Enhancing Face Recognition Performance using Triplet Half Band Wavelet Filter Bank

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Abstract—Face recognition using subspace methods are quite popular in research community. This paper proposes an efficient face recognition method based on the application of recently developed triplet half band wavelet filter bank (TWFB) as pre-processing step to further enhance the performance of well known linear and nonlinear subspace methods such as principle component analysis(PCA),kernel principle component analysis (KPCA), linear discriminant analysis (LDA), and kernel discriminant analysis (KDA). The design of 6th order TWFB is used as the multiresolution analysis tool to perform the 2-D discrete wavelet transform (DWT). Experimental results are performed on two standard databases ORL and Yale. Comparative results are obtained in terms of verification performance parameters such as false acceptance rate (FAR), false rejection rate (FRR) and genuine acceptance rate (GAR). Application of TWFB enhances the performance of PCA, KPCA, LDA, and KDA based methods.

Index Terms—Face Recognition, triplet half band wavelet filter bank (TWFB), PCA, KPCA, LDA, KDA.

I. INTRODUCTION

Face recognition has rapidly developed over past of the years with important applications in video surveillance identity authentication, security monitoring, access control, suspect tracking in commercial and law enforcement [1].Challenges in face recognition arise due to change in face image characteristics such as a change in illumination of scene, change in pose, change in facial expression, and occlusion of some portion of the face area. Appearance-based face recognition methods are categorized into linear and nonlinear subspace methods and frequency based methods. Principal component analysis (PCA) [3], Fisher discriminant analysis (FDA) [4], independent component analysis (ICA) [5] and two-dimensional PCA [6] are the widely used linear subspace methods. These methods attempt to represent face images in a lower dimensional feature space which is a linear combination of a set of basis [25]. In spite of the popularity of linear subspace methods, their performance is not satisfactory under large variation of facial images

such as illumination pose and occlusion. To overcome such variations some nonlinear subspace methods like kernel PCA (KPCA) [7] and kernel discriminant analysis (KDA) [8] are proposed which are non linear extension of PCA and LDA. These methods map an input image nonlinearly to a higher dimensional feature with the help of a kernel function [8]. Non-statistical face recognition method using local binary pattern (LBP) [26] outperforms PCA and LDA-based methods in terms of recognition performance and computational simplicity. Disadvantages are sensitivity to noise and a large size of the feature vector. Wavelet transforms based face recognition methods are extensively by the research community. Researchers have used different off the shelf wavelet filter for facial feature extraction. This paper involves the usage of recently developed triplet wavelet filter bank (TWFB) to enhance the performance of existing linear and non linear subspace methods. Application of (TWFB) provides the efficient multiresolution features compared with the existing wavelet filters. The paper is organized as follows. Section II gives the insight of the related work. In Section III, we briefly reviewed linear and non linear subspace methods such as PCA [3], LDA [4], KPCA [7], and KDA [8]. Section IV reviews the design of TWFB [19], [22]. The proposed method of face recognition using TWFB based features, used face databases, and experimental results are summarized in Section V followed by conclusion in Section VI.

II. RELATED WORK

Recent progress in face recognition efficiently uses wavelet transform that possess good time and frequency localization which helps to detect the facial geometric structures and offers robust feature extraction even under variable illumination [9]. In wavelet analysis the discrete wavelet transform (DWT) [10] and Gabor wavelet transform (GWT) [11]–[12] based face recognition methods are more popular. GWT is more successful due to its capability of effectively expressing face feature for its directional selectivity. But Gabor wavelets provide over-complete representation which increases computational complexity due to the convolution of each

face image with several Gabor wavelet kernels at many scales and orientations [13]. When DWT is applied before PCA or LDA, features like edge information are extracted more efficiently which forms meaningful feature vectors [13].Such a method proposed by Feng et al [14] applied PCA on wavelet subband and utilized a midrange frequency subband for PCA representation. Chien and Wu [10] performed face recognition by applying the wavelet transform to extract waveletfaces from face images and incorporated LDA for discriminant analysis. A comparison of the performance of face recognition systems based on the principal component analysis (PCA), Gabor wavelet transform (GWT) and discrete wavelet transform (DWT) is presented in [15]. It is demonstrated that the DWT algorithm has the ability to achieve recognition performance at levels similar to those of the GWT algorithm with a faster analysis time. Utsumi et al [9] evaluated the performance of face recognition in response to various wavelets transform (e.g. Haar, French hat, Mexican hat, Daubechies, Coiflet, Symlet, and O-spline).They demonstrated that the performance of the wavelets assessed is similar to that of the Gabor wavelet. Jadhav and Holambe [16] applied radon transform to images and DWT is applied on the generated radon feature space. Radon transform improves the low-frequency component of the face images and wavelet transform when applied on the Radon feature space provides multiresolution features. The proposed system is invariant in facial expression and illumination. Most of the existing DWT based face extraction methods use off-the-shelf wavelet filters like orthogonal (Haar, Daubechies, Coiflet, Symlet) and Biorthogonal (B-spline Biorthogonal, and CDF-9/7). But even for the same class of face images, the effect of these wavelet filters may vary for the distinct application. This is due to the fact that many of the face images do not have the same statistical characteristics due to the changes in illumination, pose, and occlusion. Designing of appropriate wavelet filters can result in robust representations with regard to changes in illumination, pose, and occlusion and provide significant feature vectors with reduce computational complexity. Hence to design wavelet filters which match the characteristics of face images for feature extraction is highly desirable. Biorthogonal wavelet filters are preferred over orthogonal wavelet filters for applications such as feature extraction and image compression. The most popular construction for the design of biorthogonal filter banks is CDF-9/7 9/7 [17] which is designed by factorizing a Lagrange half band polynomial (LHBP) to obtain wavelet filters in the filter bank. Lagrange half band polynomial is imposed with maximum no of zeros at $z = -1$ due to which they offer no degree of freedom and there is no direct control over the frequency response of the filters [19],[22]. Patil et al [18] designed a pair of biorthogonal wavelet filters to control the frequency response of the filters. In their proposed work instead of using the Lagrange half band polynomial a general half band polynomial (GHBP) is considered for factorization. A recent work on designing of biorthogonal wavelet filter bank is proposed by

Rahulkar et.al [19], [22].A general half band polynomial is used and three polynomials are generated using factorization. These triplet filters are used in the equations proposed in [21] to obtain the low pass analysis and synthesis filters. The authors used it for Iris feature extraction, however due to its properties like flexible frequency response, near-Orthogonality, and regularity; the designed filter bank can be effectively used for applications in feature extraction and image compression [22].The authors in [23] used the 10th order TWFB for iris feature extraction.

Our work is motivated from [19] and [22] to develop a face recognition system so as to derive significant and compact facial features using the TWFB as the preprocessing step and provide the essential multiresolution features to the existing subspace methods like PCA, KPCA, LDA, and KDA. Experiments are performed on two well known databases ORL [27] and Yale [28].

III. OVERVIEW OF LINEAR AND NON-LINEAR SUB-SPACE METHODS

In this section, a brief review on linear and non-linear sub-space methods is presented.

A. Principal Component Analysis

Principal component analysis is a famous linear projection method for dimensionality reduction [3]. Assuming the training set consists of N images, the data matrix $X = \{x_1, x_2, ...x_N\}, x_i \in R^t$ is obtained by row concatenation of image data. Let C be the number of classes and each image x_i belongs to one of C classes $\{1, 2, ...C\}$ .The mean face of the data matrix is defined as $m = (1/N).\sum_{i=1}^{N} x_i$ .The covariance matrix or the total scatter matrix S_t is defined as [3]:

$$S_t = \frac{1}{N}\sum_{i=1}^{N}(x_i - m).(x_i - m)^T \qquad (1)$$

The eigenvalues λ_i and corresponding eigenvectors V_i are computed from S_t defined by the following eigenvalues problem [3]:

$$S_t V_i = \lambda_i V_i \qquad (2)$$

Arranging all eigenvalues in the descending order and considering first few n highest eigenvalues and their corresponding eigenvectors generates the projection matrix W_{pca} and in turn new face space [3],

$$Z = W_{pca}^T(x_i - m) \text{, where } z_i \in R^f (f << t) \qquad (3)$$

B. Linear Discriminant Analysis (LDA)

The objective of Fisherfaces method using linear discriminant analysis (LDA) is to choose subspace of face features that makes the ratio of between-class scatter matrix to the within-class scatter matrix largest [4]. For all samples of all classes, the between-class scatter matrix S_b and the within-class scatter matrix S_w are defined as [4]:

$$S_b = \sum_{i=1}^{C} n_i.(m_i - m).(m_i - m)^T \qquad (4)$$

$$S_w = \sum_{i=1}^{C} \sum_{j=1}^{n_i} (x_j - m_i)(x_j - m_i)^T \qquad (5)$$

Where n_i is the number of samples in ith class m_i is the mean for the ith class samples and m is the mean face or global mean of all samples. If S_w is non-singular, LDA seeks to find the optimal transformation matrix W to maximize the projection ratio denoted by [4]:

$$J(W) = \arg \max_W \frac{|W^T S_b W|}{|W^T S_w W|} \qquad (6)$$

This ratio is maximized when W is constructed by considering $C-1$ leading eigenvectors of the following eigenvalue problem [4]:

$$S_w^{-1} S_b w_i = \lambda_i w_i \qquad i = 1, 2, ..., C-1 \qquad (7)$$

Where $w_i (i = 1, 2, ..., C-1)$ is the generalized eigenvectors corresponding to the largest eigenvalues.

But S_w is always singular in face recognition due to the high dimensionality of face images [4]. Thus to make the S_w matrix non-singular PCA is usually performed before LDA to reduce the dimensions from N to $N-C$ and then applying LDA defined by equation (6) to further reduce the dimension to $C-1$ [4].

C. Kernel principal component analysis (KPCA)

KPCA is a nonlinear extension of classical PCA [7]. The mapping of linear input space R^t into high dimensional feature space F is obtained by a nonlinear mapping function,

$$\phi: R^t \rightarrow F$$
$$x \mapsto \phi(x) \qquad (8)$$

This non linear mapping is achieved though kernels trick [7]. The covariance matrix on the feature space F is:

$$S_t^\phi = \frac{1}{N}.\sum_{i=1}^{N} (\phi(x_i) - m_0^\phi)(\phi(x_i) - m_0^\phi)^T \qquad (9)$$

where

$$m_0^\phi = \frac{1}{N}.\sum_{i=1}^{N} \phi(x_i) \qquad (10)$$

The corresponding eigen-value problem becomes [7]:

$$S_t^\phi V_i = \lambda_i V_i \qquad (11)$$

Applying the kernel trick, equation (11) can be transformed to

$$K \tilde{V}_i = \tilde{\lambda}_i \tilde{V}_i, \quad \text{for} \quad i = 1, ... N \qquad (12)$$

K is the $N \times N$ centralized kernel matrix defined with

$$K_{ij} = \phi(x_i)^T.\phi(x_j) = (\phi(x_i) \bullet \phi(x_j)) = k(x_i, x_j) \qquad (13)$$

where $k(x_i, x_j)$ is a kernel function employed to compute the dot product $(\phi(x_i).\phi(x_j))$ and $(i, j = 1, ..., N)$

Thus calculating the orthonormal eigenvectors $\tilde{V}_1, \tilde{V}_2, ..., \tilde{V}_n$ corresponding to n largest positive eigenvalues $\tilde{\lambda}_1, \tilde{\lambda}_2, ...\tilde{\lambda}_n$, the new face space is calculated using [7].

$$Y_i = \sum_{i=1}^{n} \frac{\tilde{V}_i}{\sqrt{\tilde{\lambda}i}}.k(x_i, x). \qquad (14)$$

D. Kernel Discriminant Analysis(KDA)

In the proposed work of KDA [8] the kernel feature space F is used instead of input space R^t to find the traditional LDA. The between and within-class scatter matrix in feature space F are as

$$S_b^\phi = \sum_{i=1}^{C} n_i (m_i^\phi - m^\phi)(m_i^\phi - m^\phi)^T \qquad (15)$$

and

$$S_w^\phi = \sum_{i=1}^{C} \sum_{j=1}^{n_i} (\phi(x_j) - m_i^\phi)(\phi(x_j) - m_i^\phi)^T \qquad (16)$$

where m_i^ϕ is the mean of i-th class mapping samples, m^ϕ is the is the global mean of all the mapping samples and n_i is the number of samples in i-th class. Fisher discriminant function in F feature space is given as [8]:

$$J_1(w) = \frac{w^T S_b^\phi w}{w^T S_w^\phi w} \qquad (17)$$

Since eigenvectors of w lies in the span of all samples in F, its eigenvectors can be represented with a linear combination of $\phi(x_i)$, i.e.

$$w = \sum_{i=1}^{N} a_i \phi(x_i) = Qa \qquad (18)$$

Substituting equation (18) in equation (17), we obtain the following maximizing function for KDA [8]

$$J_2(w) = \frac{a^T K_b a}{a^T K_w a} \qquad (19)$$

Thus from solution of equation (19) we obtain the eigenvectors corresponding to the largest eigen-values in the following eigen-value problem:

$$K_w^{-1} K_b \alpha_i = \lambda_i \alpha_i \qquad (20)$$

For n largest eigen-values we use the following formula to calculate projection of a new sample x on w in F feature space

$$y_i = (w.\phi(x)) = \alpha_i^T K_x = \sum_{i=1}^{n} \alpha_i k(x_i, x) \qquad (21)$$

IV. TRIPLET HALF BAND WAVELET FILTER BANK (TWFB) AND FEATURE EXTRACTION

A. Triplet half band wavelet filter bank (TWFB): Design Review

As per the design methodology adopted in [19],[22],[23] only FIR filters for implementation of a two channel biorthogonal channel filter bank shown in Fig.1, where $H_0(z)$ and $H_1(z)$ are the low pass and high pass filters respectively. The corresponding $G_0(z)$ and $G_1(z)$ are the low pass and high pass synthesis filters. The perfect reconstruction condition [20] is given as

$$G_0(z)H_0(z) + G_1(z)H_1(z) = 2z^{-D} \qquad (22)$$

and

$$G_0(z)H_0(-z) + G_1(z)H_1(-z) = 0 \qquad (23)$$

Where D is the amount of delay. If $H_1(z) = G_0(-z)$ and $G_1(z) = -H_0(-z)$ then equation (2) is automatically satisfied and equation (1) reduces to equation (3) by defining the product filter $P(z) = H_0(z).G_0(z)$. Thus, the design of the filter bank reduces to the design of the half band filter $P(z)$ whose factorization gives $H_0(z)$ and $G_0(z)$ [20].

$$P(z) - P(-z) = 2z^{-D} \text{, where D is odd} \qquad (24)$$
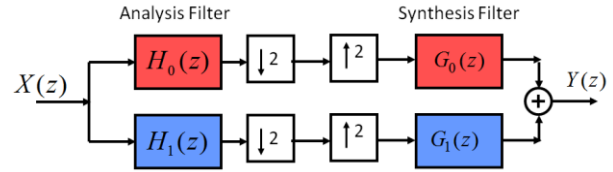

Fig.1. Two-channel Biorthogonal Filter Bank

As per the work described in [19], [22], [23], a 6th order generalized half band polynomial is used to design (13/19) wavelet filters. The design procedure for the triplet half band wavelet filter bank (TWFB) is explained as below

1) Consider a generalized half band polynomial (GHBP) $P(z)$ of 6th order i.e. $K=6$.

$$P(z) = \alpha_0 + \alpha_2 z^{-2} + z^{-3} + \alpha_2 z^{-4} + \alpha_0 z^{-6} \qquad (25)$$

2) This GHBP is used to construct three half band polynomials (HBPs) by extracting three zeros at $z = -1$ using the method of synthetic division [19], [22]. Extracting of zeros at z=-1 imposes regularity on the GHBP $P(z)$ and should satisfy the constraints of $X < ((K/2)+1)$, where X are the number of zeros at $z = -1$ and K is the order of GHBP.

3) Regularity is imposed in the design of $P(z)$ by extracting three zeros at z=-1 to construct three half band polynomials $P_1(z)$, $P_2(z)$, $P_3(z)$. These three half band polynomials are expressed in terms of α_0 only which are given as follows [19],[22],[23]

$$P_1(z) = (1 + z^{-1})^{X_1}.R_1(z)$$
$$P_2(z) = (1 + z^{-1})^{X_2}.R_2(z)$$
$$P_3(z) = (1 + z^{-1})^{X_3}.R_3(z) \qquad (26)$$

Where X_i are number of zeros at z=-1, and $R_1(z), R_2(z), R_3(z)$ the remainder polynomials.

Consider $X_1 = 0$, $X_2 = 1$ and $X_2 = 2$ such that $X = X_1 + X_2 + X_3 = 3$ which satisfies the condition of $X < ((K/2)+1)$, $K = 6$ is the order of GHBP.

$$P_1(z) = (1+z)^0 . (\alpha_0 + (-\alpha_0 + 0.5)z^{-2} + z^{-3}$$
$$+ (-\alpha_0 + 0.5)z^{-4} + \alpha_0 z^{-6})$$
$$P_2(z) = (1+z^{-1})^1 . (\alpha_0 - \alpha_0 z^{-1} + 0.5z^{-2}$$
$$+ 0.5z^{-3} - \alpha_0 z^{-4} + \alpha_0 z^{-5})$$
$$P_3(z) = (1+z^{-1})^2 . (\alpha_0 - 2\alpha_0 z^{-1} + (2\alpha_0 + 0.5)z^{-2} \quad (27)$$
$$- 2\alpha_0 z^{-3} + \alpha_0 z^{-4})$$

As these HBPs are expressed in the form of α_0 term, only a flexible frequency response can be obtained due to one degree of freedom [19], [22]. The value of $\alpha_0 = -0.062499$ is obtained using MATLAB unconstrained optimization function *fminunc* which considers the objective function designed on the basis of minimizing energy in the ripples of these three HBPs[19],[22].

4)   The analysis low pass $H_0(z)$ and synthesis low pass $G_0(z)$ are given as follows from [19] and [21]

$$H_0(z) = \frac{1+p}{2} + \frac{1}{2}T_1(z).(1 + pT_0(z))$$

$$G_0(z) = \frac{1 + pT_0(z)}{1+p} + \frac{1-p}{1+p}T_2(z).H_0(-z) \quad (28)$$

Where $T_0(z)$, $T_1(z)$ and $T_2(z)$ are half band kernels whose ideal pass band and stop band responses are 1 and 0 respectively. In order to achieve perfect reconstruction, these filters are formulated as below.

$$T_0(z) = P_1(z) - 1$$
$$T_1(z) = P_2(z) - 1$$
$$T_2(z) = P_3(z) - 1 \quad (29)$$

5)   Substituting equation (29) in equation (28) we can obtain low pass analysis $H_0(z)$ and low pass synthesis $G_0(z)$ filters of TWFB.

To obtain same magnitude response from $H_0(z)$ and $G_0(z)$ at $\omega = \pi/2$, the value of shaping parameter $p = 0.41421$ is considered [21], [22]. The length of $H_0(z)$ and $G_0(z)$ is 13 and 19 respectively.

6)   By using the below relation we can obtain the high pass analysis and synthesis filters.

$$G_0(z) = H_1(-z), G_1(z) = -H_0(-z) \quad (30)$$

Thus, the usage of a GHBP to design TWFB improves the frequency response of $H_0(z)$ and $G_0(z)$ filters. These filters not only satisfy regularity but also achieve linear phase and perfect reconstruction [19], [22]. These properties are vital in achieving higher facial discrimination capability along with linear and non linear subspace methods.

B. Facial Feature Extraction Using TWFB

We need 2-D separable filter bank for face feature extraction and we need only analysis or decomposition part of the filter bank. The implementation is carried out by applying one-dimensional wavelet filters to the rows of the face image and the columns of the row transformed data respectively. The one level-decomposition results in one approximation subband *LL* which gives a coarser approximation to the original image, one *LH* band and one *HL* band which records the changes of the image along the horizontal and vertical direction, and one *HH* band that shows the high-frequency component of the image. In our approach, TWFB is applied on face images to extract multiresolution-based facial feature. First, we perform two-level wavelet decomposition using the TWFB wavelet pairs and obtain the two-level low-frequency sub-band *LL* as the feature vectors. The low-frequency subband *LL* is an optimal approximation image of the original image which contains most important features of the face and can be sufficiently used for face recognition and the remaining high-frequency sub-bands can be neglected. These wavelet pairs provide an effective discriminatory representation of face images. Thus, after obtaining the multiresolution facial features using the TWFB, linear and non linear subspace methods are used to obtain the enhanced face recognition performance. To capture the difference between the two facial features or classification, we used Euclidean distance measures for LDA and KDA based methods and cosine distance measures for PCA and KPCA based face recognition methods.

V. EXPERIMENTATION AND RESULTS

The experiments were carried out in Matlab 2014a, on a 64-bit I3, 2.13 GHz processor, with 2 GB RAM. The performance evaluation is carried out on two standard databases, ORL [27], and Yale [28] face databases. To design the experiments for face verification we consider all the face images and applied the concept mentioned in previous section for performance measure. In this paper, to test the robustness of the proposed approach no pre-processing technique is used for face images such as face normalization. Thus to enhance the performance of PCA, LDA, KPCA, and KDA, 2-D implementation of TWFB is applied on the face images. Compared with the linear and non subspace projection methods which take raw pixel information, TWFB facial features contains more discriminating information thus shows robustness against variation in illumination, expression, and pose.

A. Performance Measures

The verification performance of our face recognition methods is estimated using false acceptance rate (FAR); false reject rate (FRR) and guanine GAR values. FAR is

defined as the ratio of the number of accepted impostors to the total number of impostor accesses, while FRR is defined as the ratio of rejected genuine claims to the total number of genuine accesses. Where impostors are defined as the face images for an individual excluding his own images. A low value for FAR and FRR is often desirable but as the FAR increases FRR decreases, this is due to the uneven distribution of genuine and impostor claims. Thus to determine the optimum balance between FAR and FRR, Receiver Operating Curve (ROC) is adopted which plot FAR versus GAR [24].A higher value of GAR is often desirable for a better verification performance.

B. Results on ORL face database

The ORL database [27] consists of 10 different images of each of 40 different persons. There are variations in the capture time, lighting, head position, facial expressions such as eyes open or closed, smiling or not smiling and facial details such as glasses or no glasses. All images are 8-bit grayscale taken against a dark homogeneous background of resolution 112x92 pixels. The face images are resized to 128x128 pixels. Some samples face images of ORL face database are shown in Fig.2. The first series of experiments are conducted using the extracted TWFB features and four subspace methods for face verification. For this purpose, all parameters like feature dimensions and distance measure are optimized to achieve the best performance.

Fig.2. Sample face images from ORL face database

Comparative results of PCA, LDA, KPCA and KDA are tabulated in Table.1 and same is shown with ROC curves in Fig. 3. For these methods, the pixel values of face images are simply concatenated to form a feature vector. For KPCA and KDA based methods, we adopted normalized polynomial kernel with the parameter *d* equal to 2.

Table 1. Sub-space results in terms of FAR, FRR, and GAR on ORL database

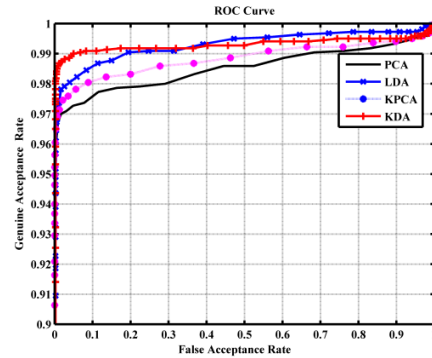| Method	FAR (%)	FRR (%)	GAR (%)
PCA	0.9744	3.2727	96.7273
LDA	0.6957	1.8636	98.1364
KPCA	0.4169	3.4545	96.5455
KDA	0.2558	1.8182	98.1818

Fig.3. ROC curves of the subspace methods for ORL database

To verify the discriminating power of extracted TWFB based pixel features over the raw pixels of subspace methods a comparative performance of TWFB+PCA, TWFB+ LDA, TWFB +KPCA and TWFB+KDA is carried out. It can be observed from Table.2 and Fig.4 that the adaptation of TWFB before PCA, LDA, KPCA, and KDA methods enhances the performance of these methods and we can achieve better performance compared to the original methods. The dimension of the feature vector for PCA and KPCA based methods is 399, whereas its 39 for LDA and KDA based methods. The great advantage of applying TWFB comes from the fact that the size for the low frequency approximation subband of size 32x32 is suffice to capture the essential discriminating characteristics of face image compared to original image size of 128x128 as in case with PCA,LDA,KPCA and KDA methods.

LDA-based method gives better performance than PCA-based method and kernel-based methods give better performance than linear-based PCA and LDA methods. Among all these methods, the KDA based methods combined with TWFB gives the best performance in terms of higher GAR when the dimension is set at 39.

Table 2. TWFB based Sub-space results in terms of FAR, FRR, and GAR on ORL database

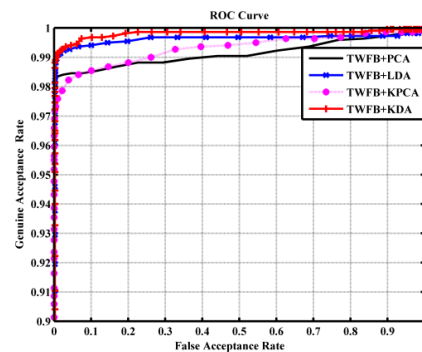| Method	FAR (%)	FRR (%)	GAR (%)
TWFB+PCA	0.3031	1.3182	98.6818
TWFB+LDA	0.7161	1.2273	98.7727
TWFB+KPCA	0.3510	1.9545	98.0455
TWFB+KDA	0.2558	1.1364	98.8636

Fig.4. ROC curves of the TWFB based subspace methods on ORL database

It is apparent from Table.2 and Fig. 4 that adaptation of TWFB based feature vectors enhances the performance of these subspace methods with difference in GAR. TWFB+PCA method achieves 2.02 % higher GAR compared with PCA, while 0.6442% higher GAR is observed for TWFB+LDA compared with LDA method. For TWFB+KPCA and for TWFB+KDA, 1.53% and 0.6944 % higher GAR is achieved respectively.

C. Results on Yale face Database

Yale face database [28] consists of face 15 individuals and for each individual there are 11 images. Images are having variations in illumination and facial expressions. The illumination variations are due to lighting changes in center-light, left-light and right-light. Different facial expressions are normal, happy, sad, sleepy, surprise and wink. We used this database to evaluate the performance of our method under the condition of change in illumination and facial expression. The face images are resized to 128x128 pixels. Samples face images of one person are shown in Fig.5.

Fig.5. Sample face from Yale face database with different illumination variation

Similar FAR and FRR test are performed on Yale database which gives 990 genuine attempts and 25575 impostor attempts. The performance values attained with the method taking raw pixel values images applying only PCA, LDA, KPCA and KDA are tabulated in Table.3 and the corresponding ROC curve is shown in Fig.6.

Table 3. Subspace results in terms of FAR, FRR, and GAR on Yale face database

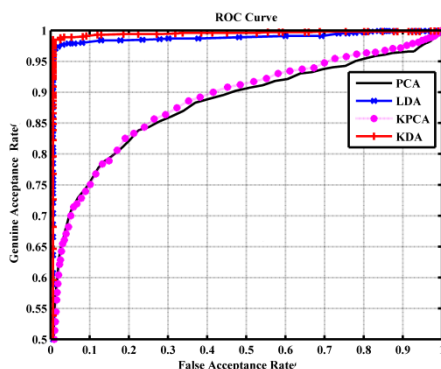| Method	FAR (%)	FRR (%)	GAR (%)
PCA	6.9169	27.1717	71.6162
LDA	0.6452	3.3333	96.6667
KPCA	6.6276	27.1717	72.8283
KDA	0.6452	1.5152	98.4848

Fig.6. ROC curves of the subspace methods on Yale database

TWFB based sup-space methods are tabulated in Table 4 and shown in Fig.7. It is evident that KPCA achieves better performance compared with PCA and KDA achieve better performance compared with LDA-based method for Yale database. For Yale databases, TWFB+PCA method achieves 0.28 % higher GAR compared with PCA, while 0.42% higher GAR is observed for TWFB+LDA compared with LDA method. For TWFB+KPCA 1.39 % and for TWFB+KDA 0.6154 % higher GAR is achieved respectively.

Table 4. TWFB based Subspace results in terms of FAR, FRR, and GAR on Yale database

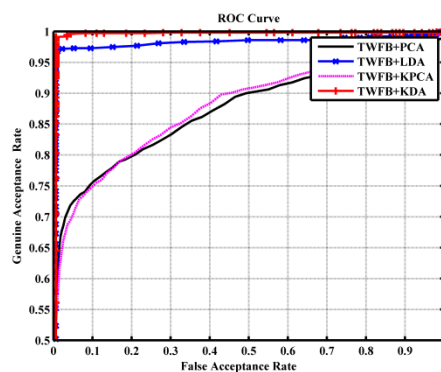| Method	FAR (%)	FRR (%)	GAR (%)
TWFB-+PCA	4.2972	28.1818	71.8182
TWFB+LDA	1.2551	2.9293	97.0707
TWFB+KPCA	10.5298	26.1616	73.8384
TWFB+KDA	0.6452	0.9091	99.0909

Fig.7. ROC curves of the TWFB based subspace methods on Yale database

D. Comparative results

We also compared the effectiveness of TWFB as facial features with CDF-9/7 wavelet filters, as these filters are mostly used for wavelet based facial feature extraction. The comparative results are depicted in Table 5.

Table 5. Comparative results

Method	ORL			Yale		
	FAR (%)	FRR (%)	GAR (%)	FAR (%)	FRR (%)	GAR (%)
CDF-9/7+ LDA	0.514	1.318	98.682	1.255	2.929	97.071
TWFB+LDA	0.716	1.227	98.773	1.857	2.323	**97.677**
CDF-9/7+ KDA	0.302	1.500	98.500	0.645	1.111	98.889
TWFB+KDA	0.255	1.136	98.864	0.645	0.909	**99.091**

VI. CONCLUSION

In this paper, we have proposed a face recognition method to enhance the performance of existing subspace methods with application of TWFB. The design of TWFB for facial feature extraction is also been discussed and experimentally tested for face verification purpose. The performance evaluation is carried out on two standard

face databases. The proposed method with TWFB+KDA achieve high GAR values of 98.86% and 99.09% method for ORL and Yale face databases respectively, which is significantly better than PCA, LDA, and KPCA based methods.

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