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COMPLETE GABOR LOCALITY PRESERVING WITH NON ZERO EIGEN VALUE BASED DISCRIMINANT ANALYSIS FOR EXPRESSION RECOGNITION

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Abstract: Inherited features from face features are in smaller in dimension. This paper mainly deals with how inherited features constitutes a subspace by preserving feature space data by discriminating various classes of expressions. Estimation of expression recognition rate by reducing dimension of feature by saving larger memory space, reducing classification time and removing multiple repeated data contents is the main goal of the work. In this paper entire Gabor based locality preserving Fisher discriminant analysis (EGLPFDA) approach is proposed to overcome the weakness of entire Gabor Fisher linear discriminant analysis (EGFLDA) for dimensional reduction. Gabor magnitude and phase congruency parts are isolated and projected separately using subspace methods. The proposed subspace approach increases the discriminant ability of the Gabor filter features vector space in low dimensional space and this approach is tested in the presence and absence of noise. Experiment is carried out on JAFFE face database by adding noises to 30% of the dataset images. It was found that 95.23% recognition accuracy in the absence of noise and 91.26% accuracy with the speckle noise for proposed approach respectively
Keywords: principal component, filter, subspace, phase, locality

1. INTRODUCTION

With the rapid technological development of pattern recognition today there are many human traits are used in biometrics authentication, mobile communication, robot control and other fields [1-3], facial expression is one trait among them and found to be more significant task in technology of high dimensional data analysis. Feature extraction is found to be more essential part lies between preprocessing and post processing of entire expression recognition system. Rahulamathavan Yogachandran et. al [4] worked on expression recognition system with encrypted domain using LFDA (Local Fisher Discriminant Analysis). Author suggested challenge to work with encrypted domain even if there is not good recognition rate for unencrypted domain. This method is applied to JAFFE and MUG database which have a recognition rate respectively 94.37% and 95.24%.

Frank et al. [5] conducted experiment on JAFFE database using 2DLDA (2 dimensional linear discriminant analysis). They used cross validation strategy for classification of seven expressions and obtained 94.13% recognition rate. The rest of this paper is organized as follows. In the beginning of this paper, brief overview of subspace approaches related to this work is introduced in section 2. Entire Gabor principal component analysis (EGPCA), entire Gabor Fisher's linear discriminant analysis (EGFLDA) and entire Gabor locality preserving projection (EGLPP) as well as entire Gabor locality preserving Fisher discriminant analysis (EGLPFDA) is proposed in section 3. Performance of these methods on JAFFE face dataset in the presence and absence of noise are provided in section 4. Finally, this work is concluded in section 5.

2. BRIEF OVERVIEW OF SUBSPACE METHODS

There are several researchers implemented subspace projection methods directly on input images to achieve dimensional reduction and feature extraction. In this work, earlier subspace methods are modified by extracting the face features using Gabor filter. Gabor filter based feature vector space dimension was found to be larger this can be transformed into subspace. From literature survey it is noted that many linear and nonlinear subspace methods was found to be robust for face and expression recognition. Subspace methods like principal component analysis (PCA) [5-11], linear discriminant analysis (LDA) and Fisher LDA [12-20], locality preserving projection (LPP) [21-25]. Nonlinear approaches include isomap mapping (Isomaps) [26], [27]. The common drawback of nonlinear embedding methods is that these techniques are too expensive to compute high dimensional data when the size of samples becomes large. Yu and Yang et. al [30] proposed a direct LDA algorithm which incorporates the concept of null space for high dimensional data with application to face recognition. A complete kernel fisher discriminant framework for feature extraction and recognition using KPCA and LDA is proposed in [32].

— Problem in LDA

The LDA method tries to find the subspace that discriminates different face classes. The within class scatter matrix is also called intra personal means variation in appearance of the same individual due to different illuminations and facial expressions. The between class scatter matrix also called the extra personal represents variation in appearance due to difference in identity. Linear discriminant methods group images of the same classes and separates images of the different classes. LDA method consumes more time for feature extraction and decorrelating the data. This method results in preserving the distance of previously well separated classes but an overlapping of neighbor classes also occurs. A critical issue using LDA is the small sample size (SSS) problem [13]. This problem arrives when there is small number of training samples but the dimension of the feature space is large. This means that the within class scatter matrix would tend to be a singular matrix and the execution of LDA may encounter computational difficulty. In the past, many LDA extensions have been developed to deal with this singularity problem. Among them most popular one is using PCA as a pre-processing step and then performs linear discriminant analysis so that dimensionality reduction occurs during PCA phase. Due to all these reasons LDA method was enhanced in several earlier works. LDA is a supervised subspace method which seeks the direction that minimizes the classified error by utilizing class labels. However, the intra class scatter matrix of LDA is often singular when it is applied to the small size of samples. Consequently, the optimal solution of LDA is unable to solve, and the projected direction is failed to achieve. Next section deals the problems overcome by LDA.

3. PROPOSED WORK

In this research work Gabor filter [36-38] features are extracted from detected face area, this feature space is found to be high dimensional. Entire feature of Gabor filter gives significant rich features, but due to its higher dimensional nature, more correlated data structure and larger time consuming process, Gabor magnitude and phase parts are extracted separately and subspace projection methods are implemented for both these Gabor vectors. Projected Gabor magnitude and phase congruency vectors are normalized by Z-score normalization [31] and final scores are fused using maximum fusion rule. Based on eigenscore matrix Euclidean distance is computed and expression recognition is carried out. Using RBF kernel based SVM (support vector machine) [33] classifier expressions are classified. In this section EGPCA, EGFLDA, EGLPP and EGLPFDA subspace approaches are introduced as shwn in figure 1.

— Entire Gabor PCA

EGPCA is an unsupervised approach, finds the global scatter as the best projected direction with the aim of minimizing the least square error of reconstruction data points. In PCA based projection class labels are not considered hence it is an unsupervised subspace method.The projected direction found by PCA [5] is usually not the optimal direction [10]. Let $G=(g_1,g_2, \ldots g_i, \ldots g_N)$ represents the nxN Gabor magnitude (also for phase part) feature data matrix , where g_i is a Gabor face vector of dimension n, combined from a axb face vector matrix and N is the number of different Gabor magnitude(also for phase part) feature data in the training set. The mean vector in the training Gabor magnitude (also for phase part) is

$$m = \frac{1}{N}\sum_{i=1}^{N} g_i \tag{1}$$

(1) is subtracted from each Gabor magnitude feature data (also for phase part). By projecting Gabor magnitude and phase vectors separately to basis vectors, then projected coefficients are used for expression recognition. Final matching score is computed from subspace methods. The matching score between train and test Gabor feature set is computed. The larger the matching score, accuracy of recognition increases. All the linear subspace methods can be considered as linear transformation from higher dimension Gabor data feature set (both magnitude and phase part) to projection feature vector.

$$Y = W^T G \tag{2}$$

In the above equation Y is dxN feature vector, d is dimension of the Gabor feature vector and W is transformation matrix. If d<<n, then dimensional of feature space can be reduced. PCA projects the Gabor data feature set of trained image into subspace to find set of weights that describe the contribution of each vector in the Gabor face space. To organize the test image Gabor feature, it requires projection of the test image Gabor feature vector onto the subspace to obtain respective set of weights. By comparing the projected weights of the test image Gabor feature space with the set of weights of the Gabor face in the training set, test face image can be recognized. Basically PCA is based on Karhumen-Loeve transformation [29]. The PCA basis vectors are defined as the eigenvectors are defined as the eigenvector of the scatter matrix

$$S_T = \sum_{i=1}^{N} (g_i - m)(g_i - m)^T \tag{3}$$

The objective function of GMPCA for Gabor magnitude part and GPPCA for Gabor phase part can be given by

$$J(W_{GMPCA}) = W^T S_T W \tag{4}$$

Similarly $J(W_{GPPCA})$ is an objective function of Gabor phase part is computed by referring the steps which are followed to calculate (4). Projected final eigenscores of both GMPCA and GPPCA feature datasets are normalized by Z-score normalization. Both the normalized scores vectors are fused by maximum score fusion rule [31]. Final score of EGPCA approach is computed as

$$NS_{GMPCA} = \frac{GMPCA_S - mean(GMPCA_S)}{Std(GMPCA_S)} \tag{5}$$

$$NS_{GPPCA} = \frac{GPPCA_S - mean(GPPCA_S)}{Std(GPPCA_S)} \tag{6}$$

$$EGPCA_S = Max[(NS_{GMPCA} + NS_{GPPCA})/2] \tag{7}$$

For both Gabor train and test image dataset final EGPCA score matrix is computed, from this score matrix Euclidean distance is evaluated as

$$\varepsilon_i^2 = \left\| W_{EGPCAQ} - W_{EGPCAT} \right\|^2 \tag{8}$$

where W_{EGPCAT} and W_{EGPCAQ} are projected vector score matrices of training and testing Gabor dataset images. If ε_i is less than some predefined threshold value θ_i, then test image belongs to class i. So that testing image is matched with trained image. Based on Euclidean distance and RBF kernel based SVM classifier [33] facial expressions are classified.

— Entire Gabor FLDA

Fisher linear discriminant analysis subspace method utilizes class specific information. By defining different class of expressions with different statistics, the data vectors in Gabor dataset are divided into the corresponding classes. Then, eigenface technique is implemented. Let g_i be the n dimension feature in Gabor space and let $\{g_i,g_2, ... g_N\}$ are Gabor feature dataset. Suppose that there are C classes of expressions and feature vector number of C^{th} class is N_c fulfils the condition.

$$N = \sum_{c=1}^{C} N^c \tag{9}$$

That is the number of all Gabor vector is the total sum of each class vector. Let g_i^c be the i^{th} Gabor vector of the C^{th} class, the corresponding Gabor feature vector mean becomes

$$m_c = \frac{1}{N^c} \sum_{i=1}^{N^c} g_i^c \tag{10}$$

Data center of all vectors is denoted by

$$m = \frac{1}{N} \sum_{i=1}^{N} g_i \tag{11}$$

Suppose that the data set G in n dimensional space (higher dimension) is distributed on a low d dimensional subspace. A general problem of linear discriminant is to find a transformation is $W \in R^{nxd}$ that maps the n dimensional data into low d dimensional subspace data by $Y=W^TG$ such that each y_i represents g_i without losing useful information. The transformation matrix W is represented by different method and different objective function. For FLDA, S_b is the between class scatter matrix and S_w is the within class matrix are given below.

$$S_w = \sum_{c=1}^{C} \sum_{i=1}^{N^c} (g_i^c - m_c)(g_i^c - m_c)^T \tag{12}$$

$$S_b = \sum_{c=1}^{C} N^c (m_c - m)(m_c - m)^T \tag{13}$$

The Fisher algorithm is results in a higher accuracy rate compare to EGPCA. Objective function of (Gabor magnitude Fisher linear discriminant analysis) GMFLDA is

$$J(W_{GMFLDA}) = \underset{w}{\arg\max} \frac{W^T S_b W}{W^T S_w W} \tag{14}$$

Similarly $J(W_{GPFLDA})$ for phase part FLDA is computed by referring the steps which are followed to calculate (14). Projected final eigenscores of both GMFLDA and GPFLDA feature dataset are normalized by Z-score normalization. Both the normalized scores vectors are fused by maximum score fusion rule [31]. Final score of EGFLDA approach is computed as

$$NS_{GMFLDA} = \frac{GMFLDA_S - mean(GMFLDA_S)}{Std(GMFLDA_S)} \tag{15}$$

$$NS_{GPFLDA} = \frac{GPFLSDA_S - mean(GPFLDA_S)}{Std(GPFLDA_S)} \tag{16}$$

$$EGFLDA_S = Max[(NS_{GMFLDA} + NS_{GPFLDA})/2] \tag{17}$$

For both train and test image Gabor dataset final EGFLDA score matrix is computed, from this score matrix Euclidean distance is evaluated as

$$\varepsilon_i^2 = \left\| W_{EGFLDAQ} - W_{EGFLDAT} \right\|^2 \tag{18}$$

where $W_{EGFLDAQ}$ and $W_{EGFLDAT}$ are projected vector score matrices of training and testing Gabor dataset images. If ε_i is less than some predefined threshold value θ_i, then test image belongs to class i. So that testing image is matched with trained image and based on Euclidean distance and RBF kernel based SVM classifier [33] facial expressions are classified. The value of both $J(W_{GMFLDA})$ and $J(W_{GPFLDA})$ is made high by maximizing the separability between inter class scatter matrix while minimizing intra class scatter variability respectively. Internally $W^T S_w W$ is assumed that is full rank, under this assumption the problem can then be attributed to the generalized eigenvector $\{w_1, w_2, w_3 \ldots w_d\}$ by solving

$$S_b w = \lambda S_w w \tag{19}$$

Finally the solution of W_{GMFLDA} is given by $W_{GMFLDA}=\{w_1,w_2,w_3 \ldots w_d\}$ and solution of W_{GPFLDA} is given by $W_{GPFLDA}=\{w_1,w_2,w_3 \ldots w_d\}$ which are associated with the first d largest eigenvalues $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots \geq \lambda_d$. Since the rank of inter class scatter S_b is at C-1, there are C-1 meaning full features in direct LDA [30].

— **Entire Gabor LPP**

Local structure of Gabor data points is not preserved by LDA method and it has multimodal property while distributing high dimensional data. This can be resolved in LPP method [28]. LPP method projects the data by preserving the local structure of neighborhood points. In order to describe the relationship between neighborhoodspoints, a graph is established using nearest neighborhood. Consider S is a affinity matrix, where $S(i,j) \in [0,1]$ represents the similarity between points g_i and g_j. The largest the value of S(i,j), the relationships becomes nearer and lies between g_i and g_j. Simple way to define affinity matrix S is given as

$$S(i,j) = \begin{cases} e^{\left(-\frac{\|g_i - g_j\|^2}{\alpha^2}\right)} & \text{if}(g_i \in KNN(g_j,k) \text{or} g_j \in KNN(g_i,k)) \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

where $\left\| g_i - g_j \right\|^2$ denotes the square 2 norm Euclidean distance, α is tuning parameter and KNN(g,k) represents the K-nearest neighborhoods of g under parameter k. The objective function of GMLPP is achieved in the following criterion.

$$J(W_{GMLPP}) = \underset{W \in R^{nxd}}{\arg\min} \left\{ \frac{1}{2} \sum_{i,j=1}^{n} S(i,j) \left\| y_i - y_j \right\|^2 \right\} \tag{21}$$

Similarly $J(W_{GPLPP})$ is computed by referring the steps which are followed to calculate (21).

$$W^T G D G^T W = I \tag{22}$$

where D=diag (D_{ii}) is a diagonal matrix whose entries are the column sum also can be a row sum since A is symmetric of S that is

$$D_{i,j} = \sum_j S_{ij} \tag{23}$$

Arbitrary scaling invariance and degeneracy are guaranteed by the constraint of (6). The solution of LPP problem can be gained by solving the eigenvector problem of

$$G L G^T w = \lambda G D G^T w \tag{24}$$

where L=D-A denotes the graph Laplacian matrix in the community of spectral analysis and can be viewed as the discrete version of Laplace Beltrami operator on a compact Rimannia manifold [29]. Projected final eigenscores of both GMLPP and GPLPP feature dataset are normalized by Z-score normalization. Both the normalized scores vectors are fused by maximum score fusion rule [31]. Final score of EGLPP approach is computed as

$$NS_{GMLPP} = \frac{GMLPP_S - mean(GMLPP_S)}{Std(GMLPP_S)} \tag{25}$$

$$NS_{GPFLDA} = \frac{GPFLDA_S - mean(GPFLDA_S)}{Std(GPFLDA_S)} \tag{26}$$

$$EGLPP_S = Max[(NS_{GMLPP} + NS_{GPLPP})/2] \tag{27}$$

For both train and test image Gabor dataset final EGLPP score matrix is computed, from this score matrix Euclidean distance is evaluated as

$$\varepsilon_i^2 = \left\| W_{EGLPPQ} - W_{EGLPPT} \right\|^2 \tag{28}$$

where W_{EGLPPT} and W_{EGLPPQ} are projected vector score matrices of training and testing Gabor dataset images. If ε_i is less than some predefined threshold value θ_i then test image belongs to class i. So that testing image is matched with trained image and based on Euclidean distance and RBF kernel based SVM classifier [33] facial expressions are classified.

— **Entire Gabor LPFDA**

Entire Gabor locality preserving Fisher discriminant analysis (EGLPFDA) measures the "weights" of two data points by the corresponding distance, and then the affinity matrix is calculated by these weights. Note that the "pairwise" representation of within scatter matrix and between scatter matrix is very important for EGLPFDA. Following simple algebra steps, the within scatter matrix (11) of EGFLDA can be transformed into the following forms

$$S_w = \sum_{c=1}^{C}\sum_{i=1}^{N^c}\left(g_i^c - m_c\right)\left(g_i^c - m_c\right)^T \tag{29}$$

$$= \sum_{c=1}^{C}\sum_{i=1}^{N^c}\left(g_i^c - \frac{1}{N^c}\sum_{j=1}^{N^c} g_j^c\right)\left(g_i^c - \frac{1}{N^c}\sum_{j=1}^{N^c} g_j^c\right)^T \tag{30}$$

$$= \sum_{i=1}^{N} g_i g_i^T - \sum_{c=1}^{C}\frac{1}{N^c}\sum_{i,j=1}^{N^c} g_i^c g_i^T \tag{31}$$

$$= \sum_{i=1}^{N}\left(\sum_{j=1}^{N} P_w(i,j)\right) g_i g_i^T - \sum_{i,j=1}^{N} P_w(i,j) g_i g_j^T \tag{32}$$

$$= \frac{1}{2}\sum_{i,j=1}^{N} P_w(i,j)\left(g_i g_i^T + g_j g_j^T - g_i g_j^T - g_j g_i^T\right) \tag{33}$$

$$= \frac{1}{2}\sum_{i,j=1}^{N} P_w(i,j)(g_i - g_j)(g_i - g_j)^T \tag{34}$$

Let g_i be the n dimensional feature in the Gabor feature vector space and let $\{g_1,g_2,g_3, \ldots .g_N)$ be the Gabor feature vectors. In case of linear supervised approach, let gl_i be label of g_i, and then the label set of all Gabor feature vector samples can be represented by notation $\{gl_1,gl_2,\ldots ,gl_N\}$.
where

$$P_w(i,j) = \begin{cases} \frac{1}{N^c}, & if(gl_i = gl_j = c) \\ 0, & if(gl_i \neq gl_j) \end{cases} \tag{35}$$

Let S_T be the total scatter mixed matrix of FLDA, and it can obtained as

$$S_b = S_T - S_w \tag{36}$$

$$= \frac{1}{2}\sum_{i,j=1}^{N} P_b(i-j)(g_i - g_j)(g_i - g_j)^T \tag{37}$$

where

$$P_b(i,j) = \begin{cases} \frac{1}{N} - \frac{1}{N^c}, & if(gl_i = gl_j = c) \\ \frac{1}{N}, & if(gl_i \neq gl_j) \end{cases} \tag{38}$$

EGLPFDA approach is achieved by weighting pair wise data points

$$\hat{S}_W = \frac{1}{2}\sum_{i,j=1}^{N} \hat{P}_w(i,j)(g_i - g_j)(g_i - g_j)^T \tag{39}$$

$$\hat{S}_b = \frac{1}{2}\sum_{i,j=1}^{N} P_b(i,j)(g_i - g_j)(g_i - g_j)^T \quad (40)$$

where

$$\hat{P}_w(i,j) \text{ and } \hat{P}_b(i,j) \quad (41)$$

(41) denote the weight matrix of different pairwise points of the within class samples and between class samples, respectively.

$$\hat{P}_w(i,j) \equiv \begin{cases} \frac{W(i,j)}{N^c}, & \text{if}(gl_i = gl_j = c) \\ 0, & \text{if}(gl_i \neq gl_j) \end{cases} \quad (42)$$

$$\hat{P}_b(i,j) \equiv \begin{cases} W(i,j)\left(\frac{1}{N} - \frac{1}{N^c}\right), & \text{if}(gl_i = gl_j = c) \\ \frac{1}{N}, & \text{if}(gl_i \neq gl_j) \end{cases} \quad (43)$$

where W indicates the affinity matrix, the formation of W is critical for the performance of classified accuracy, projected final eigenscores of both GMLPFDA and GPLPFDA feature dataset are normalized by Z-score normalization. Both the normalized scores vectors are fused by maximum score fusion rule [31]. Final score of EGLPFDA approach is computed as

$$NS_{GMLPFDA} = \frac{GMLPFDA_S - mean(GMLPFDA_S)}{Std(GMLPFDA_S)} \quad (44)$$

$$NS_{GPLPFDA} = \frac{GPLPFDA_S - mean(GPLPFDA_S)}{Std(GPLPFDA_S)} \quad (45)$$

$$EGLPFDA_S = Max[(NS_{GMLPFDA} + NS_{GPLPFDA})/2] \quad (46)$$

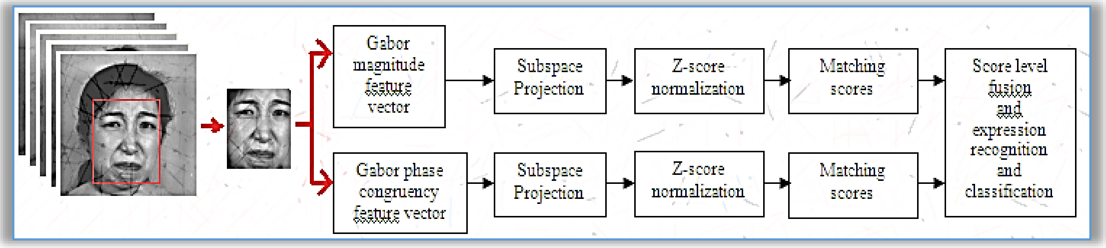

Figure 1. Typical system for entire Gabor subspace approach for expression recognition

4. RESULTS AND ANALYSIS

— Preprocessing

In this work, Japanese female facial expression (JAFFE) database is used for experiment. This database contains 213 images of 7 facial expressions. It has six basic facial expressions and one neutral expression, posed by 10 Japanese female models of 256x256 resolution. All the images of this database were pre-processed to obtain non-illumination facial expression images, which have normalized intensity, uniform size and shape. Procedure used in this work performs detecting facial feature points manually including eyes, nose and mouth. Finally using a histogram equalization method illumination effects were removed. The size of the images is resized to 111x126. Figure 2 shows some examples of normalized facial expression images after pre-processing from JAFFE database.

Figure 2. Preprocessed image samples of seven expressions of one subject without noise

— Noisy images

In this work an impulsive noise is added to 30% of JAFFE dataset of original images by detecting the required area of face without preprocessing. The size of the image is resized into 111x126. During the presence of noise performance of proposed approach is computed. This noise is also called as salt and pepper noise. In the presence of noise face images are having dark pixels in bright regions and white pixels lies in dark region. The noise density is chosen as 0.05 is added in the test image set. Figure 3 shows the sample noisy images added with spike noise.

Figure 3. Image samples of seven expressions of one subject with impulsive noise

— **Testing and analysis of results**

Support Vector Machine Classifier (SVM) [33] using (RBF) method is used to classify the expressions. To create SVM model, all 210 images of JAFFE database are considered. In that 70% of images are considered for training and 30% images are considered for testing using hold out cross validation classification method. The database is tested with all the subspace models and proposed approach in the presence of noise and in the absence of noise. In addition to a drastic reduction in the number of coefficients, it is observed that a considerable improvement in the recognition rate relative to the facial expression recognition experiment of earlier work.

Table 1. Gabor feature parameters

Number of scales of Gabor filter bank	Number of orientations of Gabor filter bank	Filter bank	Dimension of Gabor feature vector space	Coefficients before dimensional reduction	Coefficients after dimensional reduction
5	8	40	559440	564.003	205.365

Table 2. Comparison of state of art methods

Approaches	Recognition accuracy rate	Data base condition
LBP based LDA[2]	73.4%±5.6	JAFFE database was tested with
Boosted LBP based LDA[2]	77.6%±5.7	JAFFE
LDA [3]	86.33%	Person-Dependent corresponding reduced dimension using JAFFE database
LFDA[3]	90.70%	Person-dependent case corresponding reduced dimension LFDA using JAFFE database
Gabor+PCA[34]	57% to 80%	Tested o JAFFE database with 40 filters of Gabor combined with PCA features.
		Tested with FERET database cropped into 80x80 size

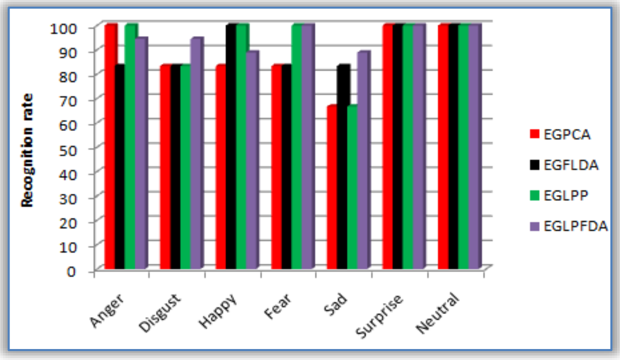

Figure 4. Performance of proposed approaches for expression recognition under absence of noise

Table 3. Comparative analysis of subspace approaches in the absence of noise

Subspace Methods	Overall accuracy rate
EGPCA	83.333%
EGFLDA	90.476%
EGLPP	88.095%
EGLPFDA(Proposed)	95.238%
Gabor+PCA+SVM [39]	81.7%
Gabor+LPP [25]	82% to 87.5%
B2DPCA[35] B2DLDA[35] 2DPCA+2DLDA+LDA[35]	82.05% 85.56% 89.20%

In most of the cases of Gabor based face and expression recognition system entire Gabor feature extraction is not used. Complete oriented phase congruency model has several features of face recognition. Table 1 demonstrates the Gabor feature dimension measures and table 2 gives te state of art approaches taken in this study to copare proposed work performace. Entire Gabor subspace projection results in the absence of noise are quoted in table 3. In the presence of noise overall accuracy of proposed method is measured as shown in table 4. The main problem of combining the magnitude and phase regions of Gabor is higher dimension and more redundant informations. This problem can be resolved in this work by dimensional reduction subspace models like EGPCA, EGFLDA EGLPP and EGLPFDA. Final matching scores are delivered by these approaches having less redundant coefficients values.These scores are normalized using Z-score normalization techniques and all the scores are fused using maximum fusion rule. 95.238% of overall accuracy is achieved by proposed approach. Angry and disgust expressions are found to be 94.44%.

Table 4. Expression recognition rate of proposed approach in the presence of noise

Anger	Disgust	Happy	Fear	Sad	Surprise	Neutral
100.00	94.44	100.00	88.89	66.67	94.44	94.44
Over all accuracy = 91.269%						

Happy and sad expressions accuracy is found to be 88.89% respectively. Fear, surprise and neutral expressions accuracy was found to be 100% as shown in figure 4. Proposed EGLPFDA approach enhances the expression classification rates compare to other subspace approaches. Overall classification time of proposed approach (EGLPFDA) is reduced as given in figure 6. Proposed approach yields good results even noises were added to images. Over all accuracy is found to be 91.269% in the presence of salt and pepper noise. In this case sad expression recognition rate is found to be 66.67% and disgused expression recognition is 94.44%. Both these expressions are sometimes looks like same.

Figure 5. Framework of expression recognition and classification system

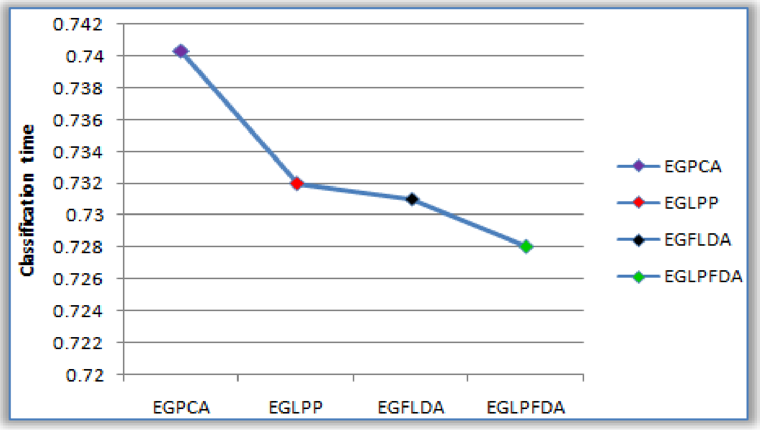

Figure 6. Comparison of classification time

5. CONCLUSION

In this paper entire Gabor locality preserving Fisher discriminant analysis approach is proposed. Dimensional reduction and enhancement of accuracy rates of expressions recognition and classification in the presence of noise and absence of noise by solving the problems of discriminant analysis are the main goals of this work. To reach these goals entire Gabor filter is used as holistic method for feature extraction and projection of high dimension space is achieved by locality preserving Fisher linear discriminant analysis subspace method. Most of the approaches are found in literature was discarded the phase part of the Gabor filter. In this work face representation are carried out by utilizing both Gabor magnitude and entire phase information. Dimension of the Gabor magnitude feature vector and Gabor phase feature vector are reduced and redundant data is reduced. Proposed EGLPFDA approach improves the performance of earlier subspace approaches in terms of dimensional reduction, recognition rate and classification time. Facial expression recognition using proposed approach in the absence of noise is found to be 95.238% and in the presence of salt and pepper noise is found to be 91.269% when tested with JAFFE database and expressions are classified using SVM_RBF classifier.

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