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MULTI-VIEW FACIAL RECOGNITION USING EIGENFACES BY PCA AND ARTIFICIAL NEURAL NETWORK

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Abstract- Face is a complex multidimensional visual model and developing a computational model for face recognition is difficult. This paper presents a methodology for face recognition based on information theory approach of coding and decoding the face image. Proposed methodology is connection of two stages - feature extraction using principal component analysis and recognition using the feed forward back propagation neural network. The algorithm has been tested on 400 images (10 classes). A recognition score for test lot is calculated by considering almost all the variants of feature extraction. The proposed methods were tested on YALE face database. Test results gave a recognition rate of 96%.
Keywords- Face recognition, principal component analysis (PCA), Artificial neural network(ANN), eigenvector, Eigenface

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Introduction

The face is the primary focus of attention in the society, playing a major role in conveying indentiry and emotion. Although the ability to infer intelligence or character from facial appearance is suspect, the human ability to recognize faces is remarkable.A human can recognize thousands of faces learned throughout the lifetiime and identify familiar faces at a glance even ofter years of separation. The word " cognition" means mental activity, which involves in acquisition, storage, and retrival of knowledge. In otherword, it is the process of psychological development of human brain. Developing a computational model of face recognition is quite difficult, because faces are complex, multidimensional visual stimuli. Therefore, face recognition is a very high level computer vision task, in which many early vision techniques can be involved. For face identification the starting step involves extraction of the relevant features from facial images. A big challenge is how to quantiae a face, given a set of features. Investigations by numerous researchers over the past several years indicate that certain facial characteristics are used by human beings to identify faces.

Related Work

There are two basic methods for face recognition. The first method is based on extracting feature vectors from the basic parts of a face such as eyes, nose, mouth, and chin, with the help of deformable templates and extensive mathematics. Then key information from the basic parts of face is gathered and converted into a feature vector. Yullie and cohen[1] used deformable templates in contour extraction of face images.
Another method is based on the information theory concepts viz. principal component analysis method. In this method, information that best describes a face is derived from the entire face image. Based on the karhuhen-Loeve expansion in pattern recognition, Kirby and sirovich [5] have shown that any particular face can be represented in terms of a best coordinate system termed as " eigenfaces". These are the eigen functions of the average covariance of ensemble of faces. Later, Turk and pentland[6] proposed a face recognition method based on the eigenfaces approach.
An unsupervised pattern recognition scheme is proposed in this paper which is independent of excessive geometry and computation. Recognition system is implemented based on eigenface, PCA and ANN. Principal component analysis for face recognition is based on the information in a face image is extracted as efficiently as possible. Further artificial neural network was used for classification. Neural network concept is used because of its ability to learn'from observed data.

Principal Component Analysis

Principal component Analysis (PCA) is a universally used dimensionality reduction technique for image processing applications. PCA is an optimal feature extraction and dimensionality reduction technique, from the information theoretic point of view. The idea is to find the components or the dimensions along which the collection of all possible images is expected to have its energy distributed. Then only those dimensions are retained, and the rest of the images are discarded for the future stages of processing.
This will become clearer with the following description of the scenario: when a set of images X1,X2,X3,..,Xn that belong to C different classes X1, X2, X3,..,XC are available as the training set, our best guess will be that all possible images we would encounter will lie in the dimensions spanned by all the available training images. Thus, these images can be arranged into vectors $X_1{}^v$, $X_2{}^v$, $X_3{}^v$,.. Xn^v to arrive at the space spanned by the training images. This will

be nothing but the range of the matrix X, where X = [X_1^v, X_2^v, X_3^v,.. X_n^v], the matrix obtained by the concatenation of the vectorized images. The dimensionality of such a space would be p X m, for an image which is p pixels in size.

Not all the space spanned by the image matrix contains significant portion of the energy of the image matrix. Those dimensions of the space in which the content of the energy is relatively low can be eliminated without significant loss of information. This recuction in dimensions by removal of relatively insignificant components is what PCA achieves.

For a linear transformation VT on the image matrix X, the resultant matrix would have the dimensions equal to the inner dimension of v and outer dimension of X. A matrix obtained by such a transformation,

$$\tau = V^T X \quad (1)$$

Will be an optimally equivalent matrix to X if the weight matrix V satisfies the equation

$$V_{opt} = \arg\max |V^T S v| \quad (2)$$

Where S is called the scatter matrix of the random variable x (here, the vector representing each image) and is defined by

$$S = \sum_{k=1}^{n} (X_k^v - \mu)(X_k^v - \mu)^T \quad (3)$$

Where µ is the sample mean of the image vectors.

It is shown in the literature that such a transformation v can obtained by performing the Eigen value Decompostion of the image matrix, and using the first ‘ d’ columns of the eigen - vector matrix to create the matrix v. such a matrix v, upon being used for transformation, sends the matrix X into a d-dimensional space from a pXm Dimensional space. Thus, multiplying each of the images by the transformation matrix will transform them into the lower dimension without significant loss of information. The amount of information lost will be dependent on the number of dimensions of the image retained.

Proposed Work

The proposed technique is coding and decoding of face images, emphasizing the significant local and global features. In the language of information theory, the relevant information in a face image is extracted, encoded and then compared with a database models. The steps for face recognition system are as follows.

A. **Preprocessing Stage:** Image size normalization, histogram equalization and conversion into gray scale are used for preprocessing of the image. This module automatically reduces every face image X*Y pixels can distribute the intensity of face images (histogram equalization) in order to improve face recognition performance. Face images are stored in a face library in the system. Every action such as training set or eigen face formation is performed on this face library. The face library is further divided into two sets - training set and testing set.

B. **Dimensionality Reduction Stage:** the required transformation is found, and then all images are transformed into the lower dimensional space

- The image matrix is converted into an image vector by appending all columns one after the other
- All the training image vectors are appended together row-wise, to obtain an image matrix X
- The optimal transformation V is found to send each image to a lower dimension
- Every image vector is then transformed to the lower-dimensional space.

C. **Classification stage:** The reduced train vectors are used to train the classifier, and when a test vector comes in, it is reduced test vector are then submitted to the classifier to make the hypothesis. The classifiers that have been used here is neural network.

Calculating Eigen Faces

The idea of using principal components to represent human faces was developed by sirvovich and Kirby [1] and used by turk and pentland [1] for face detection and recognition. The eigenface approach is considered by many to be the first working facial recognition technology, and it served by many to be the first working facial recognition technology, and it served as the basis for one of the top commercial face recognition technology products. Since its initial development and publication, there have been many extensions to original method and many new developments in automatic face recognition system.

The Following Steps are Involved in the Process

1. The first step is to obtain a set S with M face images. In our example M = 25. Each image is transformed into a vector of size N and placed into the set.

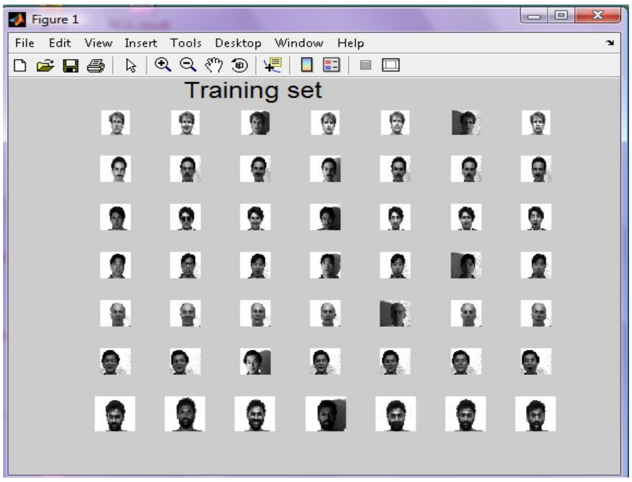

Fig. 1- Training Set

$$S = \Gamma_1, \Gamma_2, \Gamma_3, \ldots\ldots \Gamma_M \quad (4)$$

2. After you have obtained your set, you will obtain the mean image Ψ

Fig. 2- Mean image

3. Then you will find the difference Φ between the input image and the mean image

$$\Phi_i = \Gamma_i - \Psi \quad (5)$$

4. Next we seek a set of M orthonormal vectors, $\mathbf{u_n}$, which best describes the distribution of the data. The k[th] vector, $\mathbf{u_k}$, is chosen such that

$$\lambda_k = \frac{1}{M}\sum_{n=1}^{M}(u_k^T \Phi_n)^2 \quad (6)$$

is a maximum, subject to

$$u_l^T u_k = \delta_{lk} = \begin{cases} 1 & \text{if } l = k \\ 0 & \text{otherwise} \end{cases}$$

Note: u_k and λ_k are the eigenvectors and eigenvalues of the covariance matrix C

5. We obtain the covariance matrix **C** in the following manner

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n \Phi_n^T = AA^T$$

$$A = \{\Phi_1, \Phi_2, \Phi_3, \ldots\ldots, \Phi_n\} \quad (7)$$

6. A^T

$$L_{mn} = \Phi_m^T \Phi_n$$

Once we have found the eigenvectors, $\mathbf{v_l}$, u_1

$$u_l = \sum_{k=1}^{M} v_{lk}\Phi_k \qquad l = 1, \ldots\ldots, M \quad (8)$$

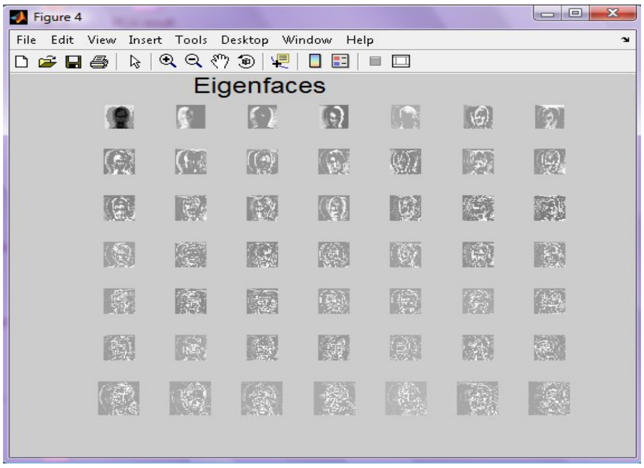

Fig. 3- The eigenfaces of our set of original images

Recognition Procedure

1. A new face is transformed into its eigenface components. First we compare our input image with our mean image and multiply their difference with each eigenvector of the L matrix. Each value would represent a weight and would be saved on a vector Ω.

$$\omega_k = u_k^T(\Gamma - \Psi) \quad \Omega^T = [\omega_1, \omega_2, \ldots\ldots, \omega_M] \quad (9)$$

2. We now determine which face class provides the best description for the input image. This is done by minimizing the Euclidean distance

$$\varepsilon_k = \left\|\Omega - \Omega_k\right\|^2 \quad (10)$$

3. The input face is consider to belong to a class if ε_k is bellow an established threshold θ_ε. Then the face image is considered to be a known face. If the difference is above the given threshold, but bellow a second threshold, the image can be determined as a unknown face. If the input image is above these two thresholds, the image is determined NOT to be a face.

4. If the image is found to be an unknown face, you could decide whether or not you want to add the image to your training set for future recognitions. You would have to repeat steps 1 trough 7 to incorporate this new face image.

Training of Neural Networks

Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, indentification, classification, speech, and vision and control systems. One ANN is used for each person in the database in which face descriptors are used as inputs to train the networks 1 [3]. During training of the ANN's, the faces descriptors that belong to same person's network and negative examples for the others network.

Simulation of ANN for Recognition

New test image for recognition (from test dataset and its face descriptor is calculated from the eigen faces M) found before. These new descriptors are given as an input to every network; further these networks are simulated. Compare the simulated results and if the maximum output exceeds the predefined threshold level, then it is confirmed that this new face belongs to the recognized person with the maximum output. A face image can be approximately reconstructed (rebuilt) by using its feature vector and the eigen faces as $\Gamma' = \varphi + \varphi f$

Where $\phi_j = \sum_{k=1}^{M} w_j u_j$ is the projected image.

The above equation tells that the face image under consideration is rebuilt just by adding each eigen face with a contribution of wj to the average of the training set images. The degree of the fit or the "rebuild error ratio" can be expressed by means of the Euclidean distance between the original and the reconstructed face image as given in below equation.

$$\mathrm{Re}\,build\ error ratio \frac{\|\Gamma' - \Gamma\|}{\|\Gamma\|}$$

It has been observed that, rebuild error ratio increases as the training set members differ heavily from each other.

Experiment

Eigenfaces are calculated by using PCA algorithm and experiment is performed by varying the number of eigenfaces used in face space to calculate the face descriptors of the images.

Multi-layer perceptron (MLP) with a feed forward learning algorithm was chosen for the proposed system because of its simplicity and its capability in supervised pattern matching. It has been successfully applied to many pattern classification problem [9]. Our problem has been considered to be suitable with the supervised rule since the pairs of input-output are available. For training the network, we used the classical feed forward algorithm. An example is picked from the training set, the output is computed. The numbers of network used are equal to number of subjects in the database. The initial parameters of neural network used in the experiment are given below:

In this paper for experimentation, 400 images from Yale database are taken and a sample of 10 face images are as shown in [Fig-4]. The mean image and reconstructed output image by PCA.

[Table-1] shows the comparison of acceptance ratio and execution time values for 40, 80, 120, 160 and 200 and 400 images of Yale database. Graphical analysis of the same is as shown in [Fig-5a] and [Fig-5b].

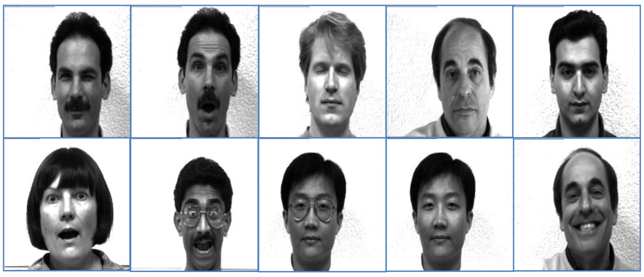

Fig. 4- Sample Yale Database Images

Table 1- Comparison of acceptance ratio and execution time

No of Images	Acceptance ratio %		Execution Time (seconds)	
	PCA	PCA with NN	PCA	PCA with NN
40	92.4	96	29	25
60	90.6	94	43	40
120	88.5	91	48	45
160	85	90	55	50
200	82	88	65	62
400	75	80	110	100

Fig. 5a-

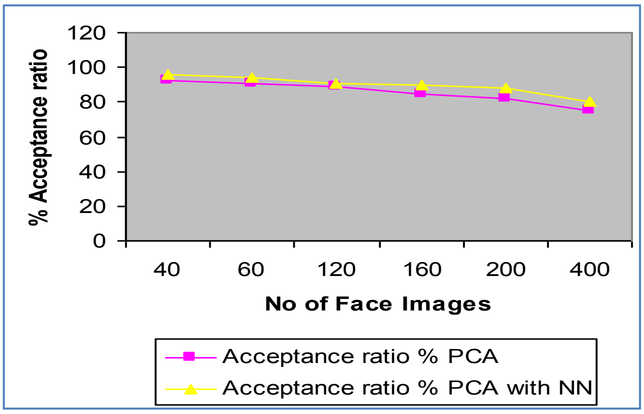

Fig. 5b-

Conclusion

The feature vector is then fed into a multilayer neural network to recognize the face image. The evaluation results by computer simulation show that the performance of proposed face identification system is quite robust against changes in illumination, wardrobe, facial expressions and additive noise, blurred images resizing, shifting and even with some age changes. The proposed identity verification system can verify correctly the input face images with different illumination level, different facial expression, with some accessories, as well as when the face images pass through some common image processing such as filtering, contamination by noise and geometrical transformation (rotating, shifting, resizing). Finally system simulation shows that better and emphasize four advantages of the proposed system: compact extraction of the face information, easy implementation, robustness against several condition changes and common image processing

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