

Subspace based Expression Recognition Using Combinational Gabor based Feature Fusion

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Abstract—This paper demonstrates mainly on enhancement of extracted feature and proposes a novel approach for feature level fusion for efficient expression recognition. Extracted Gabor filter magnitude feature vector has been fused with upper face part geometrical features and Gabor phase feature vector has been fused with lower face part geometrical features respectively. Both these high dimensional feature dataset have been projected into low dimensional subspace for de-correlating the feature data redundancy by preserving local and global discriminative features of various expression classes of JAFFE, YALE and FD databases. The effectiveness of subspace of fused dataset has been measured with different dimensional parameters of Gabor filter. The experimental results reveal that performance of the subspace approaches for high dimensional proposed feature level fused dataset yields higher accuracy rates compared to state of art approaches.

Index Terms—Discriminant analysis, Gabor filter, Expression recognition, Feature extraction, Subspace, Geometrical feature.

I. INTRODUCTION

Facial expression recognition is a kind of cognitive nonverbal task used in various applications to understand the human internal feelings. Human drowsiness of vehicle driver can be recognized with suitable facial expression recognition approach. In medical field to understand the patient situation their facial expressions might be useful. Accuracy of human expression recognition depends on the situation of face image has taken. The mobile sciences, medical diagnosis, mind training, psychological studies, security based systems all have different views of the facial expressions. Plutchik emotional model presented in [1] illustrates the relationship between one to one emotions generated by different expressions. Ekman and Friesen [2] proposed Facial Action Coding System (FACS) for expression recognition during 1978. Ekman [2] was categorized the expressions based on distinct properties of faces as anger, happy, sad, surprise, disgust and fear. Main objective of this research work is to recognize the different

expressions efficiently by enhancing the Gabor filter magnitude and phase features by fusing the upper and lower face features geometrical features. The dimensionality of the feature dataset has been reduced by implementing different subspace methods by preserving the discriminative face features. The scope of this study is to introduce the novel approach for efficient facial expression recognition for limited area of face region. In this work various linear and non linear subspace methods have been tested with three databases. The dimensional reduction of fused feature dataset has been carried out by implementing subspace methods.

In this paper section II illustrates the related work. Section III delivers proposed feature level fusion. Section IV briefly overviews the subspace methods. Results and discussions are made in Section V. Conclusions are drawn in Section VI.

II. RELATED WORK

Peng et al. (2005) [3] worked on facial expression recognition and classification using minimum redundancy –maximum relevance method which has been based on mutual information to select the subset of features during reduction of features space. Bai et al. (2009) [4] they combined LBP features and Gabor features of face images. For efficient expression recognition they used weighted LBP Gabor complex features with linear discriminant analysis. Yu and Yang [5] have been used class discriminative based approach to recognize the face by discarding null space from between class matrix and diagonalized the within scatter matrix in order to solve the problem of singularity matrix. Xie et al. [6] presented Gabor based feature extraction by separating Gabor magnitude and phase parts separately. Phase part has been modified by introducing local Gabor exclusive OR patterns. They carried out expression recognition by reducing the high dimensional space by introducing block based Fisher linear discriminant analysis. In our work a novel approach for fusion of extracted features based on geometrical and appearance methods have been proposed. Geometrical eigen feature vectors have been generated for limited areas of face part.

According to several literatures it can be viewed as Linear Discriminant Analysis (LDA) method can be used for expression recognition for different databases. If number of expression data samples reduces then performance of LDA algorithm becomes fall down and scatter matrix also becomes singular. Hence it would be difficult to maintain larger variability between two classes. Optimization for the singularity matrix problems were noticed by Belhumeur et al. [7] and proposed a Fisherface method (FF), which uses old and more useful principal component analysis (PCA) [15] based subspace projection strategy. Li et al. [8] did discriminant analysis based non parametric approach recognition. Spectral regression kernel discriminate analysis (SRKDA) have been proposed by Ming et al. [9], and suggested that SRKDA method can efficiently yields better solutions than ordinary dimensional reduced subspace learning approaches. Rahulamathavan et al [10] introduced facial expression recognition system with encrypted domain using linear Local Fisher discriminant analysis (LFDA). Author was tested JAFFE data base with the developed algorithm and achieved 94.37% recognition rates. Happy and Routray [11] worked on patch based strategy for different face appearances. For expression classification discriminative features were considered by further patches obtained from active patches. Feature extraction by Gabor filter with local binary pattern and dimensional reduction of high dimensional data concept is introduced by Abdulrahman et al. [47]. Liu et al. (2012) [48] has been carried out facial expression recognition based on the fusion of geometry features and texture features. Deng et al. [52] demonstrated about local Gabor based feature extraction with LDA and PCA projection. Zhen and Zilu [53] tested JAFFE database using fusion approach which was framed by Gabor filter and 70% of overall recognition accuracy has been achieved.

Linear and nonlinear subspace projection methods were directly implemented by some researchers on input image dataset to achieve feature extraction and dimension reduction. Different subspace methods were implemented on high dimensional feature dataset for dimensional reduction and compared the consequences of subspace methods [12]. George et al. [13] worked on facial expression recognition with SMS alert. Various state of art on facial expression recognition system was made by Bettadapura in [14]. One of the most popular and old subspace methods such as principal component analysis (PCA) [15-20] has been used in this work for projection of Fisher linear discriminant subspace [38-42]. Struc and Pavesic [21] worked on Gabor filter based feature extraction by considering magnitude and phase parts separately for face recognition application. Both magnitude and phase feature vectors were projected by Fisher LDA algorithm. Linear Fisher Discriminant Analysis for face recognition has been demonstrated by Sugiyama et al. [51]. In our work linear and nonlinear discriminant based subspace methods have been utilized for reduction of high dimensional data to low dimensional data. Different scales and orientations of Gabor filter has been utilized for construction of high

dimensional combinational based feature dataset. Zhaoyu Wang and Shangfei Wang (2011) [53] proposed a feature level fusion for efficient expression recognition for thermal and visible face images. Their approach improves the recognition accuracy of negative expressions. Thiago et al. [54] presented a feature level fusion by utilizing Gabor filter and Local Binary Pattern (LBP) for efficient recognition of expressions, they got 96.2% of expression recognition rate, their work does not support for dimensional reduction of high level feature dataset.

III. PROPOSED FRAME WORK

In this work total Gabor filter space has been divided in to two separate spaces such as Gabor filter magnitude space and phase feature space [21]. These two feature vectors have been fused with extracted geometrical feature vectors. In this section a novel approach for fusion of feature extraction have been proposed. Geometrical feature extraction has been carried out with a new concept of limited regions of the face which is compatible with textures features during the fusion of extracted features. Geometrical features are essential for expression recognition and classification. These features changes whenever the face region gets deformed with different movements in the muscles of the face. Region of interested areas have been selected from different face templates and some fiducial points were located on face image. Basic architecture of entire expression recognition system based extraction of both geometrical and holistically features supports efficient recognition and classification of expressions after subspace projection. Both geometric and holistic features are key elements for final expression recognition.

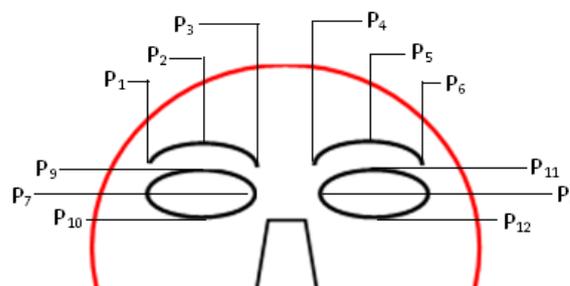


Fig.1. Locations of fiducial points on upper part of the face image

In this paper geometrical feature has been extracted which is related to AAM model feature extraction approach, points were marked on corner point of eyes, where the upper and lower eyelid meet called eye canthus.

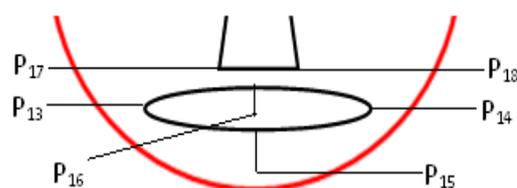


Fig.2. Locations of fiducial points on lower part of the face image

Pre marked points on upper face and lower face parts yields geometrical features, which supports texture information. Fig. 1 and Fig. 2 shows location of fiducial points on face. In this work 18 fiducial points has been located on face image and 16 dimensions eigen vectors has been computed as given in (4). In upper face part P₁ to P₁₂ points were marked by selecting eyes and eyebrows face templates as local points. In left eye brow P₁, P₂, P₃ points were marked and in right eye brow P₄, P₅, P₆ points were marked respectively as shown in Fig. 3. Some points like P₉, P₁₀, P₁₁, P₁₂ are marked on upper and lower eyelids respectively on both the eyes. Corner points of eyes are P₇ and P₈. Variation of eye brow and eyelids movements makes the different values of eigen values. Points P₇ and P₈ are to be considered as inner canthi on reference points.

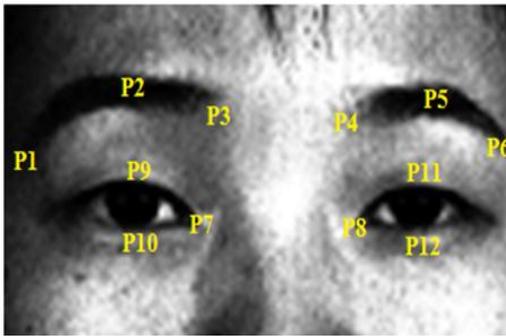


Fig.3. Upper part of the face and pre-marked fiducial points

In lower part of the face nose and mouth templates have been considered, two extreme ends of lip were marked by points P₁₃ and P₁₄ as shown in Fig. 4. Middle points of the lower and upper lip were marked as P₁₅ and P₁₆. Some of the expressions are exhibited based on compression and expansion of nostrils position. The magnitude of eigen vector and meaning of each geometry features are shown in Table 1. In this table, m_i (P₁, . . . ,P₁₈) is the abscissa of ith point and n_i(P₁, . . . ,P₁₈) is the ordinate of ith point (a point where the pre-marking has been done).

Table 1. Eigen vectors of geometrical features

Magnitude of Eigen vector	Equivalent meaning	Magnitude of Eigen vector	Equivalent meaning
EG ₁	nP ₁ - E	EG ₉	nP ₁₂ - P ₁₁
EG ₂	nP ₂ - E	EG ₁₀	nP ₁₃ - E
EG ₃	nP ₃ - E	EG ₁₁	nP ₁₄ - E
EG ₄	mP ₄ - mP ₃	EG ₁₂	nP ₁₆ - E
EG ₅	nP ₄ - E	EG ₁₃	nP ₁₆ - yP ₁₅
EG ₆	nP ₅ - E	EG ₁₄	mP ₁₄ - P ₁₃
EG ₇	nP ₆ - E	EG ₁₅	nP ₁₇ - E
EG ₈	nP ₁₀ - P ₉	EG ₁₆	nP ₁₈ - E

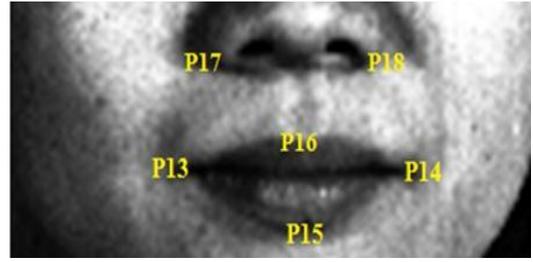


Fig.4. Lower part of the face and pre-marked fiducial points

$$E = \frac{|mP_8 - mP_7|}{2} \tag{1}$$

Where E is a reference value or base value is a constant in magnitude. Base E is the central point of the two inner canthi. In respect that the inner canthi (point P₇ and P₈) are constant in 18 feature points, these points are considered as the reference points, and then 16-dimensional eigenvector {EG₁, EG₂, EG₃EG₁₆} are obtained. During experiment validation {EG₁, EG₂, EG₃EG₁₆} has been used as facial expression eigen value features feasibility analysis. For all the databases eigen feature based geometrical feature extraction procedure has been implemented. Geometrical Feature Eigen Vector (GFEV) is computed as follows.

$$GFEV_{upper} = [EG_1, EG_2, EG_3 \dots \dots EG_{12}] \tag{2}$$

$$GFEV_{lower} = [EG_{13}, EG_{14}, \dots \dots EG_{16}] \tag{3}$$

The total dimension of geometrical feature vector (GFV) is 16 is given as

$$GFV = [EG_1, EG_2, \dots \dots EG_{16}] \tag{4}$$

Magnitude part of the Gabor filter has been enhanced by combining Gabor filter magnitude feature vector with upper face part geometrical features. Similarly phase part of Gabor filter has been enhanced by combining Gabor filter with lower face part geometrical features. Gabor magnitude feature vector (GMFV) is fused with Upper face geometrical feature vector (GFEV_{upper}) and Combinational Gabor Magnitude Feature Vector (CGMFV) have been formed. Similarly Gabor phase feature vector (GPFV) is fused with lower face part geometrical feature vector (GFEV_{lower}) and Combinational Gabor Phase Feature Vector have been formed. Proposed expression recognition system using feature level fusion and discriminant based subspace methods presented in Fig. 5. Feature level fused dataset of both combinational Gabor magnitude and combinational Gabor phase has been projected using different linear and nonlinear subspace methods. Projected subspaces of both CGM and CGP were fused using score level fusion and Combinational Entire Gabor (CEG) subspace has been formed. This CEG subspace

has been computed for both training dataset images and testing images respectively. Euclidean distance have been computed between final score matrix of both the train and testing CEG subspace. Based on the Euclidean distance metric expressions were recognized. All the expressions were classified using “Leave One Out” strategy of support vector machine classifier. Table 1 presents Eigen values of geometrical feature vectors for upper and lower face part.

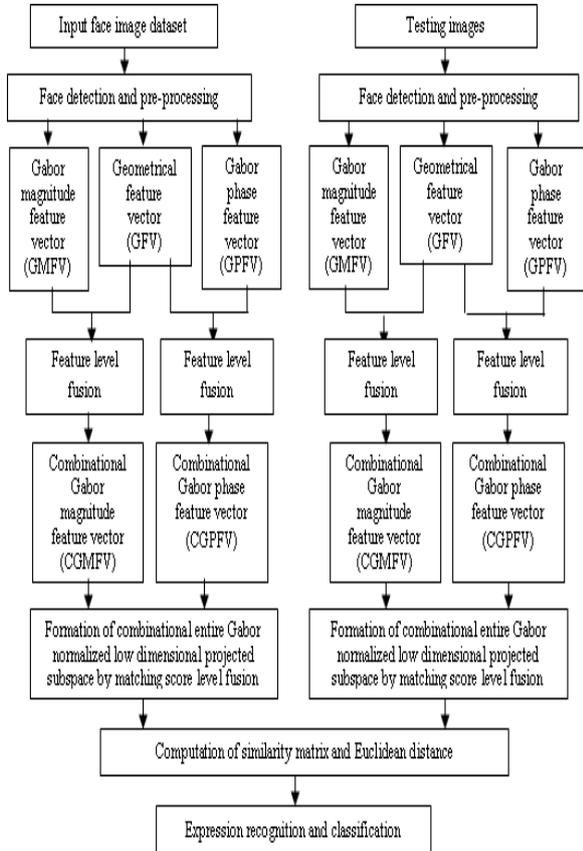


Fig.5. Proposed feature level fusion and expression recognition system

IV. DIMENSION REDUCTION BY SUBSPACE METHODS

In this section brief overview of subspace methods have been discussed. Subspace methods finds vital role for dimensional reduction of higher dimensional data. Curse of dimensionality is a problem for subspace projection. Intermediate feature dimension reduction has been implemented on proposed feature level fused dataset for different values of dimensions of images with different values of Gabor filter scales and orientation values as parameters as given in Table 2, Table 3 and Table 4 for JAFFE, YALE and FD databases respectively.

A. Subspace Formation

In this work PCA has been used for intermediate feature reduction for Fisher linear discriminant space. High dimensional data has been de-correlated by PCA method. In this method class variables are not used. Due to this reason PCA is unsupervised. It preserves global

structures of data by maximize the variance. It uses second order statistics by referring orthogonal space analysis. This method basically lies on eigenface concept. Consider a combinational Gabor dataset G , which consists of N measurements \vec{g}_i ($1 \leq i \leq N$) in a high dimensional space R^m . This can also represented as $G = [\vec{g}_1, \dots, \vec{g}_N] \in R^{m \times N}$. The main scope of the dimensional reduction strategy is to compute the respective low dimensional space can be given by $S = [\vec{s}_1, \dots, \vec{s}_2] \in R^{d \times N}$. Where $d < m$, of G . For combinational Gabor PCA projection matrix can be represented as $S = W^T G$. Where W is transformation matrix. The objective function of combinational entire Gabor PCA (CEGPCA) is given as

$$\max_W \sum_{i=1}^N (g_i - \bar{g})^2 \quad (5)$$

$$\bar{g} = \frac{1}{N} \sum_{i=1}^N g_i \quad (6)$$

Where \bar{g} is the mean value of combinational Gabor feature dataset of G samples. FLDA algorithm was developed by Belhumeur et al. [7]. It surplus the performance of eigenfaces (PCA) approach, in some cases FLDA works well even if different illumination occurs with lower error rate. Also works well even if different facial expression takes place. FLDA maximizes the between-class scatter matrix variance and minimizes the within-class scatter matrix variance. FLDA finds vital role as a basic strategy in discriminant based approaches for expression recognition and classifications. When number of features in feature space becomes larger than the number of training samples, then within scatter matrix becomes more singular. Limitation of number of training samples causes this singularity problem. In this work high dimensional combinational Gabor dataset has been reduced by class discriminative subspace approaches by referring our earlier work mentioned in [12]. In FLDA between class matrix S_b can be given as

$$S_b = \sum_{i=1}^C N_i (\bar{g}_i - \bar{g})(\bar{g}_i - \bar{g})^T \quad (7)$$

Within class scatter matrix S_w be defined as

$$S_w = \sum_{i=1}^C (N_i - 1) S_i = \sum_{i=1}^C \sum_{j=1}^{N_i} (g_{i,j} - \bar{g}_i)(g_{i,j} - \bar{g}_i)^T \quad (8)$$

Where $g_{i,j}$ is the n -dimensional pattern j from class C_i , and N_i is the number of training pattern from class C_i , and C is the total number of classes or expression groups. The total mean vector is given by

$$\bar{g} = \frac{1}{N} \sum_{i=1}^C N_i \quad (9)$$

$$\bar{g}_i = \frac{1}{N} \sum_{i=1}^C \sum_{j=1}^{N_i} a_{i,j} \quad (10)$$

Vector \bar{a}_i and matrix i are the unbiased sample mean and sample covariance of matrix of class. In above equation (9) and (10) where N is the total number of samples, that is $N=N_1+N_2+N_3 + \dots + N_C$.

Locality Preserving Projection (LPP) approach presented by He et al. [43] preserves local features of input data obtained from affinity matrix (similarity graph information). The input data are projected as same as PCA manner ie $S=W^T G$. During the preservation of local contents LPP method minimizes the different object function by putting large penalty on neighboring points g_i and g_j if both are mapped with larger difference in projected space.

$$\min_{W_k} \sum_{i,j=1} \xi_{ij} \|W_k^T g_i - W_k^T g_j\|^2 \quad k=1,2,\dots,d \quad (11)$$

Where ξ_{ij} is the weight of the connected edge between neighboring points g_i and g_j in the affinity graph. Two common methods like heat kernel and cosine model are implemented for computing the value of ξ_{ij} in the input space. If two points are not connected in a same neighborhood then $\xi_{ij}=0$. Locality preserving uses affinity graph to compute an optimal projection in an effort to preserve the local structure of the data. The objective function can modified as

$$\min_{W_k} W_k^T G L G^T W_k \quad \text{s.t. } W_k^T G D G^T W_k = 1 \quad (12)$$

Where $L=D-\xi$ is the Laplacian related graph, and D is a diagonal matrix with $D_{ii} = \sum_j \xi_{ij}$. Then computation of the required projection of subspace solution is obtained from following eigen value problem definition.

$$G L G^T W_k = \lambda_k G D G^T W_k \quad (13)$$

Locality preserving projection based Fisher discriminant Analysis (LFDA) is explicitly preserves the local discriminative features by labeling the classes of different expressions. LFDA is a dimensional reduction method of multimodal data by preserving the local structure of within scatter matrix. By increasing between class scatter matrix variances. For larger variations of features of expressions occurs linear methods fails to give good strength for efficient recognition and classification of expressions. Following section illustrates briefly the three different discriminative based nonlinear subspace

approaches. Consider set of combinational Gabor feature dataset G . where

$$G = [\vec{g}_1, \dots, \vec{g}_N] \in R^{m \times N} \quad (14)$$

The objective function of combinational entire Gabor LFDA is given by

$$\arg \max_Z \frac{Z^T S^b Z}{Z^T S^w Z} \quad (15)$$

Where S^b and S^w indicates the local inter class scatter matrix and local intra class scatter matrix respectively. W_{ij}^b and W_{ij}^w indicates the weight matrices of the local inter class adjacency graph and local intra class adjacency graph respectively. C_i is the class label of the data point g_i and $l \in \{1,2,\dots,C\}$ is the class label l this work heat kernel weight has been used for constructing affinity graph such as A_{fij}

$$S^b = \frac{1}{2} \sum_{i,j=1}^N W_{ij}^b (g_i - g_j)(g_i - g_j)^T \quad (16)$$

$$S^w = \frac{1}{2} \sum_{i,j=1}^N W_{ij}^w (g_i - g_j)(g_i - g_j)^T \quad (17)$$

$$W_{ij}^b = \begin{cases} A_{fij} \left(\frac{1}{N} - \frac{1}{N_i} \right), & \text{if } C_i = C_j = l; \\ \frac{1}{N}, & \text{if } C_i \neq C_j \end{cases} \quad (18)$$

$$W_{ij}^w = \begin{cases} \frac{A_{fij}}{N_l}, & \text{if } C_i = C_j = l; \\ 0, & \text{if } C_i \neq C_j \end{cases} \quad (19)$$

Final eigen vectors corresponding to maximum eigenvalue of the generalized eigenvalue problem is obtained from (15) and given as

$$S^b Z = \lambda S^w Z \quad (20)$$

Objective functions of KLFDA [50], KLSWFDA and KGLSWFDA are obtained by referring our earlier work as mentioned in [23]. All the subspace methods are used to reduce the dimensionality of combinational Gabor space. The reduced dimension space has been named as combinational entire Gabor (CEG) subspace. Expression recognition using all the subspace methods have been named as CEGPCA, CEGICA, CEGFLDA, CEGLPP, CEGFLDA, CEGKLFDA and CEGKLSWFDA approaches respectively [please refer our earlier work given in open access article [23][24].

B. Creation of CEG Space

Similarity score matrix of combinational Gabor magnitude $CGM(\text{Subspace})_S$ and similarity score matrix of combinational Gabor phase $CGP(\text{Subspace})_S$ has been computed. Normalized score of combinational Gabor magnitude subspace can be given as

$$NS_{CGM(\text{Subspace})} = \frac{CGM(\text{Subspace})_S - \mu(CG M(\text{Subspace})_S)}{Std(CG M \text{Subspace}_S)} \quad (20)$$

Normalized score of combinational Gabor phase subspace can be given as

$$NS_{CGP(\text{Subspace})} = \frac{CGP(\text{Subspace})_S - \mu(CG P(\text{Subspace})_S)}{Std(CG P \text{Subspace}_S)} \quad (21)$$

Final score subspace matrix (Jain, 2005) can be obtained by fusing both CGM and CGP normalized score matrices using maximum fusion rule.

$$W_{CEG(\text{Weighted_Subspace})} = \text{MAX} \left[\left(\begin{array}{cc} NS_{CGM(\text{Subspace})} & NS_{CGP(\text{Subspace})} \\ NS_{CGM(\text{Subspace})} & NS_{CGP(\text{Subspace})} \end{array} \right) \right] \quad (22)$$

Euclidean distance between trained and test image dataset have been computed

$$\varepsilon_i^2 = \left\| W_{CEG(W_Subspace)Q} - W_{CEG(W_Subspace)T} \right\|^2 \quad (23)$$

Where $W_{CEG(W_Subspace)T}$ and $W_{CEG(W_Subspace)Q}$ are projected vector final score weight matrices of training and testing combinational entire Gabor subspace images. The image set with lower Euclidean distance has been computed. Based on Euclidean distance metric and RBF kernel based SVM classifier [26] facial expressions were classified.

V. RESULTS AND DISCUSSIONS

A. Database Used

The databases used in this work are briefly illustrated below.

- **JAFFE database:** In this work, Japanese Female Facial Expression (JAFFE) database was used for experiment [27]. Figure 6 shows cropped samples of JAFFE database. Total 210 images were cropped into 111x126 size. Only required areas like mouth nose, eyes and chin areas has been considered during face detection for extraction of texture features and rest of the part was removed.



Fig.6. Cropped and preprocessed images JAFFE database

- **YALE database:** This database contains 11 images per person for 15 individuals resulting into a total of 165 images. The images in this database reveal major variations of illumination changes, different facial expressions, and the persons wearing eyeglasses/no eyeglasses not considered. The original size of the images in this database is 243x320 pixels with 256 gray levels. For experiments, the size of these images was scaled down to 64x64 pixels size. Totally 90 (15 personsx6 expression per person images) were considered for experiment without doing preprocessing the image shown in Figure 7. In this database six expressions have been considered for the experiment.



Fig.7. Cropped and preprocessed images JAFFE database

- **FD database:** This database (FD) consists of 13 subjects and each subject has 75 images with different expressions. In this work 500 images were used with 10 subjects, five expressions such as happy, surprise, angry, sad and neutral. Each class of expression has 100 images. For experiments, all the images are pre-processed and the size of these images is scaled down to 92x92 pixels size shown in Figure 8.



Fig.8. Sample images of FD expression database of size 92x92

Table 2. State of art approaches of JAFFE database

Literature	Approaches	OFERR
Zhang et al. [28]	LBP based LDA	73.4% ±5.6
Zhang et al. [28]	Boosted LBP based LDA	77.67 % ±5.7
Wang [35]	Orthogonal LDA	86.33%
Cohen et al. [29]	LFDA	90.70%
Shih et al.[36]	2DLDA+SVM	94.13%
Dongcheng [31]	Gabor+PCA, Gabor+2DPCA	91% and 94%
Bai et al. [4]	Gabor+LBP+LDA	92% to 97%
Zhi and Ruan [30]	2D discriminant LPP	95.91%
Zhang et.al.[38]	Multilayer Perceptron	90.34%
Liejun et al.[32]	SVM based	95.7%
Zhao et al. [34]	PCA and NMF	93.72%
Lee [33]	RDAB	96.67%

Table 3. Gabor Filter input parameters common to three database features

Number of scales (m)	Number of orientations (n)	Gabor filter size (GF _{mn})
5	4	20
3	8	24
3	4	12
5	8	40

Table 4. Gabor filter parameters and feature vector dimension of JAFFE database

Gabor filter feature vector dimension (GF _{FVD})	Geometrical feature vector dimension (G _{FVD})	Combinational Gabor feature vector dimension (CG _{FVD})
279720	16	279736
335664	16	335680
167832	16	167848
559440	16	559456

Table 5. Gabor Filter Parameters and feature vector dimension of YALE database

Gabor filter feature vector dimension (GF _{FVD})	Geometrical feature vector dimension (G _{FVD})	Combinational Gabor feature vector dimension (CG _{FVD})
81920	16	81936
98304	16	98320
49152	16	49168
163840	16	163856

Table 6. Gabor Filter Parameters and feature vector dimension of FD database

Gabor filter feature vector dimension (GF _{FVD})	Geometrical feature vector dimension (G _{FVD})	Combinational Gabor feature vector dimension (CG _{FVD})
169280	16	169296
203136	16	203152
101568	16	101584
338560	16	338576

Table 7. Performance of subspace approaches for JAFFE database at m=5 and n=8

Subspace approaches	Overall facial expression recognition rate in (%) (OFERR)	Classification time in (sec) (CT)	Dimension reduction feature vector (DR _{FV})
CEGPCA	82.35	1.012	147
CEGICA	85.03	1.245	147
CEGKPCA	87.52	1.045	147
CEGFLDA	90.45	0.874	126
CEGLPP	88.08	1.010	147
CEGLFDA	93.45	0.997	147
CEGKLFDA	95.83	0.982	126
CEGKGLSWFDA	99.05	0.847	105

Table 8. Performance of subspace approaches For YALE Database at m=5 and n=8

Subspace approaches	Overall facial expression recognition rate in (%) (OFERR)	Classification time in (sec) (CT)	Dimension reduction feature vector (DR _{FV})
CEGPCA	61.08	0.997	63
CEGICA	64.80	0.912	63
CEGKPCA	68.52	0.929	63
CEGFLDA	75.78	0.929	63
CEGLPP	72.27	0.802	63
CEGLFDA	77.15	0.797	63
CEGKLFDA	81.38	0.758	54
CEGKGLSWFDA	87.72	0.698	45

Table 9. Performance of subspace approaches for FD database at m=5 and n=8

Subspace approaches	Overall facial expression recognition rate in (%) (OFERR)	Classification time in (sec) (CT)	Dimension reduction feature vector (DR _{FV})
CEGPCA	79.46	1.967	175
CEGICA	80.80	1.935	175
CEGKPCA	82.02	1.781	175
CEGFLDA	85.94	1.209	175
CEGLPP	84.28	1.126	175
CEGLFDA	89.46	1.098	175
CEGKLFDA	91.20	1.012	150
CEGKGLSWFDA	95.80	0.914	100

Table 10. Confusion Matrix of JAFFE Database Using proposed Subspace Approach Using SVM Leave One Out Technique in (%)

	AN	DI	HA	FE	SA	SU	NE
AN	100	0	0	0	0	0	0
DI	0	100	0	0	0	0	0
HA	0	0	93.33	0	6.67	0	0
FE	0	0	0	100	0	0	0
SA	0	0	0	0	100	0	0
SU	0	0	0	0	0	100	0
NE	0	0	0	0	0	0	100

Table 11. Confusion Matrix of YALE Database Using proposed Subspace Approach Using SVM Leave One Out Technique in (%)

	HA	SU	SA	WI	SL	NE
HA	100	0	0	0	0	0
SU	0	100	0	0	0	0
SA	0	0	77.78	0	22.22	0
WI	15.94	15.94	0	68.12	0	0
SL	0	0	0	0	100	0
NE	0	0	0	19.12	0	80.88

Table 12. Confusion Matrix of FD Database Using proposed Subspace Approach Using SVM Leave One Out Technique in (%)

	HA	SU	AN	SA	NE
HA	98.33	0	1.67	0	0
SU	0	100	0	0	0
AN	0	0	100	0	0
SA	1.66	0	1.67	91.67	5.0
NE	0	1.06	0	10.27	88.67

B. Analysis of results

In this work SVM classifier has been implemented to classify the expressions. To create input dataset, all 210 images of JAFFE database and 90 images of YALE database were considered. In this work images were recognized using Euclidean distance metric between trained and testing images. Using "Leave One Out" SVM strategy all the expressions classes of images were classified. All the public databases have been tested with all the subspace methods by reducing proposed feature level fusion dataset. In addition to a drastic reduction in the feature level fused dataset dimension highest recognition rates have been noted. It has been observed that a considerable improvement in the recognition rate relative to the facial expression recognition. Performance of proposed approach is compared with state of art approaches listed in Table 2.

In this section to analyze the performance of subspace approaches for proposed feature level fusion three databases have been tested such as JAFFE, YALE and FD respectively. In this work CEGKPCA, CEGLPP, CEGFLDA, CEGLFDA, CEGKLFDA and CEGKGLSWFDA subspace approaches has been compared with respect to input dimensional parameters listed in Table 3. These approaches are framed for dimensionality reduction of higher dimensional baseline proposed feature level fused dataset obtained from concatenating of Gabor filter feature vector and geometrical feature vector dataset dimensions as given in Table 4, Table 5 and Table 6 respectively. For CEGLPP, CEGKPCA CEGLFDA, CEGKLFDA, CEGKLSWFDA and CEGKGLSWFDA algorithms nearest neighbor number value k has been set to 7. Where the value of σ was set to be 0.5. Overall expression recognition rate for three databases presented in Table 7, Table 8 and Table 9 respectively.

Effectiveness of proposed feature level fusion can be measured by analyzing the individual expression recognition rates. The performance of different subspace approaches varies due to variation in subspace projection vector dimension and discriminative properties. Gabor filter features are modified by adding small amount of geometrical features. It would cause the improvement for efficiency of expression recognition for several linear and non linear subspace methods. Two newly proposed subspace approaches [23][24] have been tested with proposed feature level fusion and expressions were classified for three well known public databases as illustrated below. From the results it has been noted that proposed feature level fusion improves the recognition rate of CEGKGLSWFDA approaches by consistently outperforming the CEGKPCA, CEGLPP, CEGFLDA, CEGLFDA and CEGKLFDA expression recognition approaches.

Table 10, Table 11 and Table 12 presents confusion matrix of JAFFE, YALE and FD databases using CEGKGLSWFDA subspace approach using SVM, "Leave One Out Technique" in (%) at $m=5$ and $n=8$ Gabor parameters. It has been found that for JAFFE

database happy expressions recognition rate is 93.33%. But remaining expression recognition rate is 100%. Probably it is due to confusion with sad and disgust expressions. From confusion matrix of YALE database for happy, surprise and sleep expressions correct recognition rate (CRR) is 100%. For sad expression correct recognition rate is 77.78%. For wink expression CRR is 68.12% and neutral 80.88% respectively. For FD database 100% accuracy has been achieved for surprise and angry expressions. For happy expression 98.33% accuracy and for sad expression 91.67% is obtained. For Neutral expression 88.67% accuracy has been obtained.

This work clearly analyzes that CEGFLDA algorithm performs comparatively better than CEGLPP algorithm. It demonstrates that discriminative features make an efficient recognition using class label information. Although the CEGLFDA algorithm outperforms CEGKPCA, CEGFLDA, CEGLPP algorithms by using both local subspace structure and class label information, it is still a linear algorithm and is inadequate to describe the nonlinear face image space due to high variability of the image content and style. Therefore it performs worse and weak than the kernel based KLFDA algorithm. Confusion matrix was derived from SVM_RBF kernel based using "Leave One Out" strategy. It demonstrates the correct and misclassification of expressions.

VI. CONCLUSIONS

Feature extraction is one of the vital step for enhancing the recognition accuracy of the database images. Extracted feature are key elements and finds significant role in recognition of human face expressions at different conditions of the environments. Dimensional reduction of high dimensional fused feature dataset is also an important task in various fields. In this work Gabor filter magnitude and phase features were isolated and fused with upper and lower face part fiducial points eigen vectors. Upper face part enhances the texture content of magnitude part. Similarly lower face part features enhances the texture content of phase part. Total dimension of the geometrical feature vector is 16 has been utilized for making combinational Gabor feature dataset. This geometrical features does not affect much on feature variations due to less of geometrical feature vectors in illuminations variations. Due to addition of few amount of geometrical features to Gabor filter features dimensionality of feature dataset has been increased. Dimensional reduction of high dimension dataset by preserving local and global discriminative features has been achieved using different linear and nonlinear subspace approaches. Combinational entire Gabor kernel locality and global content saving symmetrical weighted Fisher discriminant analysis based approaches outperformance higher recognition and classification rates. This work concludes that higher dimensional combinational Gabor feature vector has been created has redundant data and correlated information. This can be reduced by discriminative subspace methods by preserving local discriminative structure of data by

resolving the singularity problem at non linear region. Proposed feature level fusion makes CEGKGLSWFDA algorithm better in recognition of expressions by reduces the higher dimensionality of feature dataset. Intrinsic features dimension is varied by varying the dimensionality of images. Input Gabor filter texture content with different dimensional parameters like number of orientations and scales are essential points in this work. All the subspace approaches have been tested for four sets of Gabor filter parameters. It has been concluded that for orientations eight and scales of four outputs good accuracy of recognition. Leave one out SVM strategy has been implemented for better classification of the expressions.

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