A Multi-Linear Approach to Face Recognition based on Gabor Transformation and RBF Neural Network

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Abstract: Feature representation in face image is an important factor of representation. In the area of face recognition, face features are extracted based on the approach of Eigen feature extraction. The features are large in count, and hence to minimize the feature count dimension reduction techniques were developed. Methods such as PCA, LDA or ICA were most used approaches in this area. Wherein the past methods were developed to minimize the feature count, the selection of the feature values were made in order of selection rather to their relation. Face features when processing for recognition exhibits multiple feature similarity among training dataset. Hence considering all dataset features are not useful. In this paper, we present a multi-linear approach to feature reduction based on feature relations for dimensional reduction approach. The Gabor approach to face feature representation is been proposed. A RBF classifier is used for the classification process.

Keyword: Face Recognition, multi-linear, approach, Gabor transformation, RBF NN classifier.

I. INTRODUCTION

Human face holds important amount of information and attributes such as expression, gender and face. The vast majority of people are able to easily recognize human traits like emotional states, where they can tell if the person is happy, sad or angry from the face. Likewise, it is easy to determine the gender of the person. However, knowing person's face just by looking at old or recent pictures for them is often a bigger challenge. Representation is non-reversible process. Human face characteristics change with time which reflects major variations in appearance. The face progression signs displayed on faces are uncontrollable and personalized such as hair whitening, muscles dropping and wrinkles. The representation signs depend on many external factors such as life style and degree of stress. For instance smoking causes several facial characteristics changes. A 30 years old person who smokes a box of cigarettes each day will look like a 42 years old one. Compared with other facial characteristics such as identity, expression and gender, representation effects display three unique characteristics:

Different people face in different ways. The representation variation of each person is determined by his/her genes as well as many external factors, such as health, lifestyle, weather conditions, etc. The representation variations are temporal data. The representation progress must obey the order of time. The face status at a particular face will affect all older faces, but will not affect those younger ones. Each of these characteristics contributes to the difficulties of automatic face recognition. Overall, there are three categories of feature extraction for human facial face recognition in the proposed literature. The first category is statistical-based approaches. Xin Geng et al. [2][3] proposed the Representation pattern Subspace method for automatic face recognition. The idea of it is to model the representation pattern, which is defined as a sequence of personal representation face images, by learning a representative sub-space from EM-like (expectation maximization) iterative learning Principle Component Analysis (PCA). In other major studies [4][5], Guodong Guo et al. compared three typical dimensionality reduction and manifold embedding methods, such as PCA, Locally Linear Embedding (LLE) and Orthogonal Locality Preserving Projections (OLPP). According to the data distribution in OLPP sub-space, they proposed the Locally Adjusted Robust Regression (LARR) method for learning and prediction of human ages. The LARR applies Support Vector Regression (SVR) to obtain a coarse prediction and determine a local adjustment within a limited range of ages centered on the predicted result using the Support Vector Machine (RBF). The second category comprises appearance-based approaches. Using appearance information is the most intuitional method in all facial image analysis works. Young H. Kwon et al. [6] used visual representation features to construct an anthropometric model. The primary features are the eyes, nose, mouth and chin. The ratios of those features are computed to distinguish different face ranges. In secondary feature analysis, a wrinkle geography map is used to guide the detection and measurement of wrinkles. Jun-Da Txia et al. [7] proposed an face recognition method using the Active Appearance Model(AAM) to extract the regions of face features. Each face requires 28 feature points and is divided into ten wrinkle feature regions. Shuicheng Yan et al. [8] presented a patch-based appearance model named Patch-Kernel. This method is designed to characterize the Kullback-Leibler divergence between the models which are derived from the global Gaussian Mixture Model (GMM) using Maximum a Posteriori (MAP) for any two images. The discriminating power is further enhanced using a weak learning process, called "inter-modality similarity synchronization". Kernel regression is employed for estimating face. The third category comprises frequency-based approaches. In image processing and pattern recognition, frequency domain analysis is the most popular method for extracting image features. Guodong Guo et al. [9]investigated the biologically inspired features (BIF) for human face recognition from faces. Unlike the previous works in [4][5], Guo simulated the human visual process based on bio-inspired models [10] by applying Gabor filters. A Gabor filter is a linear filter used in image processing for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and have been found to be particularly appropriate for textural representation and discrimination.

II. FACE FEATURE REPRESENTATION

The general face recognition system consists of three stages, training, testing and classification. The training stage trains the various facial images and their feature to the database. Testing stage extracts the features of a query sample and gives it to classifier. The classifier classifies the given query sample by comparing it with the trained samples. The general system model for face recognition is given below:

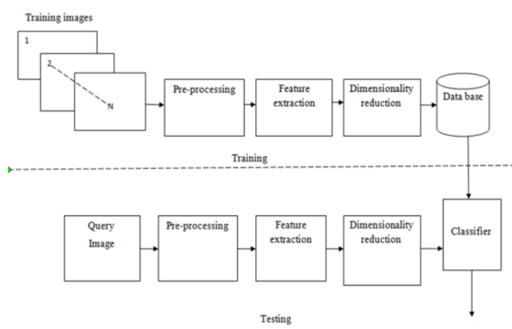

Fig.1 General facial image based face recognition system

a) Preprocessing

The aim of the face preprocessing step is to normalize the coarse face detection, so that a robust feature extraction can be achieved. Depending of the application, face preprocessing includes: Alignment (translation, rotation, scaling) and light normalization/correlation.

b) Feature Extraction

The aim of feature extraction is to extract a compact set of interpersonal discriminating geometrical or/and photometrical features of the face. Methods for feature extraction include Eigen features, singular values, frequency features, color features etc. PCA, LDA, KPCA, LBP, ICA, etc. are used to reduce the dimensionality of feature set extracted after applying feature extracting approach on the preprocessed image.

c) Feature Matching

Feature matching is the actual recognition process. The feature vector obtained from the feature extraction is matched to classes (persons) of facial images already enrolled in a database. The matching algorithms vary from the fairly obvious Nearest Neighbor to advanced schemes of Neural Networks. These representations are the ones to be

used in the recognition process. An Example of Eigen space faces recognition system. The Eigen faces approach for face recognition involves the following initialization operations:
1. Acquire a set of training images.
2. Calculate the Eigen faces from the training set, keeping only the best M images with the highest Eigen values. These M images define the “face space”. As new faces are experienced, the Eigen faces can be updated.
3. Calculate the corresponding distribution in M-dimensional weight space for each known individual (training image), by projecting their face images onto the face space.
Having initialized the system, the following steps are used to recognize new face images:
Given an image to be recognized, calculate a set of weights of the M Eigen faces by projecting them onto each of the Eigen faces.
4. Determine if the image is a face at all by checking to see if the image is sufficiently close to the face space.
5. If it is a face, classify the weight pattern as Eigen a known person or as unknown.

d) Feature Extraction Using Gabor Transformation

The Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. A set of Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image. Gabor filters have been widely used in pattern analysis applications. To visualize a Gabor function selects the option “Gabor Function” under “Output Image”. The Gabor function for the specified values of parameters “wavelength”, “orientation”, “phase offset”, “aspect ratio”, and “bandwidth” will be calculated and displayed as an intensity map image in the output window. (Light and dark gray colors correspond to positive and negative function values, respectively). The image in the output window has the same size as the input image: select, for instance, input image octagon.jpg to get an output of size 100 by 100. If lists of values are specified under “orientation(s)” and “phase offset(s)”, only the first values in these lists will be used.

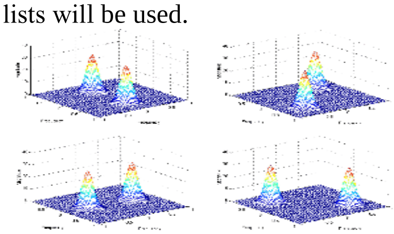

Fig 2: Plot of frequency response of the Gabor filter for different values of u0, v0 corresponding to four orientations - 0, 45, 90 and 135

This filter is used to detect line endings and edge borders over multiple scales and with different orientations. The Gabor wavelet can be defined as given in Eq.1.

$$g(x,y,\theta,\Phi) = \exp\left(-(x^2+y^2)/sigma^2\right) * \exp\left(2\pi\theta i(x\cos\Phi + y\sin\Phi)\right) \tag{1}$$

The Gabor feature representation of an image I(x, y) is the convolution of the image with the Gabor filter bank g(x,y, θ, Φ) .The Gabor filter is used for edge detection, in this paper the Gabor filter is used for the Edge-Based Feature Extraction. The edge-based facial feature include the eyes, eyebrows, nose and mouth, these feature from facial image are extracted using the edge detection properties of the Gabor filter, besides this the wrinkle and skin texture is also extracted which is used to classify the face image. Figure 3 shows how the eye, eyebrows, mouth& nose are detected using Gabor filter along with the wrinkles on from facial image.

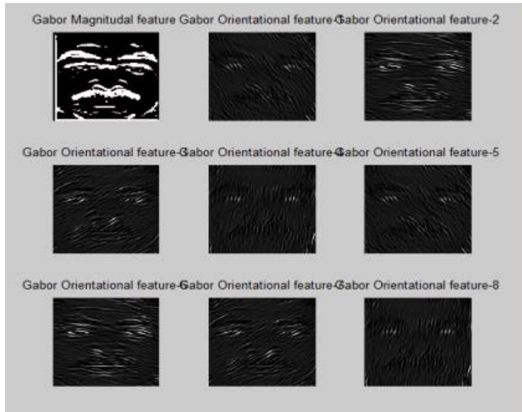

Fig 3: The output of Gabor filter for eight orientations.

In the proposed approach, Gabor filter was applied on the preprocessed sample. The Gabor filter was completely applied for eight orientations with the margin angle of 45^0. In the equation 1 shown above by changing the θ value from 45^0 to 360^0, we will obtain the facial variations in all orientations. The above figure shows the output of Gabor filter for all orientations.

III. MULTI-LINEAR REPRESENTATION

The proposed face recognition system has two stages: 1) Training stage and 2) Testing stage. In training stage, the training feature database is to be developed which contains the feature extracted from the different facial images. In testing stage, feature extracted from the input facial image (test image) are compared with the features in training feature database using RBF classifier, the feature of the matched face group is taken as result face of the test image. The block diagram of proposed work is shown below:

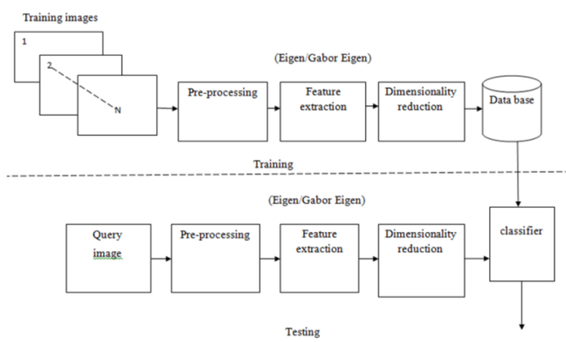

Fig.4 Block diagram of proposed approach

The proposed facial face recognition system is divided in to four steps as:
1) Preprocessing
2) Feature extraction using 2D – Gabor Filter and Eigen approach
3) Dimensionality reduction of the feature vector using ML-DR
4) Face Recognition using RBF Classifier.

The proposed approach aims in creating a system that is used to estimate the face from a facial image. Facial images are acquired from the database sources. The Proposed face recognition system from facial images constitutes of facial image in digital form as its input which is then processed further. We used 2D-Gabor filter along with Eigen approach and Multi linear Dimension reduction (ML-DR) to estimate a person's face using his/her facial image. The input facial image goes through preprocessing stage in preprocessing stage the input color image is read from the database. Then it is resized, further it is cropped for facial region and converted in to the gray scale. After preprocessing the facial image goes through feature extraction, using 2D-Gabor filter. At this stage, the Gabor filter was applied to extract the all possible variations in all possible orientations. Here, the Gabor filter is applied for eight orientations with the angle margin of 45^0. Eigen faces are extracted for the entire Gabor feature set. The next step is to reduce the available feature vector using Multi Linear Component Analysis for dimensionality reduction.

The feature vectors are then compared with the database using RBF classifier and classify the facial image as to which class it match. In this work, a self-created database was used to execute the proposed approach. The database was created voluntarily. The algorithm for the proposed system is as follows.
Algorithm
Input: Face Database, Test Face Image
Output: Face class of Person
Step 1: Face image is read from data base.
Step 2: Image is resized uniform dimensions
Step 3: Color image is converted in to Gray scale Image.
Step 4: The Gray scale image is cropped for the face region.
Step 5: 2D-Gabor filter and Eigen method is applied to cropped image to extract the feature from facial image.
Step 6: The extracted feature are processed for dimensionality reduction using ML-DR.
Step 7: Test Image Features are compared with the Features available in Training Feature database using RBF classifier for classification.
ML-DR stands for Multi Linear Principle Component Analysis. It is a multi linear subspace learning method that extracts features directly from multi-dimensional objects. The ML-DR is the extension to the PCA, which operates linearly whereas ML-DR operates multi-linearly. The PCA need to reshape the multidimensional object in to the vector, whereas ML-DR operates directly on multidimensional object through two-mode processing. In this paper the Gabor filtered image is used as input image to the ML-DR. The feature extracted from the facial image using Gabor filtered is given to the ML-DR for dimensionality reduction. The resultant output of the ML-DR is the dimensionally reduced feature projection matrix of face Images. Figure.5 and figure.6 shows the pictorial representation of PCA and ML-DR operations respectively.

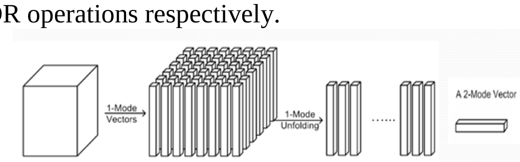

Fig.5 Principal Component analysis

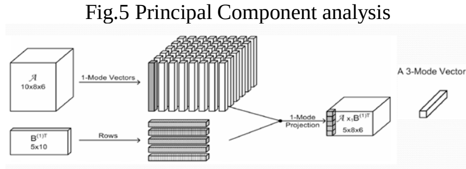

Fig.6. Multi-Linear Dimension reduction

The PCA operates in the one dimensional mode, whereas ML-DR operates along multi-dimensional mode. For a given feature space of a single class, PCA evaluates the principal components individually, whereas ML-DR evaluates by considering the feature space of remaining classes also.
The pseudo code for ML-DR is described as follows:
Step 1: take the whole Gabor feature set having MxN dimensional space
Step 2: compute the mean along each ‘n’ dimensions
Step 3: obtain a new matrix by subtracting the mean from all values of dataset.
Step 4: evaluate a covariance matrix
Step 5: compute Eigen vectors and the corresponding Eigen values
Step 6: sort the Eigen vectors by decreasing the Eigen values and choose k Eigen vectors with largest Eigen values from n x k dimensional matrix W_1.
Step 7: perform the same operation of step7 for each class of feature set and find out some more Eigen values those having effect on the recognition accuracy.
Step 8: finally form a new projection matrix by considering inter class Eigen values and also intra class Eigen values.
Step 9: form a dimensionally reduced subspace by multiplying the projection matrix with original values.
In machine learning, neural network are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked for belonging to one of two categories, an RBF training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An RBF model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to

belong to a category based on which side of the gap they fall on. In addition to performing linear classification, RBFs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.
More formally, a RBF neural network constructs a hyper plane or set of hyper planes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier. Whereas the original problem may be stated in a finite dimensional space, it often happens that the sets to discriminate are not linearly separable in that space. For this reason, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space. To keep the computational load reasonable, the mappings used by RBF schemes are designed to ensure that dot products may be computed easily in terms of the variables in the original space, by defining them in terms of a kernel function k(x,y) selected to suit the problem. The hyper planes in the higher-dimensional space are defined as the set of points whose dot product with a vector in that space is constant. The vectors defining the hyper planes can be chosen to be linear combinations with parameters α_i of images of feature vectors x_i that occur in the data base. With this choice of a hyper plane, the points x in the feature space that are mapped into the hyper plane are defined by the relation:

$$\sum_i \alpha_i k(x_i, x) = constant \qquad (2)$$

Note that if k(x,y) becomes small as y grows further away from x, each term in the sum measures the degree of closeness of the test point x to the corresponding data base point x_i. In this way, the sum of kernels above can be used to measure the relative nearness of each test point to the data points originating in one or the other of the sets to be discriminated. Note the fact that the set of points x mapped into any hyper plane can be quite convoluted as a result, allowing much more complex discrimination between sets which are not convex at all in the original space.
In this project, RBF classifier is used as a classifier to obtain the exact class of face for given query image. The basic RBF classifier works for two classes. Each and every class is trained using “nntrain” in matlab. Here for a given class, it was labeled as “+1” and “-1”. i.e., during the classification if the query sample belongs to the given particular class, it was labeled as “+1” and if it was not, it was labeled as “-1”.If the query sample is labeled as “-1” it will be processed to second class. The query sample was classified by “sim” in matlab.

IV. EXPERIMENTAL RESULTS

For the experimental record of the developed system, a dataset of Indian ehentic dataset is created.

Fig 7: Facial Image from the Indian Facial image Database.

Near about 60% images from the above database are selected for training stage, in training stage the feature are extracted from the facial image first, and further these feature are dimensionality reduced using ML-DR. These dimensionality reduced feature Vector are used in the testing stage. The following flow chart shows the complete working of proposed work for automatic face recognition.

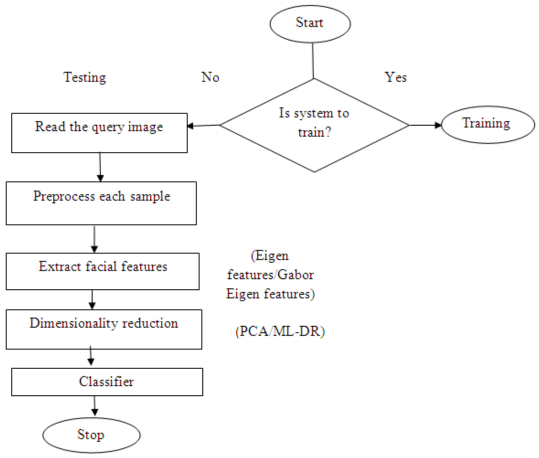

Fig 8: operational flow chart

The flow chart shown above describes the complete details about the working flow of proposed as well as earlier approaches. Initially, the system checks to train or test. Then the system performs the training and testing operation.

a) Case 1: Known sample

Under this case, a known sample was taken as a query sample. The known sample means the feature information about the given sample is already trained to database. A known sample was given for both approaches and the obtained results are shown below:

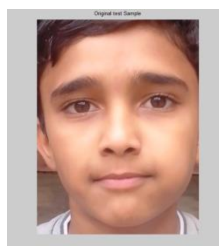

Fig.9: Original query sample

The above figure represents an original color query or test sample given as input for testing stage. This sample was given under known category. i.e., the feature information is already trained to database.

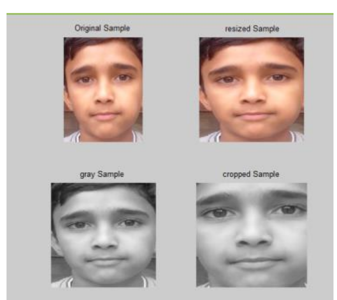

Fig.10: preprocessed output (resized, gray and cropped sample)

After reading the query sample, it was subjected to preprocessing. Under preprocessing, the query sample was resized into uniform dimensions, because, the images captured in real time should have various dimensions. By converting it into a uniform dimensional image, the processing will become less complex. After resizing, the image was converted into gray format, because the color image have various effects like illumination, brightness etc. by converting it into gray format, only pixel intensities are obtained which are less sensitive to above mentioned effects. Next, the gray image was processed to cropping. To extract only facial region, the proposed work applied cropping on image. The images were also self-created under fixed conditions, thus each and every image having almost similar dimensions. Thus cropping with fixed dimensions gives only and exact face region.

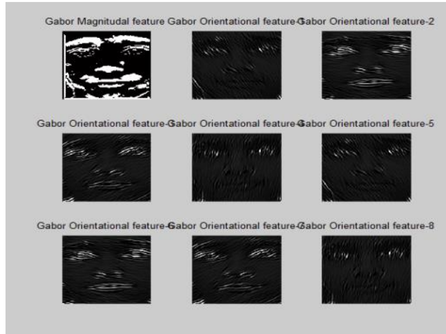

Fig.11: Gabor filter output along eight orientations

The above figure represents feature set of Gabor filter applied preprocessed image. After cropping the image, a 2-D Gabor filter was applied on it to extract the variations in all orientations. Gabor filter was applied completely for eight directions with an angle margin of 45^0. In the above figure, the figure shown in first slot shows the magnitudes of image. The remaining figures shown in remaining slots gives the variations is their particular orientations. It is clear that, at each and every orientation, only few components are dominating for example, at third orientation. The features at eyes and nose are highly dominating and mouth features are less dominating. Similarly at fifth orientation only eye features are dominating. Like this the Gabor filter gives variations at all possible orientations. After extracting all variations, Eigen values are extracted for all of them and then dimensionality reduction method was applied, PCA in earlier and ML-DR in proposed approach. After reducing the dimensions, principal components are obtained and are compared with the feature set of database samples using RBF classifier. The RBF classifier is defined for a n-level classifier, i.e. it works for multiple classes. A RBF separates the query sample into any one of the class trained with it.

5.2.2 Unknown Sample

Under this case, an un-known sample was taken as a query sample. The un-known sample means the feature information about the given sample is not present in the database. An un-known sample was given for both approaches and the obtained results are shown below:

Fig.12: original unknown testing sample

The above figure represents an original color query or test sample given as input for testing stage. This sample was given under un-known category. i.e., the feature information is not present in the database.

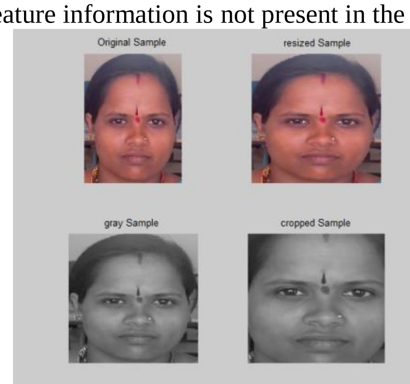

Fig.13: preprocessed output (resized, gray and cropped sample)

After reading the query sample, it was subjected to preprocessing. Under preprocessing, the query sample was resized into uniform dimensions, because, the images captured in real time should have various dimensions. By converting it into a uniform dimensional image, the processing will become less complex. After resizing, the image was converted into gray format, because the color image have various effects like illumination, brightness etc. by converting it into gray format, only pixel intensities are obtained which are less sensitive to above mentioned effects. Next, the gray image was processed to cropping. To extract only facial region, the proposed work applied cropping on image. The images were also self-created under fixed conditions, thus each and every image having almost similar dimensions. Thus cropping with fixed dimensions only gives the exact face region.

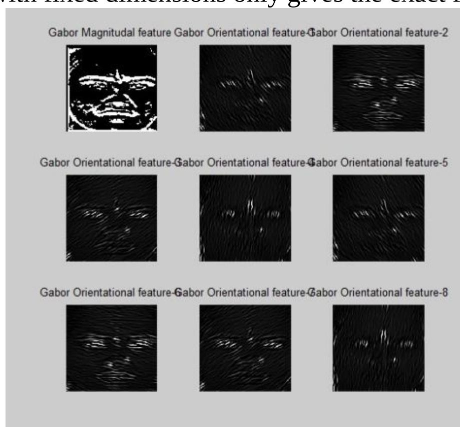

Fig.14: Gabor filter output along eight orientations

The above figure represents feature set of Gabor filter applied preprocessed image. After cropping the image, a 2-D Gabor filter was applied on it to extract the variations in all orientations. Gabor filter was applied completely for eight directions with an angle margin of 45^0. In the above figure, the figure shown in first slot shows the magnitudes of image. The remaining figures shown in remaining slots gives the variations is their particular orientations. It is clear that, at each and every orientation, only few components are dominating. For example, at third orientation, the features at eyes and nose are highly dominating and mouth features are less dominating. Similarly at fifth orientation, only eye features are dominating. Like this the Gabor filter gives variations at all possible orientations. After extracting all variations, Eigen values are extracted for all of them and then dimensionality reduction method was applied, PCA in earlier and ML-DR in proposed approach.

The earlier approach having 18 true counts and the proposed approach having 19 true counts for a given 20 samples for testing. Thus the retrieval accuracy is calcuated as;

Retrieval Accuracy = (number of correct outputs/number of test samples)*100 (5)

RetrievalAccuracy = (18/20) = 90% (PCA[4])

RetrievalAccuracy = (19/20) = 95% (ML-DR)

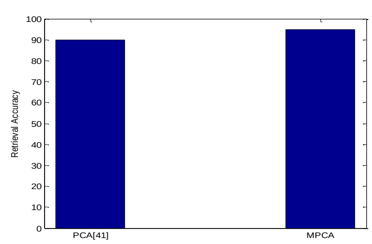

Fig.15: Retrieval accuracy

The above figure represents the Retrieval accuracy of the earlier and proposed approaches. From the above figure it is clear that the proposed approach having high Retrieval accuracy compared to PCA. To evaluate the performance of proposed approach, one more numerical parameter, True Positive Factor (TPF) and False Positive Factor (FPF) used. TPF is defined as the ratio of the number of truly classified samples over the total available data samples. It finds the number of query samples classified truly according to their labels. FPF is defined as number of falsely classified samples over the total available data samples. FPF finds the number of samples that are classified wrongly. Mathematically, TPF and FPF can be expressed as

$$TPF = \frac{\text{No.of truely recognized samples}}{\text{total available samples in dataset}} \quad (6)$$

$$FPF = \frac{\text{No.of falsely recognized samples}}{\text{total available samples in dataset}} \quad (7)$$

Totally, out of 49 database samples, 20 samples were taken for testing. Among the 20, the proposed approach classified 19 samples truly and the earlier approach classified 18 samples truly. The details are illustrated in table 1 and table.2. Table 1 gives the details about the input test sample and the classified samples for both approaches, table 2 shows the details about the evaluated TPF and FPF for the obtained output of both approaches.

Table.1: Input and outputs of proposed and earlier approaches

Test Samples	**PCA [4]**		**ML-DR**	
	Truly Classified	Falsely Classified	Truly Classified	Falsely Classified
20	18	2	19	1

Table.2: TPF and FPF performance comparison

Total Samples	**TPF**		**FPF**	
	PCA[4]	**ML-DR**	**PCA[4]**	**ML-DR**
49	18/49=0.3673	19/49=0.3878	2/49=0.0408	1/49=0.0204

A generalized plot for the above observation was created and shown in fig.16. The plot was drawn between FPF and TPF, also can be called ROC plot.

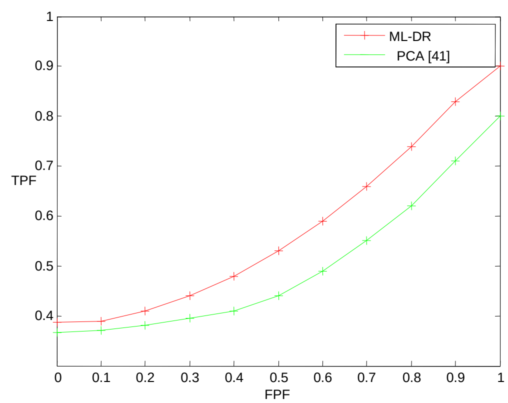

Fig.16: ROC analysis

The above figure represents the ROC curve for proposed approach and earlier approaches. The proposed approach was carried out under various tests by varying number of testing samples and FPF and the obtained results are shown in the fig.16. Form the above figure, as the FPF is increasing, the TPF is also increasing. The increment in the FPF shows the probability of getting false results. The increment if TPF denotes the probability of getting true results. The increment of TPF with the increment if FPF describes the probability of getting true results even under false conditions. This shows the robustness of proposed work. Compared to earlier approach, the increment in the roc curve for proposed approach is high. I.e. even under false probability conditions, the proposed approach is able to give efficient results compared to earlier approach. From the fig.16, at a particular FPF the TPF of proposed approach is high compared to earlier approach, thus the proposed approach provides robust classification results.

V. CONCLUSION

The proposed approach extracts the all possible variations from facial images with Gabor filter. By applying the Gabor filter on various orientations, respective variations are obtained. At each and every orientation, only few features are dominating in nature. When the Gabor filter was applied on image, the respective dominant features are obtained. After obtaining all possible variations from the facial image, Eigen features were extracted. In conventional approach, the Eigen features are directly extracted from facial image thus finding the dominating features will become complex. The proposed work applied dimensionality reduction method in multi nature, reduces the dimensions of feature set by considering the intra class feature and also inter class features, whereas, the conventional approach reduces the dimensions by considering only intra class features. Then RBF classifier was used at classifier to classify the testing sample. Testing was performed under two cases (known and un-known) for conventional and proposed approaches. The performance was analyzed through Retrieval accuracy. Both approaches have 100% Retrieval accuracy under known category, thus the system was robust. The enhancement of proposed work was shown in the un-known. Under un-known case, the proposed work obtained 95% Retrieval accuracy, whereas the conventional approach obtained 90% Retrieval accuracy, thus the proposed work was efficient.

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