Face Recognition Employing Principle Component Analyais

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Abstract— Face recognition is an important and challenging field in computer vision. This research present a system that is capable of recognizing a person's face by comparing facial structure to that of a known person which is achieved by using frontal view facing photographs of individuals to render a two-dimensional representation of a human face. The system is based on Eigenface approach. Various symmetrization techniques are used for preprocessing the images in order to handle bad illumination and face alignment problem. Experimental results demonstrate that the implemented eigenface-based technique classified the faces with accuracy more than 90%.

Index Terms— Principle component analysis, Eigenvector, Eigenvalue, Eigenface, Face recognition.

1 Introduction

FACE recognition has become an important issue in many applications such as security systems, credit card verification and criminal identification. Although it is clear that people are good at face recognition, it is not at all obvious how faces are encoded or decoded by the human brain. Developing a computational model of face recognition is quite difficult, because faces are complex, multi-dimensional visual stimuli. Therefore, face recognition is a very high level computer vision task, in which many early vision techniques can be involved. A formal method of classifying faces was first proposed by Francis Galton [1],[2].

The first step of human face identification is to extract the relevant features from facial images. Research in the field primarily intends to generate sufficiently reasonable familiarities of human faces so that another human can correctly identify the face. Investigations by numerous researchers [3, 4, 5] over the past several years have indicated that certain facial characteristics are used by human beings to identifying faces. There are three major research groups which propose three different approaches to the face recognition problem. The largest group [6, 7, 8] has dealt with facial characteristics which are used by human beings in recognizing individual faces. The second group [9, 10, 11, 12, 13] performs human face identification based on feature vectors extracted from profile silhouettes. The third group [14, 15] uses feature vectors extracted from a frontal view of the face. Although there are three different approaches to the face recognition problem, there exist two basic methods from which these three different approaches arise. The first method is based on the information theory concepts named principal component analysis methods. In this approach, the most relevant information that best describes a face is derived from the entire face image. Based on the Karhunen-Loeve expansion in pattern recognition, M. Kirby and L. Sirovich [6, 7] have shown that any particular face could be economically represented in terms of a best coordinate system that they termed "eigenfaces". These are the eigenfunctions of the averaged covariance of the ensemble of faces. Later, M. Turk and A. Pentland [16] have proposed a face recognition method based on the eigenfaces approach. The second method is based on extracting feature vectors from the basic parts of a face such as eyes, nose, mouth, and chin. In this method, with the help of deformable templates and extensive mathematics, key information from the basic parts of a face is gathered and then converted into a feature vector. L. Yullie and S. Cohen [17] played a great role in adapting deformable templates to contour extraction of face images.

This paper focuses on Principle Component Analysis (PCA) which is applied on a representative dataset of images of faces. The system functions by projecting face images onto a feature space that spans the significant variations among known face images. These significant features termed as "Eigenfaces" are the principal components of the set of training face images. These features do not necessarily correspond to facial features such as eyes, nose and ears and merely capture the image points that cause meaningful variations between the faces in the database that allow them to be differentiated. Face images are then classified within the low-dimensional

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model using a nearest-neighbor classifier.

The rest of the paper is organized as follows. Section II describes the basics of Principle Component Analysis (PCA). The process of face detection is described in section III. The face image normalization is presented in section IV. Section V illustrates the algorithms for face recognition. The experimental result has been showed in section VI. And finally section VI concludes the paper.

2 PRINCIPLE COMPONENT ANALYSIS (PCA)

The objective of the Principal Component Analysis is to take the total variation on the training set of faces and to represent this variation with just some little variables. When the size of training set is increased, the reduction of space dimension is very important. PCA intends to reduce the dimension of a group or to space it better so that the new base describes the typical model of the group.

The image space is highly redundant when it describes faces. This happens because each pixel in a face is highly correlated to the others pixels. The objective of PCA is to reduce the dimension of the work space. The maximum number of principal components is the number of variables in the original space. Even so to reduce the dimension, some principal components should be omitted. This means that some principal components can be discarded because it only has a small quantity of data, considering that the larger quantity of information is contained in the other principal components. The eigenfaces are the principal components of the original face images, obtained by the decomposition of PCA and eigenfaces has been constructed using eigenvector. Eigenfaces and Eigenvectors are described as follows:

2.1 Eigenvectors

An eigenvector of a matrix is a vector such that, if multiplied with the matrix, the result is always an integer multiple of that vector. This integer value is the corresponding eigenvalue of the eigenvector. This relationship can be described by the equation M × u = c × u, where u is an eigenvector of the matrix M and c is the corresponding eigenvalue.

2.2 Eigenfaces

Eigenfaces are the set of eigenvectors which are used for human face recognition. They can be simply defined as the eigenvectors which represent one of the dimensions of face image space. The eigenfaces are a group of important characteristics that describe the variation in the group of face images. All eigenvectors have an eigenvalue associated to it and the eigenvectors with the largest eigenvalues provide more information on the face variation than the ones with smaller eigenvalues. Any new face can be expressed as linear combination of these Eigen faces.

3 FACE DETECTION

To locate the face, an image pyramid is formed from the original image. An image pyramid is a set of copies of the original image at different scale, thus representing a set of different resolutions. A mask is moved pixel wise over each image in the pyramid and at each position, the image section under the mask is passed to a function that assesses the similarity of the image section to a face. If the similarity value is high enough, the presence of a face at that position and resolution is assumed. From that position and resolution, the position and size of the face in the original image can be calculated. From the position of the face, a first estimate of the eye position can be derived. A search for the exact eye position is started. This search is very similar to the search for the face position, the main difference being that the resolution of the images in the pyramid is higher than the resolution at which the face was found before. The positions yielding the highest similarity values are taken as final estimates of the eye positions. The basic steps of face detection are illustrated in Fig. 1.

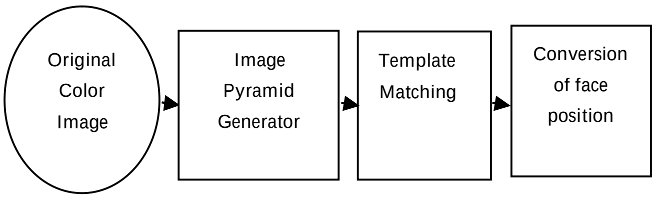

Fig. 1 Basic Steps of Face Detection.

4 FACE IMAGE NORMALIZATION

After detecting the face area, it is normalized before passing to the face recognition module. A sequence of image pre-processing techniques is applied so that the image is light and noise invariant. Standard face recognition prerequisite such as gray image conversion and scaling into a suitable sized image are also employed. Detected face is converted to grayscale using Eq. 1

$$Gr_i = \frac{R_i + G_i + B_i}{3}, \qquad i = 1,2,3,\ldots M \times N \tag{1}$$

where Gr_i is the gray level value of i^{th} pixel of the gray image, R_i, G_i, B_i correspond to red, green and blue intensity value of the i^{th} pixel in the color image and the resolution of the image is $M \times N$. And then the converted grayscale image is scaled to 60×60 pixel using Eq. 2 in this paper.

$$Q(x_q, y_q) = P(\frac{x_p}{60} x_q, \frac{y_p}{60} y_q) \tag{2}$$

Here the coordinate of p^{th} pixel of original grayscale image, $P(x_p, y_p)$ is converted into the q^{th} pixel of the scaled image and the coordinate of that pixel will be $Q(x_q, y_q)$. This scaled image is saved as a gray jpg image and finally linear interpolation technique was employed to determine the scaled output image.

5 FACE RECOGNITION

In this paper, the face recognition system is divided into two parts: initialization and recognition. In initialization phase, the system is learned by creating eigenvectors of a training set of face images. The Algorithm 1 is applied for initialization of face recognition system.

Algorithm 1 (Initialization)
Input: A set of face images known as Training set (Γ_i).
Output: Form the feature vectors of each face image.
Method: The feature vector is constructed in the following steps.

1. The average matrix Ψ has to be calculated. Then subtract this mean from the original faces (Γ_i) to calculate the image vector (ϕ_i), where
$$\psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i \quad , \tag{3}$$
$$\phi_i = \Gamma_i - \psi \tag{4}$$
2. Find the covariance matrix **c** as follows:
$$\mathbf{c} = \frac{1}{M}\sum_{n=1}^{M}\phi_n\phi_n^T = AA^T \tag{5}$$
3. Compute the eigenvectors and eigenvalues of **c**.
4. The **M** significant eigenvectors are chosen as those with the largest corresponding eigenvalues.
5. Project all the face images into these eigenvectors and form the feature vectors of each face image.

After getting the feature vectors, Algorithm 2 is employed to recognize an unknown face.

Algorithm 2 (Recognition)
Input: An unknown image ***I***.
Output: Recognize the image ***I***.

Method: The FP-tree is constructed in the following steps.
1. For given input image ***I***, calculate a set of weights based on ***M*** eigenfaces by projecting this new image onto each of eigenfaces.
2. Compute the difference between the projected vector and each face image feature vector.
3. Classify the weight pattern as either known or unknown person.
4. The weight pattern can be compared with known weight patterns to match faces.

Fig. 2 Training set face images.

Fig. 3 Eigenfaces with highest eigen values.

With this analysis, the calculations are greatly reduced, from the order of the number of pixels in the images (N^2) to the order of the number of images in the training set (Γ_i). The success of this algorithm is based on the evaluation of the eigenvalues and eigenvectors of the real symmetric matrix L that is composed from the training set of images.
The sample face images and the corresponding eigenfaces are shown in Fig. 2 and Fig. 3, respectively. Each eigenface

deviates from uniform gray where some facial feature differs among the set of training faces. Eigenfaces can be viewed as a sort of map of the variations between faces.

6 Implementation and Result Analysis

The experiments were carried out over a training set of 175 (5 per individual) images of 35 persons. All images were in RGB color level which were normalized to gray level with dimension of 60×60. There were 27 subjects in the training set. Each subject had 5 images with frontal view with ± 5 different poses (like left, right, up and down). The training procedure is summarised in Table 1. In this research, firstly an overall average image has been constructed by adding all images and dividing by number of images in the training set. The eigenvectors of covariance matrix was formed by combining all deviation of training set images from average image. Since the training set contains 35 individuals, 35 eigenvectors have been used to represent the training set. The distribution of the feature vectors for different images are shown in Fig. 4. The overall results underdifferent lighting conditions is shown in Table 2.

TABLE I

TRAINING PROCEDURE OF IMAGES

Training Procedure of images	
No. of images taken for the training procedure	35×5
Size	60×60
Format	JPG
Output	Normalized images of the face images
	Eigenface

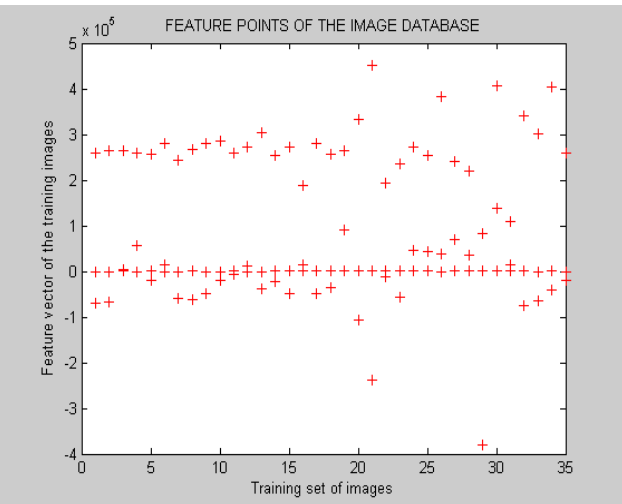

Fig. 4 Distribution of the feature vectors of a typical user.

TABLE 2

RESULTS FOR DIFFERENT SETS OF FACE IMAGES

Lighting condition	Total number of images taken for the test	Correctly recognized (Success rate)
Bright sunny day	60	98.33%
Dark lighting condition	60	95%
Foggy weather	55	90.9%

7 Conclusion

This paper presents a principal component analysis based face recognition system, where the eigenvectors of the covariance matrix of a small set of characteristic pictures are sought. These eigenvectors are called eigenfaces due to their resemblance of face images. Recognition is performed by obtaining feature vectors from the eigenvectors space. This eigenface approach for face recognition process is robust which works well under constrained environment. It is one of the best practical solutions for the problem of face recognition. Eigenfaces are a set of features that extracted from the training faces. Eigenfaces do not represent facial characteristics of the face, however, if they extracted carefully, they can classify any new images with good accuracy.

For given set of images, due to high dimensionality of images, the space spanned is very large. But in reality, all these images are closely related and actually span a lower dimensional space. The eigenface approach leads to reduce this dimensionality. The lower the dimensionality of this image space, the easier it would be for face recognition. Any new image can be expressed as linear combination of these eigenfaces. This makes it easier to match any two images and thus face recognition.

One of the limitations for eigenface approach is in the treatment of face images with varied facial expressions and with glasses. Also as images may have different illumination conditions. This can be removed by RMS (root mean square) contrast stretching and histogram equalization.The face database in this work contains 175 face images and the proposed method provides satisfactory result. It can recognize both the known and unknown images in the database in various conditions with accuracy more than 90%. One can improve this work by enhnching the eigenface technology and recognition procedure for live video stream so that any person can be identified at his or her own workplace.

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