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Research paper

Face recognition system based on principal components analysis and distance measures

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Abstract

Face recognition plays a vital role and has a huge scope in the field of biometrics, image processing, artificial intelligence, pattern recognition and computer vision. This paper presents an approach to perform face recognition using Principal Components Analysis (PCA) as feature extraction technique and different distance measures as matching techniques. The proposed method is developed after the deep study of a number of face recognition methods and their outcomes. In the proposed method, Principal Components Analysis is used for facial features extraction and data representation. It generates eigenvalues of the facial images, hence, reduces the dimensionality. The recognition is produced using three different matching techniques (Euclidean, Manhattan and Mahalanobis) and the results are` presented. Yale and Aberdeen Face Databases are used to test and analyze the results of the proposed method.

Keywords: *PCA, Eigenface, euclidian distance, mahalanobis distance, manhattan distance.*

1. Introduction

Face recognition is the process of identifying human faces based on their facial visual appearances. Today, high definition cameras have made an easy and convenient access to digital images and videos [1]. Recognizing human face using face recognition techniques has become an important research area for computer vision scientists. Face recognition has been widely used in various applications such as forensics, surveillance, banking security, gaming, UAVs systems and many more [2]. A powerful and effective face recognition system would definitely make these applications more reliable and accurate.

Face recognition has always been a popular and challenging task in the field of image processing, pattern recognition and computer vision. There are several wild facial images which have been used as training image after pre-processing. Pre-processing involves removing unwanted background and noise from facial images [3]. A number of face recognition methods have been presented but most of them failed to handle poses, occlusion and illumination problems.

The process of face recognition can be divided into two sections, first is the process of salient feature extraction and second is the comparison of the extracted feature by a number of methods [4]. One of these well-known feature extraction method is Principle Components Analysis (PCA) [5]- [8]. PCA is a widely-known technique for feature extraction and data representation. It is based on the concept of dimensionality reduction and represent the correlated facial images into linearly uncorrelated Eigenfaces [9].

Most of the face recognition methods are either holistic based [10]- [11] or feature based methods [12]-[13]. In holistic based methods, the entire facial image is considered as input data. In feature based method, local facial features such as human eyes, nose, lips, eyebrows, mouth etc. are extracted using feature extraction techniques. The locations and geometric of extracted feature are then used to learn a classifier. In face recognition, along with feature extraction and classification, distance measures also play a significant role. There are several types of distance measurement namely Euclidian distance, Manhattan distance and Mahalanobis distance [14]- [15]. These distances are used to measure the similarities between the training dataset and the test image.

This paper proposes Principle Components Analysis (PCA) for face recognition, Eigenface for dimensionality reduction, feature extraction and Euclidian distance for classification of the training and test image Eigen faces. Different types of distance measurement such as Euclidean distance, Manhattan distance and Mahalanobis distance are used with PCA and the results are compared.

2. Related work

A number of research papers have been published on face recognition considering various factors such as illumination, facial accessories, facial expressions, aging, poses, occlusion etc. [16]- [18]. A number of system have been developed based on Principal Components Analysis (PCA) [19], Linear Dimensionality Analysis (LDA) [20], Neural Networks [21], Optimization techniques [22], combining Neural Networks and Optimization techniques, combining PCA and Optimization techniques etc. Despite of all these, face recognition using facial images is a challenging task.

Linear Dimensionality Analysis (LDA) is based on discriminant analysis of features to extract discriminant features. LDA generates variance face with linearity, homogeneity and normality. These features can produce accurate classification if the variance face is represented by a collection of Local Directional Pattern (LDA) codes for face recognition [23]. The minor difference between PCA and LDA is that, PCA is based on encoding information into an orthogonal linear space, while LDA is based on encoding discriminating information into a linearly separable space.

A detailed survey of a number of face recognition methods and their outcomes have been done [24]. Some of these algorithms are given in this section. The architecture of face recognition systems is mainly divided into following sections:

- Image acquisition- To convert captures facial image to digital form.
- Face detection- To detect facial region in a digital image and mark the region.
- Pre-processing- To smoothen the variations in detected facial image by converting to a standard size, rotation and alignment.
- Feature extraction-To process the facial image to extract relevant facial features and generate feature vectors for classification.
- Comparison-Final stage is to measure the similarity between the query image and gallery to perform identification and verification.

Face detection methods

Face detection methods are mainly divided on the basis of (i) Knowledge based (ii) Feature based (iii) Template matching and (iv) Appearance based [25].

Knowledge based methods are based on capturing the knowledge of face and translating into a set of rules. Translating human knowledge edge into a set of rules is difficult. Feature based method are based on using invariant facial features to detect texture, skin. Algorithms which find these invariant features are prone to illumination, occlusion and noise. Template matching methods are based on defining facial image as a mathematical function. Algorithms try to obtain a standard template for each of the faces. Appearance based methods are based on learning the images to generate a template. Machine learning methods are generally used to obtain relevant characteristics of facial or non-facial images.

Face recognition methods

Local Feature Analysis is a well-known technique for face recognition which analyzes the local facial features, such as eyes, eyebrows, lips, mouth, nose etc. These features are termed as Local Feature Analysis kernels [26]. This method is more robust to local facial features to carry out a match compared global facial features. Neural Network is also a well-known technique for face recognition. It is based on learning facial images in the training stage and recognizing them in generalization stage. Hidden Markov Model is again a popular technique for face recognition widely used by the researchers [27]. It is based on training a hidden model for each facial image and choosing the best matching model for the query image.

3. Overview of various methods

This section is an overview of some of the standard face recognition methods via Eigenfaces and Laplacianfaces.

Eigenface for face representation

The Eigenface is the most widely used method for face recognition method. It is based on dimensionality reduction which minimizes or reduces the dimensions of original facial image by some factors. It creates a linear subspace projection and maximizes scatter of all projected images [9].

LetI_{NxN} be a two-dimensional facial image of size NxN. ImageI_{NxN} can be represented as a vector of length N^2. Principal Components Analysis method is used to obtain the vectors which can best suitably represent the facial image training set. Each vector of length N^2 describes an NxN image. which are then used to find the subspace of the facial images. The subspace is actually a linear combination of the original facial image and this face like appearance of eigenvector is called Eigenface.

Let N be the total number of facial images in the training set noted as $I_1 \ldots I_N$. Thenthe average of the original images will be

$$\mu = \frac{1}{N}\sum_{i=1}^{N} I_N \tag{1}$$

The eigenvectors λ_v and eigenvalues λ_i are computed from the scatter (covariance) as

$$\phi_c = \frac{1}{N}\sum_{i=1}^{N} (I_i - \mu)\,(I_i - \mu) \tag{2}$$

Laplacianfaces for face representation

The Laplacianface is a popular method for face recognition. [28] gives a complete understanding of Laplacianfaces for subspace representation. The Laplacianface is based on Locality Preserving Projection (LPP). It is a linear dimensionality reduction technique based on linear approximation of the nonlinear Laplacian Eigen map [29]. Locality Preserving Projection builds a graph using the neighborhood information of the dataset and uses the Laplacian of a graph to compute a transformation matrix. Finally, the subspace of dataset is created.

Let a given dataset be represented by x1,…,xm in the subspace Rn. Compute a transformation matrix A which can map m points of the dataset to a set of points y1,…,ym in the subspace Rl, where l << n.

The objective function of the Locality Preserving Projection is,

$$min \sum_{ij}\left(y_i - y_j\right)^2 S_{ij} \tag{3}$$

Here, y_i is one dimension representation of x_i, $y_i=A^T x_i$, S is a similarity matrix given as:

$$s_{ij} = \begin{cases} exp\left(-\left\|x_i - x_j\right\|^2/t\right), & \left\|x_i - x_j\right\|^2 < \varepsilon \\ 0 & otherwise \end{cases} \tag{4}$$

$$s_{ij} = \begin{cases} exp\left(-\left\|x_i - x_j\right\|^2/t\right), & if X_i is among k nearest \\ \quad neighbors of X_i or X_j is among \\ \quad k nearest neighbors of X_i \\ 0 & otherwise \end{cases} \tag{5}$$

4. Methodology

A face recognition system based on Principal Component Analysis and distance measures is proposed in this paper. Various distance measures such as Euclidian distance, Manhattan distance and Mahalanobis distance has been used for classification. The proposed method involves generating the Eigenfaces, projecting the training data into face space and evaluating the projected test element as shown in Fig.1.

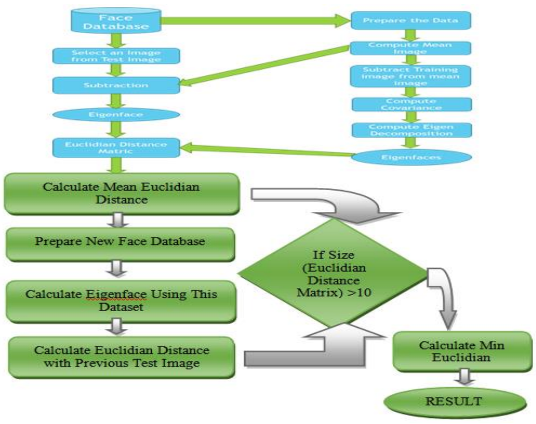

Fig. 1: Flowchart of face recognition system

The various steps to calculate Eigenfaces are:

- Generate the Dataset: A two-dimensional facial image is represented as one-dimensional vector by concatenating each column or row into a vector. Let M vectors of size N represents a set of sampled images then the training set becomes: Γ1, Γ2, Γ3......ΓM
- Subtract the mean: The average matrix Ψ is calculated. It is subtracted from the original facial images (Γi). The results are stored in the variable Φi
  $$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \quad (6)$$
  $$\phi_i = \Gamma_i - \psi$$
- Compute the covariance matrix: In this step, the covariance matrix A is calculated as per given formula:
  $$A = \Phi^T \Phi \quad (7)$$
- Compute the eigenvectors and eigenvalues of covariance matrix: In this step, the eigenvectors Xi and the corresponding eigenvalues λi are calculated.
- Compute Eigen faces:
  $$[\Phi]X_i = f_i \quad (8)$$
  Here, Xi is eigenvector and fi is eigenface.
- Classify the faces: In this step, the query facial image is transformed into its eigenface components. The resulting Weights form the weight vector Ω_K^T:
  $$\Omega_K = \Omega_K^T(\Gamma_K - \psi) \quad (9)$$
  where k = 1,2,3,4… and $\Omega_K^T = \Omega_1\Omega_1 \ldots \Omega_M$
- The Euclidian distance between two weight vectors d(Ω_i , Ω_j) measure the similarity between the corresponding images i& j.

Various distance metrics

For two eigenfeature vectors X and Y of length n, various distance measure to compute distances between them are given in this section. Sample of Eigenfaces of normal facial images is shown in Fig. 2

Fig. 2: Sample of Eigenfaces of normal facial images.

Euclidian Distance is also known as the L2-norm and is mathematically represented as:

$$d(x,y) = ||x - y|| = \sum_{i=1}^{k}(x_i - y_i)^2 \quad (10)$$

Manhattan Distance is also known as the L1- norm or the City Block Distance. It is mathematically represented as:

$$d(x,y) = |x - y| = \sum_{i=1}^{k}|(x_i - y_i)| \quad (11)$$

Mahalanobis Distance is a space in which sample variance along each dimension is always one. Each coefficient in the vector is divided by its corresponding standard deviation. It performs the transformation of a vector from image space to feature space This transformation then finally generates a dimensionless feature space having unit variance in each dimension.
Consider two vectors x and y in the unscaled PCA space and let m and n be their corresponding vectors in Mahalanobis space.Consider λ_i as PCA eigenvalues whose value is equals to σi2, (variance along dimensions). The relationship between these vectors can be mathematically represented by:

$$m_i = \frac{x}{\sigma_i} n_i = \frac{y}{\sigma_i} \quad (12)$$

$$d(x,y) = \sqrt{\sum_{i=1}^{k}(m_i - n_i)} \quad (13)$$

Here. λ_i represents i^th Eigenvalue corresponds to the i^th Eigenvector.

5. Experimental databases

The proposed method is tested against two standard databases- Yale Face Database and Aberdeen face database. The databases are elaborated in the following sections.

The yale face database B

The Yale Face Database B contains total of 856 cropped and grayscale facial images in raw Probabilistic Graphical model (PGM) format. Total 38 individuals are used to obtain 856 different facial images such as center-face, left-face, right-face, with and without glasses, happy, sad, normal and many more emotions [30]-[31]. Each image resolution is (168 x 192) pixels [32]-[33]. Sample images from Yale Face Database is shown in Fig.3.

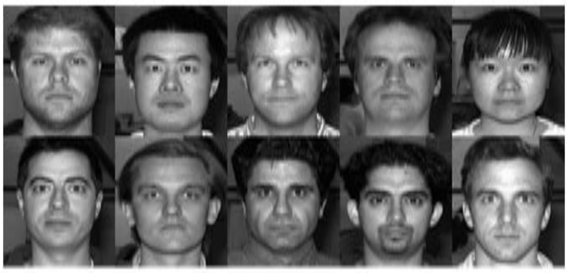

Fig. 3: Sample images from yale face database

Aberdeen face database

Aberdeen face database contains 687 Color faces with 1 and 18 images of 90 individuals. 8 have varied viewpoint. The image resolution varies 336 x 480 to 624 x 544[34]. Sample images from Aberdeen Face Database is shown in Fig. 4.

Fig. 4: Sample images from aberdeen face database

6. Results and analysis

The proposed method for face recognition using multiple iteration of Principal Components Analysis and distance measures have been discussed. The simulation is performed using MATLAB. For implementation, different sample images for train and test Databases has been taken.In this section, the experiments results using the Face databases namely Yale and Aberdeen Face Database is presented. The result shows the efficiency of the proposed methodfor face recognition problem.

Overall results

The results of the proposed method for the two databases are described below in Fig.5 and comparison with previous PCA is given in Table 1.

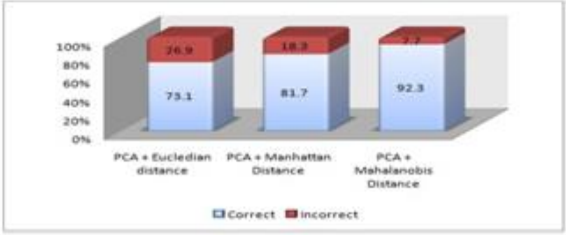

Fig. 5: Overall recognition rate (%)

Table 1: Comparison with Previous PCA

Cyclic PCA	Euclidian	Manhattan	Mahalanobis
	78.1%	81.7%	92.3%
PCA(Previous)	66.9%		

The yale face database B

The results of proposed method on the Yale Face database B are described below in Fig.6 and Table 2 and Table 3.

Table 2: Results on the Yale Face Database B

Method Used	Correct	Incorrect	Recognition accuracy
PCA with Euclidian	201	99	67.1%
PCA with Manhattan	237	63	79.1%
PCA with Mahalanobis	275	25	91.7%

Table 3: Comparison in Yale Face Database B

Cyclic PCA	Euclidian	Manhattan	Mahalanobis
	67.1%	79.1%	91.7%
PCA(Previous)	66.9%		

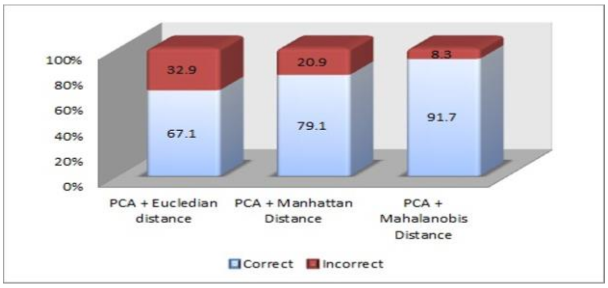

Fig. 6: Recognition Rate (%) on Yale Face database B

The aberdeen face database

The results of proposed method on the Aberdeen Face Database are described below in Fig.7 and Table 4 and Table 5.

Table 4: Results on the Aberdeen Face Database

Method Used	Correct	Incorrect	Recognition accuracy
PCA with Euclidian	447	53	89.4%
PCA with Manhattan	444	66	88.8 %
PCA with Mahalanobis	470	30	94.1%

Table 5: Comparison in Aberdeen Face Database

Cyclic PCA	Euclidian	Manhattan	Mahalanobis
	89.47%	88.8%	94.17%
PCA(Previous)	66.9%		

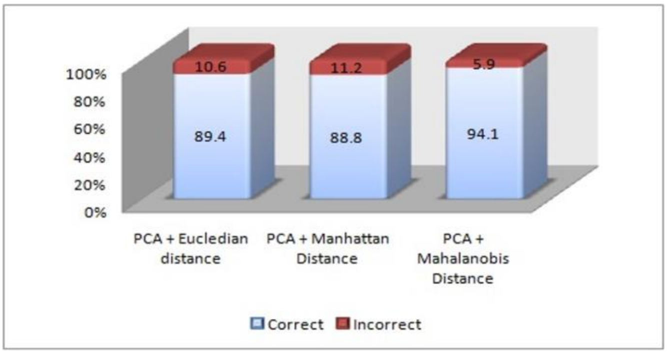

Fig. 7: Recognition rate (%) on aberdeen face database

7. Conclusion

In this paper, a novel approach for face recognition is presented and experimentally evaluated. In the proposed method, Face recognition system using Principal Components Analysis for feature extraction and distance measures for is developed. The distance measures used in this paper are Euclidian distance, Manhattan Distance and Mahalanobis distance. The experimental results clearly showed that the face recognition system based on PCA with Mahalanobis distance has performed far better than the conventional Euclidian distance and Manhattan distance.

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