I.J. Image, Graphics and Signal Processing, **2018, 11, 54-64**
Published Online November 2018 in MECS (http://www.mecs-press.org/)
DOI: 10.5815/ijigsp.2018.11.06

Facial Expression Recognition by Holistic and Geometrically Integrated Subspace

G.P.Hegde
SDM Institute of Technology, Department of ISE, Ujire, 574240, India
Email: gphegde123@gmail.com

Seetha M.
GNITS, Department of CSE, Hyderabad India
Email: smaddala2000@yahoo.com

Nagartna P Hegde
VCE, Department of CSE, Hyderabad, India
nagaratnaph@gmail.com .com

Received: 06 July 2017; Accepted: 12 July 2018; Published: 08 November 2018

***Abstract*—**This paper demonstrates mainly on feature extraction by analytic and holistic methods and proposes a novel approach for feature level fusion for efficient expression recognition. Gabor filter magnitude feature vector is fused with upper part geometrical features and phase feature vector is fused with lower part geometrical features respectively. Both these high dimensional feature dataset has 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 compared with state of art approaches.

***Index Terms*—**Discriminant analysis, Gabor filter, Expression recognition, Feature extraction, Subspace, geometrical feature

I. Introduction

Facial expression recognition is a cognitive task for various applications where one can understand the human internal feelings. Drowsiness of vehicle driver can be recognized with suitable facial expression recognition approach. 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. Facial expression recognition for static images of three different databases have been utilized in this work for comparing the related works as mentioned in next section. In this work section 2 demonstrates related work, section 3 focuses on proposed frame work, section 4 delivers brief overview of subspace manifolds, section 5 discuses about results and analysis. Conclusion is drawn in section 6.

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] used discriminative 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.

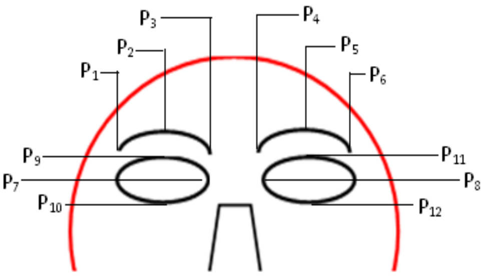

Fig.1. Locations of fiducial points on upper part of the face image

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 a principal component analysis (PCA) [15] [53] based projection strategy. Li et al. [8] did discriminant analysis based non parametric approach recognition. Ming et al. [9] proposed spectral regression kernel discriminate analysis (SRKDA), and suggested that SRKDA method can efficiently yields better solutions than ordinary 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 discriminiant 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.

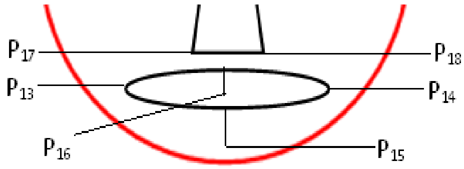

Fig.2. Locations of fiducial points on lower part of the face image

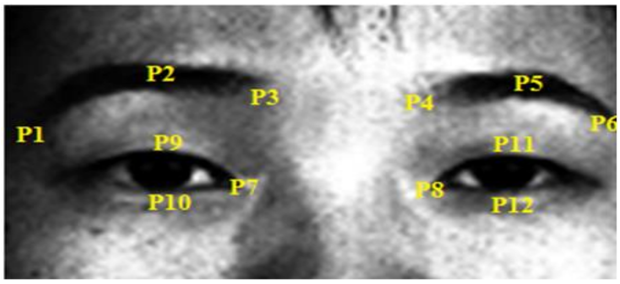

Fig.3. Upper part of the face and pre-marked fiducial points

III. Proposed Feature Level Fusion

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 on extraction of both geometrical and holistically extracted features supports efficient recognition and classification of expressions after subspace projection. Both geometric and holistic features are key elements for final expression recognition.

In this paper geometrical feature has been extracted which is related to AAM model [22] feature extraction approach, points are marked on corner point of eyes, where the upper and lower eyelid meet called eye canthus.

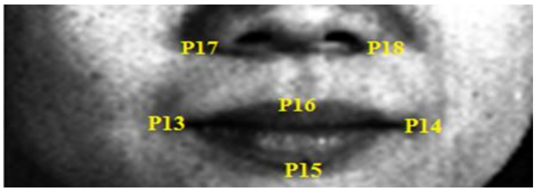

Fig.4. Lower part of the face and pre-marked fiducial points

Pre marked points on upper face and lower face parts yields geometrical features, which supports texture information. Figure 1 and Figure 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 (3). In upper face part P_1 to P_{12} points were marked by selecting eyes and eyebrows face templates as local points. In left eye brow P_1, P_2, P_3 points were marked and in right eye brow P_4, P_5, P_6 points were marked respectively as shown in Figure 3. Some points like P_9 , P_{10}, P_{11}, P_{12} are marked on upper and lower eyelids respectively on both the eyes. Corner points of eyes are P_7 and P_8. Variation of eye brow and eyelids movements makes the different values of eigen values. Points P_7 and P_8 are to be considered as inner canthi on reference points.

In lower part of the face nose and mouth templates have been considered, two extreme ends of lip were marked by points P_{13} and P_{14} as shown in Figure 4. Middle points of the lower and upper lip were marked as P_{15} and P_{16}. 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 showed in Table 1. In this Table, m_i (P_1, . . . ,P_{18}) is the abscissa of i^{th} point and n_i(P_1, ...P_{18}) is the ordinate of i^{th} point (a point where the pre-marking has been done).

$$E = \frac{|mP_8 - nP_7|}{2} \qquad (1)$$

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 P_7 and P_8) are constant in 18 feature points, these points are considered as the reference points, and then 16-dimensional eigenvector {EG_1, EG_2, EG_3 . . . .EG_{16}} are obtained. During experiment validation {EG_1, EG_2, EG_3 . . . .EG_{16}} 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.

$$GFEV_{upper} = \lfloor EG_1, EG_2, EG_3 \cdots\cdots EG_{12} \rfloor \qquad (2)$$

$$GFEV_{lower} = \lfloor EG_{13}, EG_{14}, \cdots\cdots EG_{16} \rfloor \qquad (3)$$

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

$$GFV = \lfloor EG_1, EG_2, \cdots\cdots EG_{16} \rfloor \qquad (4)$$

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 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 Figure 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.

Table 1. Eigen values of geometrical feature vectors for upper and lower face part

Magnitude of Eigen vector	Equivalent meaning	Magnitude of Eigen vector	Equivalent meaning
EG_1	$\|yP_1 - E\|$	EG_9	$\|yP_{12} - P_{11}\|$
EG_2	$\|yP_2 - E\|$	EG_{10}	$\|yP_{13} - E\|$
EG_3	$\|yP_3 - E\|$	EG_{11}	$\|yP_{14} - E\|$
EG_4	$\|xP_4 - xP_3\|$	EG_{12}	$\|yP_{16} - E\|$
EG_5	$\|yP_4 - E\|$	EG_{13}	$\|yP_{16} - yP_{15}\|$
EG_6	$\|yP_5 - E\|$	EG_{14}	$\|xP_{14} - P_{13}\|$
EG_7	$\|yP_6 - E\|$	EG_{15}	$\|yP_{17} - E\|$
EG_8	$\|yP_{10} - P_9\|$	EG_{16}	$\|yP_{18} - E\|$

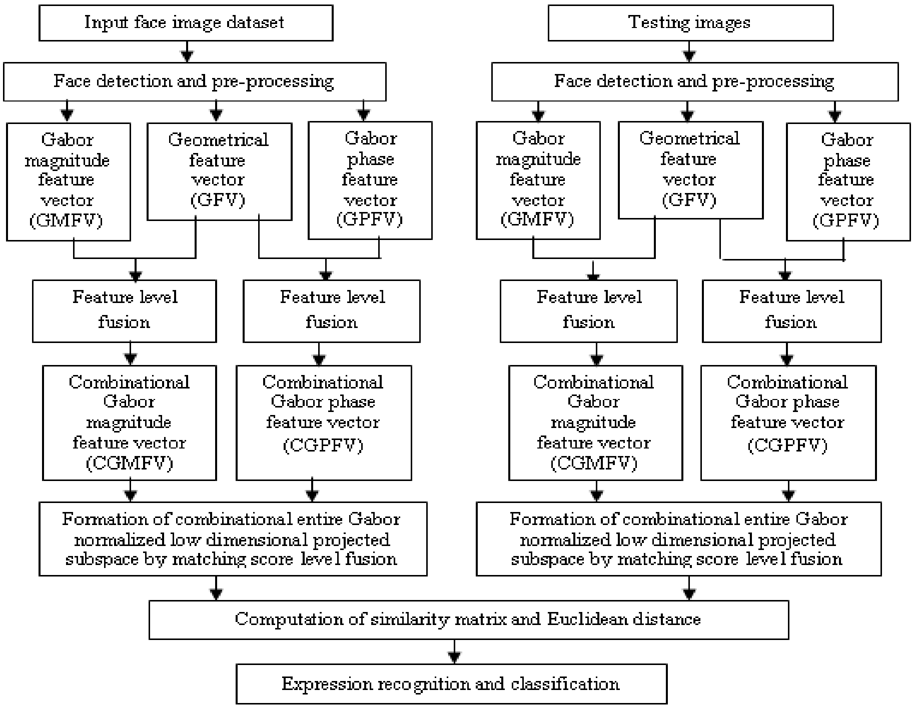

Fig.5. Methodology of the entire work

IV. Overview Of 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. Principal Component Analysis subspace method 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.

A. Subspace Formation

In this work PCA has been framed and made it into increases the sample variances by reducing correlation between data vectors. PCA is a dimensional reduction subspace method and relatively simple. It speeds up the computational time during recognition of expressions moderately. 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≤i≤N)in a high dimensional space R^m. This can also represented as $G=[\vec{g_1},\cdots\vec{g_N}]\in R^{m\times N}$. The main scope of the dimensional reduction strategy is to compute the respective low dimensional space can be given by $S=[\vec{s_1},\cdots\vec{s_2}]\in R^{d\times N}$. Where d<m , of G. For combinational Gabor PCA projection matrix can be represented as $S=W^TG$. where W is transformation matrix. The objective function of combinational entire Gabor PCA (CEGPCA) is given as

$$\max_{W} \sum_{i=1}^{N}\left(g_i-\bar{g}\right)^2 \tag{5}$$

$$\bar{g}=\frac{1}{N}\sum_{i=1}^{N} g_i \tag{6}$$

Where $\bar{g}$ is the mean value of combinational Gabor feature dataset of G samples.

FLDA algorithm was developed by P.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

$$S_b=\sum_{i=1}^{C} N_i\left(\overline{g_i}-\bar{g}\right)\left(\overline{g_i}-\bar{g}\right)^T \tag{7}$$

Within class scatter matrix S_w be defined as

$$S_W = \sum_{i=1}^{C}(N_i - 1)S_i = \sum_{i=1}^{C}\sum_{j=1}^{N_i}\left(g_{i,j} - \overline{g_i}\right)\left(g_{i,j} - \overline{g_i}\right)^T \quad (8)$$

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 meanvector is given by

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

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

Vector $\overline{a_i}$ 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 $N=N_1+N_2+N_3+ - - - N_C$.

Locality Preserving Projection (LPP) approach [43-46]preserves local features of input data obtained from affinity matrix (similarity graph information). The input data are projected as same as PCA manner ie $S=W^TG$. 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.

$$\min_{W_k} \sum_{i,j=1} \xi_{ij}\left\|W_k^t g_i - W_k^t g_j\right\|^2 \quad (11)$$

$k = 1,2,\cdots d$

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

$$\min_{W_k} W_k^T GLG^T W_k \quad \text{s.t.} \quad W_k^T GDG^T W_k = 1 \quad (12)$$

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.

$$GLG^T W_k = \lambda_k GDG^T W_k \quad (13)$$

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

$$G = [\overrightarrow{g_1}, \cdots \overrightarrow{g_N}] \in R^{m \times N} \quad (14)$$

The objective function of combinational entire Gabor LFDA is given by

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

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 $l \in \{1,2,\cdots C\}$ is the class label I this worl heat kernel weight has been used for constructing affinity graph such as A_{fij}

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

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

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

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

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

$$S^b Z = \lambda S^w Z \tag{20}$$

Objective functions of KLFDA [50], KLSWFDA and KGLSWFDA are found 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, CEGLFDA, CEGKLFDA, CEGKLSWFDA and CEGKGLSWFDA 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(Subspace)$_S$ and similarity score matrix of combinational Gabor phase (CGP(Subspace)$_S$ has been computed. Normalized score of combinational Gabor magnitude subspace can be given as

$$NS_{CGM(Subspace)} = \frac{CGM(Subspace)_S - \mu(CGM(Subspace)_S)}{Std(CGMSubspace_S)} \tag{21}$$

Normalized score of combinational Gabor phase subspace can be given as

$$NS_{CGP(Subspace)} = \frac{CGP(Subspace)_S - \mu(CGP(Subspace)_S)}{Std(CGPSubspace_S)} \tag{22}$$

Final score subspace matrix [25] can be obtained by fusing both CGM and CGP normalized score matrices using maximum fusion rule.

$$W_{CEG(Weighted\_Subspace)} = MAX\left[\left(NS_{CGM(Subspace)} + NS_{CGP(Subspace)}\right)\right] \tag{23}$$

Euclidean distance between trained and test image dataset have been computed

$$\varepsilon_i^2 = \left\| W_{CEG(W\_Subspace)Q} - W_{CEG(W\_Subspace)T} \right\|^2 \tag{24}$$

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 is computed. Re-perform the operation on this image set with lower threshold value to get the image having the expression closer to the defined image. The image with smaller value of Euclidean distance in between score matrices of both trained and testing expression images will be represented as the resultant expression image. So that testing expression image is matched with trained image. Based on Euclidean distance metric and RBF kernel based SVM classifier [26] facial expressions are classified.

V. RESULTS AND DISCUSSIONS

A. Database Used

- **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 243×320 pixels with 256 gray levels. For experiments, the size of these images was scaled down to 64×64 pixels size. Totally 90 (15 persons×6 expression per person images were onsidered 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 92×92 pixels size shown in Figure 8.

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

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**		**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**

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 in adequate 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.

ACKNOWLEDGMENT

The authors wish to thank Dr. M. Seetha for her kind support and proper guidance to frame this work.

REFERENCES

[1] Rizwan Ahmed Khan, (2013). Ph D thesis on, “Detection of emotions from video in non-controlled environment,” (Public defense).

[2] P. Ekman, W. Friesen, (2003). “Facial Action Coding System: A Technique for the Measurement of Facial Movements,” *Consulting Psychologists Press, California*, 19.

[3] Peng, H., Long, F., and Ding, C. (2005). “Feature selection based on mutual information: criteria of max-dependency, max-relevance, and min-redundancy,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 27, No. 8, pp.1226-1238.

[4] Gang Bai. (2009). “Facial Expression Recognition Based on Fusion Features of LBP and Gabor with LDA,” *2nd International Congress on Image and Signal Processing, E-ISBN* : 978-1-4244-4131-0,, pp 1-5.

[5] H. Yu and J. Yang, (2001). “A direct LDA algorithm for high dimensional data - with application to face recognition,” *Pattern Recognition*, vol. 34, 2067-2070.

[6] Shufu Xie, Shiguang Shan, Xilin Chen, Jie Chen, (2010). “Fusing Local Patterns of Gabor Magnitude and Phase for Face Recognition,” *IEEE Transactions on Image Processing* Volume:19 , Issue: 5. pp1349-1361.

[7] P. Belhumeur, J. Hespanda, and D. Kiregeman, (1997) “Eigenfaces versus Fisherfaces: Recognition using class specific linear projection,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 19, no. 7, pp. 711–720.

[8] Z. Li, D. Lin, and X. Tang, (2009). “Nonparametric discriminant analysis for face recognition,” *IEEE Transactions. Pattern Analysis. Machine. Intelligence.*, vol. 31, no. 4, pp. 755–761.

[9] Yue Ming, Qiuqi Ruan, Xiaoli Li, Meiru Mu, (2010). “Efficient Kernel Discriminate Spectral Regression for 3D Face Recognition,” *Proceedings Of ICSP*, pp:662 - 665 .

[10] Rahulamathavan, Yogachandran, RC-W. Phan, Jonathon A. Chambers, and David J. Parish, (2013). "Facial expression recognition in the encrypted domain based on local fisher discriminant analysis," *Affective Computing, IEEE* Transactions on 4, no. 1, 83-92.

[11] S L Happy, Aurobinda Routray, (2015). “Automatic Facial Expression Recognition Using Features of Salient Facial Patches,” *IEEE Transaction on Affective Computing*, Vol.6, No. 1.

[12] Ashok Rao, S. Noushath, (2010). “Subspace methods for face recognition –survey,” *Elsevier, Computer Science Review by Science Direct* pp 1-17 –ELSIVER Series.

[13] St.George, B., Chang, C. C., Lin, C.J., (2013). “Facial expression recognition with SMS alert,” *IEEE International Conference on Optical Imaging Sensor and Security (ICOSS).*

[14] Vinay Bettadapura, “Face Expression Recognition and Analysis: The State of the Art” URL: https://arxiv.org/ftp/arxiv/papers/1203/1203.6722.pdf.

[15] GRS Murthy, R.S. Jadon, (2000). “Effectiveness for Eigenspaces for Facial Expressions Recognition,” *International Journal of Computer Theory and Engineering*, Vol. 1, No. 3. 1793-8201.

[16] Jamal Hussain Shah, Muhammad Sharif, Mudassar Raza, and Aisha Azeem, (2013). “A Survey: Linear and Nonlinear PCA Based Face Recognition Techniques,” *The International Arab Journal of Information Technology*, Vol. 10, No. 6.

[17] Dimitris Bolis, Anastasios Maronidis, Anastasios Tefas, and Ioannis Pitas, (2010) “Improving the Robustness of Subspace Learning Techniques for Facial Expression Recognition,” pp. 470–479.

[18] A. Adeel Mohammed, M. A. Sid-Ahmed Rashid Minhas, and Q. M. Jonathan Wu, (2011) “A face portion based recognition system using multidimensional PCA,” *IEEE 54th International Midwest Symposium on Circuits and Systems*, pp. 1 – 4.

[19] Abegaz, T., Adams J, Bryant, K., Dozier, G., Popplewell, K., Ricanek, K., Shelton, J., and Woodard, D.L., (2011). “Hybrid GAs for Eigen-based facial recognition,” *IEEE Workshop on Computational Intelligence in Biometrics and Identity Management*, pp. 127 – 130.

[20] Chengliang Wang, LibinLan, MinjieGu, and Yuwei Zhang, (2011). “Face Recognition Based on Principle Component Analysis and Support Vector Machine,” *3rd International Workshop on Intelligent Systems and Applications*, pp. 1 – 4.

[21] Vitomir Struc and Nikola Pavesic, (2010). “The Complete Gabor–Fisher Classifier for Robust Face Recognition,” *EURASIP Journals on Advances in Signal Processing*.

[22] Pedro Alexandre Dias Martins, (2008). “Active Appearance Models for Facial Expression Recognition and Monocular Head Pose Estimation,” *Master of Science thesis*.

[23] G.P. Hegde , M. Seetha, Nagaratna Hegde, (2016). “Kernel Locality Preserving Symmetrical Weighted

Fisher Discriminant Analysis based subspace approach for expression recognition", *Engineering Science and Technology, an International Journal. Elsevier Publishers*.

[24] G. P. Hegde , Shubhada V. P. , M. Seetha , Nagaratna P. Hegde, (2016). "Recognition of Expressions Based on Kernel Global and Local Symmetrical Weighted Fisher Discriminant Nonlinear Subspace Approach," *International Journal of Applied Engineering Research* ISSN 0973-4562 Volume 11, Number 5. pp 3558-3569.

[25] Anil Jain, Karthik Nandakumar, Arun Ross, (2005). "Score normalization in multimodal biometric systems," *International Journal of Pattern Recognition* 38, 2270–2285. ELSEVIER Publishers.

[26] C.W.Hsu,C.C. Chang and G.J.Lin. (2009). A practical guide to support vector classification. :http//www.csie.ntu.edu.tw/cjlin/papers/gui d e/guide.pdf.

[27] http://www.kasrl.org/jaffe.html

[28] Shiqing Zhang, Xiaoming Zhao, Bicheng Lei, (2012). "Facial Expression Recognition Based on Local Binary Patterns and Local Fisher Discriminant Analysis," *Wseas Transaction on Signal Processing* Issue 1, Volume 8.

[29] I. Cohen, N. Sebe, A. Garg, L. Chen, T.S. Huang, (2003). "Facial expression recognition from video sequences: temporal and static modeling," *Computer Vision and Image Understanding* 91, 160–187.

[30] R Zhi, Q Ruan, (2008). Facial expression recognition based on two dimensional discriminant locality preserving projections. Neuro Computing. 71, 1730–1734.

[31] Shi Dongcheng , Cai Fang, (2013). "Facial Expression Recognition Based on Gabor Wavelet Phase Features," pp 520 – 523.

[32] W Liejun, Q Xizhong, Z Taiyi, (2009). "Facial expression recognition using improved support vector machine by modifying kernels," *Information. Technology*. 8(4), pp 595–599.

[33] Chien-Cheng Lee, Shin-Sheng Huang and Cheng-Yuan Shih, (2010). "Facial Affect Recognition Using Regularized Discriminant Analysis-Based Algorithms," *EURASIP Journal on Advances in Signal Processing*.

[34] L Zhao, G Zhuang, X Xu, (2008). "Facial expression recognition based on PCA and NMF," *Proceeding of the 7th World Congress on Intelligent Control and Automation*, pp. 6822–6825.

[35] Wang Z., Ruan Q., (2010). "Facial Expression Recognition Based Orthogonal Local Fisher Discriminant Analysis," *Proceedings of the International Conference on Signal Processing (ICSP)*, pp. 1358–1361.

[36] F. Y. Shih, C.-F. Chuang, and P. S. P. Wang, (2008). "Performance comparisons of facial expression recognition in JAFFE database," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 22, no. 3, pp. 445–459.

[37] Z Zhang, M Lyons, M Schuster, S Akamatsu, (1998) "Comparison between geometry based and Gabor wavelet based facial expression recognition using multi layer perceptron ," *Proceeding 3rd International Conference on Automatic Face and Gesture Recognition*, pp. 454–459.

[38] H. Ling, S. Soatto, N. Ramanathan, and D. Jacobs, (2010). "Face verification across age progression using discriminative methods," *IEEE Transactions. On Information. Forensic Security*, vol. 5, no. 1, pp. 82–91.

[39] X. Wang and X. Tang, (2004). "Random sampling LDA for face recognition," in *Proceedings of IEEE Conference of Computer Vision & Pattern Recognition*., pp.259–265.

[40] Jiadong Song, Xiaojuan Li, Pengfei Xu, Mingquan Zhou, (2011). "A New Face Recognition Framework: Symmetrical Bilateral 2DPLS plus LDA," *Journal of Multimedia*, Vol. 6, No. 1.

[41] M. Loog, R. P. W. Duin and R. Hacb-Umbach, (2001). "Multi-class Linear Dimension Reduction by Weighted Pair Wise Fisher Criteria," *IEEE Transaction on Pattern Recognition and Machine Intelligence*, Vol. 23, No. 7, pp. 762-766.

[42] E. K. Tang, P. N. Suganthan, X. Yao and A. K. Qin, (2003). "Linear Dimensionality Reduction Using Relevance Weighted LDA," *Pattern Recognition*, Vol. 38, No. 4, pp. 485-493.

[43] X. He and P. Niyogi, (2003). "Locality preserving projections," In Advances in Neural Information Processing Systems.

[44] Lin Kezheng, Lin Sheng and Chen Dongmei, (2008). "Enhanced Locality Preserving Projections,". CSSE (1), 985-988.

[45] Xiaofei He, Shuicheng Yan, Yuxiao Hu, Partha Niyogi, and Hong- Jiang Zhang, (2005). "Face RecognitionUsing Laplacianfaces", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, No. 3.

[46] Yi Jin and Qiu-Qi Ruan, (2007). "An image matrix compression based supervised LPP for face recognition," *International Symposium on Intelligent Signal Processing and Communication Systems*.

[47] Abdulrahman, Muzammil, Tajuddeen R. Gwadabe, Fahad J. Abdu, and Alaa Eleyan. (2014) "Gabor wavelet transform based facial expression recognition using PCA and LBP," *In Signal Processing and Communications Applications IEEE Conference and Communications Applications* pp. 2265-2268.

[48] Shuaishi Liu, Ning Ding, Mao Yang, Keping Liu, (2011). "Facial Expression Recognition Method Based on the Fusion of Geometry Features and Texture Features," *International Conference on Electrical and Computer Engineering, Advances in Biomedical Engineering*, Vol.11.

[49] Ziqiang Wang, Xia Sun, (2012). "Manifold Adaptive Kernel Local Discriminant Analysis for face Recognition," *Journal of Multimedia* Vol 7. No. 9.

[50] M. Sugiyama, (2006). "Dimensionality reduction of multimodal labeled data by local Fisher discriminant analysis," *Journal of Machine Learning Research*, vol.8, pp.1027- 1061.

[51] Hong-Bo Deng, Lian-Wen Jin, Li-Xin Zhen, Ian-Cheng Huang, (2005). "A New Facial Expression Recognition Method Based on Local Gabor Filter Bank and PCA plus LDA," *International Journal of Information Technology* Vol.11, No.11.

[52] Wang Zhen, Ying Zilu; (2012). "Facial expression recognition based on adaptive local binary pattern and sparse representation", IEEE.

[53] Zhaoyu Wang , Shangfei Wang, (2011). "Spontaneous facial expression recognition by using feature-level fusion of visible and thermal infrared images," *2011 IEEE International Workshop on Machine Learning for Signal Processing* - 2011 pp:1 – 6.

[54] Thiago H.H. Zavaschi, Alceu S. Britto Jr., Luiz E.S. Oliveira, (2013) Alessandro L. Koerich Fusion of feature sets and classifiers for facial expression recognition Expert Systems with Applications, 40, pp. 646–655, 20

[55] Rongrong Fu, Hong Wang ,, Wenbo Zhao, (2016). "Dynamic driver fatigue detection using hidden Markov model in real driving condition," *Expert Systems with Applications*, Volume 63, pp. 397–411.

Authors' Profiles

G. P. Hegde received PhD degree in Computer Science and Engineering from Visvesvaraya Technical University (VTU) Belgaum. India, in 2018. Presently he is working as Assistant Professor in Information Science Engineering department of SDMIT Ujire affiliated to Visvesvaraya Technical University (VTU) Belgaum. He has published over 32 technical publications and proceedings. His research interests include Image processing, Pattern recognition, Computer Networks, Software engineering, Software architecture. He is a reviewer committee member of many international journals.

M. Seetha received M.S. degree in Software System Engineering from the Birla Institute of Technology and Science (BITS), Pilani, India, and awarded Ph.D. degree in Computer Science and Engineering from the Jawaharlal Neharu Technological University (JNTU) Hyderabad, India during 2007. Since from 1999 to 2005, she has worked as Assistant Professor in Computer Science Engineering Department of Chaitanya Bharathi Institute of Technology, Hyderabad. Also worked as Associate Professor in 2005 to 2008. She is currently working as Professor and HOD in the Department of Computer Science and Engineering of G. Narayanamma Institute of Technology and Sciences, affiliated to JNTU, Hyderabad, India. Second-Author is the author of over 51 technical publications. Her research interest includes Image Processing, Pattern Recognition, Artificial Intelligence Neural Networks, Data communication and Interfacing, Data mining and Computer Organization. She is recognized as supervisor from Osmania University, Reviewer for International journals of Information Fusion. and also for ACM journal .

How to cite this paper: G.P.Hegde, Seetha M., Nagartna P Hegde, "Facial Expression Recognition by Holistic and Geometrically Integrated Subspace", International Journal of Image, Graphics and Signal Processing(IJIGSP), Vol.10, No.11, pp. 54-64, 2018.DOI: 10.5815/ijigsp.2018.11.06