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An Enhanced Two-Pass Classifier for Face Recognition Using Back-Propagation Neural Networks and Support Vector Machines

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ABSTRACT

A novel two-pass classification technique is presented in this paper to apply to the face recognition problem. Two approaches are integrated together to solve the face recognition problem efficiently: Back-propagation neural networks (BPNN) and Support Vector Machines (SVM). The face recognition task is realized in two passes. An intermediate result of classification is obtained in the first pass for an input using BPNN which indicates the classification status, and the second pass re-classifies the sample using SVM, considering the input sample and the intermediate result. Feature extraction is performed using principal component analysis (PCA) and the final classifier is designed by combining the advantages of artificial neural network and support vector machine. Testing on LFW and AT&T benchmark datasets showed that the proposed system outperforms state of the art face recognition techniques.

Key words: Back-propagation neural network, Face recognition, Principal Component Analysis, Support Vector Machine

INTRODUCTION

Face recognition is a pertinent area of research with an extensive range of application in surveillance, biometric security systems, and human computer interaction and so on. This term refers to the advanced field of technology that automatically identifies individuals using physiological or behavioral traits [1]. Face recognition has the benefit of demanding very little cooperation from the subjects in order to collect the required data. Humans often use face to recognize individuals. It is a real challenge to develop an automatic system that mimics the human capacity to recognize faces.

A face recognition system is a computer application which automatically identifies a person from a digital image or a video frame. This can be achieved by comparing the chosen facial features from the image with that of each face in the stored database. Perfectly modeled face recognition systems functioning in public places like airports should recognize individuals among the mass without their co-operation. Other biometric authentication systems like fingerprints, iris scans and speech recognition cannot achieve such mass identification. Face recognition system generally works well with full frontal faces and up to 20 degree angle, but beyond that, the task becomes difficult. Challenges for building an optimal face recognition system are poor image quality, illumination problems, pose variations, aging, and presence or absence of spectacles, beard, etc. [2]. Many face recognition systems are less effective because of variations in facial expression between the images in the stored database and the test image. Even a big smile can leave the system performance unpredictable.

Li et al. proposed a method to improve the Bayesian Face Recognition system using Support Vector Machines [3]. This direct Bayesian SVM needs only a single SVM that is trained to classify the face difference between intrapersonal variations and interpersonal variation, yielding comparable face recognition rates.

Chih-Hsueh Duan et al. proposed a local sparse method for face component representation to handle the face recognition problem [4]. A dictionary of local patches of face images has

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been collected. A novel local descriptor has been introduced using sparse coefficients extracted from the dictionary and the local face patches extracted from the face elements. The performance of the face recognition system has been demonstrated by experiments on LFW and CMU PIE dataset. A novel robust kernel representation model with statistical local features (SLF) has been proposed by Meng Yang et al [5]. A multi partition max pooling method has been adopted to improve the invariance of SLF together with robust regression to handle occlusion in face images. Evaluation on LFW, FERET and FRGC databases have shown promising results.

A single sample face recognition technique based on locality preserving projection (LPP) feature transfer has been proposed by Jie Pan et al [6]. In this method, the source and target faces are projected onto the LPP feature subspace and the feature transfer matrix has been calculated, which is used on training samples for transferring the actual macro characteristics to the desired macro characteristics. The final face recognition step is realized by the nearest neighbor classifier. The results have been verified on the AT & T, FERET and YALE databases. A holistic method to recognize faces at distinct perspective variations has been proposed by Kin-Man Lam et al. [7].

Fifteen feature points are located and a head model has been used to estimate the rotation of the face using geometric measurements. Using a similarity transform, these feature points are compared with that in the database. Using correlation, feature windows set up for eyes, mouth and nose is compared with those in the database. Results show good performance in different viewing angles of a face. The method proposed by Li Fei-Fei utilizes the fact that one can take advantage of the knowledge from previously learned object categories, and this technique was implemented using the Bayesian classifier [8]. Comparisons with category models learned by Maximum Likelihood (ML) and Maximum A-Posteriori (MAP) methods show that, for a small training set, the Bayesian approach produces informative models than the other methods.

Even though a lot of research has been carried out in this area, a face recognition system that has achieved optimum recognition rates and minimum misclassification rates, for faces including those under varying pose and illumination, is yet to be realized. A two-pass classification method has been proposed by Chengan et al [9] that integrates Hyper Ellipsoid neural networks (HENNs) and Support Vector Machines (SVMs) with Error Correcting Output Codes (ECOC) to apply to the face recognition problem. Comparison with HENNs and SVMs individually on the standard AT & T database has proven that the two-pass method shows a significant improvement in the recognition rates.

In this paper, we propose an efficient face recognition system robust to variations in illumination and orientation along with minimum misclassification rates, by adopting the concept of two-pass classification proposed by Chengan et al [9]. In the proposed work, we have used a two-pass classifier using Back -propagation Neural Networks (BPNN) and multiclass Support Vector Machines (SVM) for implementing the face recognition system. Better recognition rates could be achieved by combining BPNN and SVM, while reducing their shortcomings. Simulations performed on the unconstrained LFW database and the standard AT&T databases have shown improved performance over state-of-the-art classifiers.

The two-pass classification process is as follows. A BPNN designed with appropriate number of input and output neurons is used in the first pass to classify the face images. The intermediate result obtained from this classification process indicates whether classification was successful or not, and is passed to the next stage. In the case of a rejection in the first phase, the classifier in the next stage reclassifies the sample using the SVM classifier. Simulation results show that a remarkable improvement of recognition rates over the individual classifiers has been obtained by the proposed method.

The rest of the chapter is organized as follows. Section II describes the feature extraction techniques used in this paper. Section III details the classification procedure using cascaded back -propagation neural network and SVM classifier. The simulation experiments and results are presented in Section IV. Finally, conclusions are drawn in Section V.

II. FEATURE EXTRACTION

Feature extraction is a core component of any classification system. Feature extraction techniques used in the proposed method are detailed in the following sections.

A. PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA) is a standard feature extraction as well as a data representation method extensively applied in the areas of pattern recognition and computer vision. It is a mathematical technique that transforms numerous correlated variables into a reduced set of uncorrelated variables called principal components [10]. This feature extraction technique finds the Eigenvectors of covariance matrix corresponding to an input face and projects the data onto the Eigenvectors with the largest Eigen values, which are the retrieved features. Thus, PCA can be utilized to compute the feature set for face recognition [11].

The number of principal components indicates the number of uncorrelated variables. In PCA, the first principal component has the top priority and shows the highest variance. Only if the data set is distributed normally, the principal components are sure to be independent of the other variables. Even though dimensionality reduction takes place, the information is preserved without loss [12]. The best lower dimensional space can be computed by the best Eigenvectors corresponding to the covariance matrix. Any particular face can be optimally represented along the Eigen face coordinate space, and reproduced using a minimal set of Eigen faces.

Let Γ_1, Γ_2 ...Γ_m be the training set of images. The average face ψ is defined by

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n$$

Each individual face varies from the average face by the vector Φ given by

$$\Phi_i = \Gamma_i - \Psi$$

The Co- Variance matrix is formed by the vector C, given by

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

Where the Matrix A = (Φ_1, Φ_2, Φ_3... Φ_M). The set of vectors is then subject to PCA, which seeks a set of M orthonormal vectors U_1... U_M. To get the weight vector Ω =(w_1, w_2, w_3, ...w_M) of the face image Γ, the face is converted to Eigen face components. The weight vector Wk is computed as follows.

$$W_k = U_k(\Gamma - \Psi)$$

Where k is the number of Eigen faces used, which ranges from 1 to M

B. EIGEN VECTORS

The Eigenvectors are a set of features that characterize the variation between the face images [13]. Every face can be presented by a linear combination of the Eigen faces. Each face can be modeled using only the best Eigen faces: those that have the highest Eigen values and which therefore contribute to the maximum variance. The best t Eigen faces span a t-dimensional space of all possible images. For an input image, the weights are obtained by mapping the image into the Eigenvector space. The classifier works by matching the distances between the weighted vectors of the input image and the trained images from the database. Conversely, the original image can be reconstructed using the Eigen faces so that the input image should match perfectly with the original image using the Eigen faces obtained from the original images. Figure 1 show the faces constructed with varying number of Eigen faces corresponding to the input face.

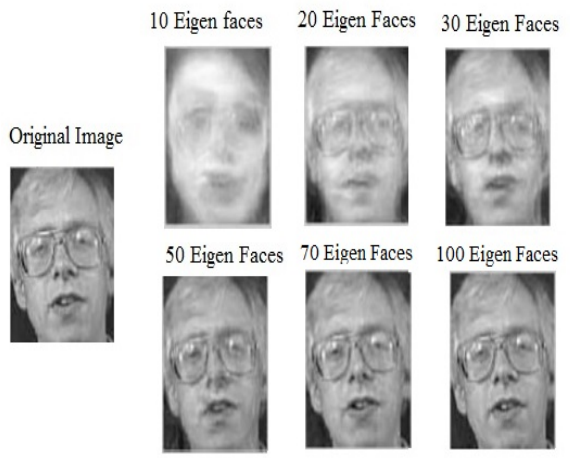

Figure 1: Faces constructed with varying number of Eigen Vectors.

III. CLASSIFICATION USING CASCADED BPNN-SVM CLASSIFIER

The two-pass classification system for face recognition is build on two well established classifiers, Back-Propagation Neural Network and Support Vector Machines, the description of which are given below.

A. BACK-PROPAGATION NEURAL NETWORK CLASSIFIER

The training phase in back-propagation network needs pairs of input and target vectors. The obtained output vector and target vector are compared and if there is a difference, then weights are modified to reduce this error. Initially, the neural network assumes random thresholds and weights. The weights are modified in each cycle to reduce the mean square error between the actual vector and the target vector.

Input to the hidden layer is net_m given by

$$net_m = \sum_{z=1}^{m} x_z w_{mz},$$

where x_z is the input value of neuron z and w_{mz} is the weight between neuron m and z.

The obtained vector units of hidden layer after going through the activation function is h_m given by

$$h_m = \frac{1}{1 + \exp(-net_m)}$$

Similarly, input to the final layer k is net_k given by

$$net_k = \sum_{z=1}^{m} h_z w_{kz},$$

where h_z is the output vector of hidden layer z and w_{kz} is the weight between neuron k and z

The output vector units of final layer is o_k given by

$$o_k = \frac{1}{1 + \exp(-net_k)}$$

The difference in weights is Δw_{ij} given by

$$\Delta w_{ij} = \alpha \delta_i h_j,$$

where α is the learning rate coefficient, which is limited to the range [0.01, 1.0], output of neuron j in the hidden layer is represented by h_j, and the error δ_i is given by

$$\delta_i = (t_i - o_i) o_i (1 - o_i),$$

where t_i and o_i are the target and actual output of i^{th} neuron, l is the number of layers. If the error falls below a certain preset limit, the training needs to stop; else weights should be modified.

The difference in weights between intermediate layer and output layer, is given by

$$\Delta w_{ij} = \beta \delta_{Hi} X_j,$$

where β is the learning rate coefficient, limited to the bounds [0.01, 1.0], and X_j is the output of the neuron j in the input layer. Error δ_{Hi} is computed as follows.

$$\delta_{Hi} = x_i (1 - x_i) \sum_{j=1}^{k} \delta_j w_{ij},$$

where xi is the output of neuron i in the input layer and the summation term represent the weighted sum of all δj values corresponding to neurons in the output layer. After computing the change of weight in all the layers, the weights can be updated by

$$w_{ij}(new) = w_{ij}(old) + \Delta w_{ij},$$

This process is repeated, until the error value reaches the minimum. The Eigen faces corresponding to the AT&T face database is given below.

B. SUPPORT VECTOR MACHINE CLASSIFIER

Face recognition is an N class problem, where N is the number of stored individuals. Support vector machines (SVM) were formulated to solve two class pattern recognition problems, and later it has been expanded to multiclass [14]. Figure 2 show the support vector machine classifier that uses an optimal hyper plane to separate the two classes.

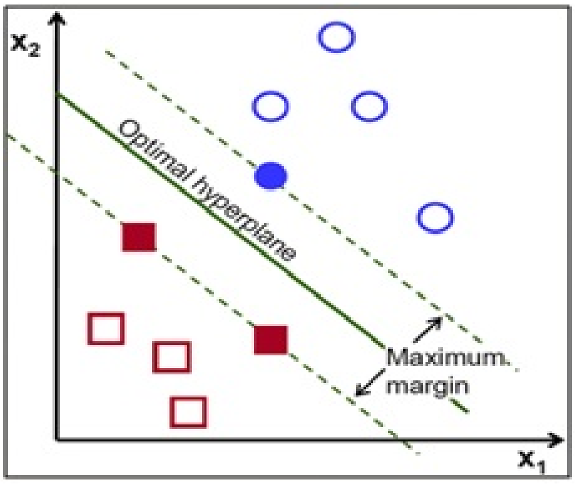

Figure 2: SVM Classifier

SVM is adopted to solve the FR problem by varying the interpretation of the result of an SVM classifier and defining a model for facial images that is concordant with the binary classification problem [15]. Classical SVM returns a binary value, which represents the label of the object. To train the SVM, the task is formulated in a different space, which explicitly tracks the differences between two face images. This is a deviation from classical face space, which formulates each face image as a separate view of the face. The optimization criterion is to maximize the width of the margin between the classes, which is the distance between the support vectors. These support vectors define the classification function.

C. PROPOSED TWO-PASS CLASSIFICATION METHOD BASED ON BPNN AND SVM

Both BPNN and SVM classifiers have their own advantages and disadvantages. Investigations on whether a better classifier could be built by integrating the two techniques such that the advantages of both the methods are retained while rectifying their drawbacks led to the design of the proposed two-pass classification approach. Here, a novel two-pass face recognition system has been proposed by integrating BPNN and SVM, for better recognition accuracy and reduced misclassification rates. PCA and the Eigenvectors are used for feature extraction and representation respectively.

The extracted features are stored in a database and are used for training the face images. In the training phase, the features of each person are trained separately. The neural network is designed with an appropriate number of input and output neurons. Both the neural network and SVM are trained to the required accuracy. For an incoming unknown face, the features are extracted first. Then, it is classified using the Neural Network classifier. If the face has been successfully recognized, there is no further classification required, which is indicated in the intermediate result. If the face was rejected without classification, the extracted features are passed to the next stage along with intermediate results which are used for classification by the SVM classifier, and the result is finalized. Figure .3 shows this cascaded recognition process.

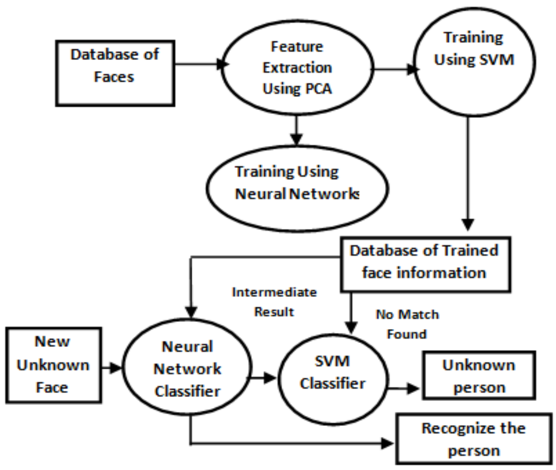

Figure 3: Cascaded Recognition Process

IV. SIMULATION EXPERIMENTS AND RESULTS

The simulations are performed on the large scale LFW database which contains 13233 face images of 5749 individuals taken under unconstrained environment [16] and the standard AT&T face database that stores 400 face images of 40 different persons with 10 images per person [17]. LFW contains face photographs developed for unconstrained face recognition in which the face images possess large variations in pose, illumination, expression, misalignment and occlusion. Sample images from LFW database and AT&T database are shown in Figure 4 and 5 respectively. The Eigen faces based on PCA is used as the feature template to represent face images, and the input feature vector for the two-pass classifier is extracted by projecting the sample images onto the Eigen faces. .

For the simulation experiment, a subset of 200 images from the AT&T database has been used for training (5 images per person) and the other 200 images (remaining 5 images of each person) for testing. From the LFW dataset, a training set containing randomly selected 360 face images was built. The testing dataset is also a subset randomly chosen from the images other than the training set.

Figure 4: Sample images from LFW Database

Figure 5: Sample images from AT&T Database

Precision and recall can be used as measures for analyzing recognition accuracy, given by the following equations.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN},$$

Where TP represents True Positives and FP represents False Positives. Table 1 and 2 show the evaluation results of the proposed system in LFW database and AT&T database respectively.

TABLE 1: EVALUATION ON LFW DATABASE

	No. Of Recognitions	Recognition Rate (Percentage)
True Positive	305	84.7
Total No. of images trained	360	
Total No. of images tested	360	
Precision	91	
Recall	93.8	

TABLE 2: EVALUATION IN AT & T DATABASE

	No. Of Recognitions	Percentage of Recognition
True Positive	197	98.5
Total No. of images trained	200	
Total No. of images tested	200	
Precision	98.99	
Recall	99.5	

The evaluation results of the proposed face recognition technique using cascaded neural network- support vector machine classifier has been compared with some of the state of the art face recognition systems on LFW and AT & T databases. Table 3 lists the recognition rates of the competing state-of-the-art methods on the LFW database and Table 4 shows the recognition rates in the AT&T database. The results of the existing techniques on both LFW and AT & T databases have been taken directly from their published papers [19], [20], [21] [22], [23], [24] for comparison with the proposed method. Figure 6 and Figure 7 shows the graphical analysis of recognition rates of the proposed method with that of the state of the art techniques on LFW and AT&T database respectively. It can be seen that the proposed method achieves the best performance over the listed techniques on both these databases.

TABLE 3: FACE RECOGNITION RATES ON LFW DATABASE

Method	**Recognition Rate (Percentage)**
Local Binary Pattern, Original[19]	69.6 ± 2
Local Binary Pattern with PCA[19]	74.8 ± 1
Local Binary Pattern with WPCA [19]	79.5 ± 1
LSR_W, Original [19]	71.1 ± 2
LSR_W with PCA [19]	75.9 ± 2
LSR_W with WPCA [19]	82.1 ± 2
LSR_O, Original [19]	70.5 ± 2
LSR_O with PCA [19]	72.9 ± 3
LSR_O with WPCA [19]	81.8 ± 2
SLF + SRC [20]	75.5
SLF + KSRC [20]	77.9
SLF + CRC [20]	76.8
SLF + KCRC [20]	78.8
SLF-RKR_l2 [20]	81.9
Proposed Method	**84.7**

TABLE 4: FACE RECOGNITION RATES ON AT & T DATABASE

Method	Recognition Rate (Percentage)
Block FLDA [22]	66
EPS-SEE [21]	76
FT-PCA [23]	74
FT-LDA [23]	86
FT-LPP [23]	92
HENN+SVM with ECOC [24]	98.1
Proposed Method	**98.5**

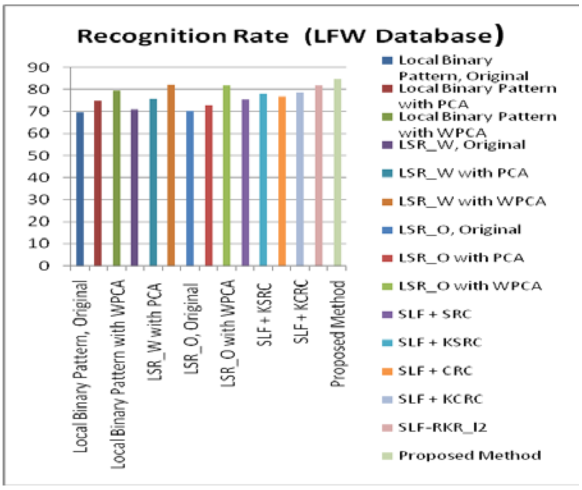

Figure 6: Comparison of the proposed method with the state of the art techniques on LFW database

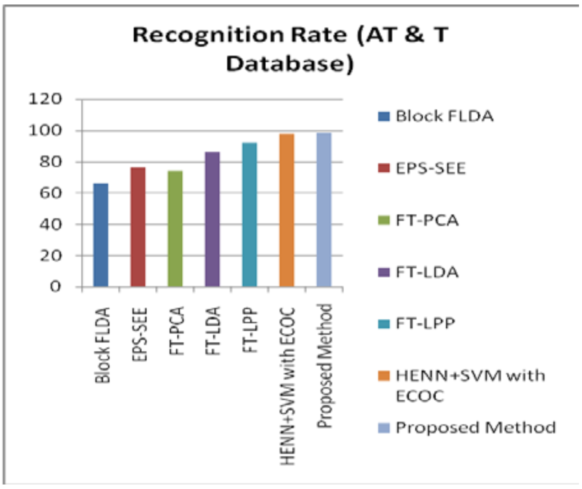

Figure 7: Comparison of the proposed method with the state of the art techniques on AT&T database

V. CONCLUSION

An efficient two-pass classification technique was presented to solve the problem of face recognition, by integrating two methods, the back-propagation neural network and the SVM. The classification function was performed in two passes: the first one classified the input image using a neural network classifier and the intermediate results were passed to the next stage. The second classification stage using SVM was activated based on the intermediate result. Simulation results showed that the two-pass method retains the advantages of both the back-propagation neural network and SVM while remedying their disadvantages. The method was evaluated on the unconstrained LFW database and the standard AT & T databases and has shown superior recognition rates than many of the state-of-the-art classifiers, and has the capability to be applied in practical face recognition systems.

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