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**CHAPTER 2**

**REVIEW OF RELATED LITERATURES AND SYSTEMS**

**I. Foreign Literatures**

According to **Wei-Lun Chao, “Face Recognition” of 2010**, the illumination variation has been widely discussed in many face detection and recognition researches. This variation is caused by various lighting environments and mentioned to have larger appearance difference than the difference caused by different identities. Fig. 7 shows the example of illumination changes on images of the same person, and it’s obviously that under some illumination conditions, we can neither assure the identification nor accurately point out the positions of facial features.

Face Recognition: After formulizing the representation of each face, the last step is to recognize the identities of these faces. In order to achieve automatic recognition, a face database is required to build. For each person, several images are taken and their features are extracted and stored in the database. Then when an input face image comes in, we perform face detection and feature extraction, and compare its feature to each face class stored in the database. There have been many researches and algorithms proposed to deal with this classification problem, and we’ll discuss them in later sections. There are two general applications of face recognition, one is called identification and another one is called verification. Face identification means given a face image, we want the system to tell who he / she is or the most probable identification; while in face verification, given a face image and a guess of the identification, we want the system to tell true or false about the guess.

According to **Sushma Jaiswal, Dr. (Smt.) Sarita Singh Bhadauria and Dr. Rakesh Singh Jadon’s, “Comparison between Face Recognition Algorithm-faces, Fisherfaces and Elastic Bunch Graph Matching” of 2011,** eigenface is a practical approach for face recognition. Due to the simplicity of its algorithm, we could implement an Eigenface recognition system easily. Besides, it is efficient in processing time and storage. PCA reduces the dimension size of an image greatly in a short period of time. The accuracy of Eigenface is also satisfactory (over 90 %) with frontal faces. However, as there has a high correlation between the training data and the recognition data. The accuracy of Eigenface depends on many things. As it takes the pixel value as comparison for the projection, the accuracy would decrease with varying light intensity. Besides, scale and orientation of an image will affect the accuracy greatly.

Pre-processing of image is required in order to achieve satisfactory result Advantages of this algorithm are that the eigentfaces were invented exactly for that purpose what makes the system very efficient. A drawback is that it is very sensitive for lightening conditions and the position of the head, it Fast on Recognition, and Easy to implement Disadvantages-Finding the eigenvectors and eigenvalues are time consuming on PPC The size and location of each face image must remain similar PCA (Eigenface) approach maps features to principle subspaces that contains most energy.

According to **Young Kyung Lee, Eun Ryung Lee. and Byeong U. Park's, “Principal Component Analysis in Very High-Dimensional Spaces” in 2011,** A particular disadvantage of PCA is that the principalcomponents are typically linear combinations of all variables Xj , which makes the results difficult to interpret, especially when d is very large. Recent years have seen several proposals that give ‘sparse’ solutions, that is, solutions that 934 YOUNG KYUNG LEE, EUN RYUNG LEE AND BYEONG U. PARK involve only a few nonzero loadings; see Jolliffe, Trendafilov, and Uddin (2003),Zou, Hastie, and Tibshirani (2006), d’Aspremont et al. (2007), d’Aspremont,Bach, and Ghaoui (2008), Shen and Huang (2008), Leng and Wang (2009), andWitten, Tibshirani, and Hastie (2009).

We are concerned with the case where d, the dimension of X, is comparable to, or even larger than, the sample size n. The standard PCA is known to yield inconsistent results in such a high-dimensional case, see Johnstone and Lu(2009). We propose a method that gives consistent estimators of the principal component loading vectors.

**II. Local Literatures**

According to **Prospero C. Naval, Jr, “Recognizing Faces using Kernel Eigenfaces and Support Vector Machines” of 2003,** Principal Component Analysis (PCA) is used for extracting relevant features from high-dimensional data sets. It performs an orthogonal transformation of the coordinate system in which the data is originally described. After coordinate transformation, it is often the case that only a subset of the new coordinate values is necessary to describe most of the data. This subset is called the principal components of the data. The principal components possess large variance.

According to **Jerome Paul N. Cruz, et al., “Object recognition and detection by shape and color pattern recognition utilizing Artificial Neural Networks” of 2013,** the value of the weight and bias varies in every neuron. The process of determining the value of weight and bias is called learning or training. The algorithm used for learning is called back propagation algorithm. In this learning method, a desired output or target is given with a corresponding set of inputs. In the architecture of the artificial neural networks, back propagation algorithm requires 52 input elements and five output or target elements per set.

According to **Ma. Christina D. Fernandez, et al., “Simultaneous Face Detection and Recognition using Viola-Jones Algorithm and Artificial Neural Networks for Identity Verification” of 2014,** there are 7 facial features to be extracted and these are the skin color, color of the eye, the distance   
between the two eyes, the width of the nose, the height and width of the   
lips, and the distance between the nose and the lips. These are then   
detected, extracted, and measured from the person’s processed face   
image. These measurements are then passed through processes which will produce a representation of these characteristics in numerical vector form.

According to **Ralph Gross, et al., “Face Recognition Across Pose and Illumination”,** Besides face pose, illumination is the next most significant factor affecting the appearance of faces. Ambient lighting changes greatly within and between days and among indoor and outdoor environments. Due to the 3D structure of the face, a direct lighting source can cast strong shadows that accentuate or diminish certain facial features. It has been shown experimentally and theoretically for systems based on Principal Component Analysis that differences in appearance induced by illumination are larger than differences between individuals.

According to **P. T. Chavda and S. Solanki, “Illumination Invariant Face Recognition based on PCA (Eigenface)”** **of 2014,** Principle Component Analysis (PCA) The PCA Method of Turk and Pentland is one of the main methods applied in the literature which is based on the Karhunen-Loeve expansion. Their study is motivated by the earlier work of Sirowich and Kirby. It is based on the application of Principal Component Analysis to the human faces. It treats the face images as 2-D data, and classifies the face images by projecting them to the eigenface space which is composed of eigenvectors obtained by the variance of the face images. Eigenface recognition derives its name from the German prefix eigen, meaning own or individual. The Eigenface method of facial recognition is considered the first working facial recognition technology. Principal component analysis (PCA) is standard technique used in statistical pattern recognition and signal processing for data reduction and Feature extraction. As the pattern often contains redundant information, mapping it to a feature vector can get rid of this redundancy and yet preserve most of the intrinsic information content of the pattern. These extracted features have great role in distinguishing input patterns. PCA is also known as eigenface method.

Illumination change: The direction where the individual in the image has been illuminated greatly effects face recognition success. A study on illumination effects on face recognition showed that lighting the face bottom up makes face recognition a hard task

Eigenface Method:An image space can be thought of as a space having dimensions equal to the number of pixels making up the image and having values in the range of the pixels values. Thus, for example for a grey scale image of size (Nx x Ny), the dimension of the image space is P, P being Nx times Ny. For the case of gray scale images, in each dimension the image could have a value in between 0 and 255. An image can be thought as a point in the image space by converting the image to a long vector by concatenating each column of the image one after the other. When all the face images are converted into vectors, they will group at a certain location in the image space as they have similar structure, having eye, nose and mouth in common and their relative position correlated. This correlation is the main point to start the eigenface analysis. The Eigenface method tries to find a lower dimensional space for the representation of the face images by eliminating the variance due to non-face images; that is, it tries to focus on the variation just coming out of the variation between the face images. Eigenface method is the implementation of Principal Component Analysis (PCA) over images. In this method, the features of the studied images are obtained by looking for the maximum deviation of each image from the mean image. This variance is obtained by getting the eigenvectors of the covariance matrix of all the images. The eigenface space is obtained by applying the eigenface method to the training images. Later, the training images are projected into the eigenface space. Next, the test image is projected into this new space and the distance of the projected test image to the training images is used to classify the test image. Euclidean distance is used for the classification of test images.

The implementation steps of PCA based eigenface is as follows:

**Step 1**. Image I : (Nx x Ny) pixels. The image matrix I of size (Nx x Ny) pixels is converted to the image vector Γ of size (P x 1) where P = (Nx x Ny); that is the image matrix is reconstructed by adding each column one after the other. Training Set **Γ = [Γ1 Γ2 … Γmt]** is the training set of image vectors and its size is (P x Mt) where Mt is the number of the training images.

**Step 2**. Mean Face Ψ = Γi is the arithmetic average of the training image vectors at each pixel point and its size is (P x 1).   
  
**Step 3**. Mean subtracted image Φ = Γ − Ψ is the difference of the training image from the mean image (size P x 1).

**Step 4**. Difference Matrix Α = [ Φ1 Φ2 ... ΦMt ] is the matrix of the entire mean subtracted training image vectors and its size is (P x Mt).

**Step 5**. Covariance Matrix **Χ = Α ⋅ ΑT = Φi ΦI Γ** is the covariance matrix of the training image vectors of size (P x P). (sample covariance matrix, N\*N, characterizes the scatter of the data)

An important property of the Eigenface method is obtaining the eigenvectors of the covariance matrix. For a face image of size (Nx x Ny) pixels, the covariance matrix is of size (P x P), P being (Nx x Ny). This covariance matrix is very hard to work with due to its huge dimension causing computational complexity.

This method has been developed by Mathew Turk and Alex Pentland. Eigen-space based approach is derived from information theory. In the language of information theory, we extract the relevant information, encode it as efficiently as possible, and compare one encoding with a database of models encoded similarly. A simple approach to extract the information contained in the image of a face is to capture the variation of images, independent of judgment of features, and use this information to encode and compare individual face images. In Eigen-space based approaches, Principal Component Analysis [7] is used to encode the information. In mathematical terms; we find principal components of the distribution of faces, or the eigenvectors of the covariance matrix of images, treating an image as a point in a high-dimensional space. This technique is known as Principal Component Analysis. The eigenface technique is a powerful yet simple solution to the face recognition. In fact, it is really the most intuitive way to classify a face. As we have shown, old techniques focused on particular features of the face. The eigenface technique uses much more information by classifying faces based on general facial patterns. These patterns include, but are not limited to, the specific features of the face. By using more Information, eigenface analysis is naturally more effective than feature-based face recognition. Eigenfaces are fundamentally nothing more than basis vectors for real faces. The eigenface approach is divided into two phases:-

A. Training phase (Initialization phase): This phase has three major steps.   
i) Acquire an initial set of face images (the training set) ii) Calculate the eigenfaces from the training set, keeping only the M images that correspond to highest eigenvalues. These M values describe a face space. iii) Calculate the corresponding distribution in M-dimensional weight space for each known individual by projecting his or her face image onto the "face space".

B. Query phase (Recognition phase): It has four major steps:- i) Calculate the set of weights based on the input image and the M eigenfaces by projecting the input image onto each of the eigenfaces. ii) Determine if the image is a face or not (by checking whether the image is sufficiently close to the face space). iii) Classify the weight pattern as a person or unknown. iv) Update the eigenfaces and weight patterns (optional). Many algorithms are devised for face recognition using the eigen-space based approach.

Principle components analysis PCA is a useful statistical technique that has found application in fields such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension. It includes various mathematical concepts such as eigenvalue, eigenvector, deviation and covariance. This background knowledge is meant to make the PCA section very straightforward. Principle Components Analysis (PCA), [7] also known as Karhunen-Loève expansion or Eigen-XY analysis, has found a number of applications in the fields of computer vision and pattern recognition. PCA is based on representing typical images in terms of a compact set of orthogonal basis images. PCA is used in computer vision, first showing how images are usually represented, and then showing what PCA can allow us to do with those images. It is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. It is use for extracting relevant information from confusing data sets.

Facial Recognition using Eigenfaces by PCA One of the main applications of the PCA in Computer Vision is in facial recognition. A. Generating Eigenfaces Assume a face image I(x,y) be a two-dimensional M by N array of intensity values, or a vector of dimension MxN. The Training set used for the analysis is of size 110x129, resulting in 14,190 dimensional space. A typical image of size 256 by 256 describes a vector of dimension 65,536, or, equivalently, a point in 65,536-dimensional space. For simplicity the face images are assumed to be of size NxN resulting in a point in N2 dimensional space. An ensemble of images, then, maps to a collection of points in this huge space. Images of faces, being similar in overall configuration, will not be randomly distributed in this huge image space and thus can be described by a relatively low dimensional subspace. The main idea of the principal component analysis (or Karhunen-Loeve transform) is to find the vectors which best account for the distribution of face images within the entire image space. These vectors define the subspace of face images, which we call "face space".Each vector is of length N2 , describes an N by N image, and is a linear combination of the original face images. Because these vectors are the eigenvectors of the covariance matrix corresponding to the original face images, and because they are face like in appearance, we refer to them as “eigenfaces”.

According to **Tarun Kumar** and **Karun VermaIt, “A Theory Based on Conversion of RGB image to Gray image” of 2010,** Grayscale Image is also known as an intensity, gray scale, or gray level image. Array of class uint8, uint16, int16, single, or double whose pixel values specify intensity values. For single or double arrays, values range from [0, 1]. For uint8, values range from [0,255]. For uint16, values range from [0, 65535]. For int16, values range from [-32768, 32767].

Gray levels represent the interval number of quantization in gray scale image processing. At present, the most commonly used storage method is 8-bit storage. There are 256 gray levels in an 8 bit gray scale image, and the intensity of each pixel can have from 0 to 255, with 0 being black and 255 being white