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Entire Gabor Subspace Approach for Expression Recognition Using Locality Preserving Projection

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***Abstract*— This work presents the extraction of entire Gabor features for efficient expression recognition and classification. Phase information available in Gabor filter bank is not properly utilized in several existing works for face and expression recognition. In this work both Gabor magnitude feature vector (GMFV) and Gabor phase congruency vectors (GPFV) are projected separately by subspace methods with respect to preserving non redundant data and reducing redundant coefficients. Locality preserving projection (LPP) subspace method is used for preserving and projecting the Gabor vector feature space. Projected vectors are normalized and fused. This EGLPP approach is tested with Yale and FD database respectively. Proposed approach improves the recognition rate while compared with EGPCA, EGICA and EGKPCA approaches. Support vector machine classifier is used for expression classification.**

***Keywords*— Principal components, subspace, Gabor filter, locality preserving projection**

I. Introduction

Facial expression feelings are a real kind of human traits to communicate others. Facial expression is highly effective nonverbal, natural and immediate media for human beings to expose their feelings, emotions, opinions and intensions. Facial expression recognition finds important applications in many areas such as computer interaction by humans, medical diagnosis, psychological study, medical diagnosis, game playing and data driven animation. Due to its wide range of applications, facial expression recognition system has attracted in various fields [1]–[4]. Deriving an effective facial representation from original face images is a vital step for successful facial expression recognition. There are two common approaches to extract facial features: approaches based on appearance of faces features and approaches based on geometric feature [4]. Gabor wavelets are generally used in appearance based approaches as image filters, are applied to either the whole face or specific face regions to extract the changes in appearances of face images. Due to their superior performance, the major works on appearance based methods have focused using Gabor wavelet representations [5]-[7]. In this paper entire Gabor filter locality preserving projections (EGLPP) approach using both magnitude and phase parts of Gabor filter bank is introduced.

II. Construction of Gabor Filter

In this section overview of Gabor based face recognition representation is introduced. Gabor wavelet transform allows description of spatial frequency structure in the image while preserving information about spatial relations which is known to be robust to face variances like expressions and pose. Gabor filters are used in this study is only to extract the texture features required for expression recognition. Gabor filters are also called Gabor wavelets they represent complex band limited filters with an optimal localization in both the spatial as well as the frequency domain. Thus, when employed for facial feature extraction, they extract multi-resolution, spatially local features of a confined frequency band. Spatial domain 2D Gabor filter can be represented as

$$\psi_{mn} = (x, y) = \frac{f_m^2}{\pi\kappa\eta}\left(\left(f_m^2/k^2\right)x'^2 + \left(f_m^2/\eta^2\right)y'^2\right)e^{j2\pi f_m x'} \quad (1)$$

Where,

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

$$f_m = f_{\max}/2^{(m/2)}, \theta_n = n\pi/8$$

As can be seen from the filters definition, each Gabor filer represents a Gaussian kernel function modulated by a complex plane wave whose centre frequency and orientation are given by f_m and θ_n, respectively. The parameters κ and η determine the ratio between the centre frequency and the size of the Gaussian envelope and, when set to a fixed value, ensure that Gabor filters of different scales behave as scaled versions of each other. It should also be noted that with fixed values of the parameters κ and η, the scale of the given Gabor filter is uniquely defined by the value of its centre frequency f_m. While different choices of the parameters determining the shape and characteristics of the filters define different families of Gabor filters, the most common parameters used for face recognition also used in this work as $\kappa = \eta = \sqrt{2}$ and f_{max} = 0.25. Generally most of the researchers used and presented a

Gabor filter bank for feature extraction from face of different appearances with five scales and eight orientations, that is, m = 0, 1. . . . s − 1 and n = 0, 1, . . . t − 1, where s = 5 and t = 8. Fig. 1(a) shows magnitude output of the filtering operation with the entire Gabor filter bank of 40 Gabor filters, while Fig. 1(b) shows the phase part of the Gabor filter bank commonly used for feature extraction in the field of face recognition.

Let I(x, y) stand for a grey scale face image of size p×q pixels and, moreover, let $\psi_{m,n}(x, y)$ denote a Gabor filter given by its centre frequency f_m and orientation θ_n. The feature extraction procedure can then be defined as a filtering operation 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

$$G_{m,n}(x,y) = I(x,y) * \psi_{m,n}(x,y) \quad (2)$$

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

$$E_{mn}(x,y) = re[G_{mn}(x,y)] \quad (3)$$

$$O_{mn}(x,y) = img[G_{mn}(x,y)] \quad (4)$$

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.

$$A_{m,n}(x,y) = \sqrt{E^2_{m,n}(x,y) + O^2_{m,n}(x,y)} \quad (5)$$

$$\phi_{m,n}(x,y) = \arctan\left(\frac{O_{m,n}(x,y)}{E_{m,n}(x,y)}\right) \quad (6)$$

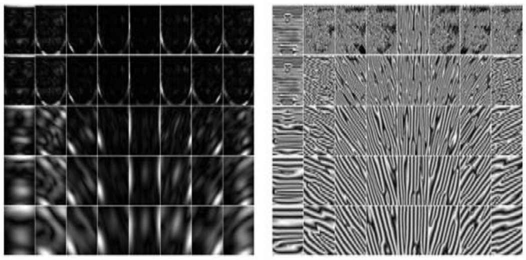
Equations 4 and 5 are defined for standard Gabor filter bank design.

A. *Gabor Magnitude Face Representation*

Entire feature vector space of face in the database is considered as input for the subspace method for dimensional and redundancy reduction. So it is needed to construct the Gabor filter bank after deriving the Gabor magnitude and phase congruency vectors. According to literature survey most of the authors defined about filter bank consists of Gabor filter with five scales (m=0,1, ... 4) and eight orientations (n=0,1. . . . 7). The given face image set is filtered with all 40 filters from the filter bank resulting in an inflation of data dimensionality to 40 times is initialize size. The resized dimension of each image is 66x86 pixels for Yale database. The 40 magnitude responses reside in 227040 dimensional feature spaces which is more excessive size for processing and storage. Similarly for FD database the resized dimension of each image is 64x64 pixels and the 40 magnitude responses reside in 163840 dimensional feature space. Thus to overcome this large dimensionality of the Gabor magnitude and phase feature vector responses linear dimension reduction methods are used to convert Gabor feature vector space into subspace. Before considering the Gabor magnitude for extraction of feature vector it is down sampled using rectangular sampling grid superimposed over the image to be sampled. These down sampled values are normalized. In this experiment, rectangular sampling grid with 16 horizontal and 16 vertical lines is used with dimension of the image size.

B. *Gabor Phase Information*

Due to slow recognition processing of Gabor phase with respect to spatial position of image most of the earlier Gabor based face recognition work discarded the phase information. In this paper phase congruency model is used based on face representation developed by Vitomir Struc and Nikola Pavesic for ceratin extent [8]. For 1D signals, the phase congruency (PC(x)) is defined implicitly by the relation of the energy at a given point in the signal E(x) and sum of the Fourier amplitudes A_n as shown by Venkatesh and Owens in their work [9].



(a) (b)

Fig. 1 (a) Gabor magnitude part and (b) Gabor phase part

$$E(x) = PC(x)\sum_n A_n \quad (7)$$

Here *n* denotes the number of Fourier components. Thus phase congruency at a given location of the signal x is defined as the ratio of the local energy at this location and the sum of Fourier amplitudes. Kovesi [10] extended the above concept to 2D signals by computing the phase congruency with logarithmic Gabor filters using the following equation

$$PC_{2D}(x,y) = \frac{\sum_{n=0}^{r-1}\sum_{m=0}^{p-1} A_{m,n}(x,y)\Delta\Phi_{m,n}(x,y)}{\sum_{n=0}^{r-1}\sum_{m=0}^{p-1} A_{m,n}(x,y) + \varepsilon} \quad (8)$$

Where $A_{m,n}(x,y)$ denotes the magnitude response of the logarithmic Gabor filter at scale m and orientation n, ε represents a small constant that prevents divisions with zero, and $\Delta\Phi_{m,n}(x,y)$ stands for a phase deviation measure defined as

$$\Delta\Phi_{m,n}(x,y) = \cos(\phi_{m,n}(x,y) - \overline{\phi}_n(x,y)) - \left|\sin(\phi_{m,n}(x,y) - \overline{\phi}_n(x,y))\right| \quad (9)$$

Vitomir Struc and Nikola Pavesi [8], defined about oriented Gabor phase congruency model. In this work Gabor filter bank is designed by extracting the required Gabor parameters from [8].

III. PROPOSED APPROACH

Most of the existing Gabor filter based methods are relying only on the Gabor magnitude information and ignored the actual use of Gabor phase information due to larger dimension and slow processing. In this paper, both magnitude and phase information is properly utilized for face representation. Gabor magnitude feature vector and Gabor phase congruency feature vectors are also found to be more dimensional. This would occupy larger memory area and consumes more computation time. Therefore in this work these two Gabor vectors feature space is reduced using subspace methods by preserving local information by removing redundant data from image set. Output of Gabormagnitude+LPP and Gaborphase+LPP vectors are normalized using Z-score normalization and fused using maximum fusion rule [29] shown in figure 1. The feasibility of the proposed approach is assessed in a series of face recognition experiments performed on the popular Yale and FD databases. Assessment understands that the proposed approach compares favourably with earlier expression recognition approaches from the literature in terms of robustness as well as face recognition performance. Main objective of this work is to reduce the dimensional space of feature space in to subspace by drastically reducing the redundant coefficients by preserving local information of the face images. Gabor wavelet transform [11]–[14] allows description of spatial frequency structure in the image while preserving information about spatial relations which is known to be robust to some variations, e.g., pose and facial expression changes. Although Gabor wavelet is effective in many domains, it nevertheless suffers from a limitation. The dimension of the feature vectors extracted by applying the Gabor wavelet to the whole image through a convolution process is very high. To solve this dimension problem, subspace projection is usually used to transform the high dimensional Gabor feature vector into a low dimension one. In this study Gabor based Principal component analysis (PCA), independent component analysis (ICA) and Kernel PCA [15]-[24] subspace models are compared with Gabor based LPP subspace approach as shown in figure 1.

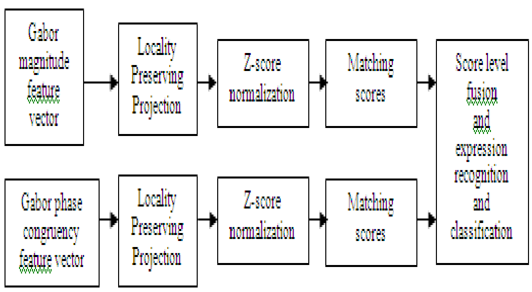


Fig. 2 Entire Gabor LPP subspace approach

A. Brief Overview of LPP Approach

Locality Preserving Projections (LPP) is a linear subspace projection method preserves the neighbourhood structure of the data set for larger variations of face appearances. LPP represents a linear approximation of the nonlinear Laplacian eigenmaps introduced in [25]. When high dimensional data available in a low dimension subspace embedded in the data space, then LPP approximate the eigen functions of the Laplace Beltrami operator of the subspace. LPP aims at preserving the properties of local structure of the data. But PCA method preserves the global properties of data. LPP is unsupervised subspace method and performs a linear transformation. By constructing the adjacency graph LPP models the correct structure of data. This is highly desirable for face recognition compared to nonlinear local structure preserving, since it is significantly less computationally expensive.

Xiaofei He [25] introduced the Locality Preserving Projections (LPP) as when the high dimensional data lies on a low dimensional manifold embedded in the ambient space, the Locality Preserving Projections are obtained by finding the optimal linear approximations to the eigen functions of the Laplace Beltrami operator on the manifold. Because of this, LPP, being linear, shares many of the data representation properties of nonlinear techniques such as Laplacian Eigenmaps or Locally Linear Embedding (LLE). The combination of both PCA and LPP [25], [27] captures only the most expressive features. Yi Jin et al. [28] presented a new manifold learning algorithm in which a bilateral-projection-based 2DPCA (B2DPCA) for image matrix compression is performed before supervised locality preserving projections. The bilateral projection-based DPCA algorithm is used to obtain the meaningful low dimensional structure of the data space. Also those works that uses PCA captures the variation in the samples without considering the variance among the subjects. Consider an objective function of LPP in order to preserve the local face traits features of image set.

$$W = \min_{w} \sum_{ij} (y_i - y_j)^2 S_{ij} \tag{10}$$

$$S_{ij} \begin{cases} \exp\left(-\|x_i - x_j\|^2 / t \right), & \|x_i - x_j\|^2 < \varepsilon \\ 0 & otherwise \end{cases} \tag{11}$$

Where ε is sufficiency small, and also ε >0, Here, ε defines the radius of the local neighborhood. In other words, ε defines the locality. If neighboring points x_i and x_j are mapped far apart then symmetric weights S_{ij} indices large penalty. This also proves for $(y_i\text{-}y_j)^2$ is large. So that minimizing it is an attempt to ensure that, if x_i and x_j are close, then y_i and y_j are also equal. This optimization can be evaluated as

$$= \frac{1}{2} \sum_{ij} (y_i - y_j)^2 S_{ij} \tag{12}$$

$$= \frac{1}{2} \sum_{ij} (w^T x_i - w^T x_j)^2 S_{ij} \tag{13}$$

$$= \sum_{ij} w^T x_i S_{ij} x_i^T w - \sum_{ij} w^T x_i S_{ij} x_j^T w \quad (14)$$

$$= \sum_{ij} w^T x_i S_{ij} x_i^T w - \sum_{ij} w^T x_i S_{ij} x_j^T w \quad (15)$$

$$= \sum_{i} w^T x_i D_{ii} X_i^T w - w^T XSX^T w \quad (16)$$

$$= w^T XDX^T w - w^T XSX^{-T} w \quad (17)$$

Where X=[x_1,x_2,….x_n], and D is a diagonal matrix., its entries are coloumn sums of S, $D_{ii}=\sum_j S_{ij}$, and L=D-S is the Laplacian matrix. Matrux D provides a natural measure on data ponts. The bigger the value of D_{ij} (corresponding to y_i). the more important is y_i. Therefore, a constraint can be seen as

$$y^T Dy = 1 \quad (18)$$

$$\Rightarrow w^T XDX^T w = 1 \quad (19)$$

Finally, the minimization problem reduces finding

$$\arg\min_{w} w^T XLX^{Tw} \quad (20)$$

$$w^T XDX^T w = 1$$

The transformation vector w that minimizes the objective function is given by the minimum eigenvalue solution to the generalized eigen problem.

$$XLX^T w = \lambda XDX^T w \quad (21)$$

Note that the two matrices XLX^T and XDX^T are both symmetric and positive semidefinite since the Laplacian matrix L and the diagonal matrix D are both are symmetric and positive semidefinite.

B. Construction of Adjacency Graph

The following steps can be carried out by using ε-neighbourhoods and K nearest neighbors. Let G denote a graph with n nodes. The i^{th} node corresponds to the face image x_i. Connect the i and j nodes by an edge. If x_i and x_j are close it means x_j is among k nearest neighbors of x_i or x_j is among k nearest neighbors of x_j. The constructed nearest neighbor graph is an approximation of the local manifold structure. E-neighbourhoods nodes i and j are connected by an edge if equation 21 is satisfied.

$$\left\| x_i - x_j \right\|^2 < \varepsilon \quad (22)$$

Here norm is the usual Euclidean norm in R^n. Choosing the weights, If node i and j are connected then

$$S_{ij} = e^{-\frac{\left\| x_i - x_j \right\|^2}{t}} \quad (23)$$

Where i is a suitable constant. Otherwise, put S_{ij}=0. The weight matrix S of G models the face manifold structure by preserving local structure. The justification for this selection of weights can be seen in [31]. Compute the eigenvectors and eigenvalues for the generalized eigenvector problem,

$$XLX^T w = \lambda XDX^T w \quad (24)$$

Where D s a diagonal matrix whose entries are column or row since S is symmetric sums of S, $D_{ii}=\sum_j S_{ij}$, and L=D-S is the Laplacian matrix. The i^{th} row of the matrix X is x_i.

Let w_0, w1, w2 . . . . . w_{k-1} be the solution of above equation ordered according to their eigenvalues $0 < \lambda_0 < \lambda_1 < \lambda_1 < \ldots < \lambda_{k-1}$ These eigenvectors are equal to or greater than zero because the matrices XLX^T and XDX^T are both symmetric and positive semidefinite. Thus the embedding is as follows.

$$x \rightarrow y = W^T x, \quad (25)$$

$$W = W_{PCA} W_{LPP}, \quad (26)$$

$$W_{LPP} = [w_0, w_1, \ldots, w_{k-1}] \quad (27)$$

Here y is a k-dimensional vector. W is the transformation matrix. This linear mapping best preserves the manifolds estimated intrinsic geometry in linear senses. The column vector of W is called as Laplacianfaces.

C. Z-score Normalization

In the proposed approach Z-score normalization and fusion technique is used by considering the parameters of paper [29]. Anil Jain, Karthik Nandakumar, Arun Ross [29], have shown that the performance of different normalization techniques and fusion rules in the context of a multimodal biometric system based on the face, fingerprint and hand geometry traits of a user. Their experimental results on a database of 100 users indicate that the application of min–max, z-score, and tanh normalization schemes followed by a simple sum of scores fusion method results in better recognition performance compared to other methods. However, experiments also reveal that the min–max and z-score normalization techniques are sensitive to outliers in the data, highlighting the need for a robust and efficient normalization procedure like the tanh normalization.

$$NS_{GMLPP} = \frac{GMLPP_S - mean(GMLPP_S)}{Std(GMLPP_S)} \quad (28)$$

$$NS_{GPLPP} = \frac{GPLPP_S - mean(GPLPP_S)}{Std(GPLPP_S)} \quad (29)$$

$$EGLPP = Max[(NS_{GMLPP} + NS_{GPLPP})/2] \quad (30)$$

IV. RESULTS AND DISCUSSIONS

In this section the experiments are performed in order to analyse the performance of the proposed approaches on two databases. The first one is the Yale database consisting of illumination and expression variations images, and the second is FD database consists of different facial expression variations. Experiments are performed using MATLAB, R2013a, version-32-bit under Microsoft Windows environment on a computer system with 3.0 GHz CPU and 4 GB RAM. The Yale face database [32] 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. The original size of the images in this database is 243×320 pixels with 256 gray levels. For experiments, the size of these images is scaled down to 66×86 pixels in order to extract their Gabor features as shown in Fig. 3. In this work only three expressions are used for experiment such as happy, surprise and sad. Among 165 images only 45 images were used for experiment. 50% of 45 images were used for training and remaining 50% images were used for testing. Facial expression) face database (FD) consists of 13 subjects and each subject has 75 images with different expressions. This database has total 975 images. These face images were collected in the same lightning conditions. 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, the size of these images is scaled down to 64x64 pixels in order to extract their Gabor features as in Fig. 4.

Fig 3. Three expressions of Yale database of image size 66x86

Fig 4. Expressions of FD database of image size 64x64

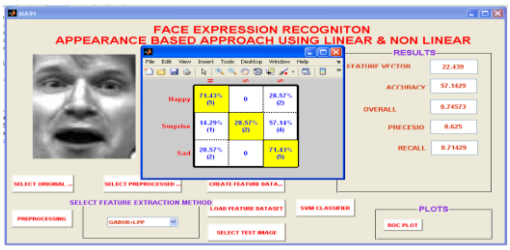


Fig 5. Expression recognition and classification for Yale database

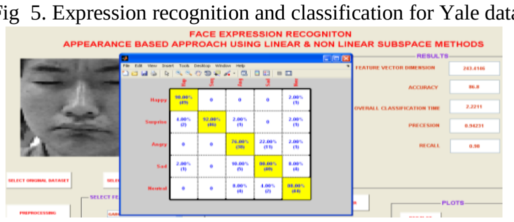


Fig 6. Expression recognition and classification for FD database

TABLE I
BRIEF ABOUT DIMENSION REDUCTION

Expressions	Subspace Approaches			
	EGPCA	EGICA	EGKPCA	EGLPP
Happy	42.86%	57.14%	71.43%	57.14%
Surprise	14.29%	71.43%	14.29%	57.14%
Sad	42.86%	14.29%	71.43%	57.14%

TABLE II
COMPARISON OF CLASSIFICATION RATES FOR YALE DATABASE

Data base	Resized dimension of image	Filter bank	Original dimension of feature space	Reduced mean Eigen coefficient
Yale	66x86	40	227040	22.439
FD	64x64	40	163840	243.4146

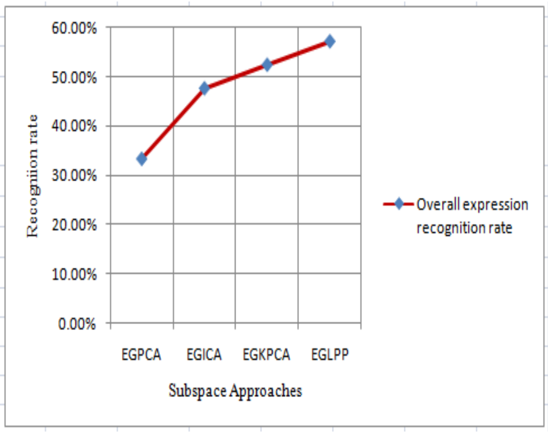


Fig 7. Comparative analysis of FERR for Yale database.

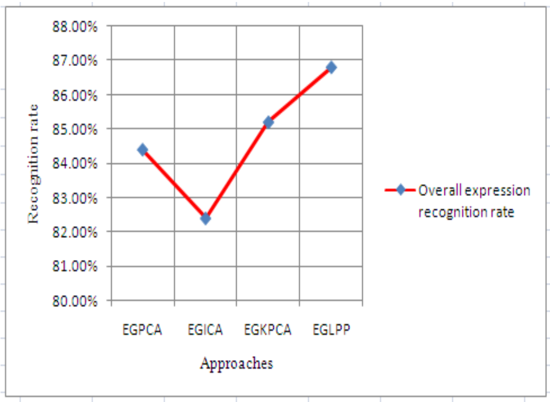


Fig 8. Comparative analysis of FERR for FD database.

TABLE III
COMPARISON OF CLASSIFICATION RATES FOR FD DATABASE

Expressions	Subspace Approaches			
	EGPCA	EGICA	EGKPCA	EGLPP
Happy	98.00%	98.00%	100.00%	98.00%
Surprise	98.00%	98.00%	96.00%	92.00%
Angry	80.00%	84.00%	76.00%	76.00%
Sad	60.00%	66.00%	76.00%	80.00%
Neutral	86.00%	66.00%	80.00%	88.00%

Results obtained in table 2 and table 3 indicates that proposed EGLPP approach improves the expression classification rate compare to EGPCA, EGICA and EGKPCA subspace approaches. For Yale database happy, surprise and sad expressions are classified equally by EGLPP approach. Five expressions are classified using FD database; EGLPP approach yields better expression recognition and classification accuracy rates. Comparative analysis of facial expression recognition rates for Yale and FD database are shown in Fig. 7 and Fig. 8 respectively.

V. CONCLUSIONS

Expression recognition and classification performance of subspace approaches depends on database and parameters are utilized for experiment. Most of the existing expression recognition appearance based approaches ignored the phase information due to its slow feature formation in spatial domain. In this paper Gabor magnitude feature vectors are extracted and projected in to low dimension space by subspace methods. Similarly Gabor phase congruency feature vectors are also extracted and projected in to low dimension space by subspace methods. Eigen score obtained from subspace methods are normalized and fused together. Using these strategy four subspace approaches has been formed such as EGPCA, EGICA, EGKPCA and EGLPP. Global features of Gabor magnitude and Gabor phase vectors projected in to subspace by preserving local geometrical information by locality preserving projection. Z-score normalization technique makes adjustment of measured values of Gabor magnitude and phase vectors of different scales to a common scale. In this work EGLPP was found to be more efficient than EGPCA, EGICA and EGKPCA subspace models. The recognition accuracy of EGLPP is 57.14% for Yale database and 86.4% for FD database. For Yale database in this work only three expressions were considered such as happy, surprise and sad. Classification accuracy was found to be high in EGLPP approach. Similarly from FD database five expressions were used in that happy, surprise, sad and neutral expressions found to be 80% to 98% of accuracy rates while testing different images for EGLPP approach.

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