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ORICS Based Kernel Discriminant Analysis

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Abstract: An optimal random image component selection algorithm using greedy approach is presented in this study. The proposed algorithm when evaluated with hierarchical ensemble classifier has an enhanced recognition rate with large variations in illumination, pose and facial expression. In the proposed technique, features are extracted from the optimal random image components which are then projected to the multiple discriminant analysis and kernel discriminant analysis subspace for solving linear and non-linear problems. The number of local image components is varied from 1-40 and by means of optimality checking, it is observed that at least 10-20 image components are sufficient for reasonable recognition. The FERET and ORL face datasets were used to generate the results. The method has achieved 99.44 and 100% recognition accuracy and 82.5 and 99.64% recognition accuracy on FERET and ORL datasets for 30% training, respectively. This is a considerably improved performance than one attainable with other standard methodologies described in the literature.

Key words: Face recognition, multiple discriminant analysis, optimal random image component selection, kernel discriminant analysis, recognition accuracy

INTRODUCTION

Face recognition (Zhao *et al*., 2003) has been a classical research for more than three decades where the face region is large enough and contains sufficient information for recognition. Various disciplines such as computer vision, neural networks and pattern recognition community attract researchers for handling the problems of machine recognition of human faces. In a controlled imaging condition such as frontal faces with indoor lighting conditions and normal expressions, high accuracy can be achieved but this is not possible for all real-world applications. The performance of the present face system may dramatically degrade under the variations of pose, illumination and expression which are uncontrollable.

The key issue in face recognition process is the feature extraction process in which a suitable face representation is selected so that processing a face is robust to facial variations and computationally feasible. Face representations can be divided into two categories: holistic-based (or) global-based and constituent-based (or) local-based. In the global-based (Kumar *et al*., 2011) face representation, it tries to capture and identify the face as a whole. The whole face can be considered as a 2D pattern of intensity deviation and it can be matched by geometrical regularities. In contrast, for the constituent-based (Zou *et al*., 2007) face representation, recognition is based on the relationship between human facial features such as eye (s), mouth, nose and face boundary. Here, each dimension of the feature vector corresponds to merely certain local region in the face thus only encodes the detailed qualities within this specific area. Non-rigid facial features such as eyes and mouth provide high flexibility which greatly relies on the exactness of the facial feature detection scheme which in turn increases the computational load.

Heisele *et al*. (2003) compared local component and global (holistic) approaches and observed that the component system outdid the global systems for recognition rates >60%. Due to increasing importance, stand-alone segments were explicitly dedicated to local matching (Fang *et al*., 2002) approaches in current investigations.

Among various local features, specially, Gabor wavelets (Lei *et al*., 2011) have been renowned as one of the majority thriving local feature extraction methods for face representation due to their biological relevance. The two dimensional Gabor wavelets whose kernels are analogous to the 2D receptive ground profiles of the mammalian cortical simple cells, reveal popular

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distinctiveness of spatial locality and orientation selectivity and are optimally localized in the space and frequency domains. Elastic Bunch Graph Matching (EBGM) (Wiskott *et al*., 1997), Gabor-Fisher Classifier (GFC) (Liu and Wechsler, 2002), AdaBoost-based Gabor feature selection (Yang *et al*., 2004) and Local Gabor Binary Pattern (LGBP) (Zhang *et al*., 2005) are the facial recognition methods based on Gabor features. Now a days, Gabor wavelets are concatenated with various subspace methods to further improve the performances of face recognition systems.

According to the survey for face recognition, subspace-based methods such as Principal Component Analysis (PCA), Multiple Discriminant Analysis (MDA) and Independent Component Analysis (ICA) and spatial-frequency techniques such as Fourier transform and Discrete Cosine Transform (DCT) have been widely renowned as the foremost and thriving face representation methods for extracting global features. The subspace methods attempt to identify a set of basis images from a training set and signify any face as a linear arrangement of these basis images. Similarly, spatial-frequency techniques transform the face images into frequency domain and for face representation, only the coefficients in the low-frequency band are taken into account. The major difference between these two methods is that the subspace methods need training to learn the basis images whereas the spatial frequency techniques do not need training to learn the basis images. Previously, global-based face representations were popular for face recognition, but recently, more works are carried out to extend face recognition systems based on local features which are believed more robust to the variations of facial expression, illumination and pose.

In the case of Kernel Discriminant Analysis (KDA) (Xu *et al*., 2004), researchers attain a linearly distinguishable distribution in the feature space, if researchers define a non-linear mapping from the input space to a high-dimensional feature space. Then, MDA (Belhumeur *et al*., 1997), the linear technique can be performed in the feature space to extract the most significant discriminating features. However, the calculation may be tricky or even unworkable in the feature space due to high dimensionality. By launching a kernel function which corresponds to the non-linear mapping, all the calculation can conveniently be carried out in the input space. The problem can be finally solved as an eigen decomposition problem like PCA, MDA and Kernel Principal Component Analysis (KPCA).

In this study, a novel approach, Optimal Random Image Component Selection (ORICS) is generated for face recognition which is robust to facial variations such as pose, expression and illumination. Here, at first local random image components are generated based on the position and of size [16, 64] [16, 64] via selection method using greedy approach. In the approach, initially an empty set is created. Once the image component is generated then selection algorithm is applied to find out whether it satisfies optimality based on overlapping of components. If it meets optimality then that component is added to a set. Likewise, the process is repeated until suitable numbers of components are selected. After selecting those components for the first pattern of a class, this can be extended to all the remaining patterns of the same class. Likewise, the process is repeated for each and every class of the face dataset thereby it gives high discriminability from a large quantity of potential local random image components. The proposed method is widely calculated on the FERET and ORL databases and exciting outcomes are achieved.

Related works: Gabor filter exhibits desirable characteristics of spatial locality and orientational selectivity. Subspace approach by MDA is used for dimensionality reduction which preserves class separability and KDA an enhanced method which combines the kernel trick with MDA an effectual technique of extracting discriminant information is addressed.

Gabor filter: The physical characteristics of the Gabor filter (Shen *et al*., 2007), specifically for scaling and orientation representations are analogous to those of the human visual system and they have been found to be predominantly appropriate for texture representation and discrimination. The two dimensional Gabor wavelets may be obtained by Eq. 1:

$$\varphi_{\pi(f,\theta,\gamma,\eta)}(x,y) = \frac{f^2}{\pi\gamma\eta}\exp\left(-(\alpha^2 x'^2 + \beta^2 y'^2)\right)\exp\left(j2\pi f x'\right) \tag{1}$$

$$x' = x\cos\theta + y\sin\theta$$

$$y' = -x\sin\theta + y\cos\theta$$

Where:

f	=	The central frequency of the sinusoidal plane wave
θ	=	The anti-clockwise rotation of the Gaussian and the plane wave
α	=	The sharpness of the Gaussian along the major axis parallel to the wave
β	=	The sharpness of the Gaussian minor axis perpendicular to the wave
$\gamma = f/\alpha$ and $\eta = f/\beta$	=	Defined to keep the ratio between frequency and sharpness constant

In Gabor wavelet, the filters are self-similar that is in the shape of plane waves with frequency f, restricted by a Gaussian envelope function with relative width α and β generated from one mother wavelet by dilation and rotation:

$$\varphi_{u,v} = \varphi_{\pi(f, \theta, \gamma, \eta)}, f_u = \frac{f_{max}}{\sqrt{2^u}}, \theta_v = \frac{v}{8}\pi$$
$$u = 0, 1, \ldots\ldots, U-1, v = 0, 1, \ldots\ldots, V-1 \quad (2)$$

In Eq. 2, f_{max} represents the highest peak frequency, u and v represent the number of scales and orientations, respectively.

MDA Method: MDA is a renowned method for feature extraction and dimension reduction. It is used to determine the low-dimensional features from a high-dimensional space that helps to group images of the same class and separate images of different classes. It has been used widely in many applications such as face recognition, text classification and so on. Classical MDA (Xiang *et al.*, 2006) Method aims to find an optimal transformation by applying the eigen decomposition to scatter matrices by minimizing the within-class distance and maximizing the between-class distance simultaneously thus achieving maximum discrimination. The algorithm can be described as follows: let the between-class scatter matrix defined by Eq. 3 as:

$$S_B = \sum_{i=1}^{c} N_i (\mu_i - \mu)(\mu_i - \mu)^T \quad (3)$$

and the within-class scatter matrix defined by Eq. 4 as:

$$S_W = \sum_{i=1}^{c} \sum_{X_k \in class_i} (X_k - \mu_i)(X_k - \mu_i)^T \quad (4)$$

Where:

μ = The mean image of class X_k

N_i = The number of samples in class X_k

If S_W is non-singular, the optimal projection W_{opt} is chosen as the matrix with orthonormal columns which maximize the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples, i.e.:

$$W_{opt} = \arg\max_W \frac{|W^T S_B W|}{|W^T S_W W|} = [w_1\ w_2\ w_3 \ldots w_m]$$

where, $\{w_i | i = 1, 2, \ldots, m\}$ is the set of generalized eigenvectors of S_B and S_w corresponding to the m largest generalized eigen values defined by Eq. 5 as:

$$S_B w_i = \lambda_i S_W w_i, \ldots \quad i = 1, 2, \ldots, m \quad (5)$$

There are utmost c-1 non-zero generalized eigen values therefore upper bound on m is c-1 where c is the number of classes.

Enhanced method with KDA: In face recognition, it is extensively accepted that discriminant based approaches imply high potential performance and enhanced strength to perturbations such as lighting variations, pose and expression where Kernel Methods provide a well-founded means of incorporating domain knowledge in the discriminant. KDA (Liu *et al.*, 2002) is an enhanced method proposed for face recognition which combines the kernel trick with MDA. In general, KDA has been verified to be an effectual technique of extracting discriminant information from a high-dimensional kernel.

Let $Z = \{Z_i\}^c_{i=1}$ be a training set containing C classes and each class $z = \{z_{ij}\}_{j=1}^{N_i}$ consists of N_i samples where $z_{ij} \in R^J$ and R^J denotes the J-dimensional real space. At foremost, the input data is projected into an implicit feature space F by non-linear mapping defined in Eq. 6 as:

$$\phi : z \in R^J \rightarrow \phi(z) \in F \quad (6)$$

Let $\phi(.)$ be a non-linear mapping from the input space R^J to a kernel feature space F, i.e., ϕ: $z \in RJ \rightarrow \phi(z) \in F$ where F denotes the F-dimensional kernel feature space. Then, $\phi = [\phi(z_{11}), \ldots, \phi(z_{CNc})]$ is the corresponding training feature set in F. Moreover, it is unnecessary to calculate ϕ unequivocally but compute the inner product of two vectors in F with an inner product kernel function.

Let z be a vector of the input set Z with n elements, Z_i be the subsets of Z with n_i elements and $Z = U^c_{i=1} Z_{i,}\ n = \sum^c_{i=1} n_i$ where C is the number of classes. Define between-class scatter matrix S_B and with-in class matrix S_W in the feature space F defined by Eq. 7 and 8 as:

$$S_B = \frac{1}{C\,(C-1)} \sum_{i=1}^{C} \sum_{j=1}^{C} (u_i - u_j)(u_i - u_j)^T \quad (7)$$

$$S_W = \frac{1}{C} \sum_{i=1}^{C} \frac{1}{n_i} \sum_{j=1}^{n_i} (\phi(X_j) - u_i)(\phi(X_j) - u_i)^T \quad (8)$$

where, $u_i = 1/n_i \sum^{ni}_{j=1} \phi(X_j)$ denotes the sample mean of class i in F. Since, the dimensionality of F is much better than that of R^J and even unbounded, direct analysis in F is very difficult. As an alternative, the so-called kernel trick is used where the dot (scalar) products in F are computed in R^J via a kernel function. k(.): $\phi(z_i).\phi(z_j)$ = k (z_i, z_j) where z_i and z_j are two vectors in R^J. Here, polynomial kernel is used which is defined in Eq. 9 as:

$$K_p(X, Y) = (1+X.Y)^d \quad (9)$$

Define between-kernel scatter matrix K_B and with-in kernel matrix K_W in the feature space F defined by Eq. 10 and as:

$$K_B = \frac{1}{C(C-1)}\sum_{i=1}^{C}\sum_{j=1}^{C}(m_i-m_j)(m_i-m_j)^T \quad (10)$$

$$K_W = \frac{1}{C}\sum_{i=1}^{C}\frac{1}{n_i}\sum_{j=1}^{n_i}(\zeta_j - m_i)(\zeta_j - m_i)^T \quad (11)$$

Where:

$$m_i = \frac{1}{n_i}\sum_{j=1}^{n_i}K(z_i, z_j)\ \forall\ i \text{ varies from 1 to c}$$

$$\zeta_j = (K(z_1, z_j), (z_2, z_j), ..., K(z_n, z_j))^T$$

Similar to that of MDA, this problem can be solved by finding the leading Eigen vectors (i.e.) Eigen vector corresponding to the largest Eigen value of the generalized eigen value problem involving K_B and K_W of $K_w^{-1}K_B$ and the projection of a point z onto w (eigen vector) in F is given by Eq. 12 as:

$$(w.\phi(z)) = \sum_{i=1}^{n}\alpha(i)\times K(z_i, z) \quad (12)$$

MATERIALS AND METHODS

As shown in Fig. 1, the proposed framework for local image component matching consists of two major steps: image component selection with optimality checking and feature extraction. To evaluate the proposed method under comparatively reasonable experimental conditions, an enhanced method with Kernel Discriminant Analysis is proposed for this research.

Image component selection and optimality checking: The local image components are generated according to the facial features such as eyes, nose, mouth and skin areas. However, this requires exact localization of facial features which is still very tricky. In the earlier mentioned research, the image components are ill-posed and empirically designed.

The face dataset is normalized to a size 128×128 in the research to shrink the processing speed. In the approach, initially an empty set is created. Then, for the first pattern of each and every subject, initially random image component of size range from [16, 64] [16, 64] are generated using greedy search algorithm as shown in Fig. 2. Now, the component is given for optimality checking to find whether it is optimal (or) not. This can be done by comparing the currently generated component with the already created component.

If the already created component overlapped the currently generated component by >40% then the currently generated component can be excluded. If not, the currently generated component can be appended to the set. Next, the currently generated component is compared with the image in a pixel basis for optimality checking and if it meets the threshold value then that component can be considered as an optimal component. Otherwise, the process is repeated until suitable numbers of optimal image components are selected. After selecting those image components, this can be extended to all the remaining patterns of the same class. Likewise, the process is repeated for each and every class of the face dataset. General steps for the proposed searching optimal image component technique for an image are as follows:

```
Algorithm searchOptimalComponent ()
// Input: Given Image I
//Output: Optimal number of Image Components (OICs)
{
      OICs = { }
      I1 = fillZeros (I)      // I1: Image I fill with zeros
      CIC = selectRandomIC (I)
                              // CIC: CurrentImageComponent
      OICs = OICs U CIC // U: union operation
      while (true)
      {
            for each IC in OICs
                              //IC: ImageComponent
            {
                        if (! isSimilar(IC, CIC))
                        {
                              OICs = OICs U CIC
                              I1 = placeAt (I1, CIC)
            }
            Cnt = countMatchPixels (I, I1)
            if (!Cnt < threshold)
            break
      }
            CIC = selectRandomIC (I)
      }
}
```

Feature extraction using gabor filter: Once the optimal image component is selected, visual feature enhancement is applied. Considering that Gabor features have been recognized as a successful visual feature representation

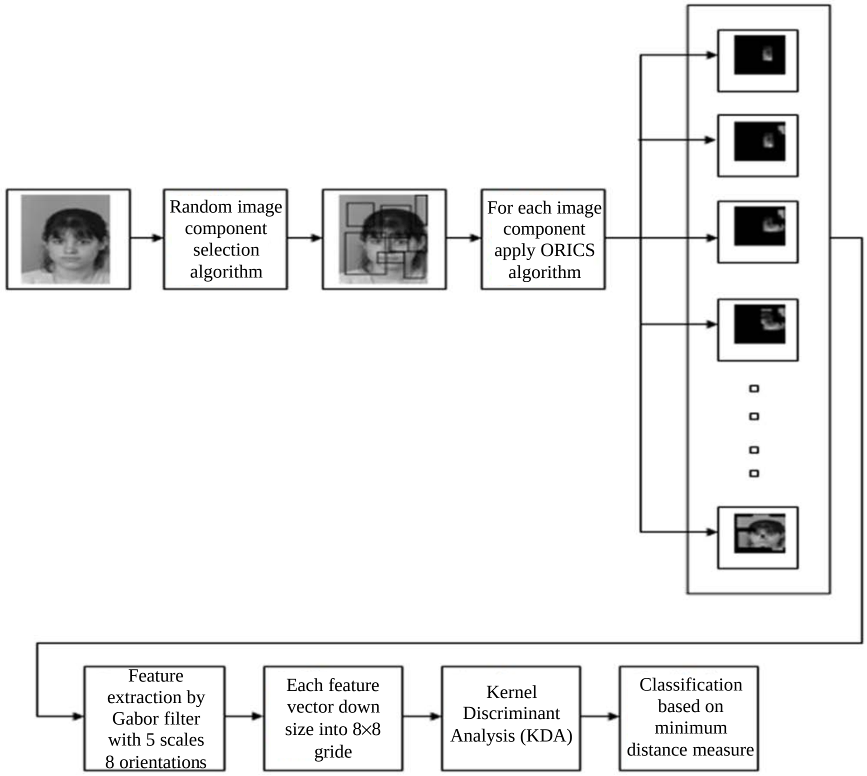

Fig. 1: Illustration of the concept of local image component creation and dimensionality reduction of the feature vector

Fig. 2: Creation of optimal random local image components of size [16, 64] [16, 64] using Greedy approach

method in face recognition, researchers extract Gabor features from the image components for more enhancements.

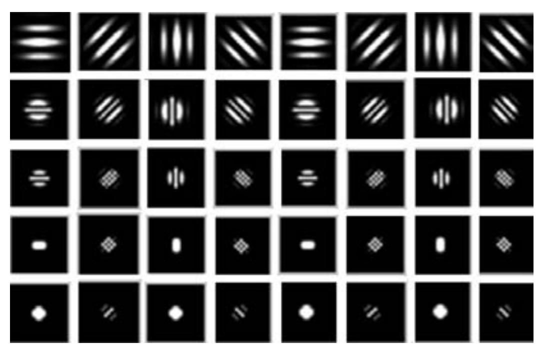

Fig. 3: Real part of the 2D Gabor wavelets with 5 scales and 8 orientations

The first step is to convolve the optimal image component of face image with a bank of Gabor filters with different orientations and scales and then is down sampled to 8×8 grids. As shown in Fig. 3, the Gabor magnitude features of five scales and eight orientations are extracted from the optimal image components. These Gabor features are then projected onto the respective MDA subspace for dimension reduction and KDA subspace for extracting discriminant information from a high-dimensional kernel.

RESULTS AND DISCUSSION

The performance of ORICS, ORICS plus MDA and ORICS plus KDA was evaluated with two image databases FERET and ORL, respectively. FERET (Phillips *et al*., 1998) database is tested on a subset of 2200 image samples from 200 classes and ORL on 400 image samples from 40 classes. Both databases shown in Fig. 4 and 5 are publicly released along with standard evaluation protocols. For FERET database, the proposed method is tested on fa, fb, hl, hr, pl, pr, ql, qr, rb, rc, bk images. fa indicates a regular frontal image, fb indicates an alternative frontal image, taken seconds after the corresponding fa, hl and hr indicate half left and right images with pose angle -67.5 and +67.5, pl and pr indicate profile left and right with pose angle -90 and + 90, ql and qr indicate quarter left and right with pose angle -22.5 and +22.5, rb and rc indicate random images with pose angle +10 and -10 and bk indicates frontal image taken under different lighting.

For ORL database, there are ten different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying the lighting, facial expressions (smiling/not smiling, open/closed eyes) and facial details (glasses/no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement). Table 1 shows the details of experimental image dataset.

Table 1: Experimental image dataset

Dataset	Number of subjects	Number of samples in each class	Image size
FERET	200	11	256×384
ORL	40	10	112×92

Researchers divide the total number of images into training and testing which are disjoint. The number of image components generated is 10-40. By means of ORICS Method, optimal image components are selected and by means of Gabor wavelets (Shen and Bai, 2004), local features are extracted. Here, 40 Gabor filters (5 scales and 8 orientations) are used. Since, the local image component size ranges between [16, 64] [16, 64], the maximum dimensionality is 1, 63, 840 (64 64 5 8) which is too high dimensional. To solve this problem, the Gabor features are uniformly down-sampled to 8×8 grids and is averaged on all the orientations and scales. The down-sampled Gabor features are then projected onto the respective MDA subspace and also to the implicit KDA feature space through non-linear polynomial kernel mapping, after that MDA is carried out in this implicit feature space for dimensionality reduction and thus a non-linear discriminant can be obtained for the input data. A similar method of image component creation is applied for the query image and each image component is projected onto the respective subspaces where both the recognition accuracy can be taken based on minimum distance measure.

Results for expression, pose and illumination variation of varying image size: In LEC (Local Ensemble Classifier) Method used by Su *et al*. (2009) after the local image components are selected, Gabor features are extracted from each local image component using Gabor filters (five scales and eight orientations). The down-sampled features of each feature vector are then further used to train a local image component. Finally, local image components are combined to form the LEC whose

Fig. 4: Images of an individual of FERET dataset

Fig. 5: Images of an individual of ORL dataset

Table 2: Comparison of the highest accuracy achieved by several methods for varying image size for 30% training. The result of existing method is cited from the corresponding study

Database	Approach	Method	Image size 128×160	96×120	64×80	48×60
FERET	Existing	LEC Used by Su *et al.* (2009)	83.00	81.00	75.00	68.00
FERET	Proposed	ORICS	58.13	74.38	79.38	81.25
		ORICS+MDA	88.13	91.88	98.75	98.13
		ORICS+KDA	100.00	100.00	100.00	99.44
ORL	Proposed	ORICS	61.43	69.29	74.28	77.25
		ORICS+MDA	72.86	90.36	97.75	98.13
		ORICS+KDA	98.75	100.00	100.00	99.13

Table 3: Performance comparison of FERET and ORL. The result of existing method is cited from the corresponding study

Database	Approach	Methods	Image size 128×128
FERET	Existing	GC used by Su *et al.* (2009)	96.00
		LEC	99.00
		HEC	99.00
FERET	Proposed	ORICS	95.00
		ORICS+MDA	99.44
		ORICS+KDA	100.00
ORL	Proposed	ORICS	77.50
		ORICS+MDA	82.50
		ORICS+KDA	99.64

recognition accuracy along with the proposed approach ORICS, ORICS+MDA and ORICS+KDA for 30% training for varying size of an image is shown in Table 2.

From the performance of these four algorithms, it is noticed that even at 30% training, the proposed method ORICS with subspace approach with KDA yields better recognition accuracy for varying the size of an image as shown in Fig. 6. It is observed that ORICS with KDA shows better performance than LEC and ORICS with MDA and without subspace approach.

Also, researchers observe from the results that the proposed method ORICS with subspace approach KDA outperforms all the methods with significant improvement under the condition of varying poses, illumination, expression, etc.

Results for expression, pose and illumination variation of image size 128×128: In GC (Global classifier) method used by Su *et al.* (2009) the Fast Fourier Transform (FFT) algorithm is applied onto the holistic image of size 128×128 in which 16×16 low-frequency Fourier coefficients which cover about 50% of all the energy to form the global features are taken into account.

These features are then projected to the fisher subspace MDA and the recognition accuracy on FERET is noted. To make full use of the discriminative information in both the global and the local features for improving the system performance, GC and LEC are combined to form the Hierarchical Ensemble Classifier (HEC) whose recognition accuracies on FERET are also noted. For the proposed approach ORICS, features are extracted using Gabor filters and is then projected onto MDA and KDA subspace. The recognition accuracies of ORICS, ORICS plus MDA and ORICS plus KDA on FERET and ORL dataset are shown in Table 3.

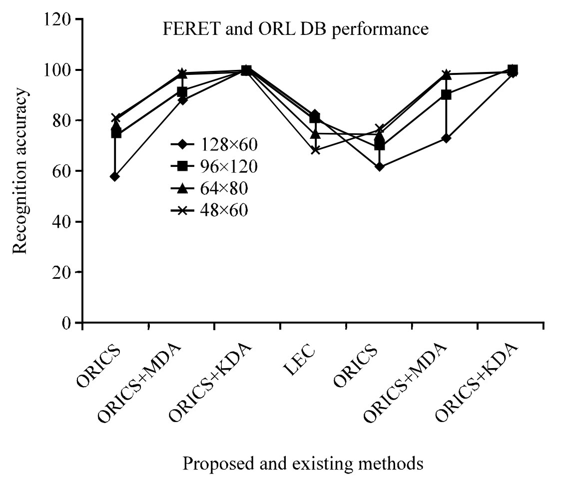

Fig. 6: Performance comparisons of existing and proposed methods of FERET with varying image size

Researchers observed from the results that the ORICS plus KDA method completely outperforms the existing GC, LEC, HEC Methods in all aspects, specifically for optimal local image components with varying size [16, 64] [16, 64].

CONCLUSION

This study highlights a face recognition technique using FERET and ORL face databases. The feature selection approach is robust to pose, illumination and expression in the face images. By using greedy approach, random image components for eyes, nose, mouth, skin areas, etc. are generated and by optimality checking, limited random image components are taken into account for every pattern. For large variations in pose, illumination and expression, the proposed method ORICS with KDA completely outperforms GC, LEC, HEC, ORICS and ORICS using subspace approach with MDA Method. The number of local image components is varied from 1-40 and by means of optimality checking, it is observed that at least 10-20 image components are sufficient for reasonable recognition. The recognition accuracy is better at using 30% training as against the existing methods. But all this occurs at the cost of surplus overhead of processing each local image component. However, nowadays computational assets could be exploited for fast response.

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