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Research Article

Efficient Discriminate Component Analysis using Support Vector Machine Classifier on Invariant Pose and Illumination Face Images

R. Rajalakshmi and M.K. Jeyakumar
Department of Computer Application, Noorul Islam University, Kumaracoil, Tamil Nadu, India

Abstract: Face recognition is the process of categorizing a person in an image by evaluating with a known face image library. The pose and illumination variations are two main practical confronts for an automatic face recognition system. This study proposes a novel face recognition algorithm known as Efficient Discriminant Component Analysis (EDCA) for face recognition under varying poses and illumination conditions. This EDCA algorithm overcomes the high dimensionality problem in the feature space by extracting features from the low dimensional frequency band of the image. It combines the features of both LDA and PCA algorithms and these features are used in the training set and is classified using Support Vector Machine classifier. The experiments were performed on the CMU-PIE datasets. The experimental results show that the proposed algorithm produces a higher recognition rate than the existing LDA and PCA based face recognition techniques.

Keywords: Face recognition, histogram equalization, LDA and PCA

INTRODUCTION

In recent years, face recognition has attracted much attention and its research has rapidly expanded by not only engineers but also neuroscientists, since it has many potential applications in computer vision communication and automatic access control system. Especially, face detection is an important part of face recognition as the first step of automatic face recognition. However, face recognition is not straightforward because it has lots of variations of image appearance, such as pose variation (front, non-front), occlusion, image orientation, illuminating condition and facial expression. In computer graphics, computer vision and biometric applications, the class of objects is often the human face. Registration of facial scan data with a face model is important in face recognition, facial shape analysis, segmentation and labelling of facial parts, facial region retrieval, partial face matching, face mesh reconstruction, face texturing and relighting, face synthesis and face motion capture and animation. Face Recognition (FR) under varying lighting conditions is challenging and exacting illumination invariant features is an effective approach to solve this problem.

In addition, we propose a new appearance-base model uses the proposed Efficient Discriminant Analysis (EDCA) as a feature extractor and the Support Vector Machine (SVM) as a feature recognizer. This proposed model is evaluated and compared with another reported technique Choi *et al*. (2011) uses same database. The database used in Choi *et al*. (2011) and here is a benchmark face database across variation in subjects' poses and illumination conditions. Usually, such databases are large enough to include all possible pose orientations for each subject. For our comparison different datasets are adopted to hold a comparison with the approach described in Choi *et al*. (2011). The proposed method has the following advantages compared to other face recognition methods under illumination and pose variations, which is based on 2D images, does not require to estimate the face surface normals or the albedos and thus there is no need for any special equipment such as a 3D laser scanner (Romdhani *et al*., 2002, 2003; Romdhani and Vetter, 2005) or complicated computation. Its recognition rate is also better than or comparable to other face recognition systems based on other techniques of existing system.

LITERATURE REVIEW

Maxwell (1892) proposed a methodological improvement to raise face recognition rate by fusing the phase and magnitude of Gabor's representations of the face as a new representation, in the place of the raster image, although the Gabor representations were largely used, particularly in the algorithms based on global approaches, the Gabor phase was never exploited, followed by a face recognition algorithm, based on the principal component Analysis approach and Support Vector Machine (SVM) is used as a new classifier for

Corresponding Author: R. Rajalakshmi, Department of Computer Application, Noorul Islam University, Kumaracoil, Tamil Nadu, India

pattern recognition. The performance of the algorithm is tested on the public and largely used databases of FRGCv2 face and ORL databases. Experimental results on databases show that the combination of the magnitude with the phase of Gabor features can achieve 85% of the Recognition Rate.

Simon (1998) presented an evaluation of using various methods for face recognition. As feature extracting techniques we benefit from wavelet decomposition and Eigenface method which is based on Principal Component Analysis (PCA). After generating feature vectors, distance classifier and Support Vector Machines (SVMs) are used for classification step. We examined the classification accuracy according to increasing dimension of training set, chosen feature extractor-classifier pairs and chosen kernel function for SVM classifier. As test set ORL face database which is known as a standard face database for face recognition applications including 400 images of 40 people. At the end of the overall separation task, we obtained the classification accuracy 98.1% with Wavelet-SVM approach for 240 image training set.

Li and Chen (2012) proposed a novel illumination normalization method called Selective Illumination Enhancement Technique (SIET) wherein the dark regions are selectively illuminated by using a correction factor which is determined by an Energy function. Also, we propose a Threshold based Discrete Wavelet Transform feature extraction for enhancing the performance of the FR system. Individual stages of the FR system are examined and an attempt is made to improve each stage. A Binary Particle Swarm Optimization (BPSO)-based feature selection algorithm is used to search the feature vector space for the optimal feature subset. Experimental results show the promising performance of Threshold based DWT extraction technique on ORL and UMIST databases and SIET on illumination variant databases like Extended Yale B and Color FERET with the recognition rate 98%.

METHODOLOGY OF THE PROPOSED WORK

The proposed EDCA algorithm mainly considers dimensionality problem in feature space. Instead of taking features from complete face image pixels, the features are extracted from the frequency components only. Then the extracted frequency component features are reduced by the LDA and PCA algorithms. The proposed EDCA algorithm combines the recognition rates of both LDA and PCA techniques.

The Fig. 1 represents the flow of Face Recognition Algorithm, Which taken the Training set through this algorithm and matched against the test set. The primary concept of this study is the dimensionality reduction in facial feature space for diminishing the complexity of extracted features. The proposed algorithm combines the recognition rates of both Linear Discriminant Analysis and Principal Component Analysis algorithms. The proposed algorithm recognizes both pose and illumination invariant face images. Instead of projecting the non frontal face images to frontal pose, in our proposed algorithm we have trained the face images of different illumination conditions and different poses. The recognition performance is improved by illumination normalization. The existing high feature space dimension is alleviated by wavelet transform. Each levels of wavelet transform shrink the size of the image. So the feature point dimension is highly reduced by our proposed methodology.

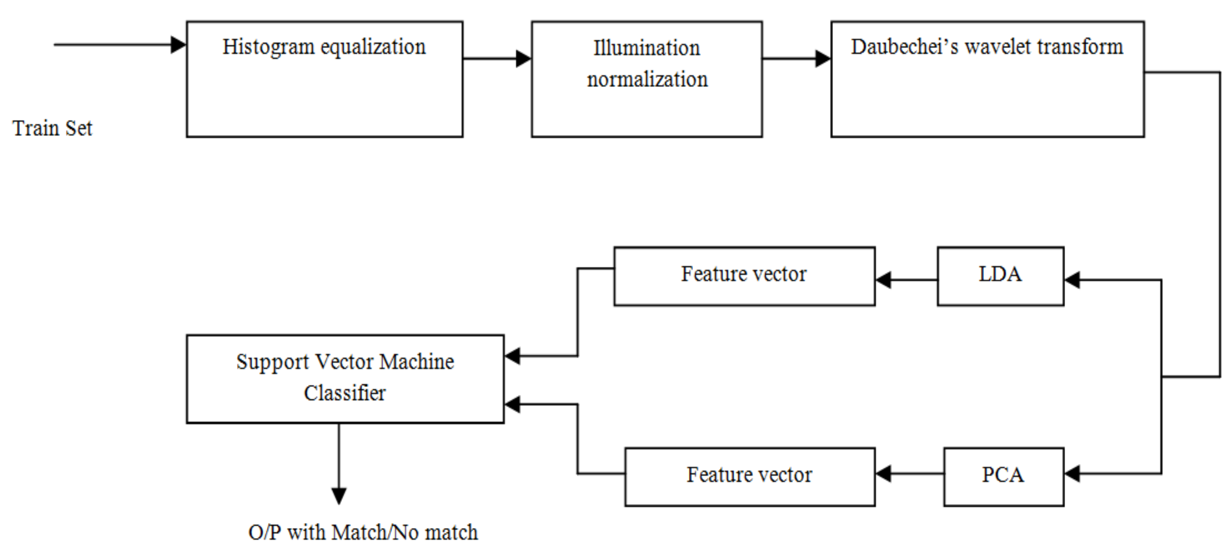

Fig. 1: Overview of the proposed work

IMPLEMENTATION OF THE WORK

The proposed face recognition work is template based linear subspace face recognition. The combination of both eigenface and fisher space will improve the face recognition performance. The high dimensionality feature space leads to computational expensive for both training and testing stages in face recognition. The proposed EDCA face recognition algorithm concentrates on the dimensionality reduction in facial feature vector. Face recognition procedure has the following steps:

- Pre-processing
- Feature extraction
- Face recognition

EDCA algorithm: The detailed explanation for the proposed EDCA algorithm is explained in this section.

Pseudo code:
Input: Test face image
Output: Recognized image from dataset

Function:
Step-1: Pre-process the image by histogram equalization
Step-2: Illumination normalization by above mentioned technique
Step-3: Apply 3 level wavelet transforms and selects the 4^{th} sub-band medium frequency coefficients
Step-4: Apply LDA and PCA feature reduction techniques
Step-5: Match the classification results of both LDA and PCA by the feature decision rules
Step-6: Recognize the image by Support Vector Machine classifier

Pre-processing: Histogram equalization is performed for Image histogram is a graph which represents grey level frequencies of image. The histogram equalization is a technique that spreads out intensity values over the entire scale to obtain uniform histogram which in turn enhances the contrast of an image. The purpose of the pre processing module is to reduce or eliminate some of the variations in face due to illumination. Normalization of the face image is used to improve the recognition performance of the system. The pre processing is crucial as the robustness of a face recognition system greatly depends on it. By using the normalization process, system robustness against scaling, posture, facial expression and illumination is increased.

Illumination normalization: The variation in illumination is an important factor which affects recognition rate of a face recognition system. This problem is solved by normalizing the illumination (Gumus *et al*., 2010). The existing illumination normalization techniques based on wavelet transform, by applying various filters, etc., (Vidya *et al*., 2012). The proposed illumination normalization is intensity normalization.

In this approach, face images are pre processed using some image processing techniques to normalize the images to appear stable under different lighting conditions. Extrinsic factors like varying illumination conditions could pose a problem in face recognition. These illumination problems can be solved using illumination normalization.
Steps to normalize the image:

- Calculate the minimum (I_{min}) and maximum (I_{max}) intensity value of the images
- Range the image value by using $I_{range} = I_{max} - I_{min}$
- Assign the minimum (N_{min}) and maximum (N_{max}) normalized intensity values for normalizing the image
- Calculate normalization range by $N_{range} = N_{max} - N_{min}$
- Scale and calculate the normalization illumination value for every pixels of the image:

$$I_{scale} = (I_{initial} - I_{min}) / I_{range}$$

$$I_{norm} = (N_{range} * I_{scale}) + N_{min}$$

To the best of our knowledge, one ideal way of solving the illumination variation problem is to normalize a face image to a standard form under uniform lighting conditions. In fact, the human visual system usually cares about the main features of a face, such as the shapes and relative positions of the main facial features and ignores illumination changes on the face while recognizing a person.

Edge detection: Edge enhancement is done to emphasize the fine details in the original image. The perceptibility of edges and small features can be improved by enlarging the amplitude of the high frequency components in the image. To accentuate details, we multiply each element in the detail coefficient matrices with a scale factor. As the decomposition level increases, the contrast and edges are enhanced further. A normalized image is obtained from the modified coefficients. This normalized reconstructed image is given to the next level for further contrast and edge enhancements using canny edge detector algorithm.

Canny edge detector algorithm: Canny edge detector is the optimal and most widely used algorithm for edge detection. Compared to other edge detection methods like Sobel, etc canny edge detector provides robust edge detection, localization and linking. It is a multi-stage algorithm. The kernels involved in the canny edge detector algorithm are discussed in detail in this section. At each stage, for computing the output pixel at a particular row, we need input pixels at rows below and above. Thus, output at the first and the last row are undefined. The same happens in the case of columns too. Thus, the size of the valid pixels in the output reduces after each step. To incorporate this, the output width and height and the output buffer's position changes after each step. This is illustrated in each stage as API argument adjustments (Manikantan *et al*., 2012). Steps in canny Edge Detection.

Smoothing: Blurring of the image to remove noise.

Finding gradients: The edges should be marked where the gradients of the image has large magnitudes.

Non-maximum suppression: Only local maxima should be marked as edges.

Double thresholding: Potential edges are determined by thresholding.

Edge tracking by hysteresis: Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge.

Feature extraction: In the current feature extraction methods, the commonly used methods are Eigen faces (Yuan *et al*., 2013; Kumar, 2009), template matching method, Fourier Transform and wavelet decomposition method, etc. Wavelet transform is adapted to decomposed images, the appropriate size of low frequency sub images has fewer characteristic features and the extracted features from human face images by wavelet decomposition are less sensitive to facial expression variations.

PCA (Principle Component Analysis): PCA algorithm is a template based face recognition technique. It is one of the most commonly used face recognition technique. The eigenface method is motivated by face reconstruction based on PCA. The main principle PCA algorithm is to reduce the high dimensionality dimension vector into intrinsically low dimension feature vector. The projection of face images into the principal component subspace achieves information compression, de correlation and dimensionality reduction to facilitate decision making (Sirovich and Kirby, 1987). The PCA algorithm generates a eigen face for a face image by joining the eigen vectors (Turk and Pentland, 1991). Principal Component Analysis (PCA) is one of the most accepted techniques for reducing the number of variables used in face recognition. In PCA, faces are represented by means of Eigen faces, a linear combination of weighted eigenvectors. These eigenvectors are attained from covariance matrix of a training image set known as basis function. In this way, we can obtain Eigen faces for each image in the training set. Eigen faces takes benefit of the resemblance among the image pixels in a dataset by means of their covariance matrix. A new face space is defined by these eigenvectors for representing the images. To fix the requisite notation, the following symbols are used (Fang *et al*., 2002).

Let training image set I_t consist of M images each having size m×n pixels. Using usual row appending technique converts each of the images into m×n dimensional column vector:

$$I_t = \{i_{t1}, i_{t2}, \ldots\ldots\ldots\ldots, i_{tm}\} \tag{1}$$

Covariance matrix C of training image set is calculated by using Eq. (2):

$$C_M = \frac{1}{M} \sum_{m=1}^{M} (i_{tm} - \bar{i})(i_{tm} - \bar{i}) \tag{2}$$

where, $\bar{i}$ is the mean vector of all images in the training set. Eigen value and eigenvectors of covariance matrix is calculated using Eq. (3):

$$C_M V = lV \tag{3}$$

$$E = (i_{tm} - \bar{i}) \times v \tag{4}$$

where m = 1, 2... M. The Eigenvectors originated, E has a face like appearance and they are termed as Eigen faces. Sometimes, they are also known as Ghost Images due to their peculiar appearance. After the face space has been built, the feature vectors are created as a linear combination of the eigenvectors of the covariance matrix. An image is projected into the face space with the aid of following Eq. (5):

$$P_m = E^T \times (i_{tm} - \bar{i}) \tag{5}$$

where P_m, m = 1, 2,..., M are the weight vectors associated with the eigenvectors in c. One can try out with the number of eigenvectors to calculate the weights, usually only a few amount offers adequate information for sufficiently representing the images in the face space. For recognition of unknown face or test image, normalize it by performing subtraction from mean vector of all images in the training set. Then using Eq. (6) project the normalized test image as shown in the following equation:

$$T = E^T.D \tag{6}$$

where, D is normalized test image. After the feature vector (weight vector) for the test image have been found out, next step is to classify it. For classification, we could basically use Euclidean distance classifier as in Eq. (7):

$$e_d = \min\|T - P_m\| \tag{7}$$

m = 1, 2,..., M. If the distance is little, we state the images are alike and hence we can decide which the most similar image in the database.

LDA (Linear Discriminate Analysis): The linear combination of fisher's discriminant analysis vectors is called fisher face. This algorithm increases the ratio of within-class variance and between-class variance. The optimal linear function derived by this LDA algorithm maps the feature values to a specific feature space (Sifuzzaman *et al*., 2009). The principle of discriminant analysis is to categorize objects into a number of classes based on a set of features that illustrate the objects are linearly separable and then Linear Discriminate model (LDA) can be used. Linearly separable recommends that the groups can be alienated by a linear combination of features that express the objects. If there are only two features (independent variables), then the separators between groups of objects will turn out to be lines. If there are three features, then the separator is a plane and if the number of features is greater than three, the separators become a hyper-plane. Linear Discriminant Analysis (LDA) is a frequently used method for the purpose of classification of data and for its dimensionality reduction. It is also known as fisher's discriminant analysis and it explores for those vectors in the fundamental space that best distinguishes among classes. The purpose of LDA is to carry out dimensionality reduction whereas probably conserving as a lot of the class discriminatory information. The objective of LDA is to increase the between-class scatter matrix measure while diminishing the within-class scatter matrix measure.

In existing system, a two-stage PCA+LDA method was proposed, where PCA is used to and make the within-class scatter generate by projecting images from the original image space to the low-dimensional space. Though, the first dimensionality reduction using PCA can also eliminate the discriminant information that is useful for classification. The most efficient technique which plans the between-class scatter into the null space of the within-class scatter and prefers the eigenvectors equivalent to the biggest Eigen values of the relocated between-class scatter.
The steps in LDA are as follows:

- Samples for class 1 and class 2
- Calculate the mean of class 1 and class 2 i.e., μ1 and μ2
- First class and second class covariance matrices i.e., C_{M1} and C_{M2}
- Calculate within-class scatter matrix by using given equation $Cw = C_{M1} + C_{M2}$
- Calculate between-class scatter matrix by using equation $C_B = (\mu 1 - \mu 2)*(\mu 1 - \mu 2)$
- Calculate the mean value of all classes
- Compute the LDA projection invCw = inv (Cw) invCw_by_C_B = invCw * C_B
- The LDA projection is then obtained as the solution of the generalized Eigen value problem Cw-1CBW = lW W = eig (Cw-1 C_B) Where W is projection vector

Wavelet transform: Wavelet is a mathematical tool. Wavelets allow complex image to be decomposed into

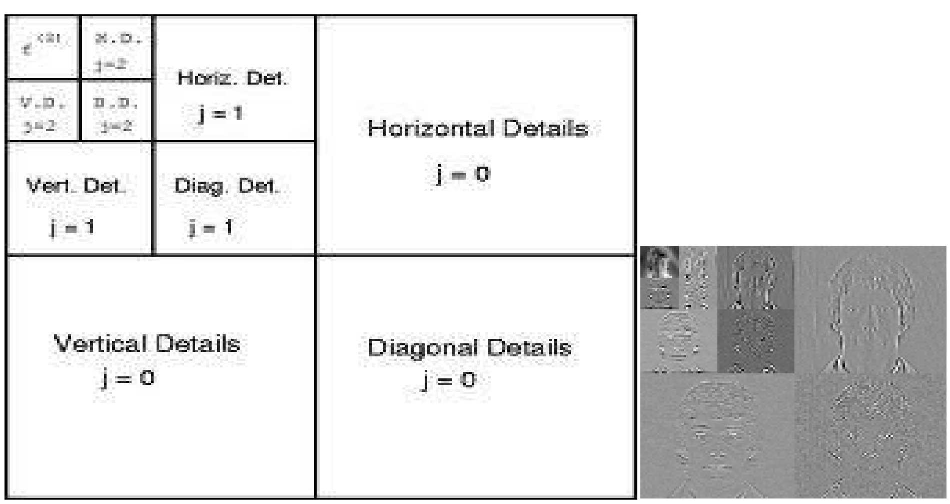

Fig. 2: Four-level wavelet transformation

elementary forms at different positions and scales and subsequently reconstructed with high precision (Du *et al*., 2002):

$$f(x) = \sum_{n=0}^{\infty} a_n f_n(x) \tag{8}$$

where f (x) is simple functions and α_n is coefficients.

The concept of wavelet transform is to represent any function f (x) into superposition of wavelets. Each superposition has a scale level. Thus the wavelet transform change the image into different resolution. It consists of a mother wavelet and a scaling function. The wavelet transform decompose the image into spatial domain and frequency domain. The purpose of wavelet transform in our approach is to reduce the dimension. So the feature dimension also reduced. In the proposed algorithm daubechei wavelet transform is applied and the fourth level frequency component features are extracted as in the following Fig. 2.

Face recognition:

Combination of PCA and LDA:

Training stage: This section discusses about the synthesis of both LDA and PCA methods. Our proposed algorithm utilizes the recognition concerts of both. i.e., during training phase the train image features are extracted by both PCA and LDA algorithms separately then the distance between the train image features and the dataset features is found by Euclidean distance. Thus the face image is recognized to the minimum distance dataset images. Instead of projecting a non-frontal pose images we proposed a trained system in which for a single face image we have trained six different poses of the same image to a single class.

Testing stage: Test face images are first pre-processed by histogram equalization algorithm then the illumination is normalized by the proposed normalization algorithm. Then features are extracted by proposed EDCA algorithm. The match results of both LDA and PCA are checked with the recognition rules mentioned in the Table 1.

Thus either a correct recognition by PCA or LDA our proposed method recognition result is correct. Similarly if any one of LDA and PCA recognition result is correct our technique produce correct recognition output. If and only if both LDA and PCA recognition results are wrong our approach result is a wrong match.

Support vector machine: Support Vector Machine as the classification tool for face authentication is a good choice because SVM do not need large amounts of training data (Dai and Zhou, 2003). The task of face authentication is accomplished using two phases: training phase and classification phase. During the training phase, the training set is constructed from input images and decision function is found. For the classification phase, testing images different from the training set are used to validate the decision function. The way the data are pre processed affects the accuracy of the system because good data will produce a more accurate decision function that can then be used for image classification.

Table 1: Match results on LDA and PCA

Recognition factors	LDA	PCA	Recognition decision
Correct recognition	T	F	Correct recognition
	F	T	
	T	T	
	F	F	
Wrong recognition	T	F	Correct recognition
	F	T	
	T	T	
	F	F	
No result	T	F	Correct rejection
	F	T	
	T	T	
	F	F	

The main idea of the SVM algorithm is that given a set of points which belong to one of the two classes, it is needed an optimal way to separate the two classes by a hyperplane as seen in the below figure. This is done by:

- Maximizing the distance of either class to the separating hyper plane.
- Minimizing the risk of misclassifying the training samples and the unseen test samples.

Depending on the way the given points are separated into the two available classes, the SVMs can be:

- Linear SVM
- Non-Linear SVM

Suppose there are two classes: C_1 is the object class and C_0 is the non-object class (non-member faces for this application). The task of one-class classification is to find the decision region R_1 for C_1 such that if the input $x \in R_1$, x is assigned to C_1; otherwise, it is rejected as C_0. Suppose that we are given N training vectors $\{x_1, x_2, \ldots, x_N\}$ from C_1. The training task is to find an evaluation function f_1 (x), which gives the confidence of the input x being in the object class. We define the region $R_1 = \{x: f_1(x) \geq T\}$ to contain those object samples x giving evaluation function values above some threshold T. To achieve a high recognition rate, training vectors should produce high evaluation function values.

SVM is a classification method that aims to separate two data sets with maximum distance between them. It is proposed by Vapnik (1995). This method separates two data sets by searching for an Optimal Separating Hyperplane (OSH) between them. Bounds between data sets and OSH are called ‘‘support vectors”.

Each point in total data set is referred as $x_i \in IR^n$, i = 1, 2, ..., N and belongs to a class yi e {_1, 1}. For linear classification we can identify two classes and the OSH separating them like:

$$w \cdot x_i + b \geq 1, \quad y_1 = 1 \tag{9}$$

$$w \cdot x_i + b \leq -1, \quad y_1 = -1 \tag{10}$$

We can generalize (9) and (10) with the form:

$$y_i \cdot [(w \cdot x_i) + b] \geq 1, \quad i = 1, \dots . l \tag{11}$$

The distance between support vectors are pre-defined as:

$$d = \frac{2}{\|w\|} \tag{12}$$

The bigger d is, a better separation between two classes can be achieved. For this reason to maximize d we need to minimize norm of w. This problem can be solved using Lagrange function:

$$L(w,b,\alpha) = \frac{\|w\|^2}{2} - \sum_{i=1}^{l} \alpha_i . \{y_i . [(w.x_i) + b] - 1\} \tag{13}$$

Here α_i represents Lagrange multipliers. Solving (13) by minimizing according to w and b, maximizing according to $\alpha_i \geq 0$ values, most suitable OSH parameter w can be obtained in (14) according to condition $\sum_{i=1}^{l} \alpha_i \cdot y_i = 0, \ \alpha_i \geq 0, i = 1, \dots \dots \dots . l$,:

$$w = \sum_{i=1}^{l} \alpha_i y_i . x_{i,} \alpha_i \geq 0, i = 1,2,3 \dots . l \tag{14}$$

Distance of any data point x to OSH is defined as:

$$d(w,b;x) = \frac{|w.x + b|}{\|w\|} \tag{15}$$

We can get a more generalized form of (15) by replacing w with its value shown in (14):

$$d(x) = \frac{(\sum_{i=1}^{l} \alpha_{i.} . y_i . x_i). x + b}{\left\| \sum_{i=1}^{l} \alpha_i . y_i . x_i \right\|} \tag{16}$$

Sign of distance calculated in (16) shows us to which class point x belongs and |d| shows distance of x to OSH. As |d| increases a better classification result can be obtained.

Linear separation of data sets cannot be achieved successfully all the time. In such cases a simple conversion of feature space is done. Point x in first data space is expanded to a feature space with higher dimension and linear separation is retried. This expansion process is realized with operator $\Phi(\cdot)$ OSH function turns into the form:

$$f(x) = w . \Phi(x) + b \tag{17}$$

By replacing w with its value in (17) we can get a more generalized form as:

$$f(x) = \sum_{i=1}^{l} \alpha_{i.} y_i . (\Phi(x_i) . \Phi(x)) + b \tag{18}$$

In a high dimensional space realization of $(\phi(\mathrm{x_i}) \cdot \phi\mathrm{x}$ multiplication is intractable. For this reason ‘‘Kernel Functions” in $K(x_i, x) = (\phi(\mathrm{x_i}) \cdot \phi(\mathrm{x}))$ form are used. In such processes there are two widely used kernel functions:

- Polynomial Kernel Function:

$$K(x_i, x) = (x_i . x + 1)^P \tag{19}$$

- RBF Kernel Function:

$$K(x, x_i) = \exp[-\gamma \|x - x_i\|^2] \tag{20}$$

EXPERIMENTAL RESULTS

We use the CMU-PIE databases collected from 2005 to 2008 including 70 subjects with different Pose and illuminated face images and taken for 213 poses. One has 5 different kinds of pose variation and under varying light condition to test. The training set should be chosen representatively and attempt to include different pose variation. The experiments were conducted in four dataset parts as presented in Table 2.

The first dataset part, 65×5 face images experiment was to chosen from for training and the 59×5 dataset for testing per person, hence, each training set and testing set has 575 face images as db1. The second dataset part, 55×5 face images and the 45×5 were taken for training set and taken as db2 and so on.

Table 2: Datasets

Dataset	Training set	Testing set	Total size
Dataset 1 (db1)	65×5	50×5	575
Dataset 2 (db2)	55×5	45×5	500
Dataset 3 (db3)	45×5	30×5	375
Dataset 4 (db4)	40×5	20×5	300

Table 3: Comparison of EDCA algorithm with LDA and PCA based on recognition rate

Datasets	Feature extraction technique	Total positive samples (tp/test set)	Accuracy (%)
db1	LDA	224/250	89.70
	PCA	238/250	95.50
	EDCA	247/250	99.00
db2	LDA	199/225	88.60
	PCA	211/225	93.80
	EDCA	222/225	98.80
db3	LDA	128/150	85.40
	PCA	140/150	93.30
	EDCA	147/150	98.30
db4	LDA	85/100	84.78
	PCA	92/100	91.50
	EDCA	96/100	97.50

Table 4: Recognition rate (%) for several methods and experiments on the CMU-PIE databases

Techniques	Recognition rate (%)
G abor + PCA + SVM (Wang *et al*., 2012)	93.10
Gabor + KPCA + SVM (Wang *et al*., 2012)	94.50
Wavelet + SVM (Manikantan *et al*., 2012)	96.78
EDCA + SVM (Our proposed method)	99.00

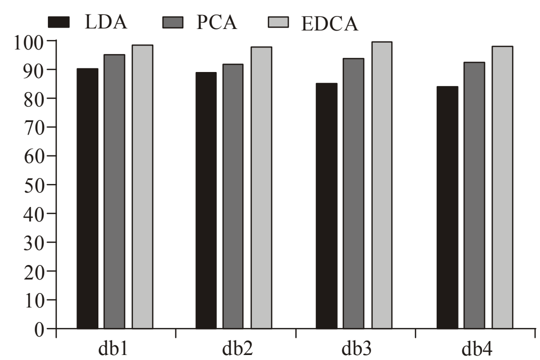

Fig. 3: Accuracy comparison between LDA, PCA and EDCA methods

The following Table 3 shows the recognition rate results of the proposed method for Support Vector Machine classifier (SVM) were performed using MATLAB R2012b running on Intel (R) Core (TM) i7 CPU, 2.80 Ghz. The classification results obtained by three different Feature extractors such as LDA, PCA EDCA are different with better recognition rates with proposed system.

This study proposed a novel approach to reduce the degradation of the face recognition rate caused by illumination and pose variations. We constructed a feature space for each pose using an appearance based face recognition method and compensate for illumination variation. We experimented under different datasets for both profile and illuminated invariant images. The experimental results shows that our proposed algorithm outperforms the existing LDA and PCA face recognition methods. The Recognition accuracy of the largest set achieves almost 99%. Moreover, the EDCA features make the face recognition system more reliable for the entire pose.

Table 4 summarizes a comparative analysis on the CMU-PIE database. For comparative purpose, we report classifiers performance at Recognition Rate. The performance is better than the references (Wang *et al*., 2012; Manikantan *et al*., 2012) the experimental results demonstrate the effectiveness of the proposed algorithm in this study. Manikantan *et al*. (2012) extracted the facial features using Wavelet which reduces the size of the feature vectors and classified by SVM, the recognition rate is 93.10%. And in reference (Wang *et al*., 2012) were used for the Gabor + PCA + SVM and Gabor + KPCA + SVM methods respectively, obtained 93.10 and 94.5% recognition rates. The proposed method based on SVM kernel function achieved a recognition rate of 99.0%.

Figure 3 shows that the comparison of accuracy in detecting faces on various pose estimation between the LDA, PCA and EDCA methods. To evaluate the efficiency of the proposed method, different databases, db1, db2, db3 and db4 are taken into the simulation. It is obviously proved that the EDCA method has achieved higher accuracy than the other models in all the databases.

CONCLUSION

In this study, a scheme of face recognition under pose and illumination variation using color images was proposed. For the purpose of obtaining the discriminative, low dimensional facial representation for the classifier, wavelet decomposition and EDCA were adopted subsequently and compared with other feature extractors such as LDA and PCA. For the purpose of resolving the problems of face recognition that face sample are of limited number and linear non-separable, SVM were applied as the classifiers. Experiments on the indoors photographs with different orientation and lighting conditions demonstrate the efficiency of this methodology.

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