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MATLAB Based Face Recognition System Using PCA and Neural Network

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Abstract: Artificially recognizing the human face is a challenging problem and is one of those challenging problems having no technique that provides a robust solution to all situations. This paper provides a new technique for human face recognition. Principal Component Analysis (PCA) is used for dimensionality reduction and for feature extraction. A Self Organize Map (SOM) is used as classifier to identify whether the subject is present or not present in the image database. Recognition with SOM is carried out by classifying intensity values of gray scale pixels into different groups. Evaluation of the procedure is performed in MATLAB using an image database of 20 people containing 4 subjects and each subject have 5 diverse facial expressions. After training about 500 epochs system achieved approximately 98.31% recognition rate for consecutive 5 trials. The main advantage of this technique is its low computational requirement and high speed and better recognition rate.

Keywords: Face Recognition, Principal Component Analysis, Self Organize Map

I. Introduction

In the last few decades face recognition had become very challenging and active area of research mainly due to increasing security demands and its potential commercial and law enforcement applications. A dramatic progress has shown in this area in last decade, with emphasis on such applications as human-computer interaction (HCI), biometric analysis, content-based coding of images and videos, and surveillance [1]. It is a trivial task to recognition human face artificially as compared to human brain, since although commonalities do exist between faces; they vary considerably in terms of age, skin, color and gender. The problem is further complicated by differing image qualities, facial expressions, facial furniture, background, and illumination conditions [2]. Among various solutions to the problem [3] the most successful seems to be those appearance-based approaches, which generally operate directly on images or appearances of face objects and process the image as two dimensional patterns. Appearance based methods extract features to represent faces belong to a class optimally and separate faces from different classes. Ideally, it is desirable to use only features having high separability power while ignoring the rest. The main trend in feature extraction has been representing the data in a lower dimensional space computed through a linear or non-linear transformation satisfying certain properties. Principal component analysis (PCA) [4],[5] and linear discriminate analysis (LDA) [6] and discrete cosine transform (DCT) [7],[8],[9],[10] are three main techniques used for data reduction and feature extraction in the appearance-based approaches. This paper presents a novel approach to recognize face using principal component analysis and self organize map as classifier. A block diagram of proposed technique for face recognition is shown in the figure. In the first stage principal component of each image is computed and feature vector is formed. In next stage uses a self-organizing map (SOM) with an unsupervised learning technique to classify vectors into groups to recognize if the subject in the input image is “present” or “not present” in the image database. If the face is classified as present, the best match image found in the training database is displayed as the result otherwise a message “image is not found in the database” come.

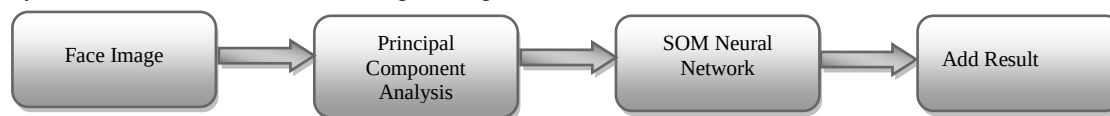


Figure 1 proposed technique of face recognition system.

II. Overview of Work

A. Principal Component Analysis

Principal component analysis is a most successful statistical technique that has been used for dimension reduction and widely used for feature extraction and recognition. This is a powerful appearance based feature

extraction technique, first introduced to the field of face recognition by Pentland and Turk in [1]. It is known as Eigen space Projection which is based on linearly Projection the image space to a low dimension feature space that is known as Eigenspace. It applies the Karhunen-Loève transform to a set of training images and derives a number of projection axes that act as the basis vectors for the PCA subspace. Each face image is represented as a vector of projection coefficients in this subspace, in which information compression, dimensionality reduction and de-correlation of the pixel values of the face images is achieved.

B. Mathematics for Eigenfaces

A face image $f(x, y)$, is a two-dimensional N by N matrix. Each x and y pair denotes a position in the image. An image is represented with a vector of dimension N^2 instead of having a matrix of dimension N by N . As an example, a typical image with size 200 by 200 pixels becomes a point in a 40000-dimensional space. To find the eigenface for a training set it is decisive to first determine the mean vector, deviation-from-mean vectors and the covariance matrix for the particular training set. Let the images in the training set are represented by $\{X_1, X_2, X_3, \dots, X_n\}$, where each X_n is a vector of N^2 dimension. The value of N is the number of images in the training set. With this representation, the mean vector is:

$$M = \frac{1}{M \sum_{i=1}^M X_n}$$

The set of deviation-from-mean vectors, $\{w_1, w_2, \dots, w_i\}$ contains the individual difference of each training image from the mean vector. Kirby and Sirovich refer to these vectors as caricatures. They are simply defined as:

$$w_i = X_n - m$$

To obtain the description of eigenface for the training set the training images are subjected to Principal Component Analysis (PCA), which seeks a set of orthonormal Eigen vectors, U_m , which significantly describes the variation of the data [a]. The k^{th} vector, U_k , is chosen such that

$$M\lambda_k = \frac{1}{M \sum_{i=1}^M ((U_k^T w_i)^2)}$$

is maximized with the orthonormality constraint as follows:

$$U_m^T U_k = \delta_k$$

It has been shown that the U_m 's and λ_k 's are given by the eigenvectors and eigenvalue of the covariance matrix defined as:

$$C = WW^T$$

where W is a matrix composed of the column vectors w_i placed side by side. The size of C is $N \times N$ which could be enormous but since we only sum up a finite number of image vectors M the rank of this matrix can not exceed $M-1$. Let d_i and V_i be the eigenvectors and eigenvalues of WW^T respectively.

$$WW^T d_i = d_i V_i$$

By multiplying left to both sides by W

$$WW^T (d_i W) = (W d_i) V_i$$

which means that the first $M-1$ eigenvectors d_i and λ_k eigenvalues of WW^T are given by $W d_i$ and V_i , respectively. The eigenvectors are sorted in descending order according to their corresponding eigenvalues. The eigenvector having largest eigenvalue is one that reflects the greatest variance in the image. A facial image can be projected onto $M' (< M)$ dimensions by computing

$$\Omega = [V_1, V_2, \dots, V_m]^T$$

The vectors d_i are also images, so called, *eigenimages*, or *eigenfaces* in our case, which was first named by [1]. They can be viewed as images and indeed look like faces. So, Ω describes the contribution of each eigenface in representing the facial image by treating the eigenfaces as a basis set for facial images.

III. Self Organizing Map

Self organizing map also known as kohonen map is well known artificial neural network. It is unsupervised learning process in which the learning is based upon the input data which is known as unlabeled data and is independent of the desired output data. Self organizing map can also be termed as a topology preserving map. There is a competition among the neurons to be activated and only one neuron that wins the competition is fired and is called the "winner" [11]. Kohonen rule is used to learn the winner neuron and neurons within a certain neighborhood of the winning neuron. This rule allows the weight of neuron to learn an input vector so this makes it perfect for recognition. Hence in this system SOM is used as classifier. The SOM network used in this system contains N nodes ordered in two dimensional lattice architecture and each node has 2 or 3 neighbor nodes. SOM has three phases of life cycle: learning phase, training phase and testing phase.

A. Unsupervised Learning

During the learning the neurons having weight closest with the input vector declare as winner. Based on winning neuron weights of all neighborhood neurons are adjusted by an amount inversely proportional to the Euclidean distance. The learning algorithm is summarized as follows [11].

- (i) *Initialization: Choose random values for the initial weight vectors $w_j(0)$, the weight vectors being different for $j = 1, 2, \dots, l$ where l is the total number of neurons.*

$$W_j = [w_{j1}, w_{j2}, \dots, w_{jn}]^T \sum R^n \quad (3.1)$$

- (ii) *Sampling: Draw a sample x from the input space with a certain probability.*

$$x = [x_1, x_2, x_3, \dots, x_n] \sum R^n \quad (3.2)$$

- (iii) *Similarity Matching: Find the best matching (winning) neuron $i(x)$ at time t , $0 < t \leq n$ by using the minimum distance Euclidean criterion:*

$$i(x) = \operatorname{argmin} \|x(n) - w_j\|, \quad j = 1, 2, 3, \dots, l \quad (3.3)$$

- (iv) *Updating: Adjust the synaptic weight vector of all neurons by using the update formula:*

$$w_j(n+1) = w_j(n) + \eta(n) h_{j,i(x)}(n) (x(n) - w_j(n)) \quad (3.4)$$

where $\eta(n)$ is the learning rate parameter, and $h_{j,i(x)}(n)$ is the neighborhood function centered around the winning neuron $i(x)$. Both $\eta(n)$ and $h_{j,i(x)}(n)$ are varied dynamically during learning for best results.

- (v) *Continue with step 2 until no noticeable changes in the feature map are observed.*

B. Training

During the training phase feature vector are presented to the SOM one at a time. For each node net determines the output unit that is best matches for current input sample. The weight vector for the winner is adjusted with respect to the learning algorithm described in learning phase. At the end of this phase each node has two values: total number of winning times for the subject present in the database, and total number of winning times for the subject not present in the database [2].

C. Testing

During the testing phase firstly every input vector is compared with the all the SOM nodes and then the best match is found based on minimum Euclidean distance as given in eq.(3.3). After that final output result is shown.

IV. Experimental Work

A. Image Database

A database was created for the purpose of benchmarking the face recognition system. The database is divided into two subsets, for separate training and testing purposes. During SOM training, 20 images were used, containing five subjects and each subject having 5 images with different facial expressions. Figure 2 shows the training and testing image database constructed.



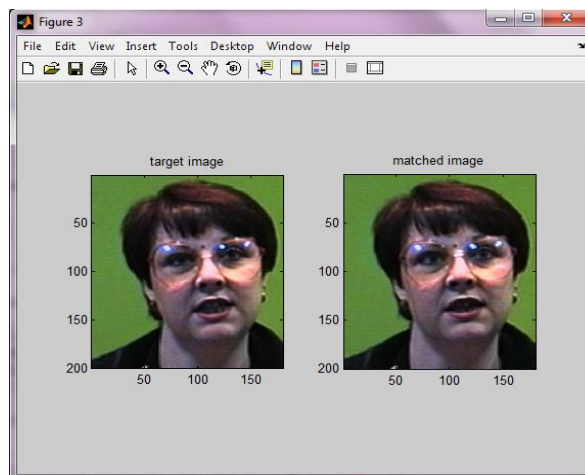
**Figure 2 training and testing database (a) Image database for Training
(b) Untrained testing image.**



B. Validation Technique

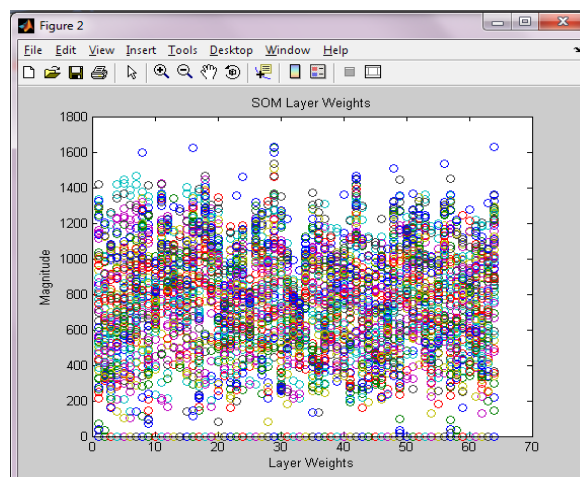
The preprocessed grayscale images are reshaped in MATLAB having size 8×8 pixels into a 64×1 array with 64 rows and 1 column for each image. To test the recognition system the technique is performed on all 4 test images. Similarly, the image database for training uses 20 images and forms a matrix of 64×20 with 64 rows and 20 columns. To represent the intensity level of grayscale pixels the input vectors defined for the SOM are distributed over a 2D-input space varying over $[0 \ 255]$. The input vectors used to train the SOM with dimensions $[64 \ 2]$, where 64 minimum and 64 maximum values of the pixel intensities are represented for each image sample. The SOM created with these parameters is a single-layer feed forward SOM map with a competitive transfer function and 128 weights. The weight function of this network is the negative of the Euclidean distance [3]. The 5 images are used to test the network and without any overlapping the training and testing set were used. Figure 3 shows the result of the face recognition system.

Figure 3: result of face recognition system.



The result obtained from this simulation shows that a facial image having different facial expression can be easily identified. After SOM training, the 20-dimensional trained image database is transformed into a 64-dimensional map where the magnitude of the layer weights is increased and Euclidean distance for feature vector for trained image is smaller than untrained image, as shown in figure 4. This transformation produces better classification by grouping similar clusters together.

Figure 4: Euclidean Distance Weight for Trained Image Database with SOM Network.



A 3-D SOM network map for the simulation which displays the neurons position is shown in figure. The next section show the experimental result for 2 experiments, in the first experiment the recognition rate with different epochs is shown and in the next experiment concern with processing time of overall system.

C. Epochs with Recognition Rate

The first experiment studies the effect of number of epochs on recognition rate of the system. Table 1 show the best recognition rate with 1000 epochs.

D. Reducing Processing Time Based on Epochs

This experiment concern with the processing time of overall system and this is the time that required for training the SOM network. Main goal of this experiment is to reduce the training time while maintaining the recognition rate. Table 2 shows the best recognition rate that achieved with the least amount of recognition rate is for the case of 500 epochs. Recognition rate obtained from the experiment are the average of 5 simulations.

Table I Effect of Epochs on Accuracy

Number of Epochs	50	100	200	300	500	1000	2000
Network Accuracy for 5 Trials (%)	64.54	79.09	80.95	85.66	98.31	99.02	99.02

V. Conclusions

This paper has presented a novel face recognition technique that uses PCA as dimensionality reduction and SOM as a classifier. The system was evaluated in MATLAB using an image database of 20 face images having 4 subjects and each subject having 5 images with different facial expressions. After training for approximately 500 epochs the system achieved recognition rate 98.31% for 5 simulation trials. The system having less computational requirement this make system well suited for low cost, real-time hardware implementation. Commercial implementations of this technique do not currently exist and hoping a practical SOM based face recognition system possible in coming future.

VI. References

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