarra Jon Krueger Doug Kochelek

University. Since then, jillion people have fabricated and expanded on the basic ideas described in their original paper. We acknowleged the idea for our approach from a paper by Turk and Pentland based on related research conducted at MIT.

METHODOLOGY

3.1 PROPOSED SYSTEM

3.1.1 PRINCIPAL COMPONENT ANALYSIS(PCA)

Principal Component Analysis(PCA) was formulated in 1901 by Karl Pearson. PCA is a variable reduction procedure and helpful when acquired data have some redundancy. This will result into reduction of variables into smaller number of variables which are called Principal Components which will reckon for the most of the variance in the observed variable. Our method modifies face images into a small set of characteristic feature images, called eigenfaces,which are the linear combination of weighted eigenvectors for every image in the training set.Recognition is carried out by projecting a new image into a sub-space covered by eigenfaces("face space") and then classification is done by measuring minimum Euclidean distance**.**Instinctively mastering and later recognizing new faces is practical within this framework. Recognition under fairly varying conditions is accomplished by training on a limited number of characteristic views(e.g. a frontal view and a 45° view).The method has dominance over other face recognition strategies due to its simplicity, speed and learning capability.

3.2 EIGEN FACE APPROACH

It is adequate and eficient 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[2] 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 suficient. 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 eficiently 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 eficiency.

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[2] When a vector is plotted, it's direction is along its span. Now, there are some special vectors, which when transformed linearly, their directions don't change, that is, they don't get knocked off their span.

3.3 EIGENFACE ALGORITHM

Let a face image Γ(x, y) be a two dimensional M by N array of intensity values. An image can also be treated as a vector of dimension M × N, so that a typical image of size 200 × 149 becomes a vector of dimension 29,800 or fairly a point in a 29,800 dimensional space.

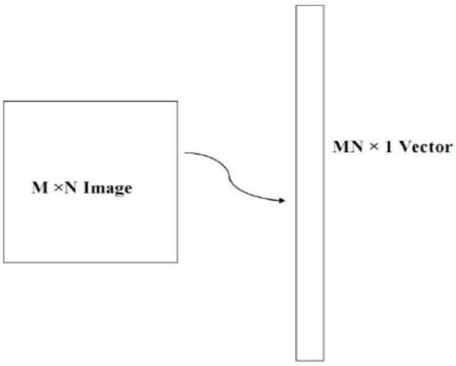

Fig-3.1:-Transformation of M × N image into MN ×1 vector

3.3.1 FACE IMAGE REPRESENTATION

Gather face images I_1, I_2, I_3, I_4, ... I_M (training faces). The face images must be centered and of the equal size.

Each face image I_i in the database is transformed into a vector and placed into a training set S.

$$S = \{\Gamma_1, \Gamma_2, \Gamma_3, \Gamma_4, \ldots \ldots . . \Gamma_M\}$$

Each image is transformed into a vector of size MN × 1 and placed into the set. For simplicity, the face images are assumed to be of size N × N resulting in a point in N^2 dimensional space (further described in Appendix 1).

3.3.2 Mean and Mean Centered Images

The average face vector (Ψ) has to be determined by using the following formula:

$$\Psi = \frac{1}{M}\sum_{n=1}^{M} \Gamma_n$$

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

3.3.3 Covariance Matrix

We retrieve the covariance matrix C in the following manner

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

3.3.4 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).

The covariance matrix C in step 5 has a dimensionality of N^2 x N^2, so one would have eigenface N^2 and eigenvalues.

Consider the eigenvectors v_i of A^T A such that

$A^TAX_i = \lambda_i X_i$

The eigenvectors v_i of A^TA are X_1 and X_2 . Now multiplying the above equation with A both sides we get-

$AA^TAX_i = A\lambda_i X_i$

$AA^T (AX_i) = \lambda_i(AX_i)$

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

3.3.5 EIGENFACE 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.

3.3.6 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

$\varepsilon^2 = ||\Omega - \Omega_k||^2$; 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 Θc. 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

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

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

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

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

IMPLEMENTATION AND RESULTS

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

Fig 4.1 A colored face image

Fig 4.2 Grey scale face image

4.1 TRAINING SET

Database of four different expressions for a different set of conditions is maintained .

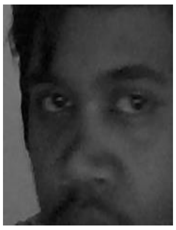


Fig 4.3 Single face image for four expressions

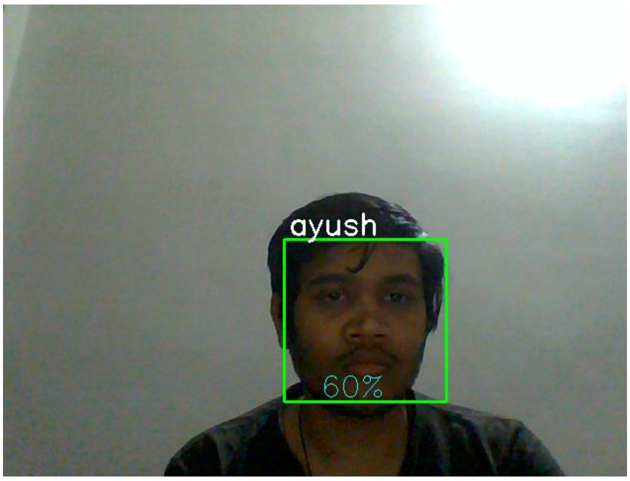

Fig 4.4 Recognition of face image

CONCLUSION

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

APPENDICES

APPENDIX 1 FACE IMAGE REPRESENTATION

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

Each face is represented by Γ_1,Γ_2,Γ_3,,Γ_M.

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

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

Each face image is represented by the vector Γ_i.

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

APPENDIX 2 EIGENVALUES AND EIGENVECTORS

$AX = \lambda X$, 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-

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

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