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FACE RECOGNITION USING PRINCIPAL COMPONENT ANALYSIS

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Abstract: **Security and authentication of a person is a crucial part of any industry. There are many techniques used for this purpose. One of them is *face recognition*. Face recognition is an effective means of authenticating a person. The advantage of this approach is that, it enables us to detect changes in the face pattern of an individual to an appreciable extent. The recognition system can tolerate local variations in the face expression of an individual. Hence face recognition can be used as a key factor in crime detection mainly to identify criminals. There are several approaches to face recognition of which Principal Component Analysis (PCA) and Neural Networks have been incorporated in our project. The system consists of a database of a set of facial patterns for each individual. The characteristic features called 'eigenfaces' are extracted from the stored images using which the system is trained for subsequent recognition of new images.**

Keywords: **Face Recognition, Neural Networks, Principal Component Analysis.**

1. INTRODUCTION

A face recognition system has to associate an identity or name for each face it comes across by matching it to a large database of individuals. Automatic face detection and recognition has been a difficult problem in the field of computer vision for several years. Furthermore, the ability to find faces visually in a scene and recognize them is critical for humans in their everyday activities. Consequently, the automation of this task would be useful for many applications including security, surveillance, gaze-based control, affective computing, speech recognition assistance, video compression and animation. Robust face recognition requires the ability to recognize identity despite many variations in appearance that the face can have in a scene. The face is a 3D object which is illuminated from a variety of light sources and surrounded by arbitrary background data (including other faces). Therefore, the appearance a face has when projected onto a 2D image can vary tremendously. A system capable of performing non-contrived recognition need to find and recognize faces despite these variations. The applications of facial recognition range from a static, controlled "mug-shot" verification to a dynamic, uncontrolled face identification in a cluttered background (e.g., airport). The most popular approaches to face recognition are based on either (i) the location and shape of facial attributes, such as the eyes, eyebrows, nose, lips, and chin and their spatial relationships, or (ii) the overall (global) analysis of the face image that represents a face as a weighted combination of a number of canonical faces. . In order that a facial recognition system works well, it should automatically:

(i) Detect and locate the face in the image

(ii) Recognize the face from a general viewpoint (i.e., from any pose).

Popular recognition algorithms include Eigen face, Fisher face, the Hidden Markov model and the neuronal motivated Dynamic Link Matching. The two approaches concentrated on to face recognition are as follows:

1) Eigenface-based face recognition:

In this method the main features of the face are extracted and eigenvectors are formed. The images forming the training set (database) are projected onto the major eigenvectors and the projection values are computed. In the recognition stage the projection value of the input image is also found and the distance from the known projection values is calculated to identify who the individual is.

2) Neural Network based face recognition:

The same procedure is followed for forming the eigenvectors as in the Eigenface approach, which are then fed into the Neural Network Unit to train it on those vectors and the knowledge gained from the training phase is subsequently used for recognizing new input images. The training and recognition phases can be implemented using several neural network models and algorithm.

2. PRINCIPAL COMPONENT ANALYSIS

In statistics, principal components analysis (PCA) is a technique that can be used to simplify a dataset.

It is a linear transformation that chooses a new coordinate system for the data set such that the greatest variance by any projection of the data set comes to lie on the first axis (called the first principal component), the second greatest variance on the second axis, and so on. PCA can be used for reducing dimensionality in a dataset while retaining those characteristics of the dataset that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. The idea is that such low-order components often contain the "most important" aspects of the data.

3. EIGEN VALUES AND EIGEN VECTORS

An eigenvalue of a square matrix is a scalar that is usually represented by the Greek letter λ, an eigenvector is a non-zero vector denoted by the small letter x. For a given square matrix, *A*, all eigenvalues and eigenvectors satisfy the equation

$Ax = \lambda x$

STEPS FOR RECOGNITION USING PCA

The step by step instructions along with the formulas for the recognition of faces using Principal Component Analysis (PCA) are as follows:

STEP 1: **Prepare the data**

The first step is to obtain a set S with M face images. Each image is transformed into a vector of size N and placed into the set.

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

STEP 2: **Obtain the mean**

After obtaining the set, the mean image **Ψ** has to be obtained as,

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

STEP 3: **Subtract the mean from original image**

The difference between the input image and the mean image has to be calculated and the result is stored in **Φ**.

$$\Phi_i = \Gamma_i - \Psi$$

STEP 4: **Calculate the covariance matrix**

The covariance matrix **C** is calculated in the following manner,

$$C = \frac{1}{M}\sum_{n=1}^{M} \Phi_n \Phi_n^T$$
$$= AA^T$$
$$A = \{\Phi_1, \Phi_2, \Phi_3, \ \ldots\ldots \ , \Phi_n\}$$

STEP 5: **Calculate the eigenvectors and eigenvalues of the covariance matrix and select the principal components**

In this step, the eigenvectors (eigenfaces) u_i and the corresponding eigenvalues λ_i should be calculated. From M eigenvectors, u, only M' should be chosen, which have the highest eigenvalues. The higher the eigenvalue, the more characteristic features of a face does the particular eigenvector describe. Eigenfaces with low eigenvalues can be omitted, as they explain only a small part of the characteristic features of the faces. After M' eigenfaces are determined, the "training" phase of the algorithm is finished.

Once the training set has been prepared the next phase is the classification of new input faces. The recognition procedure consists of two major steps:

STEP 1: **Transform the new face**

The new face is transformed into its eigenface components and the resulting weights form the weight vectors.

$$\omega_k = u_k^T(\Gamma - \Psi)$$

Where,

ω = weight, **μ** =eigenvector, **Γ** = new input image, **Ψ** = mean face

The weight vector $\mathbf{\Omega^T}$ is given by,

$$\Omega^T = [\omega_1, \omega_2, \ \ldots\ldots, \omega_M]$$

STEP 2: **Calculate Euclidean Distance**

The Euclidean distance between two weight vectors $\mathbf{d(\Omega_i, \Omega_j)}$ provides a measure of similarity between the corresponding images i and j. If the Euclidean distance between the new and other faces exceeds - on average - some threshold value θ, one can conclude whether it is a known or unknown face. This distance also allows one to construct "clusters" of faces such that similar faces are assigned to one cluster. It can be calculated as,

$d(\mathbf{\Omega_i, \Omega_j}) = \| \mathbf{\Omega_i - \Omega_j} \|^2$

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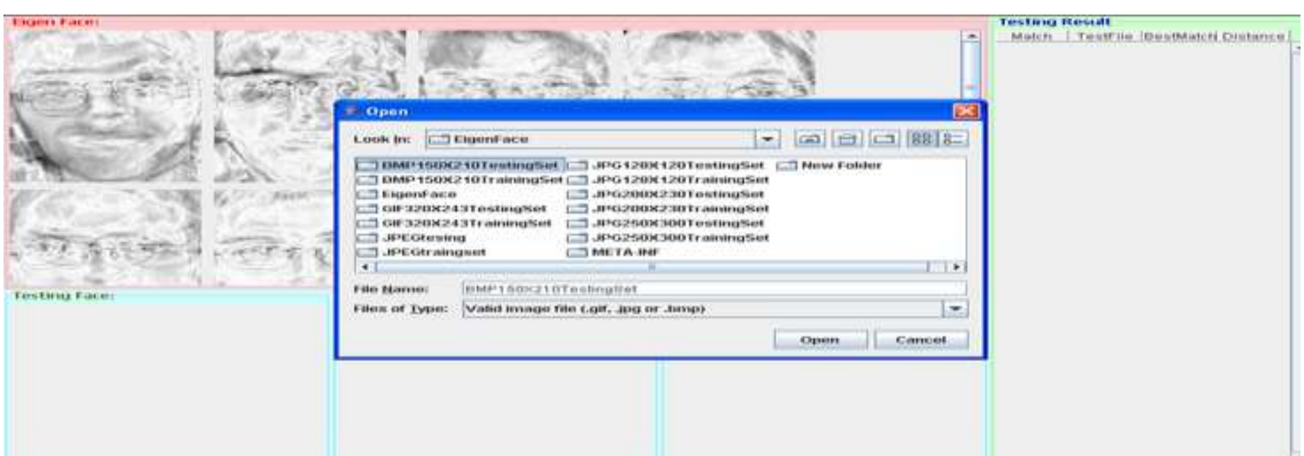
Sample Data:

Dialog for prompting the completion of training

Dialog for choosing the directory to load images for testing



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Dialog for displaying results for testing images

Dialog for identifying an unknown image

4. CONCLUSION

The proposed face recognition system based on PCA accurately identifies input face images of an individual which differ from the set of images of that person already stored in the database thus serving as an effective method of recognizing new face images. The base code for training face images using Back Propagation Neural Network has yet to be completed.

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