Face Recognition Using Neural Network Based Fourier Gabor Filters & Random Projection

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Abstract

Face detection and recognition has many applications in a variety of fields such as authentication, security, video surveillance and human interaction systems. In this paper, we present a neural network system for face recognition. Feature vector based on Fourier Gabor filters is used as input of our classifier, which is a Back Propagation Neural Network (BPNN). The input vector of the network will have large dimension, to reduce its feature subspace we investigate the use of the Random Projection as method of dimensionality reduction. Theory and experiment indicates the robustness of our solution.

Keywords: Face Recognition, Fourier Transform, Gabor Filter, Neural Network, Sparse Random Projection.

1. INTRODUCTION

Human face detection and recognition is an active area of research spanning several disciplines such as computer vision and pattern classification. A robust face recognition system is a system based on good feature extractor method and good classifier. Neural network have been successfully applied to many pattern classification problems. And among the new techniques used in the literature for feature extraction, it is proven that Gabor filters can extract the maximum information from local image regions [1][2] and it is invariant against, translation, rotation, variations due to illumination and scale [3][4][5].

In[6][7]Gabor wavelets & neural network was presented for face detection, A. Khatun et al [8] propose a hybrid neural network solution for face recognition trained with Gabor features. The

neural network employed is based on BAM for dimensionality reduction and multi-layer perception with backpropagation algorithm for training the Gabor features.
P. Latha et al [9] use Gabor wavelet to present face, and applied neural network to classify views of faces. The dimensionality is reduced by the Principal component analysis.

In this study, we present an intelligent neural network system for face recognition. We use Gabor filters and Fourier transform for feature selection as they present desirable characteristics of spatial locality and orientation selectivity. Theses feature vectors are used as input of our Back Propagation Neural Network (BPNN), it was chosen as classifier for the proposed system because of its simplicity and its capability in supervised pattern recognition [10]. The input vector of the network will have large dimension, to reduce its feature subspace, we use Random Projection (RP)that has emerged as a powerful and efficient method for dimensionality reduction that preserves the structure of the data without introducing very significant distortion.[11][12].

This paper is organized as follows: Description of our solution is presented in section II, in section III, we discuss the experimental results and section IV gives conclusion and future works.

2. THE PROPOSED SOLUTION

2.1 System Architecture

The system proposed in this research is designed for facial face recognition. The system consists of three modules: a) Facial feature extraction using Gabor filter b) dimensionality reduction using sparse random projection. Finally, the obtained feature vectors are fed up into BPNN for classification.
The overall system architecture is shown in Figure 1.

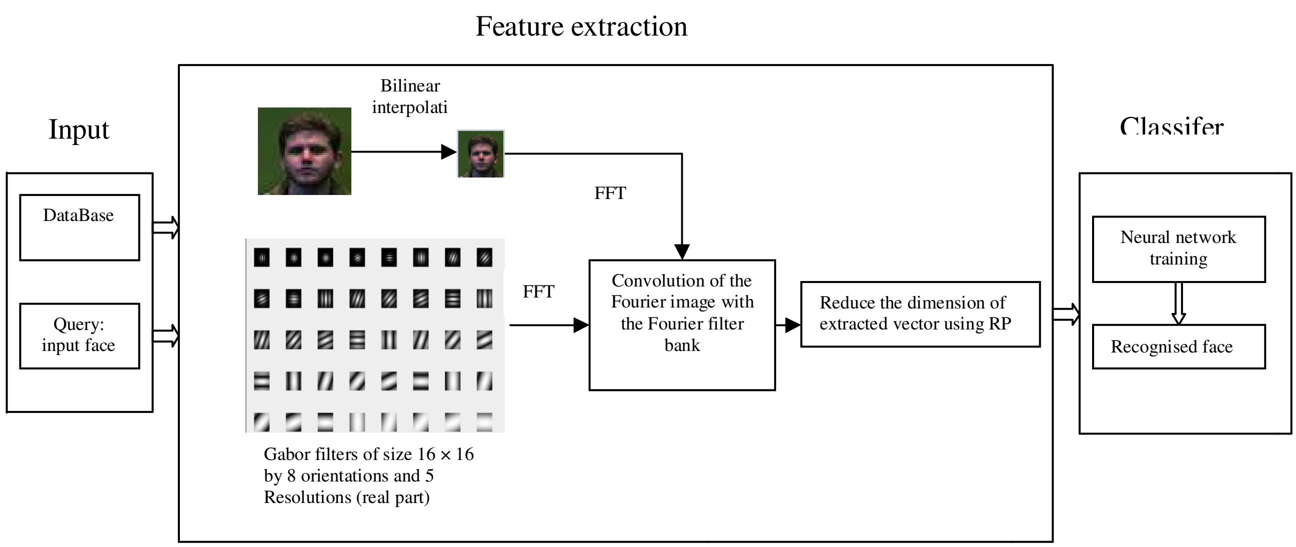

FIGURE 1: Architecture description of the proposed approach.

2.2 Extracting Feature Vectors

Several works [13] [14] have also shown that the Gabor filters representation and extraction of face images is robust. However, the high dimensional Gabor feature vectors caused the method to be computationally very expensive. Hence, the necessity to resize the original image (bilinear interpolation) and to apply a reduction dimensionality method (RP).

2.2.1 Bilinear Interpolation

The original image was reduced in size 32×32 by bilinear interpolation. This is necessary to reduce the computation time. The result is shown in (Figure 2) and then the Fourier transformed is applied to the image.

(a) (b)

FIGURE 2: Resizing of the face: a) input image, b)Bilinear interpolation resizing.

2.2.2 Fourier Transformed Image

Fourier Transformed image is the image I in the frequency domain as in this field every point represents a particular frequency contained in the image space of square image of size N × N.

$$Fourier(m,n,I)=\frac{1}{N^2}\sum_{a=0}^{N-1}\sum_{b=0}^{N-1} I(a,b)\ e^{-i2\pi\left(\frac{ma+nb}{N}\right)} \quad (1)$$

2.2.3 Gabor Filters

Gabor is a function that satisfies certain mathematical requirements extraction information is based on the use of a bank of Gabor filters [15], 8 orientations and 5 resolutions. The 2D Gabor filter is formed by modulating a complex sinusoid by a Gaussian function where each filter is defined by:

$$Gabor(x,y,\mu,\nu)=\theta(x,y,\mu,\nu)\left(\alpha-\beta\right) \quad (2)$$

Where:

$$\theta(x,y,\mu,\nu)=\frac{\left\|k_{\mu\nu}\right\|^2}{\sigma^2}\exp\left(\frac{-\left\|k_{\mu\nu}\right\|^2\left(x^2+y^2\right)}{2\sigma^2}\right)$$

$$\alpha=\exp\left(ik_{\mu\nu}*\left(x,y\right)\right)$$

$$\beta=\exp\left(\frac{-\sigma^2}{2}\right)$$

Where (x,y) represents a 2-dimensional input point. The parameters μ and ν define the orientation and scale of the Gabor kernel. ||.|| indicates the norm operator, and σ refers to the standard deviation of the Gaussian window in the kernel.

The wave vector K μυ is defined as:

$$k_{\mu\nu}=k_{\nu}\exp^{i\varphi_{\mu}} \quad (3)$$

Where: $k_{\nu}=\frac{k\max}{f^{\nu}}$, $\varphi_{\mu}=\frac{\pi\mu}{8}$

if 8 different orientations are chosen.Kmax is the maximum frequency, and f υ is the spatial frequency between kernels in the frequency domain. In our configuration, 5 different scales and 8 orientations of Gabor wavelets are used, e.g. ν € {0, ..., 4} and μ€ {0, ..., 7}. Gabor wavelets are chosen with the parameters:

kmax= $\frac{\pi}{2}$, $f = \sqrt{2}$, $\sigma = \pi$

The collection of all 40 Gabor kernels is called a filter bank. An example can be found in Figure 3.

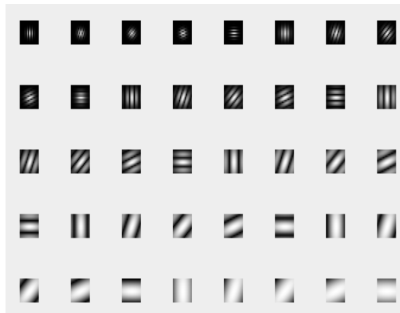

FIGURE 3: Gabor filters of size 16 × 16 by 8 orientations and 5 Resolutions (real part).

The Fourier Gabor wavelet representation of an image is the convolution of the Fourier image with the Fourier filter bank. The convolution of Fourier image F(I) and a Fourier Gabor kernel F(ψμ,v (x,y)) is defined as follows:

$$O_{\mu v}(x,y) = F\left(I(x,y)\right) * F\left(\psi_{\mu v}(x,y)\right) \quad (4)$$

and called Fourier Gabor feature. As the response Oμ,v(x,y) to each Fourier Gabor kernel is a complex function with a real part : Real{ Oμ,v(x,y)} and an imaginary part : Imag{ Oμ,v(x,y)},we use its real Real{ Oμ,v(x,y)} to represent the Fourier Gabor features.The complete set of Gabor wavelet representations of the image I(x,y) is:

$$G(I) = \{O_{\mu v}(x,y) : \mu \in \{0,..,7\}, v \in \{0,..,4\}\} \quad (5)$$

The resulting features for each orientation, scale are referred to as Fourier Gabor feature vector.The following algorithm shows the steps of respectful representation of the face with Fourier-Gabor filters.

- Algorithm 1:

1. Prepare 5 × 8 matrix Gabor each of size 16 × 16 as shown (Figure 3).

2. Apply the Fourier transform to each matrix Gabor.

3. Apply Fourier to each image in the training set of size 32×32.

4. Convolution of the Fourier transform of the image size 32×32 by each image of the Fourier transformed Gabor size 16 × 16 (8 orientations and 5 scales) .

5. Construct the image Fourier_Gabor_IMG (5×8×32×32) from the sub images (32×32 obtained in step 4) (Figure 4).

FIGURE 4: Fourier_Gabor_IMG (5×8×32×32) Results Convolution of Fourier transformed image (32 × 32) for the Fourier transformed of each Gabor filter 16× 16.

The use of Gabor filters is very expensive in computing time, due to the convolution of the whole image with filter size 16 × 16. For this reason, we limit the use of the image size of 32 × 32 convolved with 40 Gabor filters: 8 orientations and 5 scales, then we resize the image result (Fourier_Gabor_IMG) to 100*100,and Finally we reduce the vector of features by applying the method of random projection.

2.2.4 Sparse Random Projection

In the computer vision literature, many schemes have been investigated for finding projections that better represent data in lower-dimensional spaces. One benefit of feature extraction, which carries over to the proposed sparse representation framework, is reduced data dimension and computational cost. The choice of feature transformation is considered critical to the success of the algorithm.

Random Projection has been applied on various types of problems like machine learning [16]. Its power comes from the strong theoretical results that guarantee a very high chance of success [11].

Bingham. et al [17] present experimental results on using RP as a dimensionality reduction tool, their application areas were the processing of both noisy and noiseless images, and information retrieval in text documents. They show that projecting the data onto a random lower-dimensional subspace yields results comparable to conventional dimensionality reduction methods such as PCA and RP is computationally significantly less expensive than it.

Let $X \in R^n$ .The method multiplies X by a random matrix $RP \in R^{n*k}$: $Y^k = RP * X$

The idea is to preserve as much the “structure” of the data while reducing the number of dimensions it possesses; Projections are based on the Johnson-Lindenstrauss lemma [19] that states that a set of n points in a high dimensional Euclidean space can be mapped down onto a $k\rangle = o\left(\frac{\log(n)}{\varepsilon^2}\right)$ dimensional subspace and provided that RP has i.i.d. entries with zero mean and unit variance[18].

Initially, random projections were done with a normal matrix, where each entry rij was an independent, identically distributed N(0, 1) variable with not orthogonal subspace.

Achlioptas provided the sparse matrix projection that refer to a powerful concentration bounds(s=3 and s=1)[19]

Recently, Li et al. generalize Achlioptas’ result by providing the very-sparse projection matrix, they show that s>>3 can be used (for example $s = \frac{n}{\log(n)}$ [20]).

$$r_{ij} = +\sqrt{s} \begin{cases} +1 & p = \frac{1}{2s} \\ 0 & p = 1 - \frac{1}{s} \\ 1 & p = \frac{1}{2s} \end{cases} \qquad (5)$$

The Johnson-Lindenstrauss lemma proof that we can reduce to k> O(log(n)/є2) dimension in order to approximately preserve pairwise distances up to a factor of (1±є). Practically it is interested to get some explicit formula for k.

A series of simplifications to the original proof of Johnson and Lindenstrauss, culminating showed that: $k\rangle = \frac{Log(n) \ * \ 4}{\frac{\varepsilon^2}{2} - \frac{\varepsilon^3}{3}}$

This is not a strict lower-bound but deduce that the pairwise distance is probably preserved with the Johnson-Lindenstrauss guarantees[11]. We will test in the experimental section how the rate of recognition is affected with different values of k when using sparse random projection with s=1. After the generation of vector features with reduced dimension, back propagation neural network is applied for recognition.

2.3 Back propagation Neural Network

An artificial neural network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems process information. It is configured for a specific application through a specific learning process. The most commonly used family of neural networks for pattern classification tasks is the feed-forward network, which includes multilayer perceptron and Radial-Basis Function (RBF) networks.

Back propagation is a feed forward supervised learning network. The general idea with the backpropagation algorithm is to use gradient descent to update the weights to minimize the squared error between the network output values and the target output values. The update rules are derived by taking the partial derivative of the error function with respect to the weights to determine each weight's contribution to the error. Then, each weight is adjusted. This process occurs iteratively for each layer of the network, starting with the last set of weights, and working back towards the input layer, hence the name "backpropagation". The network is trained to perform its ability to respond correctly to the input patterns that are used for training and to provide good response to input that are similar.
The general overview used for the recognition task is as follow:

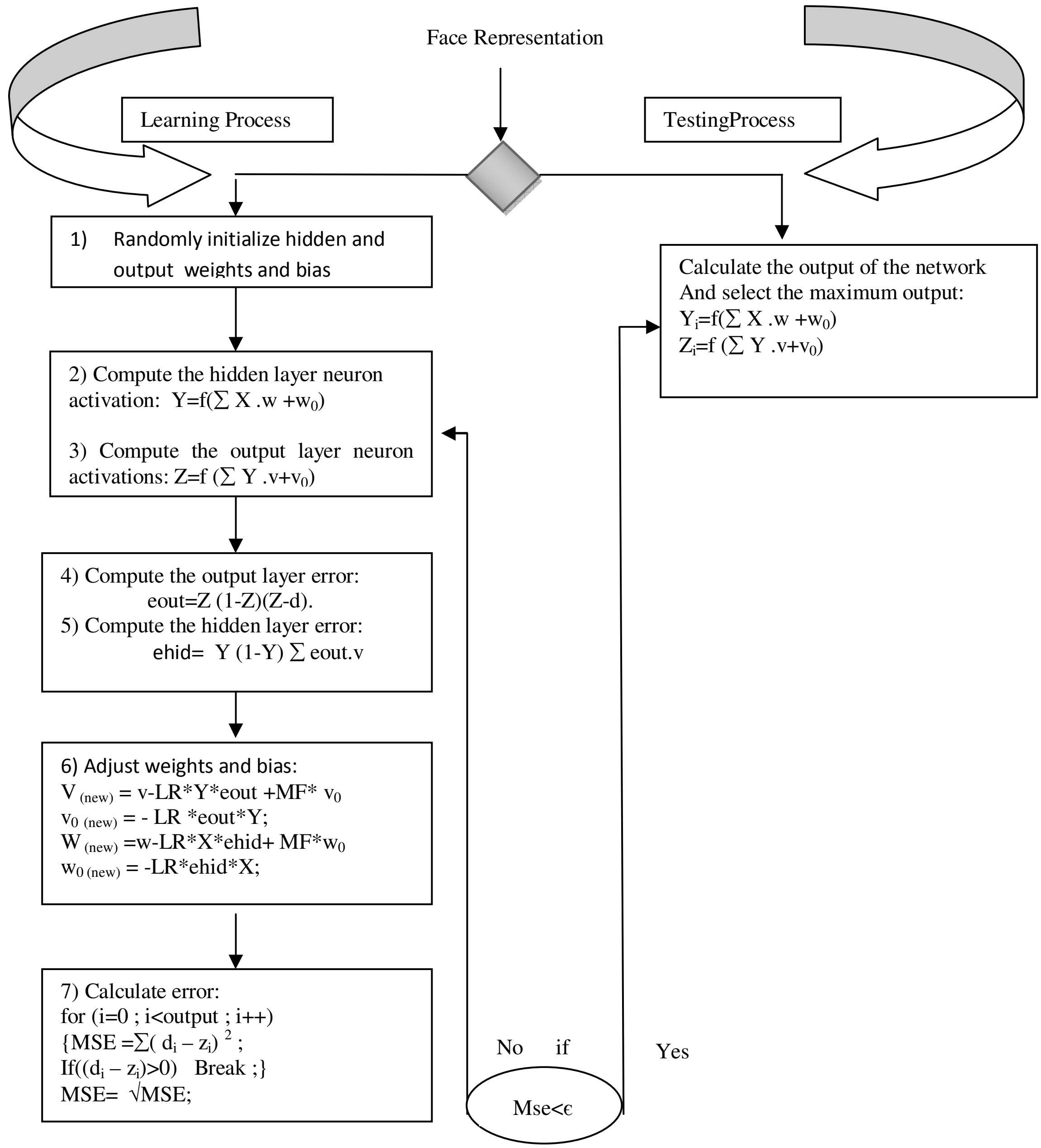

FIGURE 5: The recognition process.

Where X the vector of input layer neurons, Y is the vector of the hidden layer neurons, and Z represents the output layer neurons. w is the weight matrix between the input and the hidden layer. w_0 is the bias of the hidden layer neurons. v is the weight matrix connecting the hidden and the output layers, and v_0 is the bias of the output layer neurons. eout is the error vector for output neurons and ehid is the error vector of each hidden layer neuron and d is the desired output vector.
LR and MF are learning rate and momentum factor.

The sigmoid activation function is defined by: $f(x) = \frac{1}{(1+\exp(-x))}$

3. EXPERIMENTATION AND RESULTS

In [22] authors compare RP with PCA, their results show that PCA performs better than RP mostly for low dimensions (20-30). This result is consistent with previous studies where it has been reported that RP compares favorably with PCA for moderate or higher number of dimensions. It is clear as shown in Figure 6, that in the high dimension RP become more effective than ACP.

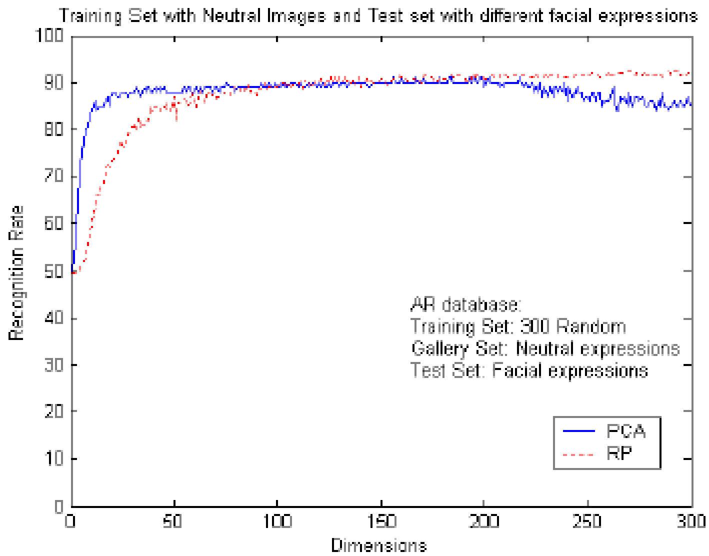

FIGURE 6: Experiments using the AR database and majority voting. The subjects in the training set were chosen randomly. The proportion of subjects in the gallery and test sets varies (neutral versus facial expressions). The blue line corresponds to PCA using closest match, while the red line corresponds to RP using majority voting [21].

In our experiments, the face image database used is a collect of 20 Persons from database [22]. These face images varies in facial expression and motion. Each person is represented by 20 samples, 10 are used for training and 10 for test.
We implement the algorithm described above and we evaluate how the rate of recognition is affected using sparse random projection (s=1) and using the lower-bound value proposed by Johnson-Lindenstrauss[11] .

$$k \rangle K_0 = \frac{Log(n) \;\; * \;\; 4}{\frac{\varepsilon^2}{2} - \frac{\varepsilon^3}{3}}$$

Then we compare the obtained results with results obtained without applying the random projection i.e. using the original data.
Some scenarios of Training are presented in the following: The error is set to 0.0009 for stopping condition.
Case1: length of the original feature vector n=10000
Case2: length of the feature original vector n=1000
Case3: length of the original feature vector and applied sparse RP with s=1 and k=260

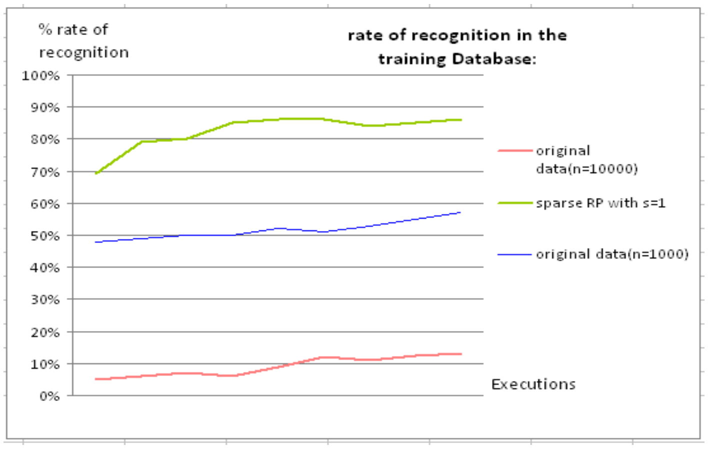

FIGURE 7: Curve of rate of recognition with original data and when applying sparse RP.

We remark that when n=10000, the rate of recognition with original data do not surpass 10%, with n=10000 is between 40% and 60% whereas it attends 87% when introducing RP(s=1 and k=260). Is seems clearly that original data cannot be adopted to train de neural network.

Some query and recognized image are shown in Figure 8.

a) Query images b) Recognized images

FIGURE 8: Example of input and output of our system

Since our features extraction vectors have high dimension, we assume that random projection is an adequate method of dimensionality reduction. In the case of our study, obtain a higher FR rate depends on the choice of the random projection matrix and the dimension of the feature vector of original data.

4. CONCLUSION AND PERSPECTIVES

This paper develops technique to extract the features vector of the whole face in image DB by using Gabor filters which are known to be invariant to illumination and facial expression.

We introduce 8 different orientations and 5 different resolutions to extract the maximum of information, to reduce the dimension of the result vector, we apply sparse random projection, it provides many advantages: it is easy to implement, fast and more effective when compared to other methods. BPNN is then applied to perform the recognition task. Our network achieves higher recognition rate and better classification efficiency when the feature vectors have low-dimensions. This solution was implemented using Java environment. The effectiveness of the proposed method is demonstrated by the experimental results.

In the future, local feature extracted methods will be investigated for classification.

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