Hybrid Approach for Face Recognition Combining Gabor Wavelet and Linear Discriminant Analysis

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***Abstract*—Face Recognition system finds many applications in surveillance and human computer interaction systems. As the applications using face recognition systems are of much importance and demand more accuracy, more robustness in the face recognition system is expected with less computation time. In this paper, a Hybrid approach for face recognition combining Gabor Wavelet and Linear Discriminant Analysis (HGWLDA) is proposed. The normalized input grayscale image is approximated and reduced in dimension to lower the processing overhead for Gabor filters. This image is convolved with bank of Gabor filters with varying scales and orientations. LDA, a subspace analysis techniques are used to reduce the intra-class space and maximize the inter-class space. The techniques used are 2-dimensional Linear Discriminant Analysis (2D-LDA), 2-dimensional bidirectional LDA ($(2D)^2$LDA), Weighted 2-dimensional bidirectional Linear Discriminant Analysis (Wt $(2D)^2$ LDA). LDA reduces the feature dimension by extracting the features with greater variance. k-NearestNeighbour (k-NN) classifier is used to classify and recognize the test image by comparing its feature with each of the training set features. The HGWLDA approach is robust against illumination conditions as the Gabor features are illumination invariant. This approach also aims at a better recognition rate using less number of features for varying expressions. The performance of the proposed HGWLDA approaches is evaluated using AT&T database, MIT-India face database and faces94 database. It is found that the proposed HGWLDA approach provides better results than the existing Gabor approach.**

Keywords—Face recognition, Gabor wavelet, LDA, k-NN classifier.

I. INTRODUCTION

Face recognition is one of the most useful applications of pattern recognition and image understanding. It has received significant attention during the recent years. This is due to its importance in potential threat applications. It is used in many surveillance applications and human computer interaction systems. The challenging task of deploying face recognition system for surveillance tasks is that it needs fast computation results.

Though many face recognition techniques were proposed in the past, it is still a challenging task due to variations in illumination, expression, etc. Deployment of the face recognition system in real time environment conditions yield results different from that of the test database. The major challenge of face recognition system is that the recognition rate depends on the training set and the database.

Zhao et al [16] in their paper surveyed various face recognition techniques and discussed various applications and pre-processing requisites pertaining to face recognition. The paper also widened the view on classification of the feature extraction methods and tabulated the different existing techniques in holistic and feature-based methods.

There are three approaches – holistic, feature based and hybrid. In holistic approach, the face is considered as a whole without looking for local features. As only global features were considered in this approach, recognition performances were significantly affected by illumination, orientation and scale. Principal Component Analysis (PCA) [16] is a commonly used statistical technique for face recognition. In PCA, the input data is represented by orthogonal projection vector. Eigenspace is a subspace represented by a set of eigenvectors of the covariance matrix of the image data. Linear Discriminant Analysis (LDA) gives the discrimination of within class and between class images. The LDA method constructs an optimal projection of the trained data by maximizing the ratio of the determinant of the between-class scatter matrix of the projected data to the within-class scatter matrix of the projected data.

Elastic Bunch Graph Matching (EBGM) is a feature-based algorithm that efficiently captures facial attributes from a face image. It extracts the facial texture features using Gabor wavelets and generates a level graph [16].

Daugman [8] proposed Gabor representations for analysis, segmentation and compression of image. The paper explained that Gabor transforms have relevance to neuro-scientific way of viewing an image.The weighting functions of Gabor transform use profiles obtained from orientation-selective neurons in visual cortex of brain. Gabor was demonstrated with Lena image that it resembles the way the human brain visualizes the image.

Wonjun et al [13] proposed a model based face recognition system with hybrid approach which is efficient under uncontrolled environment. A combination of Fourier

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transform followed by Principal Component Linear Discriminant Analysis (PCLDA) and fusion of the feature set for face recognition with varying illumination conditions is discussed in the paper. Different features are extracted using Fourier Transform at 3 different eye distances in 3 different frequency domains and 3 different frequency bands and by score fusion, they are used to obtain the similarity index.Zhiqiang et al [17] discussed an extension of $(2D)^2$LDA approach by combining with LPP. $(2D)^2$LDA performs LDA simultaneously on row and column directions thus providing more feature reduction than LDA.

The multi-resolution techniques exploitscaling and wavelet functions to analyse the image at various resolutions to obtain better features. They give better recognition rate but yield high computational cost [1], [6], [8], [11]. Subspace analysis considers *mxn* image as a point in the *N=mxn* dimensional feature space. They extract few remarkable feature points from a large image thus reducing the dimensionality of the image by a considerable amount. But the computational cost is reduced at the cost of recognition rate [2], [5]. So HGWLDA, a hybrid technique with the combination of multi-resolution analysis and frequency domain analysis is proposed which aims at a better recognition rate at varying illumination conditions using lesser number of features without affecting the computation time.

This paper is organized in 3 sections. Section II presents the proposed work that includes 3 stages namely, multiresolution analysis using Gabor wavelets, LDA and testing using *k*-NN classifier. Section III deals with the results and discussions followed by conclusion in section IV.

II. PROPOSED APPROACH– HGWLDA

The workflow for the proposed HGWLDA face recognition systemis given in Fig.1. Gabor wavelet features are proven to be robust in varying illumination conditions but processing time is very large. So the proposed HGWLDA approach aims at decreasing the processing time for Gabor wavelet by reducing the dimensionality and applying approximation which is also illumination invariant. This dimensionality reduced image is fed to Gabor filters.

Gabor mask isthe windowing function which is taken at 5 scales with 8 orientations and each image is convolved with these 40 masks. The 40 Gabor filtered features are subjected to different subspace techniques like 2-dimensional Linear Discriminant Analysis (2D-LDA), 2-dimensional bidirectional LDA ($(2D)^2$ LDA), Weighted 2-dimensional bidirectional Linear Discriminant Analysis (Wt $(2D)^2$ LDA) to extract feature subset from the large feature space of Gabor.

For the test image, the extracted features are compared with each training set features using Euclidean distance as the similarity metric. The minimum Euclidean distance is the matching set provided the Euclidean distance value crosses a particular threshold.

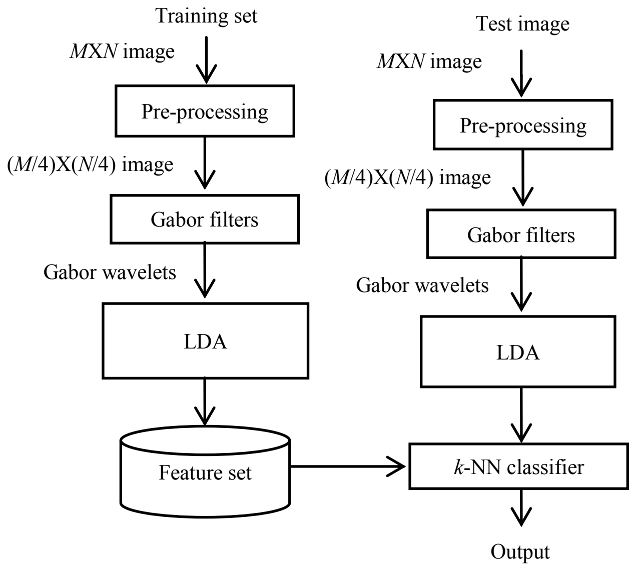

Fig.1. Proposed architecture of HGWLDA

Preprocessing phase intends to reduce the dimensionality of the original image thus considerably reducing the processing overhead for Gabor transform and also making the image illumination invariant. One level of preprocessing involves applying low pass filter to the image and performing row and column-wise down sampling. The reduced approximated information is one fourth the dimension of original image, which is further subjected to another level of preprocessing. This output is equivalent to global low pass image from a two level Discrete Wavelet Transform.

A. Gabor Transform

Fourier transform provides details about the spectral components in time series but it does not yield the time distribution of different frequency. For stationary signal conventional Fourier Transform is a favourable representation, since the frequency components of the stationary signal do not change with time, but in real world almost all the signals are nonstationary. Therefore, conventional Fourier Transform might not be suitable to analyse the real signal.

Short Time Fourier Transform (STFT) has thus been used to do the analysis of frequency with time. STFT, the simplest time-frequency representation, is a two dimensional representation created by computing the Fourier Transform and using a sliding temporal window. The narrow windows yield good time resolution and poor frequency resolution and it is vice versa with wide windows.

Gabor function is one kind of sampled Short Time Fourier Transform (STFT) that gives good time-frequency trade-off. The concept behind Gabor transform is that any signal could be expressed as sum of mutually orthogonal Gaussian envelopes with shift in time and frequency function. Gabor wavelets are biologically motivated because the cells of visual cortex of brains can be modelled and represented by a family of 2D Gabor wavelets.

Gabor filters are complex exponentials with a Gaussian envelope. Gabor filter [8] is given by Eq.1.

$$W(x,y,\theta,\lambda,\varphi,\sigma,\gamma) = e^{-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}} e^{i\left(2\pi\frac{x'}{\lambda}+\varphi\right)} \quad (1)$$

where, $x' = x\cos\theta + y\sin\theta$

$y' = -x\sin\theta + y\cos\theta$

$\theta =$ Orientation of the wavelet

(0, π/8, π/4, π/2, 5π/8, 3π/4, 7π/8, π)

$\lambda =$ Wavelength of cosine wave or frequency of the wavelet = σ

φ =Phase of the sinusoid (0)

σ =Radius of the Gaussian i.e. Scale

(2√2, 4, 4√2, 8, 8√2)

γ = Aspect ratio of the Gaussian (1)

$e^{-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}}$ is the Gauss function where x and y are range of values for the length and breadth of the Gabor mask. The Gauss function varies with scales and has no effect on differing orientations. The variation in scale is due to the variation in Gaussian radius. Smaller Gauss radius gives finer details of image and larger radius gives global details thus giving good time-frequency trade-off.

$e^{i\left(2\pi\frac{x'}{\lambda}+\varphi\right)}$isthe oscillation function.Different scales have varying periods for the oscillatory function and the period λ is equal to the radius σ of Gaussian function which gives the oscillation for Gabor function. Different orientation of oscillatory function views the variation of the face in the corresponding orientation.

σ describes the wavelength of the Gauss window, and scaling is varied by showing variation in σ. θ describes the oscillation of Gabor wavelet and varying θ controls the direction of sampling. 40 filters are constructed with five different scales and eight orientations.

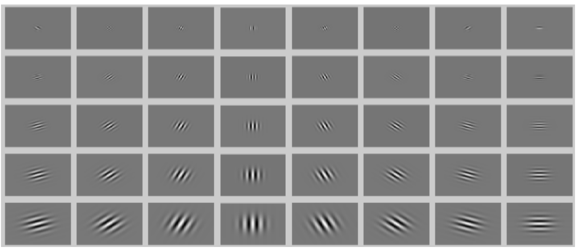

Fig.2. Gabor masks

Fig.2 shows the real part of the 40 Gabor kernels at scaleλ = 2√2, 4, 4√2, 8, 8√2 and orientation θ = 0, π/8, π/4, π/2, 5π/8, 3π/4, 7π/8, π. The difference in scale is viewed across rows and orientation variation is across columns. The filter demonstrates desirable property of orientation selectivity and spatial locality.Convolution is an operation on two functions f and g, which produces a third function that can be interpreted as a filtered version of f, where g acts as filter.

$$F[x,y] * G[x,y] = \sum_{n1=-M}^{M}\sum_{n2=-N}^{N} F[n1,n2].G[x-n1,y-n2] \quad (2)$$

where, MXN is the dimensions of filter G and image F.

A face image is represented by the Gabor wavelet transform describing the spatial frequency and spatial relations between them. In order to capture the entire frequency spectrum(both amplitude and phase), the image is convolved with complex Gabor filters. The convolution of the face image with Gabor filter bank gives 40 convolved output containing essential features of different resolutions.

B. Subspace Analysis

Subspace analysis considers an image as a point in the high dimensional feature space. They extract a few remarkable feature points from a large image thus reducing the dimensionality of the image by a considerable amount. Eigen space, Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) are commonly used subspace analysis techniques. Face images are very similar in structure, highly correlated, thus making it easier to reduce image size using subspace analysis.

1. Linear Discriminant Analysis (LDA)

The objective of LDA is to yield linear separation of classes. LDA is defined in such a way that the ratio of the determinants of the between-class scatter matrix and within-class scatter matrix of the output samples is maximum thus yielding an optimal projection. Butconcatenating the 2D matrix to 1D vector converted images lead to a highdimensional matrix.Due to large size of concatenated matrix and the relatively smaller number of training samples, computing the scatter matrices with accuracy is difficult. Also, when the Small Sample Size (SSS) problem occurs, the within-class scatter matrix becomessingular.

2. Two Dimensional Linear Discriminant Analysis (HGWLDA- 2D LDA)

The 2D-LDA method directly utilises the 2D matrices without converting them to 1D vector to avoid the SSS problem. $G_w$is the within class covariance matrix obtained by the outer products of the row vectors of the training imagesand so 2D-LDAis said to work in row-wise direction of the image. The amount of deviance that each image in a class has from the mean of the respective class is given by G_w.

$$G_W = \sum_{j=1}^{C}\sum_{i=1}^{N_j}(A_i^j-\mu_j)^T\,(A_i^j-\mu_j) \quad (3)$$

where, A_i^j is i^{th}sample of j^{th} class

μ_j is mean of j^{th} class

N_j is number of samples in j^{th} class

C is total number of classes

The between class covariance matrix is sum of difference of means from the total mean.

$$G_b = \sum_{j=1}^{C}(\mu_j-\mu)^T\,(\mu_j-\mu) \quad (4)$$

where,μ is total mean of all training images. The first q_1 Eigen vectors of $G_w^{-1}G_b$ corresponding to large Eigen values,is the feature vector X of size nxq_1. This feature vector X is projected on matrix A as AX of size mxq_1.

3. Alternative 2Dimensional Linear Discriminant Analysis (HGWLDA- Alt 2D LDA)

Alternative 2D-LDA is same as 2D-LDA except that the former works in the column direction of image whereas the later works in the row direction. The within and between class covariance matrix $H_w$and $H_b$in alternative 2D-LDA are given by Eq.5 and Eq.6 respectively.

$$H_W = \sum_{j=1}^{C} \sum_{i=1}^{N_j} (A_i^j - \mu_j)(A_i^j - \mu_j)^T \quad (5)$$

$$H_b = \sum_{j=1}^{C} (\mu_j - \mu)(\mu_j - \mu)^T \quad (6)$$

Similar to 2D-LDA, the first q_2 Eigen vectors of $H_w^{-1} H_b$is the feature vector Z which is of size mxq_2. This feature vector X is projected on matrix A as $Z^T A$ of size q_2xn.

4. Two Dimensional bidirectional Linear Discriminant Analysis (HGWLDA-(2D)^2 LDA)

To reduce the number of coefficients for image representation in 2D-LDA and alternative 2D-LDA, simultaneous row and column-wise projection on the image is devised as (2D)^{2}LDA. In face recognition, the important information needed for classification is the distance or similarity between pair of classes. (2D)^{2}LDAutilises the pairwise scatter matrix approach for the computation of between-class scatter matrix. So the between-class scatter matrix contains the information about mean variation between pair of classes rather than the difference of class mean from total mean.

G_w and H_w are within class scatter matrices and G_b and H_b are between class scatter matrices in row and column direction respectively.

$$G_b = \frac{1}{N} \sum_{j=1}^{C-1} \sum_{k=j+1}^{c} N_j N_k (\mu_j - \mu_k)^T (\mu_j - \mu_k) (7)$$

$$H_b = \frac{1}{N} \sum_{j=1}^{C-1} \sum_{k=j+1}^{c} N_j N_k (\mu_j - \mu_k)(\mu_j - \mu_k)^T (8)$$

$$G_W = \frac{1}{N} \sum_{j=1}^{C} \sum_{i=1}^{N_j} N_j (A_i^j - \mu_j)^T (A_i^j - \mu_j) \quad (9)$$

$$H_w = \frac{1}{N} \sum_{j=1}^{C} \sum_{i=1}^{N_j} N_j (A_i^j - \mu_j)(A_i^j - \mu_j)^T (10)$$

Feature matrix [12] is given by Eq.11.

$$F_i^j = W^T A_i^j X \quad (11)$$

where, X= Optimal projection matrix obtained in the original 2D-LDA method

W= Matrix obtained by an alternative 2D-LDA method

5. Weighted 2Dimensional bidirectional Linear Discriminant Analysis (HGWLDA-Wt(2D)^{2}LDA)

An approximate pairwise accuracy criterion [12] is introduced as the weight in the between class scatter matrix (2D)^2 LDA which is defined in Eq.12.

$$L_{jk} = \frac{1}{|\mu_j - \mu_k|^2} = \frac{1}{(\mu_j - \mu_k)^T (\mu_j - \mu_k)} \quad (12)$$

L_{jk}demonstrates how well classes$j$ and k are separated in the feature spaceor in other words, the dissimilarity between classes$j$ and$k$.

The between class scatter matrices G_b and H_b in weighted (2D)^{2}LDA is therefore given by Eq.13 and Eq.14 respectively.

$$G_b = \frac{1}{N} \sum_{j=1}^{C-1} \sum_{k=j+1}^{c} L_{jk} N_j N_k (\mu_j - \mu_k)^T (\mu_j - \mu_k) \quad (13)$$

$$H_b = \frac{1}{N} \sum_{j=1}^{C-1} \sum_{k=j+1}^{c} L_{jk} N_j N_k (\mu_j - \mu_k)(\mu_j - \mu_k)^T \quad (14)$$

C. k-NN Classifier

The k-Nearest Neighbour algorithm (k-NN) is a distance based classifier that predicts class memberships based on the closest match in the feature space. The reason is that two classes far apart in the space defined by the appropriate distance function are less likely than the samples belonging to the same class. The commonly used k-NN classifier is Euclidean distance which is used to find the geometric distance between two points in the feature space. The Euclidean distance between two feature set is given by Eq.15.

$$dist_j = \sqrt{\sum_{i=1}^{L} (a_{ji} - b_i)^2} \quad (15)$$

where, $dist_j$is distance between training feature set a_{ji} and the feature set of testing image b_i[13]. Here L is number of features in the feature set for j^{th} training image.

The nearest match for the test image is the minimum $dist_j$ value. Now, even for the test image which is not in training set, there exists a minimum Euclidean distance. So, a threshold is necessary to classify an image as matching or nonmatching image to the training database. If the minimum Euclidean distance is below the threshold, it is classified as not recognized image and if it is greater than threshold, it is recognized to be the match of the nearest training set. To determine the threshold, Receiver Operating Characteristic (ROC) curve is used.

III. RESULTS AND DISCUSSION

The proposed HGWLDA approach is implemented in MATLAB 2012a. AT&T, MIT-India and faces94 face database are used for training the system. "AT&T-The Database of Faces (The ORL Database of Faces)" consists of 40 distinct subjects with ten different images for each subject, each of size 112x92. The images were taken at different times and with lighting variation for few subjects.

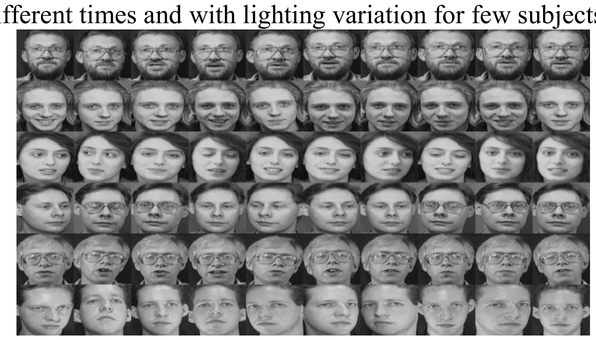

Fig.3. Dataset sample from AT&T database

To account for real time environment backgrounds, illumination conditions, image quality, an Indian database is developed with 60 distinct subjects each with six different images of 180x200 size [11].

Fig.4. Dataset sample from MIT-India database

All the images were taken at indoor environment with different facial expressions. Faces94 database consists of 153 classes with 20 images per person, each of size 180x200. Each image of a person has considerable changes in expression, position and head. The sample images from the AT&T, MIT-India and faces94 database are shown in Fig.3, Fig.4 and Fig.5 respectively.

Fig.5. Dataset sample from faces94 database

The image is first converted to grayscale, normalized and then given to feature extraction module. This preprocessing output which is one-sixteenth of original image dimension is convoluted with bank of 40 Gabor filters in 5 different scales and 8 different orientations which gives illumination invariant features. This output is shown in Fig.6.

Each of these Gabor filtered output is given to feature extraction block. For every image in the training set, this process of preprocessing, Gabor and subspace analysis is performed and the extracted features are saved in the database. For the input test image, the extracted features are compared with the training set features using k-NN classifier and the nearest match is taken to be the matching set.

True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN), are the four different possible outcomes of a single prediction for a two-class case, which is termed as confusion matrix, also called as contingency table or error matrix. True positive signifies correctly identified result, true negative implies correctly rejected, false positive indicates incorrectly identified and false negative denotes incorrectly rejected.

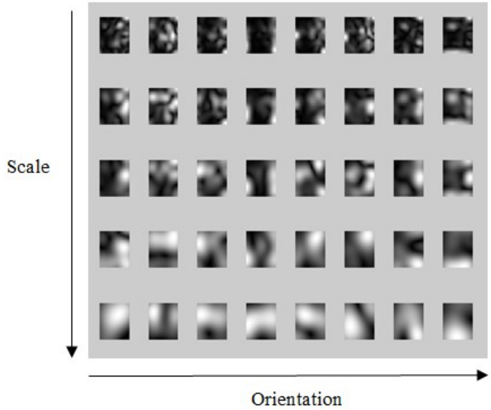

Fig.6. Gabor filtered output

The performance of the system is validated with precision, recall (True positive rate, TPR) and accuracy or recognition rate. Precision is the fraction of recognized faces that are expected and recall is the fraction of relevant instances that are retrieved. The equations for performance measures [11] in terms of precision, recall, False Positive Rate (FPR) and Recognition Rate are shown in equations Eq.16, Eq.17, Eq.18 and Eq.19 respectively.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{16}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{17}$$

$$\text{FPR} = \frac{FP}{FP+TN} \tag{18}$$

$$\text{Recognition rate} = \frac{TP+TN}{TP+TN+FP+FN} \tag{19}$$

TABLE I

RECOGNITION RATE OF HGWLDA APPROACHES USING DIFFERENT DATABASE

Method	AT&T	MIT-INDIA	FACES94
Gabor wavelet	84.3	80	88.9
HGWLDA-2D-LDA	85.5	90.625	90.27
HGWLDA-$(2D)^2$LDA	86.67	90	92.25
HGWLDA-Wt$(2D)^2$LDA	88	88.125	94.02

Table I shows the recognition rate for the proposed HGWLDA approach using different database. The result shows that HGWLDA shows better performance for all the three databases than Gabor. For training MIT-India face database, 80 classes with 5 images per class are used. One image per class which are not trained in training set and 80 images which are not included in training set are used for testing. The performance measure for AT&T database is computed by training 30 classes with 8 images in each class. 2 test images from each trained class and 4 images from 10 non-trained classes are tested. 40 classes with 8 images each are trained in faces94 database. 2 images from each trained class and 4 images for 20 non-trained persons are used for testing the faces94 database.

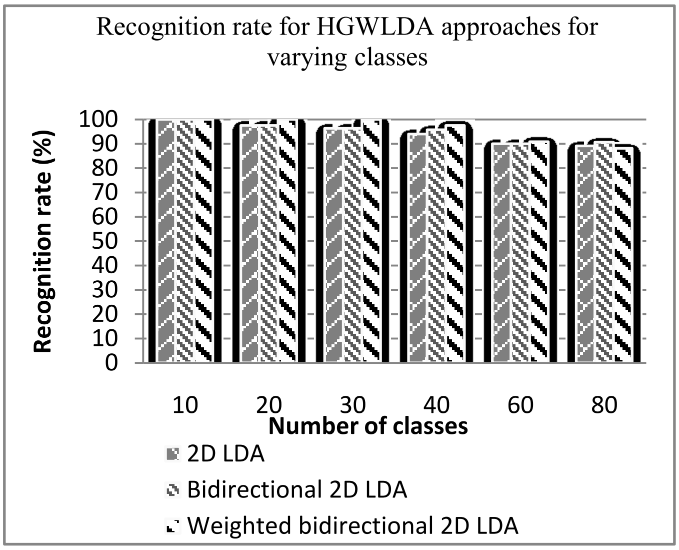

Fig.7. Comparison of Recognition rate for HGWLDA approaches for varying classes

Fig.7 illustrates the recognition rate for different number of classes. It can be seen that HGWLDA approach gives higher recognition rate even when the number of classes increase significantly.

IV. CONCLUSION

Performance of Hybrid approach for face recognition using combination of Gabor Wavelet and LDA (HGWLDA) has been analyzed. In the initial stage, the normalised input grayscale image is approximated and reduced in dimension to lower the processing overhead for Gabor filters. The global approximation image is convolved with bank of 40 Gabor filters at different scales and orientations. The Gabor features are mapped on to reduced feature space using various subspace analysis techniques- 2-dimensional Linear Discriminant Analysis (2D-LDA), 2-dimensional bidirectional LDA ($(2D)^2$LDA), Weighted 2-dimensional bidirectional Linear Discriminant Analysis (Wt$(2D)^2$LDA). Similarity computation between the testing image and the training set is done using k-NN classifier. The proposed scheme was implemented in MATLAB and validated for different data sets like AT&T, MIT-India and faces94 face database. Results show that the proposed HGWLDA algorithm gives better results than Gabor and is efficient for real time environment for varying illumination conditions and different facial expressions.

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