Gabor features and LDA based Face Recognition with ANN classifier

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Abstract— **Although many approaches for face recognition have been proposed in the past, none of them can overcome the main problem of lighting, pose and orientation. For a real time face recognition system, these constraints are to be a major challenge which has to be addressed. In this proposed work, a methodology is adopted for improving the robustness of a face recognition system based on two well-known statistical modeling methods to represent a face image: Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). These methods extract the discriminant features from the face. Preprocessing of human face image is done using Gabor wavelets which eliminates the variations due to pose, lighting and features to some extent. PCA and LDA extract low dimensional and discriminating feature vectors and these feature vectors were used for classification. The classification stage uses Backpropagation neural network (BPN) as classifier. This proposed system has been successfully tested on ORL face data base with 400 frontal images corresponding to 40 different subjects of variable illumination and facial expressions. The results are compared with standard eigen face method using distance measure as classifier. The system gives a better recognition rate compared to other standard techniques.**

Keywords—**Face recognition; Gabor Wavelet transform; Principal Component Analysis; LDA; ANN.**

I. INTRODUCTION

Human face detection and recognition is one of an energetic area of study, straddling a number of disciplines such as pattern recognition, image processing and computer vision with wide range of applications such as identity verification, video-surveillance, facial expression extraction, and advanced human-computer interaction. A necessitate to develop robust face recognition algorithm is due to highly complex distribution and worse recognition performance as a result of wide-range variations of human face due to pose, illumination, and expression. In typical face recognition system, pre processing is used to reduce noise and reliance on precise registration. Classification is done using artificial neural networks. In this paper the feature extraction is addressed by using Gabor wavelets and PCA on face images. The methods for face recognition can be divided into two different classes: template matching and geometrical features matching. A good survey of face recognition system is found in [1].

Block diagram of a typical face recognition system is shown in Fig. 1.

Figure 1. Block diagram of a typical face recognition system

In template matching, the face image is represented as a two-dimensional array of intensity values and this is compared to a single or several templates representing a whole face. In geometrical features matching, some geometrical measures about idiosyncratic facial features such as eyes, mouth, nose are extracted. With this extracted facial features, the recognition is done. The choice of the features used by the classifier results in good sensation of any face recognition method. In pattern recognition, the feature selection from the raw input data can be accomplished using a standard feature extraction method. By such methods the data used for processing are much reduced and also made simpler to provide better discriminating ability.

The salient local features that are most suitable for face recognition are obtained using Gabor filters from the raw image. The pre processing is done using Gabor filters and forms a feature vector called gabor features of face images. Gabor transformed face images exhibit strong characteristics of spatial locality, scale, and orientation selectivity. The face is treated as a two-dimensional pattern of intensity variation in template matching. In template matching approach, face is matched through identifying its underlying statistical regularities. Principle Component Analysis (PCA) is one of the popular methods for feature selection and dimensionality reduction. Recognition of human faces using PCA was first done by Turk and Pentland [2] and Reconstruction of human faces was done by Kirby and Sirovich [3]. The recognition method, known as eigenface method defines a feature space which reduces the dimensionality of the original data space. This reduced data space is used for recognition. But poor discriminating power within the class and large computational load are the well known common problems in PCA method. This limitation is prevailing over by Linear Discriminant Analysis (LDA). LDA is one of the most dominant algorithms for feature selection in appearance based methods [4]. But many LDA based face recognition system first use the PCA to project face space and then perform LDA to maximize the discriminating power of feature selection. The reason is that LDA has the small sample size problem in which dataset selected should have larger samples per class for good discriminating features extraction. Thus implementing LDA directly results in poor extraction of discriminating features. The extracted features from the test and the train sections are classified using Artificial Neural Networks.

In the proposed method, the frontal face images are filtered using Gabor filters and PCA is used to reduce these filtered feature vectors dimension. These reduced dimension vectors are taken as input to the statistical model (LDA) for feature extraction. In comparison with the conventional use of PCA, the proposed method gives better recognition rate and discriminatory power. In the proposed approach ORL face database with 400 frontal face images is taken in which 200 samples for training and 200 samples for training the algorithm. The probability of the new algorithm has been demonstrated by experimental results.

This paper is organized as follows. Section 2 deals with the basics of Gabor wavelets and Gabor features. Section 3 reviews the background of PCA and eigenfaces. Section 4 deals with LDA. Section 5 deals with classification using ANN. Section 6 reports the proposed method. Experimental results are offered in section 7 and after all, section 8 gives the conclusion.

II. Gabor Wavelets

In face recognition system the feature based method finds the important features on the face and represents them in an efficient way. Physiological studies found that the cells in the human virtual cortex can be selectively tuned to orientation and to spatial frequency. This confirmation that the response of the simple cell could be approximated using 2D gabor filters is given by J.G.Daugmann [5]. Gabor filters were introduced in image processing because of their biological relevance and computational properties [6, 7]. The kernels of gabor wavelets are similar to 2D receptive field profiles of the mammalian cortical simple cells. These kernels exhibit desirable characteristics of orientation selectivity and spatial locality. The extraction of local features in an image can be effectively done using gabor wavelets. Using Gabor wavelets is robust to illumination, poses and facial expression changes. Considering all Gabor kernels, all the features are concatenated to form a single gabor feature vector. Then this high dimensional gabor vector space is much reduced by applying statistical modelling methods first PCA and then LDA to obtain more independent and discriminating features.

The Gabor wavelets (filters, kernels) can be defined by

$$\Psi_{\mu,v}(z)= \|k\mu,v\|^2 e^{\frac{\|k\mu,v\|^2\ \|z\|^2}{2\sigma^2}} \left[e^{ik\mu,vZ} - e^{-\frac{\sigma^2}{2}}\right] \qquad (1)$$

where $k_{\mu,v}$ is the wave vector defined in (2), μ and v defines the orientation and scale of Gabor kernels, z=(x,y) and ||.||denotes the norm vector.

$$k_{\mu,v} = k_v e^{i\Phi\mu} \qquad (2)$$

where $k_v = k_{max} / f_v$ and $\varphi_\mu = \pi\mu/8$. k_{max} is the maximum frequency, and f is the spacing factor between kernels in the frequency domain . All the Gabor kernels are self similar since they are generated by scaling and rotation from mother vector using the wave vector given in (2). For representational purpose in most cases the Gabor wavelets of five different scales, v ϵ{0,1,2,3,4} and eight orientation μ ϵ {0,….7} are used. The Gabor wavelet representation of an image is the convolution of the image with a family of Gabor kernels as defined by (3). Let I(z) be the gray level distribution of an image, the convolution of image I and a Gabor kernel $\psi_{\mu,v}$ is defined as follows.

$$O_{\mu,v}(z) = I(z) * \psi_{\mu,v}(z) \qquad (3)$$

where z = (x,y). * denotes the convolution operator, and $O_{\mu,v}$ (z) is the convolution result corresponding to the Gabor kernel at orientation μ and scale v. Therefore, the set $S = \{O_{\mu,v}(z) : , \mu \in \{0,\ldots.7\}, v \in \{0,\ldots.4\}\}$ forms the Gabor wavelet representation of the image I(z) [8].

Applying the convolution theorem, we can derive each $O_{\mu,v}$ (z) from (3) through Fast Fourier Transform (FFT):

$$F\{ O_{\mu,v}(z) \} = F\{I(z)\} F\{ \psi_{\mu,v}(z)\} \qquad (4)$$

$$O_{\mu,v}(z) = F^{-1}\{ F\{I(z)\} F\{ \psi_{\mu,v}(z)\}\} \qquad (5)$$

Where F and F^{-1} denote the Fourier and inverse Fourier transform, respectively. Fig. 2 & 3 shows the Gabor wavelet representation (the real part of gabor kernels with five scales and eight orientations and the magnitude of gabor kernels at five different scales). The input frontal face image as shown in Fig. 4 is preprocessed using these kernels and the resultant convolution output of the image

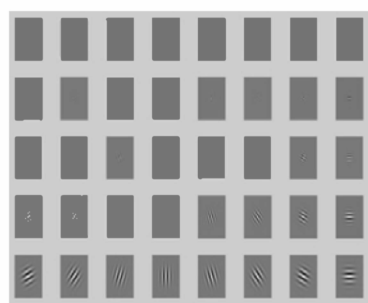

Figure 2. Gabor Kernels
(Real part with five scales and eight orientations)

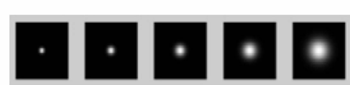

Figure 3. Magnitude of Gabor Kernel at five different scales.

and the kernels are as shown in Fig. 5 and Fig. 6. Concatenating all these gabor representation is done to encompass different spatial frequencies (scales), spatial localities, and orientation selectivity into a single augmented feature vector given in (6). Before concatenation, first down sample each $O_{\mu,v}$ (z) by a factor ρ to reduce the space dimension. Then construct a vector out of the $O_{\mu,v}(z)$ by concatenating its rows (or columns). Now, let $O^{\rho}_{\mu,v}$ denote the normalized vector constructed from $O_{\mu,v}(z)$ (down sampled by ρ), the augmented Gabor feature vector $X^{(\rho)}$ is then defined as follows:

$$X^{(\rho)} = (O^{(\rho)t}_{0,0}\ \ O^{(\rho)t}_{0,1} \ldots\ldots O^{(\rho)t}_{4,7}) \qquad (6)$$

Where t is the transpose operator. The augmented Gabor feature vector thus encompasses all the elements (down sampled) of the Gabor wavelet representation set, $S = \{O_{\mu,v}(z) : \mu \epsilon \{0,\ldots.7\}, v \epsilon \{0,\ldots.4\}\}$ as important discriminating information. Fig. 6 shows (in image form rather than in vector form) an example of the augmented Gabor feature vector, where the down sampling factor is 64, i.e. ρ = 64.

III. Principal Component Analysis

In image recognition and compression, Principal Component Analysis (PCA) is one of the most successful techniques. The large dimensionality of the data space (observed variables) is reduced to the smaller intrinsic dimensionality of feature space (independent variables). This is the case when there is a strong correlation between observed variables and main purpose of using PCA. Using PCA it is capable of transforming each original image of the training set into a corresponding eigenface. The reconstruction of any original image from the training set by combining the eigenfaces is an important feature of PCA which are nothing but characteristic features of the faces. Consequently by adding up all the eigenfaces in the right proportion the original face image can be reconstructed. Each eigenface represents only certain features of the face, which may or may not be present in the original image. If the particular feature is not present in the original image, then the corresponding eigenface should contribute a smaller part to the sum of eigenfaces. If, by contrary, the feature is present in the original image to a higher degree, the share of the corresponding eigenface in the "sum" of the eigenfaces should be greater. So, the reconstructed original image is equal to a sum of all eigenfaces, with each eigenface having a certain weight and this weight specifies, to what degree the specific feature (eigenface) is present in the original image.. That is in order to reconstruct the original image from the eigenfaces, building a kind of weighted sum of all eigenfaces is required. By using all the eigenfaces extracted from original images, exact reconstruction of the original images is possible. by choosing only the most important features (eigenfaces) losses due to omitting some of the eigenfaces can be minimized [3]. Suppose there are *C* classes in the training data. PCA is based on the sample covariance which characterizes the scatter of the entire data set, irrespective of class-membership. The projection axes chosen by PCA might not provide good discrimination power.

Figure 4. Sample frontal image

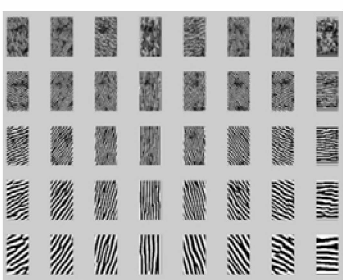

Figure 5. Real part of the convolution output of the sample image

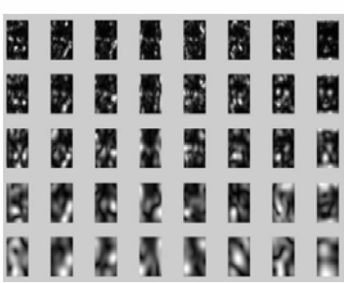

Figure 6. Magnitude of the convolution output of the sample image

The detailed description of PCA is given in the following section:

A: Mathematics of PCA

A 2-D facial image can be represented as 1-D vector by concatenating each row (or column) into a single column (or row) vector.

1) We assume the training sets of images are $\Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_m$, with each image I(x,y). where (x,y) is the size of the image. Convert each image into set of vectors and new full-size matrix (mxp) , where m is the number of training images and *p* is *x* x *y* the size of the image.

2) Find the mean face by:

$$\Psi = \frac{1}{m}\sum_{i=1}^{m} \Gamma_i \qquad (7)$$

3) Calculated the mean-subtracted face:

$$\Phi_i = \Gamma_i - \Psi \qquad (8)$$

i = 1,2,3….m. and a set of matrix is obtained with $A = [\Phi_1, \Phi_2, \ldots\ldots \Phi_m,]$ is the mean-subtracted matrix vector with its size A_{mp}.

4) By implementing the matrix transformations, the vector matrix is reduced by:

$$C_{mm} = A_{mp} \times A^{T}_{pm} \qquad (9)$$

where C is the covariance matrix and T is transpose matrix.

5) Find the eigen vectors V_{mm} and eigen values λ_m from the C matrix and ordered the eigen vectors by highest eigen values.

6) Apply the eigen vector matrix, V_{mm} and adjusted matrix Φ_m. These vectors determine the linear combinations of the training set images to form the eigen faces, U_k by

$$U_k = \sum_{n=1}^{m} \Phi_n V_{kn}, k = 1,2.....,m. \quad (10)$$

7) Instead of using m eigen faces, m′ << m which is considered as the image provided for training for each individual or m′ is the total class used for training.

8) Based on the eigen faces, each image has its face vector by

$$W_k = U^T_k(\Gamma - \Psi), k = 1,2,...., m'. \quad (11)$$

9) The weights form a feature vector.

$$\Omega^T = [w_1, w_2, w_3, \ldots\ldots w_{m'}] \quad (12)$$

This feature vectors are taken as the representational basis for the face images with dimension reduced with m.

10) The reduced data is taken as the input to the next stage for discriminating feature.

IV. Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is also one of the successful methods used for dimensionality reduction for many classification problems. The main intention of this method is to find a projection A that maximizes the ratio of between - class matrix S_b and against within - class scatter S_w. In high dimensional pattern recognition tasks Fisher Discriminant Analysis (FDA) based algorithms has small sample size problem(SSS) which exists where the number of available samples is smaller than the dimensionality of the samples [9]. Due to this problem, many variants of the original FDA algorithm have been proposed for face recognition [10]. Perform dimensionality reduction while preserving as much of the class discriminatory information as possible. LDA Seeks to find directions along which the classes are best separated. Takes into consideration the scatter within-classes but also the scatter between-classes. More capable of distinguishing image variation due to identity from variation due to other sources such as illumination and expression. The LDA is defined by the transformation [11].

$$y_i = W^t x_i \quad (13)$$

The columns of W are the eigenvectors of $S^{-1}_w S_b$, It is possible to show that this choice maximizes the ratio

$$\det(S_b)/ \det(S_w) \quad (14)$$

These matrices are computed as follows:

$$S_w = \sum_{j=1}^{c} \sum_{i=1}^{n_j} (x_i^j - m_j).(x_i^j - m_j)^t \quad (15)$$

Where $m_j = \frac{1}{n} \sum_{i=1}^{n_j} x_i^j$

Where x_i^j is the i-th pattern of j-th class, and n_j is the number of patterns for the j-th class.

$$S_b = \sum_{j=1}^{c} (m_j - m).(m_j - m)^t \quad (16)$$

where $m = \frac{1}{n} \sum_{i=1}^{n} x_i$.The eigenvectors of LDA are called "fisherfaces". LDA transformation dependence on number of classes (c), number of samples (m), and original space dimensionality (d). It is possible to show that there are almost c-1 nonzero eigenvectors. c-1 being the upper bound of the discriminant space dimensionality. We need *d*+*c* samples at least to have a nonsingular S_w [11]. LDA derives a low dimensional representation of a high dimensional face feature vector space. From (15) and (16), the covariance matrix C is obtained as follows,

$$C = S_w^{-1} * S_b \quad (17)$$

The discriminating feature vector is given by the coefficients of the covariance matrix for the LDA method. The transformation matrix w_{LDA} projects the face vector. The projection coefficients are used for the feature representation of each face image. In the proposed scheme the column vectors w_i(i= 1,2…,c-1) of the matrix w are referred as fisherfaces.

V. Classifier

In classification stage, the proposed system uses Backpropagation Neural Network (BPN). Neural Network is suitable for the proposed system as it is once trained can be used for any number of test input. Since ANN has good learning ability, simpler structure, and generalization, it is used with PCA and LDA. Classification phase consists of both training and recognition. The feature vector in train database is used for training the Back Propagation Neural network. As there are 199 features, 199 neurons are used in the input layer.

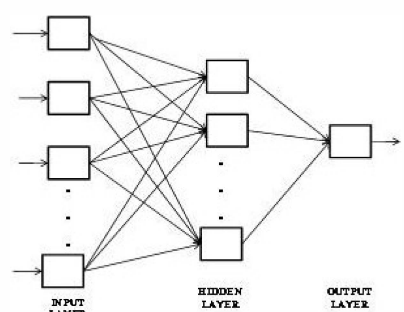

Figure 7. Architecture of BPN

For getting good results, hidden layer neurons are choose as 30 by trial and error basis. Once the Neural Network is trained with feature vectors, it can be applied to new, unknown face images of the same individuals in order to recognize them. To this end, given face image is processed to get test feature vector and presented to the Neural Network.

VI. PROPOSED METHOD

The proposed method uses the ORL database acquired at the Olivetti Research Laboratory. The block diagram of the proposed system is as shown in Fig. 8. The database consists of 400 face images that correspond to 40 individual subjects. In consequence, each theme in the database is represented with 10 different facial images of illumination, pose and facial expression. From this database, 5 images from each class were considered for training and remaining 5 images from each class were used for testing. That is totally 200 images for training the system and 200 images for testing. The images are stored at a resolution of 92×112 and 8-bit grey levels.

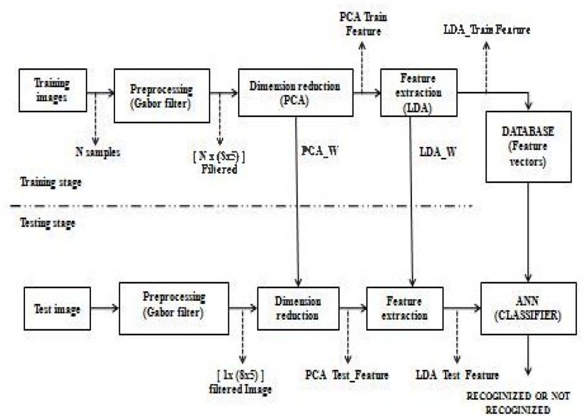

Figure 8. Block diagram of the proposed face recognition system

Face based approach is followed in this system and of two stages, training and recognition. In training, the pre-processing stage uses Gabor. To facilitate the Gabor wavelet representations, the ORL images are scaled to 128x128 using bicubic interpolation. The gabor kernels as defined in Eqn. 1 uses five different scales and eight orientations which results in 40 different filters shown in Fig.2. The input image is convoluted with the Gabor kernel and the convoluted real and magnitude response is given in Fig. 5 & 6. This convoluted feature vector is then down sampled by a factor of $\rho = 64$. An augmented Gabor feature vector is derived from concatenated Gabor wavelet features to encompass all the features produced by the different Gabor kernels.

The resulting high dimension gabor feature vector is taken as input to the next stage. This stage uses the PCA for reducing the dimension of the feature vector and extracts the principle features. Here the eigen vectors were calculated sorted in the ascending order and the top eigen vectors are used for representation of feature vectors (PCA_Feat). Also the weight matrix is computed PCA_W. This eigen projection is then used as input to the next stage of LDA. The same procedure is applied for feature extraction using LDA. Here using PCA_Feat is used as input to the LDA block. The between class (S_b) and within class scatter matrix (S_w) is obtained using this projection matrix. LDA gives the projected weight matrix LDA_W, which is used to find the LDA test features.

Figure 9. Scaled training samples

In the recognition stage, the test samples were taken and the initial pre-processing is done as done for the training frontal images. The test image matrix (Test) is multiplied with PCA_W and this result in test PCA features (PCA_test). This PCA_test when convoluted with LDA_W gives the test features (LDA _test). The classification stage uses BPN. The LDA_Train feature is stored in database as feature vectors. This feature vectors are used as input to train BPN. After training the neural network, test features (LDA _test) for a new, unknown face image of the same individuals is given to trained BPN in order to recognize it.

Figure 10. Scaled test samples

VII. RESULTS AND DISCUSSION

The proposed system is tested with ORL face database and its effectiveness is shown in results. The extracted features is used as it is using the above said feature extraction methods and classification is done using ANN and compared with Euclidean distance measure method. The recognition rate is obtained with fixed number of PCA features. The performance comparison with Euclidean Distance Measure Classifier (ED) is shown in Table I.

TABLE I. PERFORMANCE COMPARISON WITH ED CLASSIFIER.

Euclidean Distance Measure(ED) Classifier		
No. of Features	*GABOR + PCA*	*GABOR + PCA + LDA*
40	87.0	89.5
50	89.3	91.3
66	93.2	94.4
100	93.7	97.3
199	94.1	97.8

The performance comparison with ANN classifier is shown in Table II. The successfulness of the proposed system is compared with some of the popular face recognition schemes like Gabor wavelet based classification, the PCA mehod, and LDA method.

TABLE II. PERFORMANCE COMPARISON WITH ANN CLASSIFIER.

ANN Classifier		
No. of Features	*GABOR + PCA*	*GABOR + PCA + LDA*
40	87.5	90.5
50	91.0	92.3
66	94.2	94.7
100	95.7	97.0
199	96.8	98.6

TABLE III. COMPARISON OF RECOGINITION RATE WITH ED & ANN CLASSIFIER.

GABOR + PCA + LDA		
No. of Features	*ED*	*ANN*
40	89.5	90.5
50	91.3	92.3
66	94.4	94.7
100	97.3	97.0
199	97.8	98.6

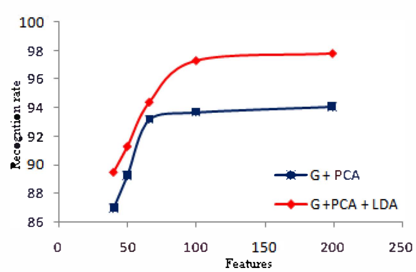

Figure11. Performance comparison with ED classifier.

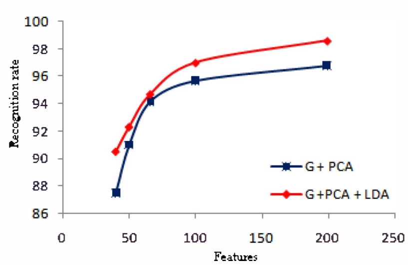

Figure12. Performance comparision with ANN classifier.

VIII. CONCLUSION

In this proposed system, a Gabor feature based method which eliminates the variations due to pose, lighting and features is used to increase the robustness of the face recognition system. For different scales and orientations of the Gabor filter, the input image is convoluted with gabor filters and from this convoluted image feature vectors were formulated using PCA followed by LDA. Using PCA, the high dimensionality of these feature vectors is reduced. LDA method follows PCA to extract the most discriminant features from the input image. This discriminating feature space is used as the training feature space for Backpropagation Neural Network in the classification stage. From the simulation results, it has been found that the recognition rate for the selected database is high with features extracted from LDA and PCA based Gabor methods than simple PCA methods. It is observable from the result, that as the number of features selected in PCA increased, it leads to obtain more discriminating features from LDA and this consecutively also increases the recognition rate. But this in turn increases the computational load. From table III it is clear from the result that the proposed Gabor features based PCA, LDA method following ANN classifier gives better recognition rate.

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