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Local Non Zero Eigen Value Preservation Based Expression Recognition

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Abstract— This work proposes an finest mapping from features space to inherited space using kernel locality non zero eigen values protecting Fisher discriminant analysis subspace approach. This approach is designed by cascading analytical and non-inherited face texture features. Both Gabor magnitude feature vector (GMFV) and phase feature vector (GPFV) are independently accessed. Feature fusion is carried out by cascading geometrical distance feature vector (GDFV) with Gabor magnitude and phase vectors. Feature fusion dataset space is converted into short dimensional inherited space by kernel locality protecting Fisher discriminant analysis method and projected space is normalized by suitable normalization technique to prevent dissimilarity between scores. Final scores of projected domains are fused using greatest fusion rule. Expressions are classified using Euclidean distance matching and support vector machine radial basis function kernel classifier. An experimental outcome emphasizes that the proposed approach is efficient for dimension reduction, competent recognition and classification. Performance of proposed approach is deliberated in comparison with connected subspace approaches. The finest average recognition rate achieves 97.61% for JAFFE and 81.48% YALE database respectively.

Index Terms— Non-inherited feature space, Gabor filter, Emotion identification, trait extraction, inherited space.

I. INTRODUCTION

FACIAL expression recognition system acts major role in various fields such as mobile technologies, Internet of Things, computer vision, biometrics and pattern recognition areas since from last two decades. In biometrics field facial expression is one attribute to deliberate transient and non transient face attributes to deliver the different emotions [1-3]. Shi Dongcheng et al. [35] noted that in order to support a high rigorous and normal person contraption interface of new multimedia yield human expression recognition system is flood over various fields like mobile communication, robotic control system, pattern recognition, psychology, security, electronic voting systems and other fields.

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Typical facial emotional appreciation has face detection, feature extraction, subspace formation and emotional classification stages. Subspace projection methods identifies major role in dimensional reduction of high dimensional feature dataset in most of the earlier approaches.

Basically seven expressions are generally classified such as angry, happy, fear, surprise, sadness, disgust and neutral. Shi Dongcheng, Cai Fang [35] contributed non-inherited features discretely based Gabor wavelets and grabbed magnitude and phase domain. The author used an approach and in that cascading of both non-inherited datasets has been carried out. Authors were tested Principal component analysis (PCA) and two dimensional PCA algorithms for minimizing the dataset size and researchers obtained 91% and 94% expression recognition rates correspondingly for JAFFE dataset. Tariq, U. et. al.[36] addressed both person dependent and person independent emotion recognition system. Author worked on fusion of Gaussianization, scale invariant features, and few common motion features. They were worked on emotional classification based on SVM classifier. Fazli, S. et al. [38] introduced Gabor filter bank platform which offers a person self-determining facial expression recognition by reduction of non-inherited space dimension which was completed by cascading PCA and linear discriminant analysis (LDA) approaches. Author has obtained 89% correctness for Cohn-Kanade database. F. Y. Shih et. al. [39], worked on 2DLDA and non-linear oriented SVM machine and tested with JAFFE database author has found to be 95.71% true precision using leave one out approach and 94.13% by means of cross authentication policy. A different method of classification of facial identifications using LDA is illustrated in [40] in which Gabor features are grabbed using Gabor filter banks and condensed by two steps PCA algorithm. Kernel non zero eigen space strategy based on non-inherited class for expression examination is illustrated in [41]. Gang Bai et. al. [46] proposed facial expression recognition approach by fusing local binary pattern (LBP) and Gabor features. In this work weighted LBP Gabor complex features were found by LDA algorithm to represent facial expressions. Gabor filter and ICA joined with SVM of dissimilar kernels [49]. Preciseness of the expression recognition is reported in the literature is about 90%. Locality preserving projection (LPP)[25] yields the inherited space by determining the best linear nearby values to the eigen values of the Laplace Betrami works on the multiple fold by undertaking out-of-sample problem . Whereas LPP has obtained more reliable recital in human identification, This becomes an unsupervised dimensionality minimizing approach and in this approach discriminative content will not be considered.

By this way, LPP is not much useful in discerning human traits with dissimilar semantics such things are eventual target of emotional recognition. In recent times local Fisher discriminant analysis (LFDA) [29] manifold based expression recognition algorithm was proposed using dimensionality minimizing steps.

By successfully cascading the virtues of LDA and LPP, LFDA contents increases among class discriminative variations and protects shortest distance-class limited configuration at the equal time. Even if LFDA has yielded realistically excellent robustness by cascading both local non-inherited space field structure and label domain consecutively, at this stage it is a linear approach by default. So LFDA might not succeed to determine the inherent manifold composition when the human traits space is extremely nonlinear. LFDA is a latest approach was proposed as linear dimensionality minimizing approach [29]. It is based on locality preserving projection and unambiguously knows the set label content of the non-inherited data space. Goal of LFDA is to decrease the size of multi folded labeled data just about by increasing inter-class discriminative variations and protecting the intra-class local arrangement at the similar instance. LFDA folds–multiply discriminatory substance by identifying the adaptation matrix means that close by data pairs in the similar classes are assigned as closer and the class content pairs in dissimilar classes are assigned as remote at a distance. It is not needed to make same class samples pairs together.

The outstanding piece of this work presented here is arranged with dissimilar parts: Section II presents short summary of drawing features n by analytical method. In Section III, short overview of Gabor filter for garbing of face feature is made. In Section IV, short overview of LDA is delivered. In Section V, proposed domain task is delivered. In Section VI, experimental testing and result analysis is carried out. In Section VII, conclusions are made.

II. BRIEF OVERVIEW OF GEOMETRICAL FEATURE

There are several models and geometrical approaches have been developed for expression recognition based on action unit principles. Prior models make the dynamic and semantic relationship between action units. Facial behavior recognition finds many applications, like in psychological phenomena, computer human communication and real time applications. Recently Yongqiang Li et. al. [37] proposed knowledge driven prior model action unit based human trait recognition system. In geometrical based algorithms, facial traits or facial non-inherited contents and information are grabbed to frame a non-inherited element vector that forms the face abstraction. Generally extraction procedure cost of geometrical features is usually high. But more robustness to facial position variations like change in scale, size and orientations. Zhang et al [42] encompass two types of geometrical pointed areas of 34 fiducial points on a face and 612 Gabor wavelets coefficients grabbed from the human traits at the fiducial points around one and half decade back. Later several researches were worked on different approaches for geometrical area extraction platform based appearance detection and Gabor features as proposed in [42].

Formation of larger dimensional vector space of feature dataset leads to high computation cost, higher memory usage and classification accuracy cost. Automatic facial extraction and localization of the face templates such as eyes, mouth and nose of frontal face is demonstrated in this section. In the beginning face boundary detection is carried out. This stage is most important for the facial expression recognition and classification. The face boundary is detected using Viola Jones algorithm [47]. This algorithm is a widely used for face detection, its training is slow but detection is extremely fast and efficient. It is scale and location invariant detector. The detection of face templates and extraction of character points is presented in Fig. 1. After detecting the face boundary then eyes, nose and mouth regions are detected. Then distance vector is formed by these three region templates. Consider the mouth template, distance among two points P_1 and P_2 is horizontal lip distance is d_{hl}. Distance among points P_3 and P_4 is vertical lip distance is d_{vl}. Similarly for eye template distance between points P_5 and P_6 is eye brow to eye beneath distance is d_{eb}. Locating the points between iris of two eyes are P_7 and P_8, distance taken as d_i. Locating two points for end of nostrils are P_9 and P_{10} is d_n. Facial feature vector is formed by combining all the above distance elements.

$$GDFV = \left[d_{hl}, d_{vl}, d_{eb}, d_i, d_n\right] \tag{1}$$

Above vector (1) is computed for each person facial expression in the database. Geometrical distance feature vector elements are represented in Fig 2.

III. BRIEF OVERVIEW OF HOLISTIC FEATURE

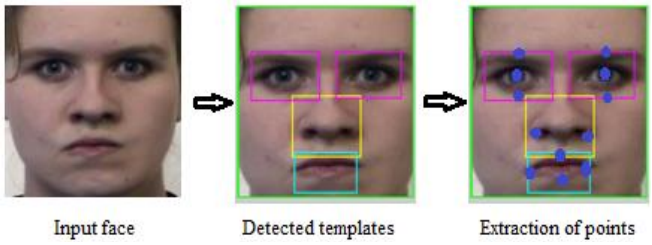


Fig. 1.Sample input face, detection of eyes, nose and mouth templates and extraction of character points.

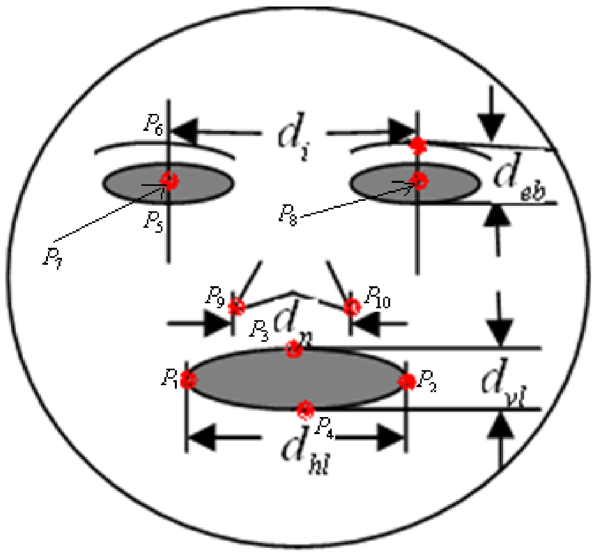


Fig. 2 Elements of facial feature points from face templates.

In this section, short overview regarding Gabor filter for large dimension features notification is made. Spatial frequency depiction of composition in the data sample could be carried by Gabor wavelet conversion procedure,

while protecting component regarding spatial dealings which is identified to be tough to face traits changes like several expressions. Gabor filters are worn in this work helps to grab the enhanced texture non-inherited space features and quantitative property coefficients necessary for expression recognition. Gabor filters are also called Gabor wavelets they forms multifaceted band partial filters with a supreme local domain in either side that is spatial area as well as the frequency field. So that when drawing the features of facial non-inherited region and implementing this principle earlier researchers gained wavelet domain, spatially non-inherited features of a limited frequency band. Spatial region oriented two dimensional Gabor filter can be formed as

$$\psi_{mn} = (x,y) = \frac{f_m^2}{\pi\kappa\eta}\left(\left(f_m^2/k^2\right)x'^2 + \left(f_m^2/\eta^2\right)y'^2\right)e^{j2\pi f_m x'}$$
(2)

Here,
$x' = x\cos\theta_n + y\sin\theta_n$, $y' = -x\sin\theta_n + y\cos\theta_n$

The filter produced in this domain which gives us some characteristics, due to this orientation θ_n and frequency f_m correspondingly helps in regeneration of compound flat wave which is exhibited by Gaussian kernel function. Centre frequency divided by the size of the Gaussian package gives a value, this value is determined by κ and η. Different scales of Gabor filter may have constant value then it effects the scale variations. Due to different scales of Gabor filter and values of κ and η are made constant , which defines f_m. The parameters like shape selection has significant importance and selection like filter characteristics has useful merits and it computes those parameters by defining various categories of Gabor wavelets, the mainly widespread parameters selected for face recognition also selected in this work as $\kappa = \eta = \sqrt{2}$ and $f_{max} = 0.25$. Several earlier works were focused on a Gabor filter bank for non-inherited feature mining from face of different traits formed spaces with five scales and eight orientations as shown in Table 1, that is, m = 0, 1. . . . s − 1 and n = 0, 1, . . . t − 1, where s = 5 and t = 8. Fig. 3(a) delivers magnitude output of the filtering process with the complete Gabor filter bank of 40 Gabor filters, similarly Fig. 3(b) shows the superior phase part of the Gabor filter bank frequently used for non-inherited region extraction in the field of face identification. Let I(x, y) denotes a grey scale face image of size p×q pixels and, furthermore, let $\psi_{m,n}(x, y)$ indicates a Gabor filter given by its centre frequency f_m and orientation θ_n. The non-inherited eigen feature grabbing route can then be defined as a filtering procedure of the given face image I(x,y) with the Gabor filter $\psi_{m,n}(x,y)$ of size m and orientation n, that is

$$G_{m,n}(x,y) = I(x,y) * \psi_{m,n}(x,y)$$
(3)

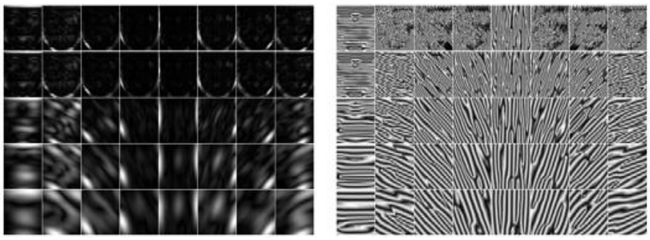
Where $G_{m,n}(x,y)$ denotes the composite filtering output that can be separated into its real ($E_{m,n}(x,y)$ and imaginary ($O_{m,n}(x,y)$) parts as

$$E_{mn}(x,y) = re[G_{mn}(x,y)]$$
(4)

$$O_{mn}(x,y) = img[G_{mn}(x,y)]$$
(5)

Based on these results, the magnitude part ($A_{m,n}(x,y)$) and phase part ($\phi_{m,n}(x,y)$) responses of the filtering operation can be computed as follows.

$$A_{m,n}(x,y) = \sqrt{E_{m,n}^2(x,y) + O_{m,n}^2(x,y)}$$
(6)


(a) (b)
Fig. 3 Gabor magnitude region and (b) enhanced Gabor phase region

$$\phi_{m,n}(x,y) = \arctan\left(\frac{O_{m,n}(x,y)}{E_{m,n}(x,y)}\right)$$
(7)

(5) and (6) are indicated for typical Gabor filter bank design.

A. Gabor Magnitude Representation

Gabor magnitude reflects the energy band of a signal [35]. In this work entire Gabor non-inherited space of face in the database was measured as input for the subspace algorithm for dimensional and repeatable content reduction. So it is needed to build the Gabor filter bank after forming the Gabor magnitude and improved phase congruency vectors. Vitomir Struc et al. [30] worked on standard Gabor filter bank, as per the state of art approached survey the majority of the researchers noted in their work about Gabor filter bank with five scales (m=0, 1, . . . 4) and eight orientations (n=0,1. . . . 7). In order to build image dimensionality for 40 times from filter bank individual face image set is filtered with all 40 filters from the filter bank at the starting point. In this work each image of JAFFE face database is resized to 111x126 pixels, hence 40 magnitude outputs reside in 559440 spaces. The maximum dimension may cause the mislead recognition of image hence Gabor magnitude and phase feature vector responses nonlinear dimension reduction method (kernel region) were implemented to convert Gabor feature vector space into subspace.

While allowing for the Gabor magnitude for drawing out of non-inherited space this area is reformed by means of specific shape based grid superimposed above the traits to be sampled. Normalization process has been carried out for these down sampled images.

It has been carried out by selecting rectangular shaped sampling grid by selecting 16 flat and 16 upright outline is utilized with dimension of the sample data volume.

B. Gabor Phase Information

Gabor phase consists of rich information of texture [35]. Cause of deliberated recognition procedure of Gabor phase part with referrers to spatial location of data sample the majority of the former Gabor based face recognition job abandoned the phase elements. The author has noticed about phase congruency model was utilized based on face depiction generated by Vitomir Struc for certain level [30]. For one dimensional signals, the phase congruency (PC(x)) is mentioned absolutely by the family member of the power at a known position in the signal E(x) and sum of the Fourier amplitudes A_n as revealed by S. Venkatesh et al. in [32].

$$E(x) = PC(x)\sum_{n} A_n \tag{8}$$

Table I. Parameters of gabor filter

No. of scales of Gabor filter bank	No. of orientations of Gabor filter bank	Filter bank
5	8	40

Here Fourier components are indicated by n. Due to this phase congruency at a known position of the feature point x is approved as the neighboring energy at this position to the amount of Fourier magnitude. P. Kovesi et. al. [31] improoved these logics to two dimensional strength lines by calculating the phase congruency with logarithmic Gabor filters by subsequent expression

$$PC_{2D}(x,y) = \frac{\sum_{n=0}^{r-1}\sum_{m=0}^{p-1} A_{m,n}(x,y)\Delta\Phi_{m,n}(x,y)}{\sum_{n=0}^{r-1}\sum_{m=0}^{p-1} A_{m,n}(x,y)+\varepsilon} \tag{9}$$

The magnitude value is denoted by $A_{m,n}(x,y)$ with respect to the logarithmic Gabor filter at scale m and orientation n, ε shows a possible tiny constant that avoids null division, and $\Delta\Phi_{m,n}(x,y)$ denotes a phase digression gauge specified as

$$\Delta\Phi_{m,n}(x,y) = \cos(\phi_{m,n}(x,y)-\overline{\phi}_n(x,y)) - \left|\sin(\phi_{m,n}(x,y)-\overline{\phi}_n(x,y))\right| \tag{10}$$

Vitomir Struc and Pavesi [30], illustrated regarding oriented Gabor phase congruency subject set. The authors have clarified that Gabor filter bank is framed and coined by parameter grabbing of necessary Gabor from [30]. Both Gabor magnitude feature vector (GMFV) and superior non-inherited Gabor phase feature vector (GPFV) are independently isolated and feature level fusion has been approved by combining with geometrical distance feature vector (GDFV) as shown in Fig 4.

CGMV=[GMFV+GDFV)], CGPV=[GPFV+GDFV)

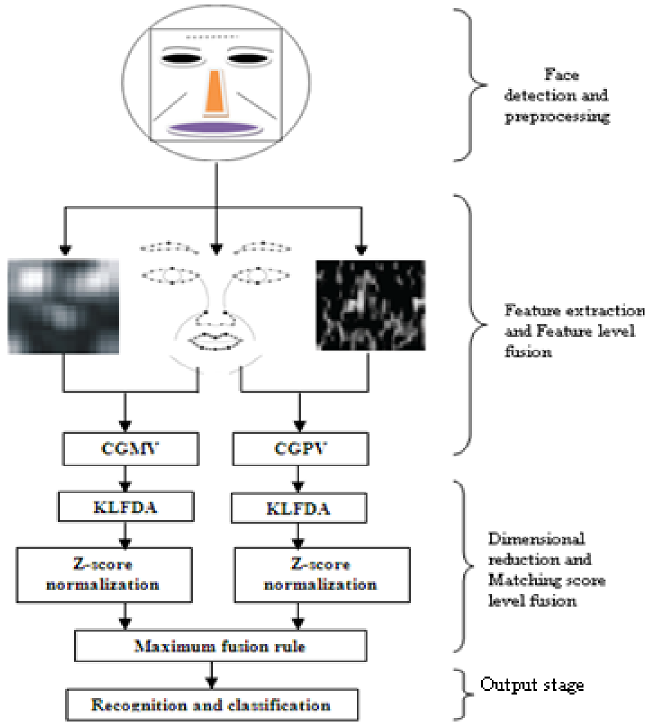


Fig. 4 Flow of entire proposed subspace approach (CEGKLFDA) for expression recognition and classification system.

IV. BRIEF OVERVIEW OF LDA

LDA is more rapid than PCA analysis [8], well defined scatter matrices are results better recognition rates. In some cases LDA has less faulty error cost and acts sound yet stipulation dissimilar illuminations and emotional variations occur only when its Fisher's ratio is increased. For improved recognition and classification Fishers ratio must be placed in superior range. Concerned with this issue several researchers worked on this area in order to maximize the Fishers ratio [13-15]. Within rank scatter matrix is perceptive to distinction in traits analysis of the identical person due to change in illumination and traits it is also referred as within individual class. Human traits variations are more effective for coefficients of object class dispersive matrix. This dispersive can be reduced by making low dimensional sets from high dimensional sets. This would causes inherited subspace. It is due to increases in the class isolation matrix coefficients [16-17]. All types of discriminate based techniques are class grouping techniques. To categorize an input quire image, the predictable quire image is related to each predictable training image, and the test image is identified as the closest training sample. The consumption of instant for inherited feature extraction by LDA strategy may take extreme time along with discarding the image zero eigen value components. Inherited low dimensional formation space is the secondary problem of LDA. When training samples decreases then certain problem causes due to larger dimension of non-inherited region..

This shows that the intra class scatter matrix would tend to be a singular matrix and the implementation of LDA may come across computational difficulty. In previous works,, most of the LDA extensions have been produced to illustrate with this singularity problem.

V. PROPOSED APPROACH

A. Description of the Problem

Most of the FLDA based earlier works has less Fishers ratio of zero eigen based discriminant analysis and non protective of vicinity pixel properties which would produces minimum recognition rate. This optimization of this problem is counted by protecting the local content of Fisher discriminant analysis (FDA) in kernel domain as mentioned here should be treated as kernel locality protecting non-zero eigen based Fishers discriminant analysis (KLFDA). Second difficulty is large dimension of complete Gabor non-inherited space when it is cascaded with analytical feature non-zero eigen space and it deserves peak expression categorization instance and poor appreciation rate. Projection method used in this work determines above problems optimized by Gabor magnitude part and enhance phase part disjointedly using KLFDA subspace method. Future work is termed as combinational entire Gabor kernel locality protecting Fisher discriminant analysis (CEGKLFDA). Fig. 4 presents extracted geometrical features from 10 fiducial points by localizing eye, mouth and nose parts of face images and holistic features were extracted using Gabor filter. Together Gabor magnitude feature vector (GMFV) and enhanced Gabor phase feature vector (GPFV) are independently isolated and feature level fusion is carried out with Geometrical distance feature vector (GDFV). Fisher ratio of discriminant analysis as well as protection of local substance determines dimensional space of fused feature dataset and it is found to be maximum and it is converted into minimum dimension inherited space by improving that ratio value under nonlinear kernel region. The normalization technique has been carried out for converted feature vector inherited space using suitable normal distribution score normalization strategy. [48]. Both Gabor magnitude KLFDA and Gabor phase normalized scores of KLFDA inherited space were cascaded using maximum fusion rule.

Euclidean distance comparing algorithm (L_2) was used to compare the input and testing image eigen scores. Lastly SVM classifier algorithm [33] is utilized to discriminate the human traits. Confusion matrix was constructed using cross validation strategy.

B. About KLPFDA

FLDA technique features were cascaded with non inherited features of LPP algorithm then locality protecting discrminant analysis (KLFDA) framework has been produced. LPP is unsupervised linear inherited region process protects the local composition of adjoining data samples in the no-inherited feature area are reserved nearer in the locality protecting projected rooted area. FLDA composed LPP protects neighborhood associations in the enclosed by introducing an "affinity" matrix as shown in (17) that is described in this framework. This paper highlights Kernel Fishers discriminant analysis which specifies parameter *w* of vectors in a maximized dimensional kernel region of non inherited area. This parameter elaborates the ration of Fisher analysis specifically in this area. Kernel discrimiant based analysis will yield an expression such that

$$J(W) = \underset{w}{\arg\max} \frac{w^T S_b^\phi w}{w^T S_w^\phi w} \tag{11}$$

$$S_b^\phi = \sum_{i=1}^{C} N_i (m_i^\phi - m^\phi)(m_i^\phi - m^\phi) \tag{12}$$

$$S_w^\phi = \sum_{i=1}^{C} \sum_{g \in G_i} (\phi(g) - m_i^\phi)(\phi(g) - m_i^\phi) \tag{13}$$

Where N_i is the number of elements from the i[th] class, m_i^ϕ is the centroid of the i[th] class, C is the number of classes, m_i^ϕ is the centroid of the i[th] class and m^ϕ is the global centroid, g is a vector for a particular class and G_i is the set of elements of non-inherited space feature of Gabor filter of the i[th] class. S_w^ϕ shows the degree of diffusion intra class of expressions and is deliberated as the addition of covariance matrices of each class, whereas S_b^ϕ indicates the degree of diffusion inter classes of expressions and is deliberated as the addition of the covariance space matrix of the resources of each class. The kernel domain space usually much higher dimension than the input space but Baudat and Anouar [22], by reformulating the discriminant analysis problem in terms of inner products of vectors in the non-inherited space and by exploiting the kernel trick, proposed a computationally tractable algorithm for KFDA. The "kernel trick" [23] which is used for the estimation of steps by step procedures in a kernel region of non-inherited pace without unambiguously analyzing the mapping, as long as the algorithm can be articulated in terms of dot products of vectors in the non-inherited space. M. Sugiyama, [24] presented local Fisher discriminant analysis (LFDA) and writer of this thesis have revealed that the outcome of attributes of cascading of both LDA and LPP. Xiaofei He [25] delivered the locality preserving projections (LPP) as when the maximized dimensional data placed on a minimized dimensional diverse rooted in the ambient space, the locality protecting projections are achieved by discovering the most favorable linear approximations to the nonzero eigen tasks of the Laplace Beltrami operator on the multifold. Due to this reason, LPP, acts as linear, scatters several of the specimens depiction characteristics of nonlinear methods such as Laplacian eigen maps or locally linear embedding (LLE). The cascading of PCA and LPP together [25-27] which acquires only the majority of meaningful points. LPP is a linear manifold-learning technique that seeks to find a linear map that protects the local composition of neighboring specimens in the non-inherited space. In other words, nearby points in the imaginative space are kept close in the LPP-enclosed space. LFDA protects neighborhood associations in the inserted space by implementing an "affinity" space as per mentioned under.

The solution of J(W) is optimized, consequent to the biggest eigen values λ, can be explained by the globalized eigen value problem.

$$S_b^{\phi} W_i = \lambda_i S_w^{\phi} W_i \quad (14)$$

Let G=(g_1,g_2, ... g_i, . . .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.

Let us consider that each data sample feature connected to one of c classes{C_1,C_2,C_3, ...C_c}. Let N_i be the number of Gabor images feature in class C_i where (i=1,2,3,. . . .C),

$$\mu_i = \frac{1}{N_i} \sum_{G \in C_i} G$$

(15)

Hereμ_i be the average of the data samples in classC_i and

$$\mu = \frac{1}{N} \sum_{i=1}^{N} G_i$$

(16)

$\mu = \frac{1}{N}\sum_{i=1}^{N} X_i$Where μ be the average of all data samples. $S_{i,j} \in [0,1]$ as the affinity between g_i and g_j given by

$$S_{i,j} = e^{-\frac{\|g_i - g_j\|^2}{\gamma_i \gamma_j}}$$

(17)

$$\gamma_i = \left\| g_i - g_i^{(k)} \right\|$$

(18)

Neighboring scaling of Gabor data g_i and $g_i^{(k)}$ is the k^th^ adjacent neighbor of g_i as mentioned in (18). Symmetric matrix is $S_{i,j}$ also referred as affinity matrix of size nxn which deals the local inter space linking the data samples in the non-inherited space. Locality linking class $S^{(lb)}$ and local intra class $S^{(lw)}$ scatter matrices are indicated by

$$S^{lb} = \frac{1}{2} \sum_{i,j=1}^{n} W_{i,j}^{(lb)} (g_i - g_j)(g_i - g_j)^T$$

(19)

$$S^{lw} = \frac{1}{2} \sum_{i,j=1}^{n} W_{i,j}^{(lw)} (g_i - g_j)(g_i - g_j)^T$$

(20)

$$W_{i,j}^{(lb)} = \begin{cases} S_{i,j}(1/n - (1/n_l)), & if\,(y_i = y_j = l) \\ 1/n, & if\,(y_i \neq y_j) \end{cases}$$

(21)

$$W_{i,j}^{(lw)} = \begin{cases} S_{i,j} / n_l, & if\,(y_i = y_j = l) \\ 0, & if\,(y_i \neq y_j) \end{cases}$$

(22)

From (11) it understands that scatter space matrix variations with good Fisher ratio and it is computed to best of its results. LFDA neighborhood pixel is saved which is given by weights as mentioned in (21) and) (22) respectively. The KLFDA approach can be noted as a kernel expansion of LFDA via the kernel trick. In this work, the kernel function implemented is the radial basis function (RBF) kernel [33], denoted by

$$K(g_i, g_j) = e - \frac{\|g_i - g_j\|^2}{2\sigma^2}$$

(23)

Here σ>0 is a user-referred parameter of the kernel. Sugiyama [24] illustrated the kernel trick and recalculates the LFDA technique in kernel-condensed spaces. This can also be said that, the local intra and inter class scatter space matrices are denoted in the kernel region space. Projection $\hat{w}$ in the kernel field that increases the adapted Fisher ratio is given by the result of the comprehensive eigen value problem, i.e.

$$KL^{(lb)} K \hat{w} = \bar{\Lambda}(KL^{(lw)} K + \varepsilon I_n) \hat{w}$$

(24)

Here $\hat{\Lambda}$ is the diagonal eigen value matrix; ε is a tiny (regularization) constant, $\hat{w}$ is the eigen vector matrix, K is the kernel matrix specified in (23), $L^{(lw)} = D^{(lw)} - W^{(lw)}$, where $D^{(lw)}$ is a diagonal matrix with the i^{th} diagonal component as given as

$$D_{ii}^{(lw)} = \sum_{j=1}^{n} W_{ij}^{(lw)}$$

(25)

As per top equations $L^{(lb)} = L^{(lw)} - L^{(lw)}$, where $L^{(m)}$ is the local jumble matrix defined as $L^{(m)} = D^{(m)} - W^{(m)}$, and $D^{(m)}$ is a diagonal matrix with the i^{th} diagonal component refers to

$$D_{ii}^{(m)} = \sum_{j=1}^{n} W_{ij}^{(m)}$$

(26)

C. Z-Score Normalization

Approach followed in this research work Z-score normalization and blending algorithm is considered by utilizing the non-inherited values of the work mentioned in [48]. Anil Jain, Karthik , Arun Ross [48], contributed in the field of biometrics by combining different human traits like face, finger print and hand geometry with dissimilar normalization schemes and fusion rules in the circumstance of a multimodal biometric system.

Authors have noted from practical results were obtained from datasets of various users and they concluded the relevance of min–max, Z-score, and tanh normalization results.

They used simple sum of scores fusion technique which results in competent recognition efficiency hence then they differed to other techniques. However, practicals also disclose that the min–max and Z-score normalization methods are susceptible to practical usage in the data, representing the requirement for a vigorous and resourceful normalization process like the tanh normalization.

$$NS_{CGMKLFDA} = \frac{CGMKLFDA_S - \mu(CGMKLFDA_S)}{Std(CGMKLFDA_S)} \quad (27)$$

$$NS_{CGPKLFDA} = \frac{CGPKLFDA_S - \mu(CGPKLFDA_S)}{Std(CGPKLFDA_S)}$$

(28)

$$CEGKLFDA_S = Max[\left(NS_{CGMKLFDA} + NSC_{CGPKLFDA}\right)/2]$$

(29)

In this work $(GMKLFDA)_S$ is inherited score space of Gabor magnitude kernel locality preserved discriminant anticipated inherited space and $(GPKLFDA)_S$ is score space of Gabor superior phase portion. Local configuration of LPP is protected by kernel locality Fisher discriminant investigation. The foremost goal of LPP is to solve the greatest locality domain preservation part. Another way is, of the objective task which is made less in LPP is intended such that it removes a superior cost, if adjacent points that are secure in the key liberty are assigned with distant separately in the projection as shown in (18), (19), and (20). The adjacent values are saved in this computation by adjacency or affinity matrix as given same as in (17).

End result of CEGKLPFDA score space have been calculated using train and quire samples of Gabor , from this score matrix Euclidean distance is evaluated as

$$\varepsilon_i^2 = \left\| W_{CEGKLFDAQ} - W_{CEGKLFDAT} \right\|^2$$

(30)

Where $W_{CEGKLPFDAT}$ and $W_{CEGKLPFDAQ}$ are converted inherited space feature vector score space of input educated and quire Gabor samples. Previously presented threshold value θ_i, is larger than value of ε. This cause's quire image related to class i. So that testing emotional sample is matched with key educated sample. Euclidean distance were utilized for Facial emotional traits classifications with RBF kernel dependent SVM classifier [33]

VI. TESTING AND RESULT ANALYSIS

A. Database Used

Proposed algorithm efficiency has been carried out by conduction investigational testing, it was implemented on two popular face datasets like JAFFE and YALE as given below.

1) JAFFE database

This dataset have 213 images of 7 facial expressions images. 6 expressions images are vital and one is neutral facial expression image. Basically all the expressions images are having 256x256 resolutions pose by 10 female specimens. The emotional effects were grouped into 6 emotions with 60 Japanese subjects. This research work considers the images from this database by preprocessing to obtain clean facial expression images, which have normalized passion, same volume and sketch. The best selection of suitable face points were used in this domain which performs identifying facial feature points automatically including eyes, nose and mouth [47]. The suitable preprocessing method was used to remove the ligh effects which have been noted in raw samples. Fig. 5 depicts resized and trimmed samples of JAFFE database.

Fig. 5 Face detection and cropped samples of JAFFE (preprocessed).

2) YALE database

The samples in this database expose foremost discriminations of intensity changes, dissimilar area of facial terminology, and the people wearing spectacles/no spectacles. The definite size of the samples in this image folder is 243×320 resolution with 256 gray formations. The experimental purpose, the size of these samples was scaled to 64×64 pixels for the purpose extraction of Gabor non-inherited features and geometrical non-inherited features shown in Fig. 6. In this work only six emotions were utilized for conduct experiment they are regular, happy, surprise, sleep, and wink and sad.

B. Testing and Result Analysis

In this domain Support Vector Machine algorithm (SVM) by means of Radial Basis Function (RBF) kernel practice was utilized to classify the emotions [33]. To generate SVM model, with 210 samples of JAFFE dataset be utilized. In this research domain 70% of samples were considered for training and 30% images were considered for testing using holdout cross validation strategy. Highest recognition is achieved for proposed approach is 97.3% for JAFFE database. Similarly for YALE database also 70% images were used for training and 30% data samples were used as quire images. Using SVM hold out cross validation classification technique all the expressions was classified. The overall accuracy of recognition rate for YALE database using proposed approach was found to be 81.48%. Both the databases were tested with CEGLPP, CEGKPCA, CEGFLDA, CEGLFDA and proposed approach CEGKLFDA as in Fig 7 and Fig 8 respectively. The coefficients are usually extremely decreases in the proposed algorithms; it causes that a substantial development in the emotional identification rate qualified to the facial expression recognition observation.

Performance of proposed approach for JAFFE database is shown in Table 2 compared with state of art approaches.

Fig. 6 Cropped face samples of YALE database (not preprocessed).

To perform the efficient facial expression recognition and classification, rich set of facial features makes a significant role on expression recognition system. In this work both geometrical features and Gabor filter features were combined and feature fusion was carried out. Total dimension of the fused feature vector dataset was found to be very high. Gabor magnitude and phase features were successfully utilized. Subspace methods like LPP, KPCA, FLDA, LFDA and KLFDA were implemented on high dimension space to project the face space into subspace. The expression recognition rate for anger expression is 94.4% and fear is 88.8% respectively. In this work compare to other subspace approaches sad expression classification accuracy rate is increased to 100%.

TABLE III
Confusion matrix for Proposed Approach of JAFFE Database Using Cross Validation Technique %.

	AY	DT	HP	FR	SD	SE	NL
AY	94.4	5.5	0	0	0	0	0
DT	0	100	0	0	0	0	0
HP	0	0	100	0	0	0	0
FR	0	0	11.1	88.8	0	0	0
SD	0	11.1	0	0	100	0	11.1
SU	0	0	0	0	0	100	0
NE	0	0	0	0	5.5	0	100

AY=Angry, DT=Disgust, HP=Happy, FR=Fear, SD=Sad, SE=Surprise, NL=Neutral.

For YALE database wink and sleep expressions were found to be confusing as in Table 4, hence its rate of recognition of classification becomes low in all the subspace

approaches. For proposed approach the classification accuracy was found to be 100% for happy, surprise and neutral expressions. For sad expression 77.77% accuracy rate was noted. But expression like wink and sleep 55.55% accuracy rate was achieved due probably eye texture information would be same.

In the above experiments nearest neighbor numeral is set to 7 and value of σ is set to 0.5 multiplied by the average of pair wise distance in the dataset. The Fig. 7 and Fig. 8 shows identification accuracy rates against the reduced dimension on the face database. The main comparison includes proposed approach constantly perform better than the GEGKPCA, CEGLPP, CEGFLDA, and CEGLFDA algorithms, which express that CEGKLFDA can efficiently exploit the data which is depend on data samples at kernel region for expression recognition. CEGKPCA approach performs weakly. It may be due to KPCA is unsupervised learning technique and not necessarily instruct precious unfairness contents. CEGFLDA method emphasizes moderately to the CEGLPP method. This is due to discrimination of class labels. Proposed approach outperforms other methods by means of both inherited subspace construction and class label content, but it is a non linear strategy based approach solves the problem of high unevenness of the image content and style.

TABLE IV
Confusion matrix for Proposed Approach of YALE Database Using Cross Validation Technique %.

	HP	SE	SD	WK	SP	NL
HP	100	0	0	0	0	0
SE	0	100	0	0	0	0
SD	0	22.2	77.7	0	0	0
WK	0	0	44.4	55.5	0	0
SP	0	0	22.2	22.2	55.5	0
NL	0	0	0	0	0	100

HP=Happy, SE=Surprise, SD=Sad, WK=Wink, SP=Sleep, NL=Neutral.

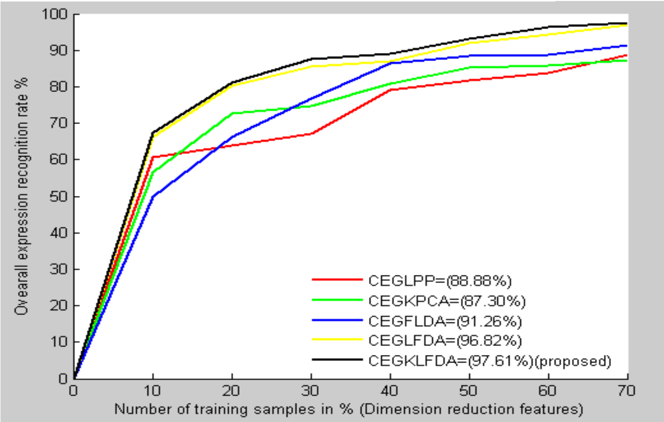


Fig. 7 Relative analysis of inherited space approaches for expression recognition of JAFFE database

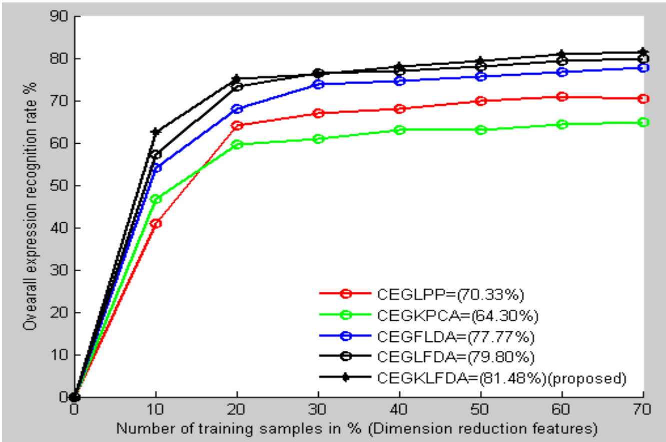


Fig. 8 Relative analysis of non inherited space for expression recognition of YALE database

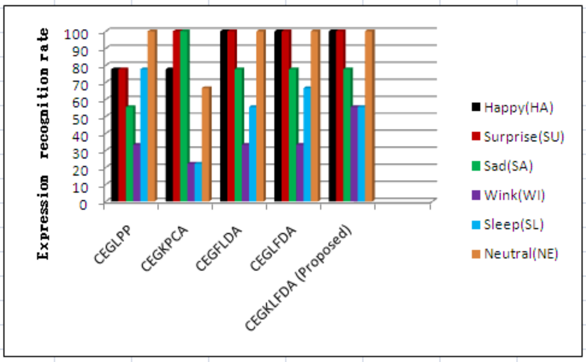


Fig. 9 Performance analysis of expression rate of subspace approaches based on combined features of geometrical and Gabor.

VII. CONCLUSION

This paper frames non zero eigen value preservation based approach. This work exclusively inherits combinational novel dimensional reduction inherited subspace approach for expression recognition called CEGKLFDA . Non-inherited texture contents grabs the micro primitive traits present in the face and analytical features describe the energetic shape details of the facial parts. But when they are applied alone, facial recognition may not turn out superior outcomes. Therefore this paper proposes to combine those two features to enhance the accuracy of expression recognition. Efficient facial expression recognition requires rich set of face image features and subspace projection for de-correlating the feature dataset. In this work higher dimensional feature space was reduced and accuracy of expression recognition and classification was improved by combining both texture and geometrical features. The combination of grabbed non-inherited analytical features was individually combined with Gabor magnitude and phase space. The proposed approach is compared with traditional art of approaches. It was found that expression recognition rate is improved in proposed method. The expression recognition rate was found to be 97.61% for JAFFE database and 81.48% for YALE face database respectively. Expression recognition rate is improved compare to earlier approaches. Non linear subspace properties were used in this work to project the high dimensional space into subspace.

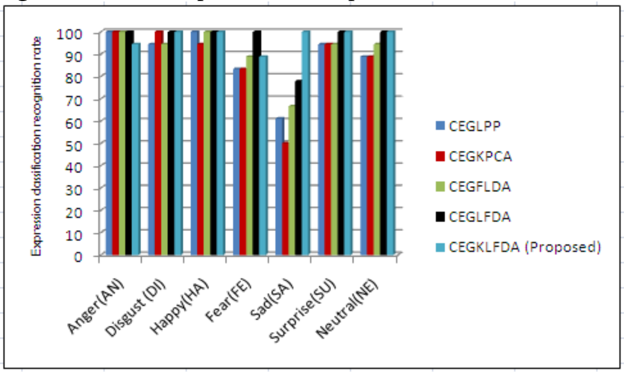


Fig. 10 Performance analysis of expression rate of subspace approaches based on combined features of geometrical and Gabor features for JAFFE database.

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