ISSN 2229-5518

# Face Recognition based on Gabor Wavelet and Backpropagation Neural Network

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**Abstract**—Face recognition is an efficient biometric technique which automatically identifies the face of an individual from adatabase of images. This paper proposes a face recognition technique using Gabor wavelet and Backpropagation Neural Network. Although there are so many existing methods, the illumination changes, out of plane rotations and occlusions still remain as challenging problems. In the proposed method, Gabor wavelet coefficients are used for creating feature vector due to its representative capability of the primary visual cortex of Human Visual System. The method also uses Principal Component Analysis for dimensionality reduction. The reduced feature vector is used as the input of the classifier, the Backpropagation neural network. Face recognition has many applications in a variety of fields such as access control, authentication and public surveillance.

**Index Terms**—Backpropagation Neural Network,Convolution, Face recognition, Feature extraction, Fourier transform, Gabor wavelet, k-nearest neighbor, Principal Component Analysis.

## 1 Introduction

With the advancement of digital technology, automatic personal identification has become a vital part in all areas of life. Face recognition [1] is preferred over traditional (password, pin number) and token-based methods which can easily be forgotten or hacked by an intruder. Face recognition is also preferred to other biometric techniques like iris, fingerprint etc. because it doesn't require any physical contact of the person and it's closely related to human's capability of recognizing a person. The face recognition technology has a wide range of commercial and law enforcement applications like security surveillance, authentication, access control and human computer interfaces.This paper is organized as follows: Section 2 gives a briefing on the previous methods of face recognition, Section 3, 4, 5 explains the Gabor wavelet, PCA and BPNN respectively, Section 4 details the proposed method, Section6 gives the results and Section 7 concludes the paper.

## 2 Previous Work

Face recognition methods can generally be classified as analytic, holistic and hybrid methods [2]. Analytic or feature-based methods uses the shape, distance or angle measures between main features of the face like eyes, nostrils, eyebrows, chin etc. Two common analytic methods[3] are template based analytic methods and geometrical feature based analytic methods.Holistic or global methods use the information from the entire face to recognize a face. Common global methods include Principal Component Analysis(PCA) [4],[5] and Linear Discriminant Analysis(LDA) where, PCA is mainly used for dimensionality reduction as it maximizes the intra-class scattering and LDA is mainly used for classification as it maximizes the inter-class scattering [6]. Independent Component Analysis(ICA) [7] is another method for extracting statistically independent variables from a mixture of them. ICA in some ways provides useful representation than PCA as it separates higher order moments of the input besides second order moments. Hybrid methods make use of both analytic and global methods.Some of the hybrid methods include Pentlands modular Eigenfaces [8], Active Shape Model (ASM) and Active Appearance Model (AAM) [9].These methods extract features tooptimally represent faces belonging to a class and to separatefaces from different classes. Ideally, it is desirable to use onlyfeatures having high separability power [10].Most of the efforts have been used to develop powerfulmethods for feature extraction and to employclassifiers like Support Vector Machine (SVM) [11],Hidden Markov Models (HMMs) [12], Neural Networks [13]for efficient classification.

Despite remarkable progress so far, the general task of face recognition remains a challenging problem due to complex distortions caused by various variations in illumination,scaling etc. It is widely believed that local features in face images are more robust against such distortions and a spatial-frequency analysis is often desirable to extract such features. With good characteristics of space-frequency localization, wavelet analysis [14] seems to be the right choice for this purpose. In particular, among various wavelet bases Gabor functions provide the optimized resolution in both the spatial and frequency domains which is used in the proposed method.

In this paper, the method uses Gabor wavelet,which closely resembles human vision, is used for feature extraction, PCA for dimensionality reduction and BPNN for classification. Gabor wavelets are Gaussian kernel function modulated by a sinusoidal plane wave. Among various available wavelet transforms, Gabor wavelet is used because of the biological (best models the primary visual cortex, of human visual system, comprising of millions of cells each of which has a specific position, frequency and orientation) and mathematical (multi resolution and multi orientation properties) motivations.

## 32D GABOR WAVELETS

The mathematical origins of Gabor wavelets show that they analyze images with the optimal spatial and frequency resolution. Motivated by the similarity of the 2D Gabor wavelet and the receptive field of the simple cells of the mammalian visual system, the wavelet family will be applied to extract local features from face images for recognition. Such local features will be robust against distortions caused by various expression, pose and illumination changes[15],[16],[17].

A family of 2D Gabor wavelets is formed by modulating a complex sinusoid by a Gaussian function where each wavelet is defined by:

$$\emptyset_{(u,v)}(z) = \frac{\left|k_{u,v}\right|^2}{\sigma^2} e^{-\left\|k_{u,v}\right\|^2 \|z\|^2 / 2\sigma^2} \left[e^{ik_{u,v}z} - e^{-\left(\frac{\sigma^2}{2}\right)}\right] \quad (1)$$

where, u and v define the orientation and scale of Gabor kernels, respectively, z=(x, y) is the co-ordinate vector,
$k_{u,v}$is the frequency vector which determines the scale and orientation of Gabor kernels i.e.

$$k_{(u,v)} = k_v e^{i\emptyset_u}$$

$$where, k_v = \frac{k_{max}}{f^v} \text{ and } k_{max} = \frac{\pi}{2},\ \emptyset_u = \frac{\pi u}{8}, u = 0, \ldots, 7$$

and f is the central frequency of the sinusoidal plane wave,$f_{max}$is the highest peak frequency and $\sigma$ is the spacing factor.

The term$e^{-\left(\frac{\sigma^2}{2}\right)}$is subtracted inorder to make the kernel DC free, thus making it insensitive to illumination effects.

In this work, Gabor wavelets at five different scales u =0…4 and 8 different orientations v=0…7 are used, giving a total of 40 Gabor wavelets which is shown in Fig. 1.

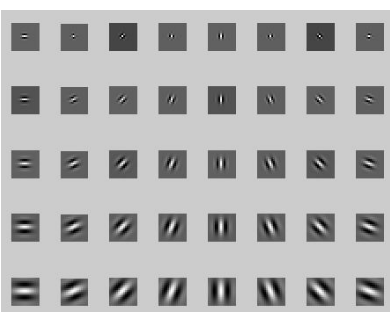

Fig. 1. Family of 40 Gabor wavelets

As the Gabor wavelets give strong response with respect to spatial location and orientation which are the characteristics of an image, it's the most suitable for feature extraction.

## 4 PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis or Karhunen-Loeve transformation is the method for reducing the dimensionality of a dataset, while retaining the majority of variation, present in the dataset. Thus PCA can be effectively used for data reduction and feature extraction. A face image in 2D with size N x N can also be written as 1D vector of dimension $N^2$.A group of images map to a collection of points in this huge space. PCA can find vectors that best account for the distribution of face images within the entire image space. These vectors represent subspace of the face images, called as "face space". Each of these vectors of length $N^2$, describes an N x N image and is a linear combination of the original face images. [18] The main steps of PCA are as follows:

1. Training set of images with 1D vector representation is formed as $I_1,I_2\ldots I_M$, where M is the number of training images.
2. Find the average matrix μ and subtract the mean from each of the images to get
   $\mu = \frac{1}{M}\sum_{n=1}^{M} I_n$and
   $\emptyset = I_i - \mu$ (2)
3. Calculate the covariance matrix A using
   $A = \emptyset^T \emptyset$ (3)
4. Calculate the Eigen vectors $X_i$ and Eigen values $\propto_i$ of the covariance matrix.
5. Calculate eigen images using $[\emptyset]\, X_i = f_i$ (4)
   where, $X_i$ are Eigen vectors and $f_i$ are Eigen images.

The new image is projected onto the Eigen space T by a simple operation, $w_k = X_k^T\,(T - \mu)$, for k=1…M. (5)

Weights w=[w1 w2 …] form a projection vector describing the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images. The projection vector is then used in a standard pattern recognition algorithm to identify which of a number of predefined face classes, if any, best describes the face. Thus, after application of PCA, the calculations become simpler as the dimensionsare reduced from the order of number of pixels in the images ($N^2$) to the order of the number of images in the training set (M).

## 5 BACKPROPAGATION NEURAL NETWORK

In its most general form, a neural network is a machine that is designed to model theway in which the brain performs a particular task or function of interest.To achieve goodperformance, neural networks employ a massive interconnection of simple computingcells referred to as neurons or processing units.A neural network is a massively paralleldistributed processor that has a natural propensity for storing experiential knowledgeand making it available for use. It resembles the brain in two respects: 1. Knowledge isacquired by the network through a learning process. 2. Interneuron connection strengthsknown as synaptic weights are used to store the knowledge. [19]

Backpropagation neural network comprises of an input layer whose number of neurons is same as the size of the input vector, one or more hidden layers (as the application demands) and an output layer whose number of neurons are same as the number of output classes. The architecture is shown below:

ISSN 2229-5518

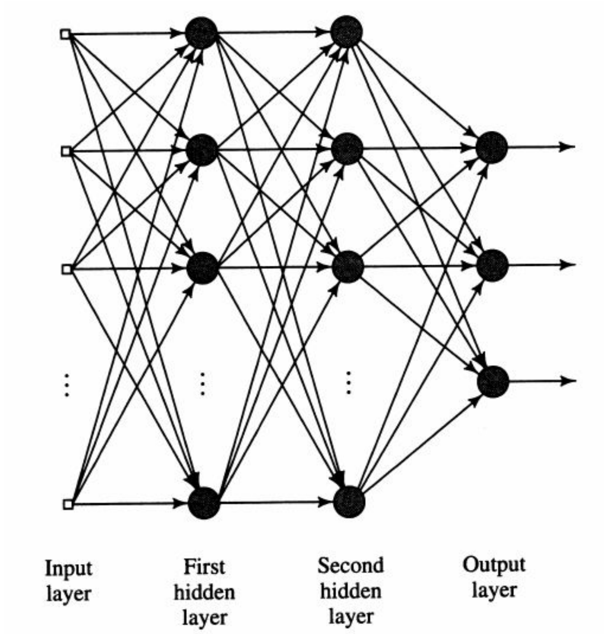


Fig. 2. Feedforward Backpropagation Neural Network

Multilayer perceptrons have been applied successfully to solve some difficult diverse problems by training them in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm. Basically, the error back-propagation process consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, activity pattern (input vector) is applied to the sensory nodes of the network, and its effect propagates through the network, layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of network are all fixed. During the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with the error-correction rule. Specifically, the actual response of the network is subtracted from a desired (target) response to produce an error signal. This error signal is then propagated backward through the network, against direction of synaptic connections - hence the name error back-propagation. The synaptic weights are adjusted so as to make the actual response of the network move closer the desired response. The error back-propagation algorithm is also referred to as the back-propagation algorithm, or simply back-prop.

## 6 Proposed System

The proposed method uses Gabor wavelet for feature extraction, PCA for dimensionality reduction and reduced feature vector is classified using Backpropagation Neural Network. The architecture of the proposed method is given below:

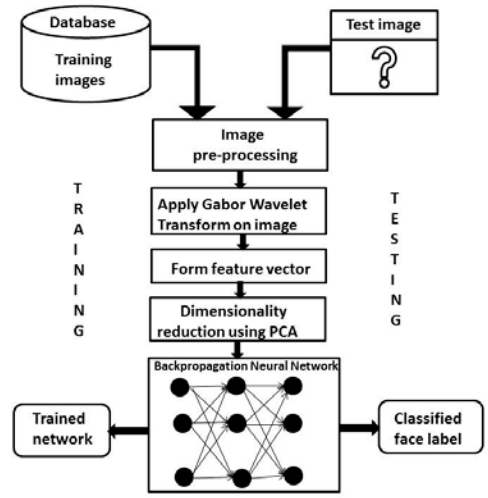


Fig. 3. Architecture of the proposed system

### 6.1 Image pre-processing

In this step, first we resize the images. After that histogram equalization is done on all input images in order to spread energy of all pixels inside the image. An example of pre-processed image is shown below:

Fig. 4. Example of pre-processed image [21]

The preprocessed images are used for further processing.

### 6.2 Feature Extraction

#### *6.2.1 Convolution with Gabor wavelets*

The pre-processed images are convolved with Gabor wavelets to get the Gabor representation of an image. To make the calculations easy, we find the Fourier transform of both image and Gabor wavelet and multiply, instead of the convolution operation. Hence, if I *is the* input image, the convolution output of image $I$ and a Gabor kernel $\Psi u,v$ is defined as

$$GW_{u,v}(z) = I(z) * \emptyset_{(u,v)}(z) \quad (6)$$

This step is depicted in the figure below:

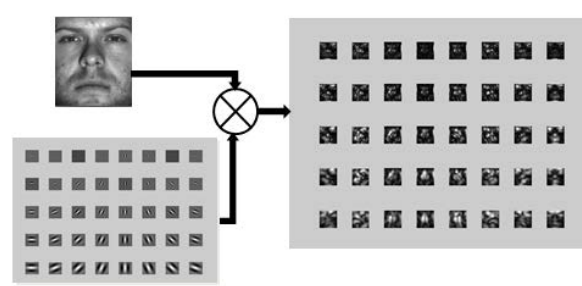

Fig. 5. Convolution of image with 40 Gabor wavelets

The transform coefficients obtained after convolution with the Gabor wavelets is used for creating feature vector.

ISSN 2229-5518

#### 6.2.2 Formation of feature vector

The steps to form the feature vector are as follows[20] :

1. Convolve the original face image with all the 40 Gabor wavelets. $G_I$ is the resultant image after finding the modulus of the convolution outputs, where, I=1, 2… k, k= total number of Gabor kernels. Here k=40.
2. Obtain the single Gabor transformed image by summing $G_I$'s i. e, $G_{IF}=\sum_{I=1}^{k} G_I$(7)
   Where, k=total number of Gabor kernels.
3. Compute the overall mean of the final Gabor transformed image $G_{IF}$ as, $\bar{g} = \left(\frac{1}{m \times n}\right)\sum_{x,y} G_{IF}(x, y)$ (8)
   where, m x n is the size of the image.
4. Divide $G_{IF}$ into windows of size w x w. Thus the total number of windows,$l = \lfloor w/m \rfloor \times \lfloor w/n \rfloor$ (9)
5. For each window $w_i$ ,

a) If$minimum(w_i) \leq \bar{g}$, extract a block $B_i$ of size c x c from $w_i$, with center pixel as minimum($w_i$). The value of c must be an odd integer and less than w/2.

b) If$minimum(w_i) \leq \bar{g}$, and there does not exist a block $B_i$ of size c x c from $w_i$with center pixel as minimum($w_i$), as mentioned in step 5(a), then create a block $B_i$ of size c x c, by considering the unavailable pixel values as $\bar{g}$.

c) If$minimum(w_i) \geq \bar{g}$, then create a block $B_i$ of size c x c with all elements as$\bar{g}$.

6. Extract feature vector $f_i$ from each block $B_i$ column-wise (or, in any systematic order), where $f_i$ contains all elements of the block $B_i$.
7. Concatenate all feature vectors $f_i$, i =1, 2… l to obtain the final feature vector X, which is the low energized feature vector which is of lower dimension than the original image.

Window size should be selected with care in such a way that it must be small enough to capture the most important features and large enough to avoid redundancy. Step 5(c) is done to avoid getting stuck at a local minimum. In this experiment, window of 7 x 7 and block size of 3 x 3 is selected.

### 6.3 Dimensionality Reduction

The extracted feature vector is a huge vector of size 3600 x 1 whose dimension needs to be reduced for easy computation and less processing time. Here, dimensionality reduction is done using Principal Component Analysis. The preprocessed feature vector is used to estimate the covariance matrix. After estimation of the covariance matrix, significant eigenvectors of the covariance matrix are computed. Number of eigenvector depends on the accuracy that the application demands. Selection of large number of eigenvectors will improve the accuracy of the method but computation complexity will increase. Considering these factors, information is taken so that only less information is lost.

In this case, there are 70 training images and 50 principal Eigen vectors are selected. The preprocessed faces are now projected onto the Eigen space with 50 Eigen faces as base vectors to get 70, 50 x 1 vectors.

### 6.4 Classification

Classification is done using Backpropagation neural network. Two hidden layers are used and number of neurons in the hidden layers is found using trial and error method to get the optimal classification. 'nntool' command is used to get the gui of Neural network toolbox using which the classification procedure is done. A snapshot of the GUI is shown below:

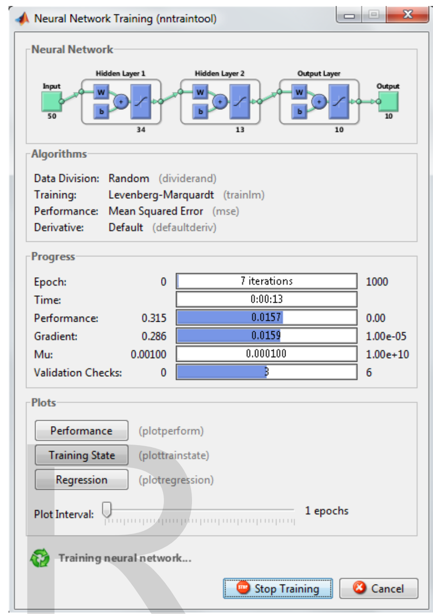


Fig.6. Snapshot of the neural network GUI

'trainlm' is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. It is often the fastest backpropagation algorithm in the toolbox which is used here, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms. This classifier shows a better performance due to its error-resilient property.

## 7 Results and Discussions

The experiment on the proposed method is done for 10 classes for different number of training and test images. It's performed on 2 databases which are described below:

*(A) Yale Face Database*

This database contains 165 gray scale images in .jpg 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, sleepy, surprised and wink. Sample images of a person are given below:

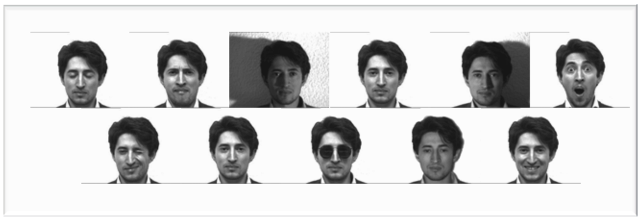

Fig.7. Sample faces of Yale face database [21]

*(B) Yale Face Database B*

This database contains 5760 single light source images of 10 subjects each seen under 576 viewing conditions (9 poses x 64 illumination conditions). For every subject in a particular pose, an image with ambient (background) illumination was also capture. Sample images of a person are given below:

Fig.8. Sample faces of Yale face database B [22]

Recognition rate was observed by varying number of training and testing images on Yale face database. The classification is done both using k-nearest neighbor method with Euclidean distance metric and proposed backpropagation neural network method whose comparison is shown in the table below:

Table 1. Result of the test conducted on Yale database

| No. of training images used for each subject | No. of test images used for each subject | Recognition rate | |
|---|---|---|---|
| | | KNN | BPNN |
| 7 | 4 | 90 | 95 |
| 6 | 5 | 86 | 88 |
| 5 | 6 | 80 | 84 |

Three cases are considered here (Number of training samples taken as 7, 6 and 5). 10 subjects are considered. The recognition rate using BPNN as classifier is found to be higher than the recognition rate using Euclidean distance knn classifier.

Fig. 9 shows the plot of recognition rate versus number of training samples, when the test is carried out on Yale database. The graph shows that the recognition rate for the system using BPNN as classifier is higher.

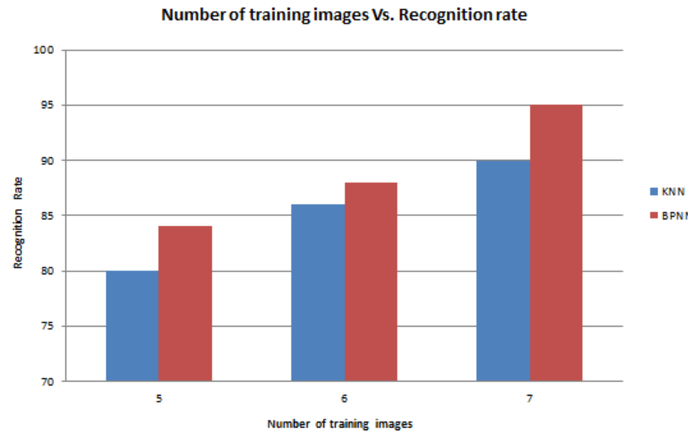


Fig.9. Number of training images Vs. Recognition rate

The above result analyses show that BPNN exhibits a very good performance in terms of recognition rate.

## 8 Conclusion and Future Scope

Motivated by the mathematical background and biological evidence, 2D Gabor wavelets have been widely applied in different computer vision and pattern recognition applications including face recognition. In this paper, BPNN based Face recognition, method is presented. Proposed method consists of four parts: i) Image pre-processing ii) Feature Extraction using Gabor wavelet iii) Dimensionality reduction using PCA and iv) Classification using BPNN.

Gabor wavelet makes the face recognition system more efficient by making it insensitive to illumination, rotation and translation effect which is the drawback of other face recognition methods. Backpropagation Neural Network is used as the classifier and is compared with k-nearest neighbour (KNN) classification. BPNN achieves a better recognition rate of 95% in comparison to KNN.

Future works include enriching the system to attain more human-like recognition capabilities and consequently provide tools that are more targeted to user's actual needs. Also, the method can be extended by using an adaptive classifier like fuzzy ARTMAP, thereby making the system more adaptive to the new inputs which are not in the training database.

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