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A FACE IDENTIFICATION SYSTEM USING NEURAL NETWORK

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ABSTRACT

Face is a primary focus of attention in social intercourse, playing a major role in conveying identity and emotion. Human face recognition plays an important role in many user authentication applications in the modern world. The face biometric is widely used in surveillance applications due to its non intrusive nature. In the present work a neural network based face identification system has been developed. In the developed system the Gabor filter bank is used to extract the facial features. The system is commenced on convolving a face image after preprocessing the image at different scales and orientations. The neural network is used as a classifier in which the weights of the neurons are updated by supervised learning using Resilient Backpropagation algorithm. The experiments conducted on Yale database reveals that an accuracy of 90% has been achieved.

Keywords: Neural Network, Gabor Filter, Convolution.

1. INTRODUCTION

A wide variety of systems require reliable personal recognition schemes to determine the identity of an individual requesting their services. Identity verification (authentication) in computer systems has been traditionally based on something that one has (key, magnetic or chip card) or one knows (PIN, password) [1]. Things like keys or cards, however, tend to get stolen and passwords are often forgotten or disclosed. To achieve more reliable verification or identification one should use something that really characterizes the given person. Biometrics offer automated methods of identity verification or identification on the principle of measurable physiological or behavioral characteristics like face, voice, fingerprints etc. Due to non intrusive and user friendly nature of the face biometric it is most commonly used in surveillance applications, crime investigations, security etc.

A fair amount of research work has been published on face authentication. Eigenfaces method proposed by Turk and Pentland in [2] uses a nearest neighbour classifier while feature-line-based methods explained by Li and Lu in [3], replace the point-to-point distance with the distance between a point and the feature line linking two stored sample points. In Fisherfaces method [4] authors uses linear/Fisher discriminant analysis (LDA/FLD). Bayesian methods proposed by Moghaddam and Pentland [5] use a probabilistic distance metric while SVM method uses a support vector machine as the classifier [6]. Utilizing higher order statistics, independent-component analysis (ICA) is argued to have more representative power than Principal Component Analysis (PCA) on which [2] to [6] depends, and hence may provide better recognition performance than PCA [7]. Being able to offer potentially greater generalization through learning, neural networks/learning methods have also been applied to face recognition.

Earlier methods belong to the category of structural matching methods, using the width of the head, the distances between the eyes and from the eyes to the mouth, etc., or the distances and angles between eye corners, mouth extrema, nostrils, and chin top [8]. More recently, a mixture-distance based approach using manually extracted distances was reported in [9] by Cox *et al.*. Without finding the exact locations of facial features, Samaria [10] proposes a Hidden Markov Model based method which uses strips of pixels that cover the forehead, eye, nose, mouth, and chin. Nefian and Hayes [11] reported better performance than [10] by using the KL projection coefficients instead of the strips of raw pixels. One of the most successful systems in this category is the graph matching system [12], which is based on the Dynamic Link Architecture (DLA). Using an unsupervised learning method based on a self-organizing map (SOM), a system based on a convolutional neural network (CNN) has been developed by Lawrence *et al*. [13]. Pentland *et al.* [14] proposes a method that uses the hybrid features by combining eigenfaces and other Eigen modules such as eyes, mouth and nose are explored.

In the present work feature based face identification system has been discussed. The Gabor filter bank has been used to extract the features while neural network has been used as a classifier.

2. PRESENT WORK

The various steps used in the present face recognition system are discussed below.

2.1. Database

The first step in a Face recognition system is to capture the face or obtain it from some available database. Face images are available from various databases such as Olivetti and Oracle Research Laboratory (ORL), Yale and FERET face databases. Each database has more than one face images with different conditions (expression, illumination etc.), of each individual. The Yale database has been used in the present work. The Yale Face Database contains 165 grayscale images in bmp format of 15 individuals. There are 11 images per subject, one per different facial expression or configuration, center-light, w/ glasses, happy, left-light, w/no glasses, normal, right-light, sad, and sleepy, surprised, and wink. Fig.1 shows all the 11 poses of one subject.

Figure 1: A Typical Face Image from Yale Face Database

2.2. Histogram Equalization

Histogram equalization assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities. In other words the image is histogram equalized to correct brightness, contrast and equalize the different intensities level of the image. In histogram equalization the new intensity values are calculated by using the formula

$$O_i\ i = \left[\sum_{j=0}^{i} N_j\right] \times \frac{I_m}{N} \tag{1}$$

O_i = New intensity value of i^{th} pixel
I_m = Maximum intensity level
N = Number of pixels

The Fig. 2 (b) shows the histogram equalized face image of Fig. 2 (a).

2.3. Image Resizing

The resizing of the image is done because it is will fix the number of nodes for the neural network otherwise extra nodes have to be created in the neural network which will greatly reduce the efficiency of the neural network during training. In present work the image is cropped to the size of 25×25. Fig. 2(c) shows the resized face image of Fig. 2 (b).

(a) (b) (c)

Figure 2: (a) A Typical Face Image (b) Histogram Equalized of a Typical Face Image (c) Resized Face Image

2.4 Gabor Filter

The principal motivation to use Gabor filters is due to its biological relevance and technical properties. The system is based on locating all the feature points on the face which contains high energy areas. Gabor filter works as a bandpass filter for the local spatial frequency distribution, achieving an optimal resolution in both spatial and frequency domains [15]. The 2D Gabor filter $\psi_{f,\theta}(x, y)$ can be represented as a complex sinusoidal signal modulated by a Gaussian function.

$$\psi_{f,\theta}(x,y) = \exp\left[-\frac{1}{2}\left\{\frac{x_{\theta_n}^2}{\sigma_x^2} + \frac{y_{\theta_n}^2}{\sigma_y^2}\right\}\right]\cos(2\pi f x_{\theta_n}) \tag{2}$$

Where,

$$\begin{bmatrix} x_{\theta_n} \\ y_{\theta_n} \end{bmatrix} = \begin{bmatrix} \sin\theta_n & \cos\theta_n \\ -\cos\theta_n & \sin\theta_n \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix} \tag{3}$$

σ_x, σ_y, are the standard deviation of the Gaussian envelope along the x and y- axis, f is the central frequency of the sinusoidal plane wave, θ_n the orientation. The rotation of x-y plane by an angle θ_n will result in a Gabor filter at the orientationθ_n. The angle θ_n is defined by:

$$\theta_n = \frac{\pi}{p}(n-1) \tag{4}$$

For $n = 1, 2, 3\ldots p$ and $p \in N$, where p denotes the number of orientations. Design of Gabor filter is accomplished by tuning the filter with a specific band of spatial frequency and orientation by appropriately selecting the filter parameters; the spread of the filter σ_x, σ_y, radial frequency f, and the orientation of the filter θ_n . Design of Gabor filters for face recognition depends upon the choice of filter parameters. Fifty Gabor channels are used consisting of ten (10) different orientation $\theta \in \{0, 0.3142, 0.2683, 0.9425, 1.2566, 1.5708, 1.8850, 2.1991, 2.5133 \text{ and } 2.8274\}$ and 5 different spatial frequencies $f \in \{.20, .22, .24, .28 \text{ and } .30\}$. The frequencies are taken from 0.20 because below that no facial features are extracted. The Gabor representation of a face image is computed by convolving the face image with the Gabor filters. Let $f(x, y)$ be the intensity at the coordinate (x, y) in a gray scale face image, its convolution with a Gabor filter $\psi_{f,\theta}(x, y)$ is defined as

$$gf, \theta\,(x, y) = f(x, y) \otimes \psi_{f,\theta}\,(x, y) \tag{5}$$

Where $\otimes$ denotes the convolution operator. Fig. 3(a) shows the convolved face image with Gabor bank at different orientations and frequency 0.20.

2.5. Thresholding

The thresholding of the image is done after convolution with the Gabor filters. Thresholding of the image is done to convert the grayscale image into the binary image. The present work uses Otsu's method, which chooses the threshold that minimizes the within-class variance. Fig. 3(b) shows the threshold face image after Gabor features extraction.

(a) (b)

Figure 3 (a) Convolved Face Image at Different Orientations and Frequency 0.20 (b) Threshold Face Image After Gabor Features are Extracted

2.6. Neural Network

The proposed multilayer neural network consists of two layers. The first layer gets the input from Gabor feature set having the number of nodes equal to the Gabor feature set. The second layer is the output layer having the number of nodes equal to the number of persons which are to be verified. The Hyperbolic tangent and linear transfer functions are used in the model. The learning algorithm used is backpropagation algorithm. The error backpropagation algorithm is Resilent backpropagation where the algorithm eliminates the harmful effects of the magnitude of the partial derivatives by just considering the sign of the derivative to determine the direction of weight update.

3. RESULT AND DISCUSSION

The face recognition system using neural network has been implemented using MATLAB version 7.3.0.267 (R2006b). There are different backpropagation algorithms for feedforward networks which use batch training available in MATLAB. Some important ones such as Gradient Decent, Gradient Decent with momentum, Adaptive rate and Resilient backpropagation at their default parameters values with the goal e^{-005}, are compared for their performance (time requirement and epochs) as shown in Fig. 4 for the face recognition. It has been concluded that resilient backpropagation shows better results.

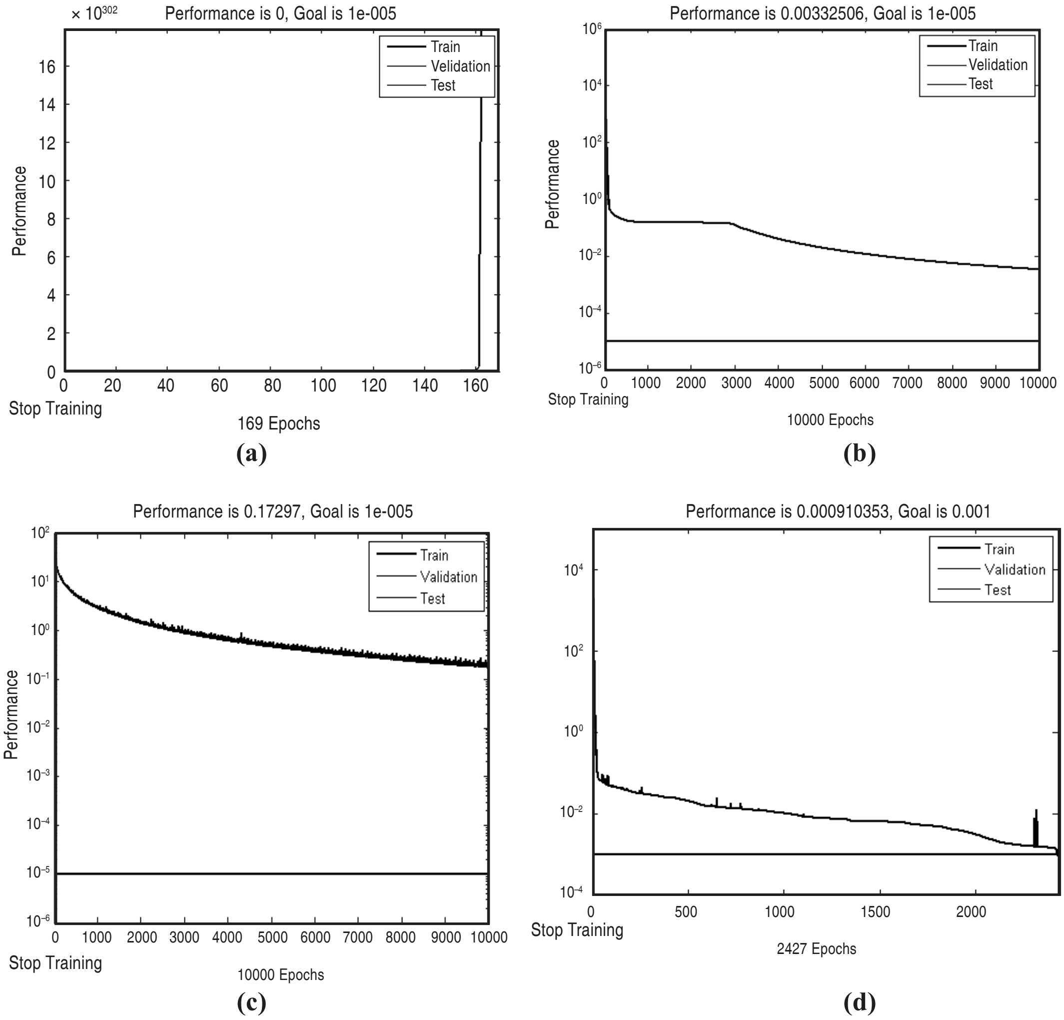

Figure 4: Training Curve for (a) Gradient Decent; (b) Gradient Decent with Momentum; (c) Adaptive Rate; (d) Resilient Backpropagation

The pre-processed face images are fed to the neural network for training which involves modifying the weights. The accumulated knowledge is distributed over all the weights, the weights must be modified very gently as not to destroy the previous learning. A constant called the learning rate is used to control the magnitude of weights modifications. The choice of learning rate is very important because if its value is too small, learning takes forever; but if the value is too large, learning disrupts all the previous knowledge. There is no mathematical formula for the choice of learning rate so experiments are performed trying different values and it has been found that at 0.5 the results are better than the others for the considered faces of Yale database.

Using the learning rate of 0.5 fifteen persons with six different poses per person has been taken for training the neural network and the network has been tested for false reject rate using the five poses which has been used for training and remaining five poses from he database. The network has also been tested for the imposer tests to find out false accept rate. The results obtained are

Table 1
True Test Results

Total Number of persons	*True test per person*	*Total true tests*	*Total false rejects*	*% False rejects*
15	10	150	14	9.3

Table 2
Imposter Test Results

Total Number of persons	*Imposter test per person*	*Total imposter tests*	*Total false accepts*	*% False accepts*
15	15	225	20	8.8

4. Conclusion

In the present work Gabor filter bank has been used to extracts the facial features and the neural network has been trained with the learning rate of 0.5 (chosen after experimentation) using the Resilient backpropagation algorithm. The targets of neural network are set as 0.9 and 0.1. If the output comes out be 0.9 then the person is correctly identified and is authenticated else it is not. Experiments conducted using the Yale database shows the false reject rate (FRR) of 9.3% and false accept rate (FAR) of 8.8%. Our future work will include the recognition of colored face images.

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