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Real Time Face Recognition under Different Conditions

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Abstract -- Face recognition is an active area of research since 1980s. It is one of the most successful and important applications of image analysis and processing. Eigenface approach is one of the earliest appearance-based face recognition methods, which was developed by M. Turk and A. Pentland in 1991 [1]. This method utilizes the idea of the Principal Component Analysis (PCA) which decomposes a face image into a small set of characteristic feature images called eigenfaces and recognition is performed by projecting a new face onto a low dimensional linear "face space" defined by the eigenfaces, followed by computing the distance between the resultant position in the face space and those of known face classes. A number of experiments are done at different conditions to evaluate the performance of the face recognition system. The results demonstrate that the face recognition using eigenfaces is quite robust to head/face orientation and illumination.

Keywords : Principal Component Analysis (PCA), Eigenfaces, Facespace, Eigenvalue, and Euclidean Distance.

I. INTRODUCTION

The face plays a major role in our social intercourse in conveying identity and emotions. The human ability to recognize faces is remarkable. We can recognize thousands of faces learned throughout our lifetime and identify familiar faces at a glance even after years of separation. The skill is quite robust, despite large changes in the visual stimulus due to viewing conditions, expressions, aging, and distractions such as glasses or changes in hairstyle. But developing a computational model of face recognition is quite difficult, because faces are complex, multidimensional, and subject to change over time [2].

Typical applications of Face Recognition System are : Human-Robot-interaction, Human-Computer-interaction, Driver's license, Smart cards, National ID, Passports, Voter registration, Security system, Criminal identification, Personal device logon, Desktop logon, Information security, Database security, Intranet security, Internet access, Medical records Video surveillance, CCTV control and Suspect tracking and investigation [3].

In this paper, the goal is to find best match of an image captured by camera from the sequence of images (Database). Using a pre-stored image database, the face recognition system should be able to identify or verify one or more persons in the scene. Before face recognition is performed, the system should determine whether or not there is a face in a given image, a sequence of images. This process is called *face detection*. Once a face is detected, face region should be isolated from the scene for the *face recognition*. The overall process is depicted in figure (1).

Generally, there are three phases for face recognition, mainly face representation, face detection, and face identification.

Face representation is the first task, that is, how to model a face. The way to represent a face determines the successive algorithms of detection and identification. There are a variety of approaches for face representation, which can be roughly classified into three categories: template-based, feature-based, and appearance-based.

The simplest *template-matching* approaches represent a whole face using a single template, i.e., a 2-D array of intensity, which is usually an edge map of the original face image. The most attractive advantage of template-matching is the simplicity, however, it suffers from large memory requirement and inefficient matching [4].

In *feature-based* approaches, geometric features, such as position and width of eyes, nose, and mouth, eyebrow's thickness and arches, face breadth, or invariant moments, are extracted to represent a face. Feature-based approaches have smaller memory requirement and a higher recognition speed than template-based ones do. They are particularly useful for face scale normalization and 3D head model-based pose estimation. However, perfect extraction of features is shown to be difficult in implementation.

The idea of *appearance-based* approaches is to project face images onto a linear subspace of low dimensions. Such a subspace is first constructed by principal component analysis (PCA) on a set of training images, with eigenfaces as its eigenvectors. Later, the concept of eigenfaces were extended to eigenfeatures, such as eigeneyes, eigenmouth, etc. for the detection of facial features. More recently, fisherface space and illumination subspace have been proposed for dealing with recognition under varying illumination [5].

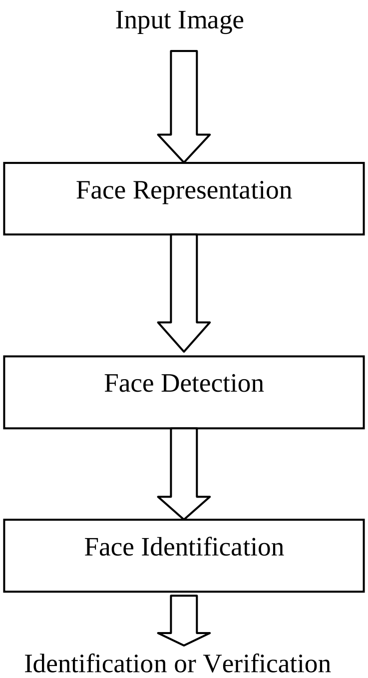


Figure 1 : Face Recognition System.

Face detection is to locate a face in a given image and to separate it from the remaining scene. Several approaches have been proposed to fulfill the task. One of them is to utilize the elliptical structure of human head. This method locates the head outline by the Canny's edge finder [4] and then fits an ellipse to mark the boundary between the head region and the background. However, this method is applicable only to frontal views, the detection of non-frontal views needs to be investigated. A second approach for face detection manipulates the images in “face space” [6]. Images of faces do not change radically when projected into the face space, while projections of nonface images appear quite different. This basic idea is used to detect the presence of faces in a scene: at every location in the image, calculate the distance between the local subimage and face space. This distance from face space is used as a measure of “faceness”, so the result of calculating the distance from face space at every point in the image is a “face map”. Low values, in other words, short distances from face space, in the face map indicate the presence of a face.
Face identification is performed at the subordinate-level. At this stage, a new face is compared to face models stored in a database and then classified to a known individual if a correspondence is found. The performance of face identification is affected by several factors: scale, pose, illumination, facial expression, and disguise [6].

II. PRINCIPLE OF THE METHOD

In this paper, we have used Principal Component Analysis (PCA) method. This is an appearance-based statistical method, the other appearance-based statistical methods are, Independent Component Analysis (ICA) and Linear Discriminant Analysis (LDA).
PCA applied to FACE RECOGNITION:

The objective of the Principal Component Analysis (PCA) is to take the total variation on the training set of faces and to represent this variation with just some little variables. When we are working with great amounts of images, reduction of space dimension is very important. PCA intends to reduce the dimension of a group or space 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 they only have 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, forming the face space from these images. So any new face can be expressed as linear combination of these Eigenfaces [7, 8]. The block diagram of PCA based Face Recognition System is shown in figure (2).

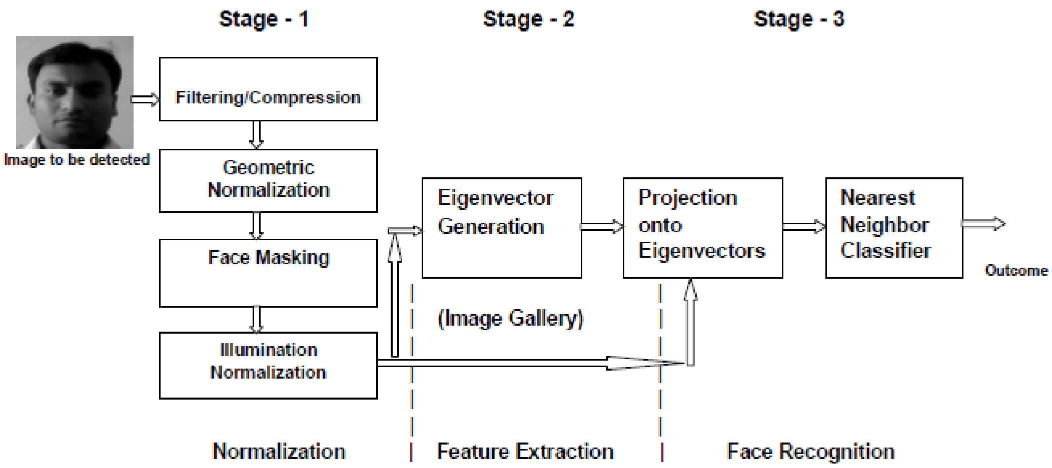


Figure 2 : Block diagram of PCA – based Face Recognition System.

Mathematically, PCA approach treats every image of the training set as a vector in a very high dimensional space. The eigenvectors of the covariance matrix of these vectors would incorporate the variation amongst the face images. Now each image in the training set would have its contribution to the eigenvectors (variations). This can be displayed as an '*eigenface*' representing its contribution in the variation between the images. These eigenfaces look like ghostly images and some of them are shown in figure. In each eigenface some sort of facial variation can be seen which deviates from the original image [8].

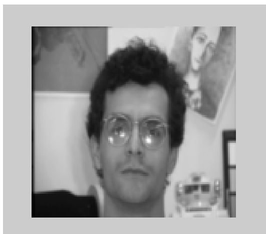
The high dimensional space with all the eigenfaces is called the image space (feature space). Also, each image is actually a linear combination of the eigenfaces. The amount of overall variation that one eigenface counts for, is actually known by the eigenvalue associated with the corresponding eigenvector. If the eigenface with small eigenvalues are neglected, then an image can be a linear combination of reduced number of these eigenfaces. For example, if there are M images in the training set, we would get M eigenfaces. Out of these, only M' eigenfaces are selected such that they are associated with the largest eigenvalues. These would span the M'-dimensional subspace 'face space' out of all the possible images (image space).

Face Recognition is performed from the projection of the analyzed face into the face space and the measuring of the euclidean distance between the new face and the face classes. If the distance is inside the threshold of a certain class and it is the smallest value, then there is recognition [9].

Calculating Eigenfaces

Let a face image Γ(x,y) be a two-dimensional *N* by *N* array of intensity values. An image may also be considered as a vector of dimension N^2, so that a typical image of size 256 by 256 becomes a vector of dimension 65,536, or equivalently, a point in 65,536-dimensional space. An ensemble of images, then, maps to a collection of points in this huge space [9].

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 is to find the vector that 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 N^2, 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, they are referred to as "eigenfaces" [10]. Some of these faces are shown in figure (3), (4) and (5).



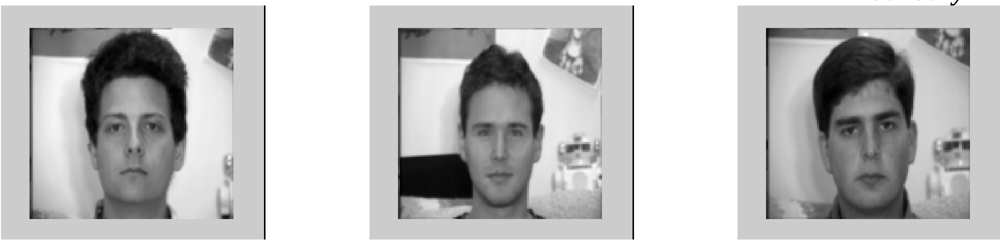


Figure 3 : Face Images

Figure 4 : Average Face of Images

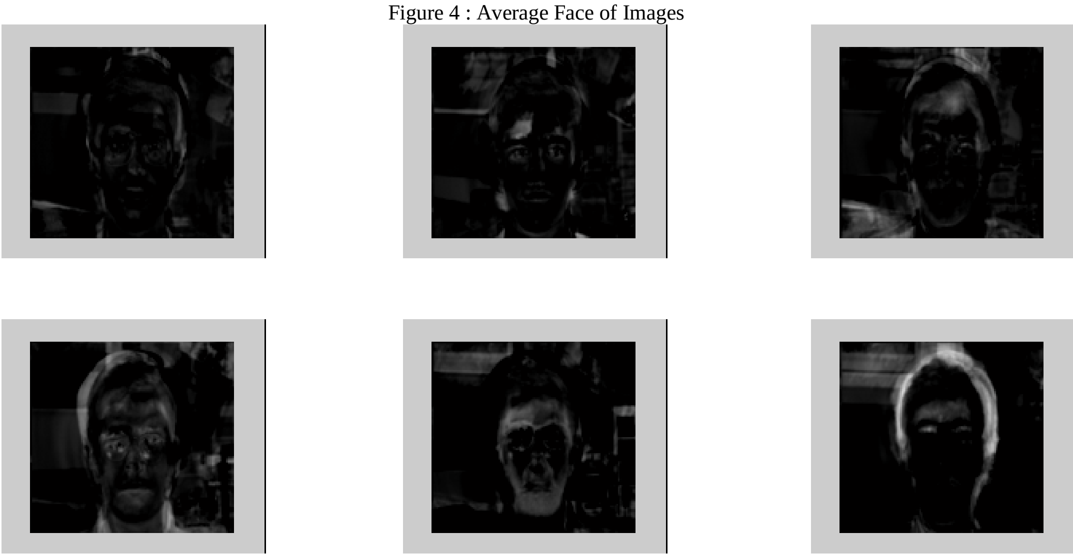


Figure 5 : Eigenfaces

III. EXPERIMENTAL ANALYSIS

The face recognition system is tested using a set of face images. All the training and testing images are grayscale images. There are 9 persons in the face image database, each having 5 distinct pictures taken under different conditions (illuminance, head tilt, and head scale, etc.).

The training images are chosen to be those of full head scale, with head-on lighting. The performance of the Eigenface approach under different conditions is studied as follows.

Recognition with different head tilts :

The robustness of the eigenface recognition algorithm to head tilt is studied by testing 2 face images of each person that is in the training set, with different head tilts—either left-oriented or right-oriented, as shown in figure (6).

If the system correctly relates the test image with its correspondence in the training set, we say it conducts a *true-positive* identification; if the system relates the test image with a wrong person, or if the test image is from an unknown individual and the system recognizes it as one of the persons in the database, a *false-positive* identification is performed; if the system identifies the test image as unknown while there does exist a correspondence between the test image and one of the training images, the system conducts a *false-negative* detection. The experiment results are illustrated in the Table 1:

a. b. c.

Figure 6 : Training image and test images with different head tilts.
a. Training Image ; b. Test Image 1 ; c. Test Image 2.

Table I : Recognition with different head tilts

Number of test images	25
Number of true-positive identifications	19
Number of false-positive identifications	04
Number of false-negative identifications	02

a. b. c.

Figure 7 : Recognition with different head tilts—SUCCESS !
a. Test Image 1 ; b. Test Image 2 ; c. Training Image.

a. b.

Figure 8 : Recognition with different head tilts—SUCCESS !
a. Test Image ; b. Training Image.

Recognition with varying illuminance :

Each training image (with head-on lighting) has two corresponding test images—one with less illuminated by light and the other with more illuminated by light. Other conditions, such as head scale and tilt, remain the same as in the training image. The experiment results are shown in Table 2. Figure (9) and (10) show the difference between the training image and test image.

Table II : Recognition with varying illuminance

Number of test images	25
Number of true-positive identifications	21
Number of false-positive identifications	03
Number of false-negative identifications	01

a. b.

Figure 9 : Training image and test image with varying illuminance.
a. Training Image ; b. Test Image .

a. b.

Figure 10 : Recognition with varying illuminance— SUCCESS !
a. Test Image ; b. Training Image.

Recognition with varying head scale :

Each training image (with full head scale) has two corresponding test images—one with a medium head scale and the other with a small one, as shown in figure (11) and (12). Other conditions, such as lighting and head tilt, remain the same as in the training image. The experiment results are shown in Table 3.

Table III : Recognition with varying head scale

Number of test images	25
Number of true-positive identifications	13
Number of false-positive identifications	12
Number of false-negative identifications	00

a. b. c.

Figure 11 : Training image and test images with varying head scale.
a. Training Image : full head scale ;
b. Test Image 1 : medium head scale ;
c. Test Image 2 : small head scale.

a. b. c.

Figure 12 : Recognition with varying head scale- SUCCESS !
a. Training Image: full scale ;
b. Test Image 1 : medium scale ;

c. Test Image 2 : small scale.

Table IV : Recognition with different views

Number of test images	25
Number of true-positive identifications	22
Number of false-positive identifications	03
Number of false-negative identifications	00

a. b. c.

Figure 13 : Training image and test images with different views.
a. Training Image : front view; b. Test Image 1 : right view;
c. Test Image 2 : left view.

a. b. c.

Figure 14 : Recognition with different views- SUCCESS !
a. Training Image : left view; b. Test Image 1 : right view;
c. Test Image 2 : front view.

Recognition with different views :

Each training image (with front view) has two corresponding test images—one with left view and the other with right view, as shown in figure (13) and (14). Other conditions, such as lighting and head scale, remain the same as in the training image. The experiment results are shown in Table 4.

Experiment result summary :

From the experiments performed, a fairly good recognition rate (22*/25*) is obtained with different views, a good recognition rate (*21/25*) is obtained with varying illuminance, an acceptable rate (*19/25*) with different head tilts, and a considerable one (13*/25*) with varying head scale.

Threshold issue is not addressed here. Yet, it does affect the performance of the algorithm. Larger threshold value leads to lower false-negative rate, but higher false-positive rate; and vice versa. In other words, a good choice of threshold value could well balance false-negative and false-positive rates, thus maximize good recognition rate.

IV. CONCLUSION

An Eigenface-based face recognition approach is implemented in MATLAB. This method represents a face by projecting original images onto a low-dimensional linear subspace—'face space', defined by eigenfaces. A new face is compared to known face classes by computing the distance between their projections onto face space. This approach is tested on a number of face images. Fairly good recognition results are obtained.

The Eigenface approach for Face Recognition is fast and simple which works well under constrained environment. It is one of the best practical solution for the problem of face recognition.

One of the major advantages of eigenface recognition approach is the ease of implementation. Furthermore, no knowledge of geometry or specific feature of the face is required; and only a small amount of work is needed regarding preprocessing for any type of face images.

However, a few limitations are demonstrated as well. First, the algorithm is sensitive to head scale and second, it demonstrates good performance only under controlled background, and may fail in natural scenes.

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