Analysis of Face Recognition using PCA and Neural Networks.

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Abstract:
Face Recognition System could be a laptop application that is employed to spot or verify someone during a digital image, supported digital image process and is a vigorous space of analysis. The Face Recognition System proves to be economical in criminal identification, information privacy, home video police work systems etc. numerous innovative face recognition systems are developed up to now employing a wide selection of algorithms. Associate in Nursing economical technique for face recognition exploitation Principal element Analysis and Back Propagation Neural Network is bestowed during this paper. during this methodology feature extraction is finished through Principal element Analysis (PCA) so a Back Propagation Neural Network is trained to act as a classifier to urge the recognized image. Later we've got compared our projected technique with the opposite algorithmic programs to indicate the effectiveness of the projected algorithm.

Keywords: Face Recognition; Principal Component Analysis (PCA); Back Propagation Neural Network (BFNN); Eigen Faces; Eigen Vectors.

I. Introduction
Face recognition and segmentation has been perpetually a vigorous analysis space and having a large vary of its applications like gender classification, identity verification…etc.with within the last many decades there square measure varied algorithms square measure enforced for face recognition. an enormous challenge is a way to quantize countenance so a laptop is ready to acknowledge a face, given acollection of options. Investigations by varied researchers over the past many years indicate that sure facial characteristics square measure utilized by groups of people to spot faces. And additional progress needed for quickly and expeditiously acknowledges the faces of pictures. during this paper, we tend to projected a replacement approach to acknowledge the human faces that's ANN with resilient back propagation algorithmic program. we are able to determine a minimum of 2 broad classes of face recognition systems: one. we wish to seek out someone at intervals an outsized information of faces (e.g. during a police database). These systems generally come back an inventory of the foremost doubtless individuals within the information [2], typically just one image is accessible per person. it's sometimes not necessary for recognition to be drained time period. 2. we wish to spot explicit individuals in time period (e.g. during a security watching system, location chase system, etc.), or we wish to permit access to a gaggle of individuals and deny access to all or any others (E.g. access to a building, computer, etc.) [3]. Multiple pictures per person square measure typically obtainable for coaching and time period recognition is needed. In our projected model we tend to acknowledge the second class of facial pictures as a result of within the case of security purpose we've got to permit the proper person to access his own details. thus we've got to follow the projected approach.

II. Connected Work:
There square measure 2 basic strategies for face recognition. the primary technique relies on extracting feature vectors from the fundamental components of a face like eyes, nose, mouth, and chin, with the assistance of deformable templates and intensive arithmetic. Then key data from the fundamental components of face is gathered and regenerate into a feature vector. Yullie and Cohen [4] used deformable templates in contour extraction of face pictures. Another technique relies on the data theory ideas viz. principal element analysis technique. during this technique, data that best describes a face comes from the whole face image. supported the Karhunen-Loeve enlargement in pattern recognition, Kirby and Sirovich [5], [6] have shown that any explicit face will be drawn in terms of a best reference frame termed as "eigenfaces". These square measure the chemist functions of the common variance of the ensemble of faces. Later, Turki and Pentland [7] projected a face recognition technique supported the eigenfaces approach. Associate in Nursing unattended pattern recognition theme is projected during this paper that is freelance of excessive pure mathematics and computation. Recognition system is enforced supported eigenface, PCA and ANN. Principal element analysis for face recognition relies on {the data|the knowledge|the data} theory approach during which the relevant information during a face image is extracted as expeditiously as attainable.
additional Artificial Neural Network was used for classification. Neural Network conception is employed owing to its ability to be told from determined information. The eigenfaces is accepted technique for face recognition. Sirovich and Kirby[8] had expeditiously representing human faces exploitation principle element analysis. M.A Turki and Alex P. Pentland [9] developed the close to time period eigenfaces systems for face. We've got develop a replacement approach for face recognition to calculate the intensity of a picture of frontal face to represent the options exploitation eigenfaces. The face recognition system will be drawn in delineated approach is shown in figure i.

**Fig 1: Face recognition system**

These advantages no face features being required, the ability to learn and later recognize new faces in an unsupervised manner and that it is easy to implement using neural network. From the above figure we take first implementation step is eigenfaces method.

**III. Face Database**

We use the face database from MIT (Massachusetts Institute of Technology) [7]. MIT face database, first time used in [8] belongs to the well known public domain face databases [9], such as Yale [10] and ORL databases [11]. It is mentioned and used in up-to-date works relating to facial biometric, e.g. [9]. MIT database consists of face images of 16 people (shown in Fig. 1), 27 of each person under various conditions of illumination, scale, and head orientation. It means, the total number of face images is 432. Each image is 64 (width) by 60 (height) pixels, eight-bit grayscale. An example of different face images (patterns) belonging to the same class.

**IV. Face Recognition Methods**

We use several different methods here; they are shown in Fig. 3, with the summary of results shown in Fig. 12. At first, we are concerned with one-stage recognition systems without feature extraction stage: a. The direct classification of input face images by multilayer perceptron (MLP) and radial-basis function network (RBF) is shown in Fig. 3a). The configuration of MLP was 64x60-16 (i.e. 3840 input neurons and 16 output neurons). The input layer of this configuration agrees with number of pixels in an input image (64x60=3840). MLP was trained on the training face set containing 48 faces (those 16 shown in Fig. 1 plus other 32 images - two different scales of Fig. 1). MLP correctly classified 78.12 % of test faces, (300 successfully recognized faces from the total 384 test faces). Receptive fields of output neurons of such classifier are visualized in Fig. 4. We trained also MLPs containing one hidden layer with a different number of hidden neurons (16, 32, 48, 96, 144, and 192). Recognition results were from 66.2 % to 78.24%. The configuration of RBF network was 64x60-48-16 (48 training faces for RBF network classifier, which gives the best results with 48 RBF neurons in the hidden layer). Receptive fields of hidden neurons of RBF classifier are shown in Fig. 5. RBF network behavior was comparable to MLP – the network correctly classified 78.12 % of test faces. These results are shown as methods No. 6 and 7 in Fig.12. We trained also RBF networks with a different number of hidden neurons (16, 32, 96, 144, and 192). Recognition results were from 47.45 % to 80.32 %. Input x1 x2 xp ... MLP or RBF classifier Decision a) ym Input xp x1 y1 x2 ... PCA ... Euclidian distance Decision b) Decision Euclidian distance Input x1 x2 xp ... MLP block compression HLO image formation & PCA ym y1... c) xp MLP or RBF classifier Input x1 x2 ... ML P block compression HLO image formation Decision &ym y1... d) Input x1 x2 xp ... Non-block MLP compression MLP or RBF classifier Decision ym y1... e) Input X1 ym y1 Xp ... ... VQ by SOM MLP or C RBF classifier Decision Index image X2 f) Fig. 3. Face recognition methods used in this paper. The methods following from this point, in contrary to the method a) are based on two-stage systems, containing both feature extraction stage and classification stage: b. Two-stage system, where PCA is applied directly to face images with Euclidian distance as a classification measure is shown in Fig. 3b). The correlation matrix was computed from 48 training faces (the same as method a)) and for classification first 48 eigenvectors of the correlation matrix are used (Fig. 6 shows the first 48 eigenfaces of the correlation matrix). 81.51 % of test faces was recognized successfully (313 from the total 384). This result corresponds to the method No. 3 in Fig. 12. c. Our proposed method is shown in Fig. 3c). As the first stage, MLP block compression is used. 64x60 input face images are divided to 16x15 blocks. MLP configuration is 16x15-15-16x15 (i.e. 240 input and output neurons and 15 hidden neurons). Each face image is then represented by 240 hidden layer outputs. The compression perceptron was trained on the first twelve faces from Fig. 1, remaining four face images were used for testing purposes. Compression capability of MLP is illustrated in Fig. 7, where a low quality of reconstructions can be seen. After training, all input faces were represented by hidden layer outputs (HLO), which...
were used for HLO image formation, 240 HLO for each input image were used for formation of the 60x4 HLO image. 16 HLO images corresponding to faces in Fig. 1 are shown in Fig. 8. Then, PCA was applied on this representation of input data - correlation matrix 240x240 was computed from 48 HLO images corresponding to 48 training images (used also in the two previous methods). These 48 eigenvectors (or, better saying, 48 principal components obtained by projection of input data onto these eigenvectors) are used for classification, where classification criterion is Euclidian distance. This proposed system recognizes 83.07 % of the test faces successfully (319 of the total 384).

e. In order to compare results of recognition using compression networks for feature extraction, we present also non-block compression MLP working in autoassociative mode [15], [16] followed by MLP or RBF network classifier (Fig. 3e). The training set for compression MLP again consisted of 48 faces (identical with the training set in method a). The configuration of compression MLP was 64x60-48-64x60 (MLPs with 16 and 96 hidden neurons were also examined, but reconstruction results were of lower quality). Fig. 9 shows reconstructions of a subset of training and test sets by such compression MLP. Its receptive and projective fields are shown in Fig. 4. Hidden layer outputs serve as input to classification networks. The best classification results were obtained by MLP 48-16 (74.74 %, i.e. 287 of 384 faces were recognized successfully) and RBF network 48-32-16 (72.40 %, i.e. 278 of 384). These results correspond to the methods No. 8 and 10 in Fig. 12. Other MLP and RBF network configurations gave the results from 46.09 % to 72.14 %. f. Our last method is based on self-organizing systems with competitive learning. This method uses feature extraction method from image data, which is based on vector quantization (VQ) of images using Kohonen self-organizing map for codebook design. The indexes used for image transmission are used to recognize faces. This method is described in detail in [17]. We perform vector quantization on 64x60 face images dividing original images to 4x4 blocks. For image vector quantization, we used the configuration of the self-organizing map of 16x16 neurons with 16-dimensional weight vectors, what corresponds to bit rate 0.5 bit/pixel compared to 8 bit/pixel original images. For training this map, first twelve 64x60 images from Fig. 1 divided to 4x4 blocks were used. Remaining four images from Fig. 1 were used for testing. Each face image is after vector quantization represented by 240 eight-bit indexes, we form them to 16x15 eight bit/pixel image (examples of such index images corresponding to original faces from Fig. 1 are shown in Fig. 11) which then serves as the input to MLP or RBF network classifier. This is shown in Fig. 3f). Both networks had 240 (16x15) inputs. The configuration of MLP was 240-15 and configuration of RBF network was 240-48-16. This system using RBF network recognizes 80.73 % test faces successfully (310 of 384 test faces). In the case of MLP classifier of configuration 240-48-16 gives recognition success 79.95 % (307 of total 384 test faces). These results are shown as the methods No. 4 and 5 in Fig. 12. Other configurations of MLP and RBF networks reached from 61.2 % to 78.39 %.
V. Proposed System
In this paper, to design and implementation of the Face Recognition System (FRS) can be subdivided into three main parts. The first part is face image acquisition and face image enhancement in which image filtering, clipping, and edge detection. The second part is to perform various facial features extraction from face image using digital image processing and Principal Component Analysis (PCA). And the third part consists of the artificial intelligence (face recognition) which is accomplished by Back Propagation Neural Network (BPNN).

VI. Face Acquisition Module
The first stage of any vision system is the image acquisition stage. The face image is captured using the Digital cam. The image is of size 480 X 640. No Physical contact is required with the cam unlike in other biometric methods like fingerprint recognition, retinal scan etc. A proper lighting should be provided and the capturing device should suffice for minimum quality. The same digital cam with a well lit room would provide highly accurate results.

VII. Face Image enhancement
Suitable enhancements should be made to the image pool so as to make the images compatible with the algorithms to be used. In this case the image is first subject to a skin colour algorithm [2] which removes the background and isolates the skin portion from the remaining image. The resulting image is then subjected to a gray scale to minimize the contrasts due to lighting, texture etc. The image is then scaled so that any image taken using different capturing devices are reduced to the same resolution so that the eigen algorithms can be efficiently applied to them.

Feature Extraction Using in PCA
PCA for feature extraction is done by using a standard algorithm [3] which is as follows
1. We assume the training sets of images are $\Gamma_1, \Gamma_2, \ldots, \Gamma_m$  
2. Find the mean face of the images by:  
$$\Psi=(1/m)\sum_{i=1}^{m} \Gamma_i$$  
3. Calculated the mean-subtracted face:  
$$\Phi_i= \Gamma_i - \Psi, \quad i=1,2,\ldots,m$$  
Mean subtracted matrix A=$[\Phi_1, \Phi_2, \ldots, \Phi_m]$  
4. Covariance matrix=$A^T \times A$  
5. Find the eigenvalues $\lambda$ and eigen vectors $\Phi$  
6. Eigen faces $U_k = \Phi V_k, \quad k=1,2,\ldots,m$  
7. Eigen weights $W_k = U_k T (\Gamma - \Psi)$, $k=1,2,\ldots,m$  
The training file will contain $m$ eigen weights for each of the $m$ images. This is written in a training file with each of the image name followed by its id and its eigenweights. The training file is train.txt. The identification image also will have $m$ eigen weights for recognition which is written in the file out.txt.

Back Propagation Algorithm
The back propagation algorithm [1] is as follows
1. Set all weights to small random values.  
2. The input to each node of the neural network is given by the equation  
$$\alpha= x_i w_i,$$  
Where $x_i$ is the input from the previous node and $w_i$ is the corresponding weight.  
3. The output of each node is given by  
$$y=f(x)=1/(1+e^{-x}),$$  
which is called the sigmoid function.
4. The output of the output layer is the actual output of the network.
5. The error, desired output-actual output is then propagated back to all the nodes in the network and the weights are updated according to the equation,  
$$w_{ij}(t+1) = w_{ij}(t) + \eta o_j,$$  
Where $wij$ is the weight from node $i$ to $j$ at time $t$, $\eta$ is the learning rate and $o_j$ is the output of node $j$ and $j$ is the error term for node $j$  
For output nodes,  
$$j = k o_j (1-o_j)(t-j o_j),$$  
For hidden nodes,  
$$j = k o_j (1-o_j) \times k w_{jk},$$  
where $k$ is the next nodal error term.

VIII. Back Propagation Neural learning
Back propagation is a kind of supervised learning employed by the neural Networks in which the derivative of the error function is propagated back to the contributing neurons in the neural network and the weights updated subsequently. In this application, eigen weights obtained from the images in the image pool are passed as inputs to the neural network and the corresponding user’s binary id is given as the desired output of the neural
network. The training is repeated until the neural network is able to identify all the images in the training set with error function reduced to an acceptable value. The weights and threshold values which are obtained while training are then stored in a file to be used during recognition.

Recognition
The eigen weights of the image to be identified is passed as the input to the Already trained neural network and the outputs obtained. The outputs of individual neurons of the output layer are then rounded off to the nearest 0 or 1 to form a valid binary id. This binary id is then checked against the database to validate the authenticity and display the details of the face if identified.

IX. Conclusion
In this paper, we have presented a technique for designing fast, secure and robust face recognition system. Our applied technique reduces the time required to recognize an image from the database. Haar wavelet transform has been applied over an image to decompose it into 2-level sub images bands. Then we apply PCA for extracting Eigen values from these bands. And finally BPNN is used for image classification and recognition. So, this combined approach develops a more accurate approach compared to the existing techniques. It reduces execution time of recognizing an image from the test database and thus increases the acceptance ratio while traversing images from the database and makes the system more secure and reliable.

Future Directions
In future, two or more functionalities can be added to the proposed approach which will allow performing many more operations and thus more securing the biometric system while it is being used for detecting and recognising human faces. One of the outlooks for this thesis future work will be to learn the system with other prominent databases that poses great variations in the lighting conditions and the positioning of the head. It is necessary to study more on the optimization process for preprocessing and parameters of neural network in the future. So we will need to acknowledge people in real-time and in much less restrained situations. The fast and accurate classification and discrimination method are also areas of research in future work.

References