جامعة القادسية

كلية علوم الحاسوب وتكنلوجيا المعلومات

قسم الحاسوب



# Design and implementation of face detection system

بحث مقدم الى مجلس كلية علوم الحاسوب وتكنلوجيا المعلومات كجزء من متطلبات نيل شهادة البكلوريوس

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بسم الله الرحمن الرحيم قَالُوا سُبِحَانِكَ لا عِلْمَ لنا إلا ما عَلامتناً إناكَ أنتَ العليمُ الحكيمُ صدق الله العلي العظيم

سورة البقرة (32)

#### الأهداء

باسم الخالق الذي اضاء الكون بنوره البهى وحده اعبد وله وحده اسجد خاشعا شاكرا لنعمته وفضله على في اتمام هذا الجهد ...المي صاحب الفردوس العلى وسراج المة المنير وشفيعها النذير البشير محمد ) صلى الله عليه واله وسلم ( فخرا واعتزازا ... المي من سهر الليالي ... ونسى الغوالي ... وظل سندي الموالي ... وحمل همي غير مبالي بدر التمام ... والدي الغالى ... المي من اثقلت الجفون سهرا ... وحملت الفؤاد هما ... وجاهدت اليام صبرا ... وشغلت البال فكرا ... ورفعت اليادي دعاءا ... وايقنت بالله املا اغلى الغوالي واحب الحباب ... امي العزيزة الغالية ... المي ورود المحبة ... وينابيع الوفاء ... الى من رافقوني في السراء والضراء الى اصدق الصحاب ... اخوتى واخواتى ... المي القلعة الحصينة التي الجأ اليها عند شدتي اصدقائى العزاء نهدي ثمرة جهدنا المتواضع

ل بد لذا ونحن نخطو خطواتنا الأخير، في الحياة الجامعية من وقفة نعود ألى أعوام قضيناها في رحاب الجامعة مع اساتذتنا الكرام الذين قدموا لذا الكثير باذلين بذلك جهودا كبيرة في بناء جيل الغد جهودا كبيرة في بناء جيل الغد وقبل أن نمضي نقدم أسمى أيات الشكر والأمتنان والتقدير وقبل أن نمضي نقدم أسمى أيات الشكر والأمتنان والتقدير والمحبة ألى الذين حملوا أقدس رسالة في الحياة ألى الذين مهدوا لذا طريق العلم والمعرفة وأخص بالتقدير والشكر

الشكر والتقدير

على أتمام هذا البحث وقدم لنا العون ومد لنا يد المساعدة وزودنا بالمعلومات اللازمة لأتمام هذا البحث له منا كل الشكر والمتنان ونعمم الشكر لجميع اساتذتنا فى الجامعة

Abstract	
CHAPTER ONE	
1.1 Introduction	
1.2 Problem of Face Recognition	
1.3 Face Recognition limit in general	
1.4 Aim of project	
CHAPTER TWO	
2.1 Introduction	
2.2 Face detection	
2.3.Feature Extraction	
2.4.Eigenface-Based Face Recognition	
2.4.1 Face recognition using Principle Component Analysis (PCA)	
2.4.3 Overview over the algorithm	
2.5 Calculation of eigenfaces with PCA	
2.6 Advantages and Limitations	

#### Abstract

With a huge progress of information technology in last years and menace on the personal data and their security, the requirement of design powerful and high accurate system for human Authentication and identification recognition become more important and most challenges topic. 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. The proposed face recognition system overcomes certain limitations of the existing face recognition system. It is based on extracting the dominating features of a set of human faces stored in the database and performing mathematical operations on the values corresponding to them. Hence when a new image is fed into the system for recognition the main features are extracted and computed to find the distance between the input image and the stored images in database.

# CHAPTER ONE Face Recognition

#### **1.1 Introduction**

Information and Communication Technologies are increasingly entering in all aspects of our life and in all sectors, opening a world of unprecedented scenarios where people interact with electronic devices embedded in environments that are sensitive and responsive to the presence of users , face recognition system is one of these technologies.

Face recognition systems have been grabbing high attention from commercial market point of view as well as pattern recognition field. Face recognition has received substantial attention from researches in biometrics, pattern recognition field and computer vision communities [10][11]. The face recognition systems can extract the features of face and compare this with the existing database.

The face recognition systems can extract the features of face and compare this with the existing database. The faces considered here for comparison are still faces. Machine recognition of faces from still and video images is emerging as an active research area [10]. The present paper is formulated based on still or video images captured either by a digital camera or by a web cam. The face recognition system detects only the faces from the image scene, extracts the descriptive features. It later compares with the database of faces, which is collection of faces in different poses. The present system is trained with the database , where the images are taken in different poses, with glasses, with and without beard.

#### **1.2 Problem of Face Recognition**

- Variations in skin color under different lighting conditions
- Presence of eyeglasses, make-up, pimples
- Different face angles with respect to the camera
- Clarity of the face image, distance from the camera
- Different facial expressions (e.g., varying levels of smile)
- Hats, caps, or hairstyles that may partially cover the face , and so on.

#### **1.3 Face Recognition limit in general**

Some facial recognition algorithms identify facial features by extracting landmarks, or features, from an image of the subject's face. For example, an algorithm may analyze the relative position, size, and/or shape of the eyes, nose, cheekbones, and jaw. These features are then used to search for other images with matching features. Other algorithms normalize a gallery of face images and then compress the face data, only saving the data in the image that is useful for face recognition. A probe image is then compared with the face data. One of the earliest successful systems is based on template matching techniques applied to a set of salient facial features, providing a sort of compressed face representation[2].

Recognition algorithms can be divided into two main approaches, geometric, which looks at distinguishing features, or photometric, which is a statistical approach that distills an image into values and compares the values with templates to eliminate variances.

Popular recognition algorithms include principal component analysis using eigenfaces, linear discriminant analysis, elastic bunch graph matching using the Fisherface algorithm, the hidden Markov model, the multilinear subspace learning using tensor representation, and the neuronal motivated dynamic link matching.

#### 1.4 Aim of project

The main aim is face identification and verification, face recognition is a method of biometric authentication, based on extraction features of the face of an individual's image. Each individual has a unique face, Biometric face recognition systems should provide a reliable personal recognition schemes to either confirm or determine the identity of a person

## **CHAPTER TWO**

# Eigenface

#### **2.1 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. Although humans perform the task in an effortless manner, the underlying computations within the human visual system are of tremendous complexity[1]. 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.[4]

The proposed face recognition system overcomes certain limitations of the existing face recognition system. It is based on extracting the dominating features of a set of human faces stored in the database and performing mathematical operations on the values corresponding to them. Hence when a new image is fed into the system for recognition the main features are extracted and computed to find the distance between the input image and the stored images. Thus, some variations in the new face image to be recognized can be tolerated. When the new image of a person differs from the images of that person stored in the database, the system will be able to recognize the new face and identify who the person is. The proposed system is better mainly due to the use of facial features rather than the entire face. Its advantages are in terms of:

• Recognition accuracy and better discriminatory power Computational cost because smaller images (main features) require less processing to train the PCA.[4]

• because of the use of dominant features and hence can be used as an effective means of authentication [4]

Since faces may not be the only objects in the images presented to the system, all face recognition systems perform face detection which typically places a rectangular bounding box around the face or faces in the images.

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 [5].



#### 2.2 Face detection

The main function of this step is to determine :

- 1 -whether human faces appear in a given image.
- 2- where these faces are located at.

The expected outputs of this step are patches containing each face in the input image. In order to make further face recognition system more robust and easy to design, face alignment are performed to justify the scales and orientations of these patches. Besides serving as the pre-processing for face recognition, face detection could be used for region-of-interest detection, retargeting, video and image classification. [3]

#### **2.3.Feature Extraction**

Directly using these patches for face recognition have some disadvantages, first, each patch usually contains over 1000 pixels, which are too large to build a robust recognition system . Second, face patches may be taken from different camera alignments, with different face expressions, illuminations, and may suffer from occlusion and clutter. To overcome these drawbacks, feature extractions are performed to do information packing, dimension reduction, salience extraction, and noise cleaning. After this step, a face patch is usually transformed into a vector with fixed dimension or a set of fiducially points and their corresponding locations. In some literatures, feature extraction is either included in face detection or face recognition. [8]

#### **2.4.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.[6] 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.

#### 2.4.1 Face recognition using Principle Component Analysis (PCA)

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 lowerorder principal components and ignoring higher-order ones. The idea is that such low-order components often contain the "most important" aspects of the data.

The task of facial recognition is discriminating input signals (image data) into several classes (persons). The input signals are highly noisy (e.g. the noise is caused by differing lighting conditions, pose etc.), yet the input images are not completely random and in spite of their differences there are patterns which occur in any input signal. Such patterns, which can be observed in all signals could be - in the domain of facial recognition - the presence of some objects (eyes, nose, mouth) in any face as well as relative distances between these objects. These characteristic features are called *eigenfaces* in the facial recognition domain (or *principal components* generally). They can be extracted out of original image data by means of the mathematical tool called *Principal Component Analysis* (PCA).[5]

By means of PCA one can transform each original image of the training set into a corresponding eigenface. If one uses all the eigenfaces extracted from original images, one can reconstruct the original images from the eigenfaces *exactly*. But one can also use only a part of the eigenfaces. Then the reconstructed image is an approximation of the original image. However, losses due to omitting some of the eigenfaces can be minimized. This happens by choosing only the most important features (eigenfaces). Omission of eigenfaces is necessary due to scarcity of computational resources. Thus the purpose of PCA is to reduce the large dimensionality of the face space (independent variables) to the smaller intrinsic dimensionality of feature space (independent

variables), which are needed to describe the data economically. This is the case when there is a strong correlation between observed variables.

To generate a **set of eigenfaces**, a large set of digitized images of human faces, taken under the same lighting conditions, are normalized to line up the eyes and mouths. They are then all resample at the same pixel resolution (say  $m \times n$ ), and then treated as mn-dimensional vectors whose components are the values of their pixels.[3] The eigenvectors of the covariance matrix of the statistical distribution of face image vectors are then extracted. Since the eigenvectors belong to the same vector space as face images, they can be viewed as if they were  $m \times n$  pixel face images: hence the name *eigenfaces*. Viewed in this way, the principal eigenface looks like a bland androgynous average human face. Some subsequent eigenfaces can be seen to correspond to generalized features such as left-right and top-bottom asymmetry, or the presence or lack of a beard. Other eigenfaces are hard to categorize, and look rather strange. When properly weighted, eigenfaces can be summed together to create an approximate gray-scale rendering of a human face. Remarkably few eigenvector terms are needed to give a fair likeness of most people's faces, so eigenfaces provide a means of applying data compression to faces for identification purposes.[7]

It is possible not only to extract the face from eigenfaces given a set of weights, but also to go the opposite way. This opposite way would be to extract the weights from eigenfaces and the face to be recognized. These weights tell nothing less, as the amount by which the face in question differs from "typical" faces represented by the eigenfaces.

Therefore, using this weights one can determine two important things:

• Determine if the image in question is a face at all. In the case the weights of the image differ too much from the weights of face images (i.e. images, from which we know for sure that they are faces) the image probably is not a face.

• Similar faces (images) possess similar features (eigenfaces) to similar degrees (weights). If one extracts weights from all the images available, the images could be grouped to clusters. That is, all images having similar weights are likely to be similar faces.[4]

#### 2.4.3 Overview over the algorithm

The algorithm for the facial recognition using eigenfaces is basically described in figure 2. First, the original images of the training set are transformed into a set of eigenfaces E. Afterwards, the weights are calculated for each image of the training set and stored in the set W. Upon observing an unknown image X, the weights are calculated for that particular image and stored in the vector WX . Afterwards, WX is compared with the weights of images, of which one knows for certain that they are faces (the weights of the training set W). One way to do it would be to regard each weight vector as a point in space and calculate an average distance D between the weight vectors from WX and the weight vector of the unknown image WX (the Euclidean distance described will be used). If this average distance exceeds some threshold value (theta) , then the weight vector of the unknown image WX lies too "far apart" from the weights of the faces. In this case, the unknown X is considered to not a face. Otherwise (if X is actually a face), its weight vector WX is stored for later classification. The optimal threshold value (theta) has to be determined empirically. [4]





#### **2.5 Calculation of eigenfaces with PCA**

In this section, the original scheme for determination of the eigenfaces using PCA will be presented. The algorithm described in scope of this paper is a variation of the one outlined here.

#### **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.

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

#### **STEP 2: Obtain the Mean**

After obtaining the set, the mean image  $\Psi$  has to be obtained as,

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

#### **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  $\Phi$ .

eigenface

$$\Phi_i = \Gamma_i - \Psi \tag{2}$$

#### **STEP 4: Calculate the Covariance Matrix**

The covariance matrix C is calculated in the following manner

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi_n \Phi_n^T$$
(3)

$$= AA^{\prime}$$
(4)

$$A = \{ \Phi_1, \Phi_2, \Phi_3, \dots, \Phi_n \}$$
 (5)

### **STEP 5: Calculate the Eigenvectors and Eigenvalues of the Covariance Matrix and Select the Principal Components**

In this step, the eigenvectors (eigenfaces) ui and the corresponding eigenvalues  $\lambda i$  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 new face is transformed into its eigenface components and the resulting weights form the weight vectors. [5]

$$\omega_{k} = u_{k}^{T} \left( 1 - \Psi \right)$$
 (6)

where  $\omega$  = weight,  $\mu$  = eigenvector,  $\Gamma$  = new input image,  $\Psi$  = mean face

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

$$\boldsymbol{\Omega}^{T} = \left[\boldsymbol{\omega}_{1}, \boldsymbol{\omega}_{2}, \ldots, \boldsymbol{\omega}_{M}\right]$$



fig3:training images

fig 4:eigenfaces of the corresponding training images.

#### **2.6 Advantages and Limitations**

As an appearance-based approach, eigenface recognition method has several advantages:

- (1) Raw intensity data are used directly for learning and recognition without any significant low-level or mid-level processing.
- (2) No knowledge of geometry and reflectance of faces is required.
- (3) Data compression is achieved by the low-dimensional subspace representation.
- (4) Recognition is simple and efficient compared to other matching approaches

These advantages reflect the power of appearance-based approach in ease of implementation. However, the experimental results also demonstrate some serious limitations of eigenface representation method for face recognition under different conditions.

Additionally, the eigenface recognition method bears some common disadvantages due to its ``appearance-based" nature. First, learning is very timeconsuming, which makes it difficult to update the face database. Second, recognition is efficient only when the number of face classes is larger than the dimensions of the face space; otherwise, the projection of an unknown image requires pixel-by-pixel multiplication of the input image by all eigenfaces, which is equivalent to or worse than templatematching with respect to computation time since an extra distance calculation is needed in the subspace. However, the occurrence of class overlapping increases when more face classes are represented by the same face space, thus lowering the recognition rate.

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