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Comparative Analysis of PCA-based Face Recognition System using different Distance Classifiers

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Abstract

The main aim of Face Recognition system is to retrieve face images which are similar to a specific query face image in large face Databases. The retrieved face images can be used for many applications, such as photo management, Visual surveillance, Criminal face identification and searching specific faces from the internet etc. This paper discusses and compares the performance of various PCA-based face recognition techniques. Based on the performance of various parameters such as distance classifier used, the DWT level used, applying histogram equalization and selecting the number of eigenfaces, we propose a system which combines these above mentioned features into one face recognition system. From the results obtained, it is observed that the proposed system outperforms the classical PCA-based face recognition system.

Keywords: PCA-based face recognition, distance classifiers, face recognition, Principal Component Analysis.

1. INTRODUCTION

1.1 Face Recognition

Face recognition is defined as the identification of a person from an image of their face. The success of any recognition method depends heavily on the particular choice of features used by the classifier. A good feature extractor is claimed to select features which are not sensitive to arbitrary environmental variations such as orientation and illumination [1]. Recognition systems can operate in well-controlled or uncontrolled environments. Image Recognition in well-controlled environments, where the imaging conditions of the trainee as well as the probe images are fixed, is relatively mature field of research [2]. Research in uncontrolled environments is much less mature and the results from well-controlled environments cannot be assumed to hold in uncontrolled environments. Recognition in controlled environments can be time and cost intensive and can be impractical to use in real world use [2]. As part of this research, main emphasis is on the assessment of suitability of image recognition systems in uncontrolled environment and their ability to use in real-world.

In this survey various methods for image recognition are categorized as Holistic methods [4]-[6], Feature-based methods [7]-[9], Hybrid methods [10]. Holistic methods use the whole face region as the raw input to a recognition system [3]. One of the most widely used representations of the face region is eigenfaces, which are based on principal component analysis and use a nearest neighbour classifier [4]. Fisherfaces which use linear/Fisher discriminant analysis (FLD/LDA) for best discriminating the face images of same class [5]-[6]. In Feature-based (structural) matching methods, local features such as the eyes, nose and mouth are first extracted and their locations and local statistics (geometric and/or appearance) are fed into a structural classifier [3]. Earlier methods belong to the category of structural matching methods, use the distances and angles between eye corners, mouth extreme, nostrils, and chin top [7]. Hidden Markov Model (HMM) based methods use strips of pixels that cover the forehead, eye, nose, mouth, and chin [8].

The Elastic Bunch Graph Matching (EBGM) algorithm stores spectral information about the neighbourhoods of facial features by convolving these areas with Gabor wavelets (masks) [9]. The Hybrid methods, just as the human perception system uses both local features and the whole face region to recognize a face. One can argue that these methods could potentially offer the better of the two types of methods [3].

1.2 Principal Component Analysis (PCA)

Principal Component Analysis is proposed by Turk and Pentland in 1991, which is often used for extracting features and dimension reduction. PCA aims to maximize between-class data separation [11]. It works by finding a new coordinate system for a set of data, where the axes (or *principal components*) are ordered by the variance contained within the training data [15]. A brief view of PCA is given below [4].

Step1: A set of M images (I_1, I_2, $I_3 \ldots I_{M)}$ with size N*N can be represented by column or row vector of size N^2
Step2: The average (μ) of the training set image is defined by

$$\mu = \frac{1}{M}\sum_{n=1}^{M} I_n \qquad (1)$$

Step3: Each trainee image differs from the average image by vector (Φ)

$$\Phi_i = I_i - \mu \qquad (2)$$

Step4: Total Scatter Matrix or Covariance Matrix is calculated from Φ as follows:

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

$= AA^T$, where A= $[\Phi_1 \Phi_2 \Phi_3 \ldots \Phi_n]$

Step5: Calculate the eigenvalues λ_k and eigenvectors u_k of the covariance matrix C.

Step6: To classify an image, it can be projected into this feature space. Calculate the vectors of weights

$\Omega^T = [\omega_1, \omega_2 \ldots \omega_{M'}]$, (4)

Where,

$$\omega_k = u_k^T (I - \mu), \qquad k = 1,2\ldots\ldots,M' \qquad (5)$$

where M' represents not the total eigenfaces, but the ones with greater values. Figure 1 shows the steps performed in PCA-based face recognition.

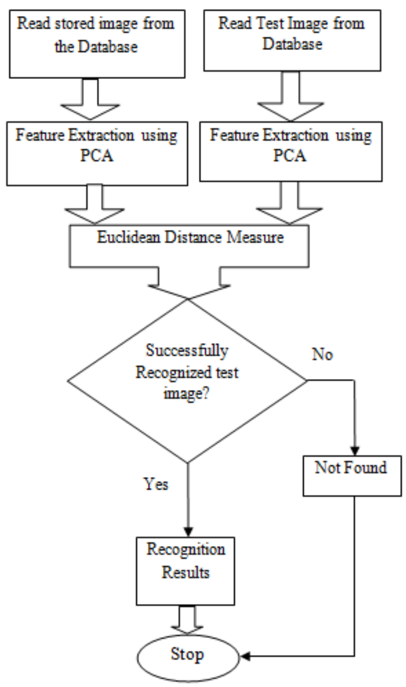

Figure 1: Steps in PCA-based Face Recognition

2. Analysis of PCA-based Face Recognition Systems

2.1 FERET Database

The FERET database contains images of 1,196 individuals, with up to 5 different images captured for each individual. The images are separated into two sets: gallery images and probes images. Gallery images are images with known labels, while probe images are matched to gallery images for identification.

The database is broken into four categories:

FB : Two images were taken of an individual, one after the other. In one image, the individual has a neutral facial expression, while in the other they have non-neutral expressions. One of the images is placed into the gallery file while the other is used as a probe. In this category, the gallery contains 1,196 images and the probe set has 1,195 images.

Duplicate I: The only restriction of this category is that the gallery and probe images are different. The images could have been taken on the same day or a year apart. In this category, the gallery consists of the same 1,196 images as the FB gallery while the probe set contains 722 images.

Fc: Images in the probe set are taken with a different camera and under different lighting than the images in the gallery set. The gallery contains the same 1196 images as the FB & Duplicate I galleries, while the probe set contains 194 images.
Duplicate II : Images in the probe set were taken at least 1 year after the images in the gallery. The gallery contains 864 images, while the probe set has 234 images.
This study uses FB, Duplicate I images.

2.2 Parameters for Analysis

2.2.1 Distance Measures

(a) Euclidean distance : Euclidean distance, or simply 'distance', examines the root of square differences between the coordinates of a pair of objects. This is most generally known as the Pythagorean Theorem. For testing we used the Euclidean distance classifier, for calculating the minimum distance between the test image and image to be recognized from the database. If the distance is small, we say the images are similar and we can decide which the most similar image in the database is [10]. Euclidean distance is one of the simplest and faster classifier as compared to other classifiers. Euclidean distance is defined as the straight-line distance between two points. Minimum Euclidean distance classifier is optimum for normally distributed classes.

$$d(x,y) = \sqrt{\sum_{i=1}^{i}(x_i - y_i)^2} \qquad (6)$$

(b) City Block distance: The sum of absolute differences between two vectors is called the L1 distance, or city-block distance. This is a true distance function since it obeys the triangle inequality. reason why it is called the city-block distance, and also as the Manhattan distance or taxicab distance is that going from a point A to a point B is achieved by walking ‘around the block’, compared to the Euclidean ‘straight line’ distance.

$$d(x,y) = |x - y| = \sum_{i=1}^{k}|x_i - y_i| \qquad (7)$$

(c) Angle: Negative Angle between Image Vectors is represented as follows:-

$$d(x,y) = -\frac{x.y}{\|x\|\|y\|} = -\frac{\sum_{i=1}^{k} x_i y_i}{\sqrt{\sum_{i=1}^{k}(x_i)^2 \sum_{i=1}^{k}(y_i)^2}} \qquad (8)$$

(d) Mahalanobis Distance: Mahalanobis distance is a distance measure introduced by P. C. Mahalanobis in 1936. It is based on correlations between variables by which different patterns can be identified and nalysed. It gauges *similarity* of an unknown sample set to a known one. It differs from Euclidean distance in that it takes into account the correlations of the data set and is scale-invariant.

$$d(x,y) = -\sum_{i=1}^{k} z_i\, x_i y_i \text{ where } z_i = \sqrt{\frac{\lambda_i}{\lambda_i + \alpha^2}} \simeq \frac{1}{\lambda_i} \text{ and } \alpha = 0.25 \qquad (9)$$

Where λ_i is the ith eigenvalue corresponding to the ith eigenvector

2.2.2 Discrete Wavelet transform (DWT)

The Discrete Wavelet Transform is effective in representing image features and is suitable in Face image retrieval**.** The wavelet transform concentrates the energy of the image signals into a small number of wavelet coefficients. It has good time-frequency localization property [12]. The fundamental idea behind wavelets is to analyse signal according to scale. It was developed as an alternative to the short time Fourier to overcome problems related to its frequency and time resolution properties [13].Wavelet transform decomposes a signal into a set of basic functions.
The advantage of DWT over DFT and DCT is that DWT performs a multi-resolution analysis of signal with localization in both time and frequency. Also, functions with discontinuities and with sharp spikes require fewer

wavelet basis vectors in the wavelet domain than sine-cosine basis vectors to achieve a comparable approximation [15]. Figure 2 shows the process of decomposing an image in DWT.

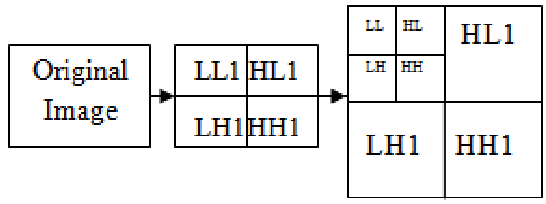

Figure 2: Process of decomposing an image [14]

The symbols L and H refer to low-pass and high-pass filter respectively. LL represents the approximation sub-band & LH, HL and HH are the detail sub-bands. LL is the low frequency sub-band gives global description of an image[16]. Horizontal coefficients (LH) correspond to the low-frequency component in the horizontal direction and high-frequency component in the vertical direction [17].
In this paper, we use DWT to decompose images into multilevel scale and wavelet coefficients, and then further dimensionality reduction is done by using PCA with which we perform image feature extraction and similarity match by means of various distance measures. The retrieval performances are compared with those of its classical counterpart on FERET database. All trainee images decomposed using discrete wavelet transform. After DWT, we are taking only low frequency components (LL) of the image for further dimensionality reduction by using PCA. Then the final feature vectors of all the trainee images are stored in the database. Same process is done for query image. Finally images are retrieved by using various distance classifiers. Analysis is done using three DWT levels: DWT level 1, DWT level 2 and DWT level 3.

2.2.3 Histogram Equalization

The purpose of the histogram equalization is to reduce or eliminate some of the variations in face due to illumination. It normalizes and enhances the face image to improve the recognition performance of the system. It is crucial as the robustness of a face recognition system greatly depends on it. Histogram equalization is the most common histogram normalization or gray level transform and its purpose is to produce an image with equally distributed brightness levels over the whole brightness scale. It is usually done on too dark or too bright images in order to enhance image quality and to improve face recognition performance. It modifies the dynamic range (contrast range) of the image and as a result, some important facial features become more apparent.

The histogram equalization process for digital images consists of four steps:
(a) Find the running sum of the histogram values
(b) Normalize the values from stepI by dividing by total number of pixels.
(c) Multiply the values from step II by the maximum intensity level value and round.
(d) Map the gray-level values to the results from step III, using a one-tone correspondence.

In this paper, we have used histogram equalization to normalize both trainee images and test image. Then, PCA is applied for further dimensionality reduction any matching of images by means of various distance classifiers. The system is compared with classical PCA- based face recognition system using FERET database.

2.2.4 Eigenfaces

Eigenfaces are a set of eigenvectors used in the computer vision problem of human face recognition. A set of eigenfaces can be generated by performing a mathematical process called principal component analysis (PCA) on a large set of images depicting different human faces. Informally, eigenfaces can be considered a set of "standardized face ingredients", derived from statistical analysis of many pictures of faces. Any human face can be considered to be a combination of these standard faces. For example, one's face might be composed of the average face plus 10% from eigenface 1, 55% from eigenface 2, and even -3% from eigenface 3. Remarkably, it does not take many eigenfaces combined together to achieve a fair approximation of most faces. Also, because a person's face is not recorded by a digital photograph, but instead as just a list of values (one value for each eigenface in the database used); much less space is taken for each person's face.
In the FERET database, images may vary because of differences in illumination, facial expression, clothing1, presence and/or style of glasses, and even small changes in viewpoint, none of which are relevant to the task of identifying the image subject. The problem, of course, is finding which Eigenvectors correspond to useful information and which are simply meaningless variation. By looking at the images of specific Eigenvectors, it is sometimes possible to determine what features are encoded in that Eigenvector. Images of the Eigenvectors used in the FERET evaluation are shown in Figure 3, ordered by Eigenvalue.

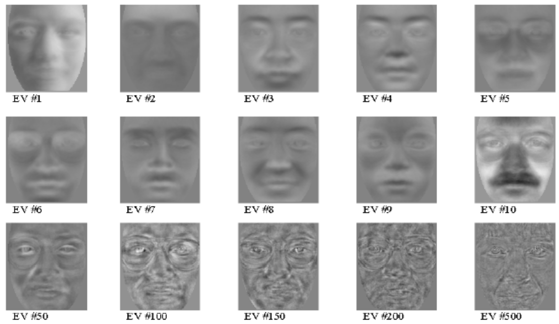

Figure 3: Images of the Eigenvectors used in the FERET evaluation

As we examine the higher order Eigenvectors (100, 150, 200, 500), they become more blotchy and it becomes difficult to discern the semantics of what they are encoding. This indicates that eliminating these Eigenvectors from the Eigenspace should have only a minimal effect on performance. Removing specific Eigenvectors could in fact improve performance, by removing noise.

In this paper, we examine the question of how many eigenfaces to select for optimal performance of PCA- based face recognition system. We compare variations in performance using different number of eigenfaces. The system is analyzed by taking number of eigenfaces equal to number of images in the database, half the number of images in the database and double the number of images in the database.

3. Proposed System

Finally, we aim at proposing a system by combining all the features which have shown optimal performance when analyzed with classical PCA- based face recognition system. The block diagram of proposed system is given in Figure 4.

The following features are cumulatively used in the proposed system.

Distance Classifier: The sum of Euclidean distance, City Block distance, Angle and Mahalanobis distance is used as distance classifier in proposed PCA- based face recognition system.

DWT: DWT level 2 shows optimal performance during analysis. Hence, the proposed system uses DWT level 2 on all the images.

Histogram Equalization: Histogram equalization shows better results where images have different illuminations.

Eigenfaces: The number of eigenfaces equal to the number of images in the database is used in the proposed system.

In this paper, we have examined the performance of our proposed system by comparing it with classical PCA –based face recognition system.

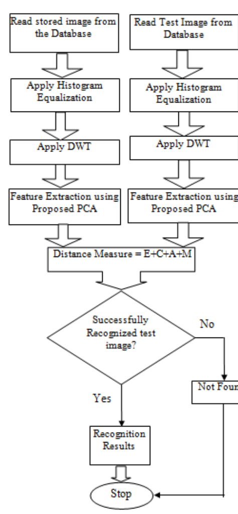

Figure 4: Block diagram of Proposed System

4. Experimental Results and Discussions

The performance of PCA is compared quantitatively in terms of various distance measures and their sum using FERET Database. Table 1 shows the recognition rate of two types of images in the FERET Database i.e. Duplicate I and FB images using different distance classifiers and their sum.

Table 1: Recognition Rate of PCA-based Face recognition using different distance classifiers

Distance Classifiers	Dup. I	FB
Euclidean Distance	35	76
City Block Distance	33	72
Angle Distance	34	70
Mahalanobis Distance	41	73
E + C + A + M	42	73

From Table 1, it is concluded that recognition rate is maximum when the sum of Euclidean Distance, City Block Distance, Angle Distance, Mahalanobis Distance(E+ C+ A= M) is used as distance classifier in PCA- based face recognition system.
The performance of PCA is compared at different DWT levels on FERET Database. Table 2 shows the recognition rate of two types of images in the FERET Database i.e. Duplicate I and FB images using different distance classifiers and their sum and at DWT level 2, 4,8.

Table 2: Recognition Rate of PCA-based Face recognition using different distance classifiers by varying DWT levels.

Distance Classifiers	DWT Level 1		DWT Level 2		DWT Level 3	
	Dup. I	FB	Dup. I	FB	Dup. I	FB
Euclidean Distance	36	77	37	79	36	78
City Block Distance	34	73	35	73	34	73
Angle Distance	35	70	35	71	35	70
Mahalanobis Distance	42	73	43	74	42	74
E + C + A + M	44	74	44	75	44	74

From Table 2 it is concluded that recognition rate is maximum when DWT level is 2.
The performance of PCA is compared by applying Histogram Equalization and without applying histogram equalization on FERET Database. Table 3 shows the the recognition rate of two types of images in the FERET Database i.e. Duplicate I and FB images, with and without applying histogram equalization.

Table 3: Recognition Rate of PCA-based Face recognition with and without applying Histogram Equalization.

Distance Classifiers	Histogram Equalization		No Histogram Equalization	
	Dup. I	FB	Dup. I	FB
Euclidean Distance	36	76	35	76
City Block Distance	34	72	33	73
Angle Distance	35	70	34	70
Mahalanobis Distance	43	74	41	73
E + C + A + M	43	75	42	74

From Table 3 it is concluded that recognition rate is better when Histogram Equalization is applied to images having different illumination.
The performance of PCA is analyzed by taking number of eigenfaces equal to number of images in the database, half the number of images in the database and double the number of images in the FERET database. Table 4 shows the the recognition rate of two types of images in the FERET Database i.e. Duplicate I and FB images when eigenfaces are half, equal and double the number of images in the database.

Table 4: Recognition Rate of PCA-based Face recognition with different number of eigenfaces .

Distance Classifiers	Eigen Value 1/2		Eigen Value 1		Eigen Value 2	
	Dup. I	FB	Dup. I	FB	Dup. I	FB
Euclidean Distance	34	74	35	76	35	76
City Block Distance	31	71	33	72	33	72
Angle Distance	32	69	34	70	34	69
Mahalanobis Distance	40	71	41	73	41	72
E + C + A + M	40	72	42	73	42	73

From Table 4, it is concluded that the recognition rate is maximum when the number of eigenfaces is equal to the number of images in the database.
Finally, from Table 1,2,3,4, it is concluded that that the performance of PCA comes out better in the cases when sum of Euclidean distance, City Block Distance, Angle, Mahalanobis Distance(E+ C+ A+ M) is taken as distance classifier, The DWT level is 2, Histogram Equalization is applied and number of eigenfaces is equal to the number of images in the database.
Therefore, our proposed system combines all the above mentioned features to develop a face recognition system. Table 5 shows the recognition rate of Duplicate I and FB images in the FERET Database for Classical PCA-based Face recognition system and the proposed system. From Table 5, it is concluded that the proposed system outperforms the classical PCA-based Face recognition system.

Table 5: Recognition Rate for Classical PCA-based Face recognition system and the proposed system.

Classical PCA-based System		Proposed System	
Dup. I	FB	Dup. I	FB
35	76	44	77

5. Conclusion

This paper discusses and compares the performance of various PCA-based face recognition techniques. From Table 1,2,3,4, it is concluded that that the performance of PCA is better in the cases when sum of Euclidean distance, City Block Distance, Angle, Mahalanobis Distance(E+ C+ A+ M) is taken as distance classifier, the DWT level is 2, Histogram Equalization is applied and number of eigenfaces is equal to the number of images in the database. Our proposed system combines all these features to form a face recognition System. From Table 5, it is concluded that the proposed system outperforms the classical PCA-based Face recognition system.

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