Canadian Journal of Pure and Applied Sciences
Vol. 9, No. 1, pp. 3299-3306, February 2015
Online ISSN: 1920-3853; Print ISSN: 1715-9997
Available online at www.cjpas.net

PERFORMANCE ANALYSIS OF PCA BASED TECHNIQUES FOR FACE AUTHENTICATION

*Krishna Dharavath, Fazal Ahmed Talukdar, Rabul Hussain Laskar
Speech and Image Processing Research Lab.,
Department of Electronics and Communication Engineering
National Institute of Technology Silchar, India

ABSTRACT

Accurate authentication is of major concern in real time applications such as an automatic authentication system in any organization. Even though there are many approaches for face recognition in the literature, no algorithm was analyzed with respect to authentication applications. In this paper, we have discussed PCA based approaches Kernel-PCA, Gabor PCA, Phase congruency PCA, Phase congruency-Kernel-PCA, Gabor-Kernel-PCA including classical PCA with Mahalanobis distance measure. The performances of these methods were analyzed with respect to important performance metrics, ROR, EER, and MER. We have also compared the percentage verification rate by varying the percentage FAR. Since we believe that the authentication or the verification rate is highly dependent on the size of available database, i.e., the number of images per subject, we have varied the size of training and testing datasets and accordingly we studied the performance of all the approaches mentioned ahead. All the observed results and graphical analysis of our results were provided in this paper. In our analysis, it was observed that Gabor-Kernel-PCA and Gabor-PCA approaches shows superior performance in recognition and verification rates with varying size of datasets. Hence these approaches are suitable for accurate authentication applications.

Keywords: Gabor PCA, PCA, KPCA, face recognition, comparative study, phase congruence, authentication.

INTRODUCTION

Face recognition has been an active area of research with numerous applications since 1970's. These applications may fall into two categories: Authentication and Identification. Authentication based applications involves one-to-one match of the face images in which a subject is supposed to be registered well in advance with database and then seek for authentication to acquire required services. Identification base applications involve identifying a single person among a group of people (Krishna *et al.*, 2013). In this kind of applications the subjects face image (probe image) will be compared against all face images (also called one-to-many match) which are available in database. However we are interested in accurate authentication because of its numerous applications.

This experiment was carried out since we wanted to implement the facial authentication based campus management system in our organization: National Institute of Technology, Silchar, India. The main aim of the project was to examine the impact of number of training images on face authentication system and to evaluate classical principal component analysis (PCA) algorithm (Mathew and Alex, 1991a; Mathew and Alex, 1991b; Moon and Philips, 2001) and other approaches based on classical PCA. As part of this project, we assess the performance of these approaches for accurate authentication purposes. We have analyzed classical Principal Component Analysis (PCA) (Mathew and Alex, 1991b), Kernel-PCA (KPCA) (Yang, 2000; Li-Hong *et al.*, 2007; Xudong and Kin-man, 2005), Phase-Congruency-PCA (PCPCA) (Tang *et al.*, 2012), Phase-Congruency-KPCA (PCKPCA) (Reddy and Reddy, 2012), Gabor-PCA (GPCA) (Wei-Lu *et al.*, 2009) and Gabor-KPCA (GKPCA) (Xudong and Kin-man, 2006; Struc and Pavesic, 2010; Struc and Pavesic, 2009) approaches due to their superior recognition rates reported in recent research papers. Even though there exist such assessment of various algorithms in the literature, research community had not attempted to compare different versions of a particular algorithm especially the classical and old algorithm PCA by varying number of images in the training as well as probe sets and percentage False Acceptance Rate (FAR).

*Corresponding author e-mail: d.krishna.2014@ieee.org

In this paper we discuss the comparative analysis of above mentioned methods of face recognition especially with an orientation towards accurate authentication. Here we study the effect of number of images in training as well as probe images on verification rate with different FARs. We have also computed other important metrics: Equal Error Rate (EER) and Minimal Half Total Error Rate (MER).

The paper is organized as follows. Section 2 briefly describes the algorithms used in our experiment as well as the performance metrics used for their assessment. Discussion about database and experimental setup is presented in Section 3. Finally, analyses the results and concludes the paper.

2. Feature Extraction Techniques

Principal Component Analysis (PCA)

A well-known classical Eigen face based principle component analysis (PCA) is used to reduce the dimension of feature vector. In the training phase, we extract feature vectors w_j from each face image in the training data set. We then use PCA algorithm to transform the high dimensional feature space into low dimensional feature space, which transforms feature vector w_j into w_k, where $w_k < w_j$. Hence PCA is used as a dimensionality reduction technique. Later in the recognition (or testing) phase, given a single face image of a person, we should compute the Eigen vectors w_t from it and then compute the similarities between w_t and w_k. The similarity between feature vectors w_t and w_k can be computed using Euclidean distance. If $k = t,$ it means that we have correctly identified the person t, otherwise if $k \neq t,$ it means that we have misclassified the person t. A schematic representation of PCA based face recognition method is shown in Figure 1. Eigen face based face recognition scheme based on PCA was published by Turk and Pentland (1999). Eigen face is obtained by using PCA technique and represents a face space. It contains certain valid features for identifying/recognizing whether a probe image belongs the user who climes to be.

Let the images in training dataset be $I_1, I_2 \ldots I_M$. Then the average face is defined as in equation (1).

$$A = \frac{1}{M}\sum_{n=1}^{M} I_n \quad \ldots (1)$$

The difference between the average face and training image is

$$D_i = I_i - A \quad \ldots (2)$$

The covariance matrix C can be obtained using eqn. 3.

$$C = \frac{1}{M}\sum_{n=1}^{M} A_n A_n^T = XX^T \quad \ldots (3)$$

Where the matrix X= $[D_1, D_2, D_3 \ldots D_M]$, here the size of C is $N^2 \times N^2$ if the size of each face image is N×N.

Kernel PCA

KPCA is just an extension to traditional PCA technique. Since PCA works directly on image and tries to find the match between probe and trained images with a suitable distance measure, it is not robust enough to handle nonlinear variations in image. To handle with this problem, a covariance matrix is replaced by kernel-matrix when extracting features. Unlike in PCA, Kernel PCA is used to find 'm' Eigen values by operating on $m \times m$ kernel matrix. Technique can be summarized as to apply non-linear mapping to the input and then solve a linear PCA in the resulting feature space.

Gabor Features

Feature extraction is an important step in face recognition system. Extracting good and valid features from a face image is a major task in facial recognition system. In order to accomplish this task successfully we use Gabor filters because of the fact that frequency and orientations of this filter are very similar to those of human visual system. Also spatial and structural characteristics at multiple directions can be extracted from the face images by using Gabor filters because of their efficiency in spatial locality and orientation selectivity. They also have certain tolerance on the variation in rotation, displacement, scaling, deformation and illumination. Features constructed from the response of Gabor filters (also known as Gabor features) (Bui *et al*., 2011; Yang and Sun, 2010) have been successful in image processing and computer vision applications. They are the top performing features among many other essentially in face recognition technology. In general, the local pieces of information is extracted by using Gabor features and then combined to recognize an object. One of the main features of Gabor filters is that the cells in human visual cortex can be selectively tuned to orientation and spatial frequency such that the response of the simple cell could be approximated using 2D Gabor filter.

Gabor filters (or Gabor wavelets) represent a band pass filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Thus a 2D Gabor filter constitutes a complex sinusoidal plane of particular frequency and orientation modulated by a Gaussian envelop. Mathematically a 2D Gabor filter is represented as in Equation (4).

$$\varsigma_{\theta_k, f_i, \sigma_x, \sigma_y}(x, y) = \exp\left(-\left[\frac{x_{\theta_k}^2}{\sigma_x^2} + \frac{y_{\theta_k}^2}{\sigma_y^2}\right]\right)\cos\left(2\pi f_i \theta_k + \varphi\right) \quad \ldots (4)$$

Where

$$x_{\theta_k} = x\cos\theta_k - y\sin\theta_k \quad \text{and}$$

$$y_{\theta_k} = y\cos\theta_k - x\sin\theta_k$$

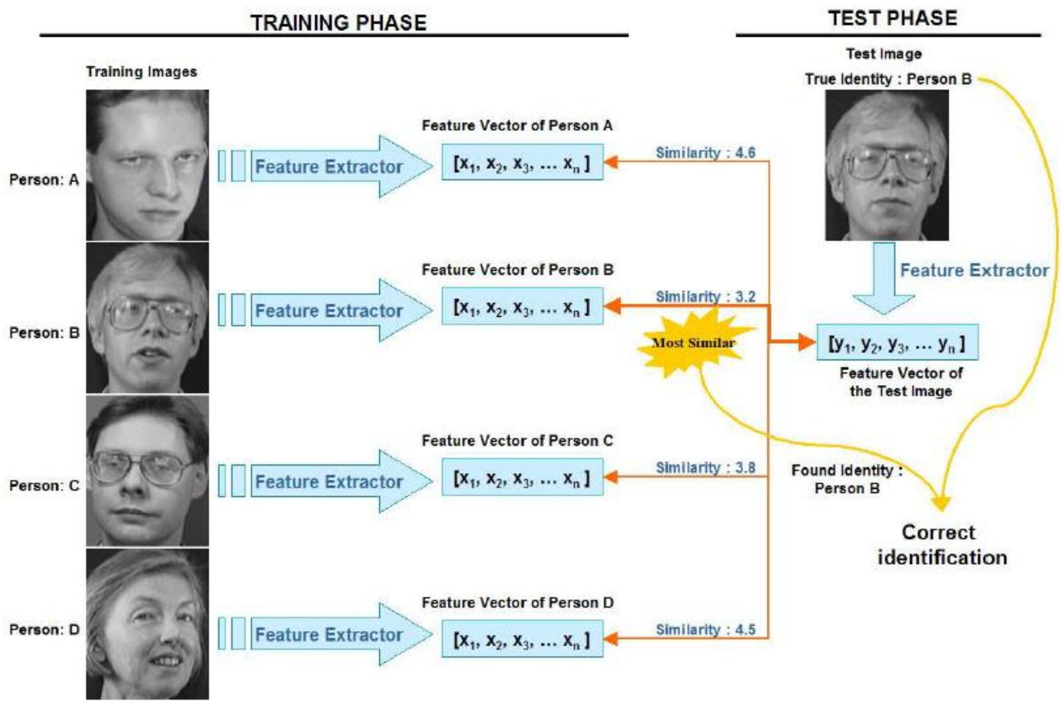


Fig. 1. Pictorial illustration of PCA based face recognition method.

f_i is the central frequency of the sinusoidal plane wave at an angle θ_k with x-axis. σ_x and σ_y represents standard deviations of the Gaussian envelope along the axis x and y. We set the phase $\varphi = \frac{\pi}{2}$ and compute each orientation as $\theta_k = \frac{k\pi}{n}$ where $k = 1, 2, 3 ... n$. Equation (4) is called mother wavelet which optimally captures both local orientation and frequency information from a digital image. Each face image is filtered with above Gabor filter at various frequencies and orientations. If $I(x, y)$ represent a face image having a size $[m \times n]$ then its feature extraction can be expressed as given in Equation (5).

$$O_{\theta_k, f_i, \sigma_x, \sigma_y}(x, y) = I(x, y) * \varsigma_{\theta_k, f_i, \sigma_x, \sigma_y}(x, y) \quad \ldots (5)$$

Where $O_{\theta_k, f_i, \sigma_x, \sigma_y}(x, y)$ is the Gabor representation of image $I(x, y)$ and $\varsigma_{\theta_k, f_i, \sigma_x, \sigma_y}(x, y)$ is the 2D Gabor filter. Alternatively equation 5 can be written as given in equation (6)

$$O_{\theta_k, f_i, \sigma_x, \sigma_y}(\mathrm{I}) = FFT^{-1}\left[FFT(I) \bullet FFT(\varsigma)\right] \ldots (6)$$

Here $O_{\theta_k, f_i, \sigma_x, \sigma_y}(\mathrm{I})$ represents the feature vector of input image. For example, a face image and its corresponding eight orientations at five different scales are illustrated in figure 2.

Phase congruence features

The experiments of Oppenheim and Lim (1981) demonstrated the importance of phase in the perception of visual features. Also it is evident from physiological research that human visual system is more sensitive to points with higher order phase information in an image. The same concept is utilized as phase congruency model (PCM) to define new image features. PCM is an important model of visual processing system and is based on frequency components. In this model, the visual data/image information is processed using the phase as well as amplitude of the each frequency component which in turn depends on Fourier transform (Kovesi, 2000; Schenk and Brady, 2003).

In order to understand the concept of phase congruence model, we restrict our discussion to one dimensional signal $f(x)$. The image $I(x, y) = f(x)$, where x and y are in some interval. It represents a horizontal pattern through the image $I(x, y)$. For instance, a simple step edge image with a white panel on the right hand side and black panel on the left can represent such a function.

Let us define the one-dimensional function in terms of its Fourier frequency components as

$$f(x) = 2\sum_{k>0} A_k \cos(k\omega x + \phi_k) \quad \ldots (7)$$

Where A_k and ϕ_k are the amplitude and phase of the k^{th} frequency component respectively. The term k is related to the size of the image window and is assumed as 1 for the simplified analysis.

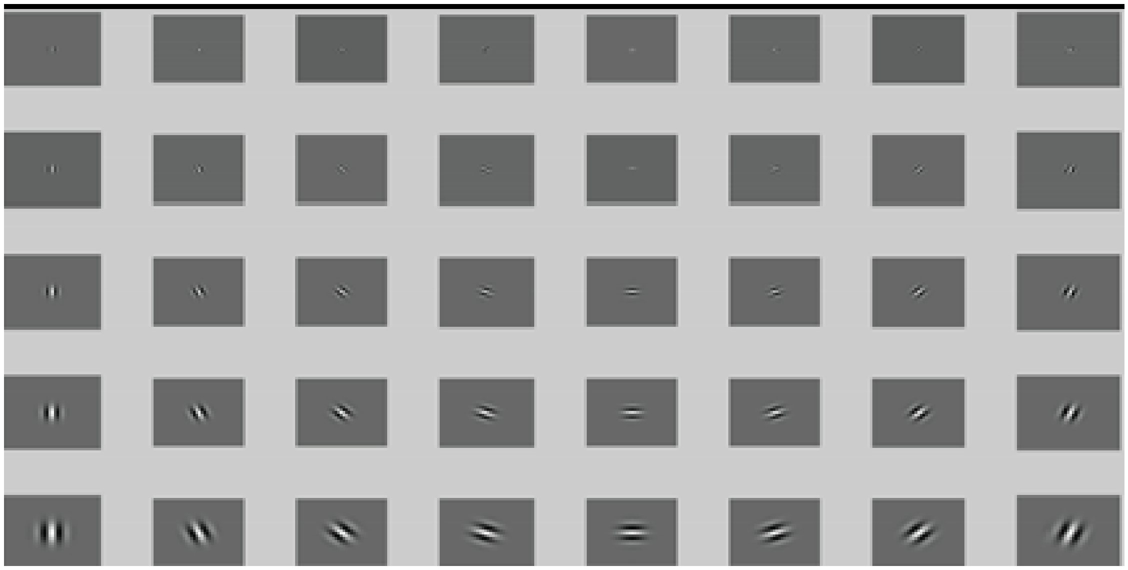
Assuming the Hilbert transform of $f(x)$ is $h(x)$. Then, by definition

$$h(x) = -2\sum_{k>0} A_k \sin\left(k\omega x + \phi_k\right) \quad \ldots (8)$$

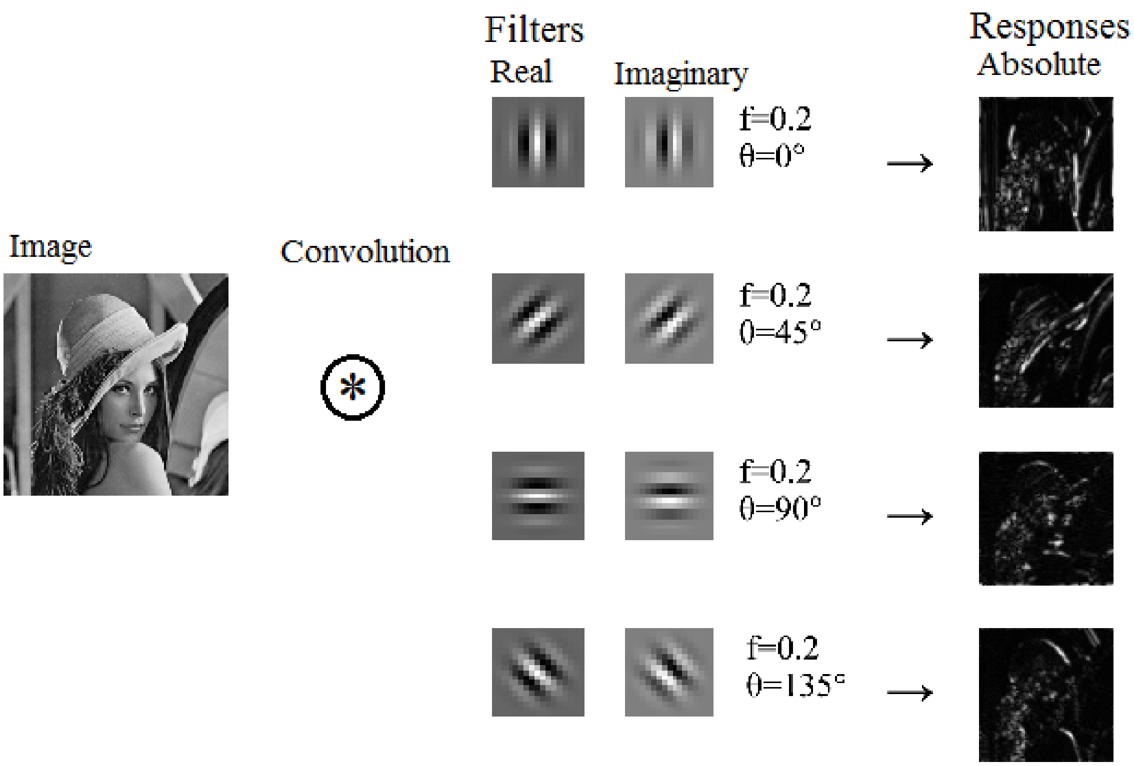
From equations (7) and (8), an energy vector can be defined as

$$e(x) = \frac{1}{2}\left[f(x), -h(x)\right] \quad \ldots (9)$$

The local energy function, E(x), is defined as the norm of



(a)



(b)

Fig. 2(a). Gabor features with five scales and eight orientations and (b) Gabor features obtained for input classical Lena image.

the energy vector. Therefore

$$E(x)=\sqrt{\left[\sum_{k>0}A_k\cos\left(k\omega x+\phi_k\right)\right]^2+\left[\sum_{k>0}A_k\sin\left(k\omega x+\phi_k\right)\right]^2}\quad \text{... (10)}$$

Alternately,

$$E(x)=\sum_{k>0}A_k\cos\left(k\omega x+\phi_k+\theta_e\right)\quad \text{... (11)}$$

where $\theta_e=\tan^{-1}\left(\dfrac{\sum_{k>0}A_k\sin\left(k\omega x+\phi_k\right)}{\sum_{k>0}A_k\cos\left(k\omega x+\phi_k\right)}\right)$ gives angle at which the phase congruency occurs, and can be used to define the feature type.

Performance Metrics used in our analysis

We use rank one recognition rate (ROR) to analyze the performance of each algorithm and are given in table 1 as well as using histogram plot. We have also used Verification rate as one of the metrics to assess the performance of each algorithm for accurate authentication. Similarly, EER and MER are the two other metrics that were used to compare the performance of mentioned algorithms using histogram plots. Also, the performance of each method with respect to verification rate is compared using linear curves. These curves are plotted using number of images in the dataset Vs verification rate. Apart from these metrics, we have also plotted ROC, CMS and DET curves as well.

Table 1. Recognition rate at 1% FAR.

Technique	Recognition Rate	Dataset
GPCA	100%	D3, D4
GKPCA	100%	D3, D4
PCPCA	95%	D4
PCKPCA	95%	D4
PCA	94.17%	D4
KPCA	85.83%	D4

3. DATABASE AND EXPERIMENTAL SETUP

We have used AT&Ts ORL face database (Samaria and Harter, 1994) which is a freely available database for research purposes. This database has a total of 400 images of 40 subjects with 10 images per subject. These include pose, expression and illumination variations as well as occlusions for some of the subjects. Since our aim was to test the impact of training data set on face recognition rate with different approaches, we have created four duplicate datasets D1 to D4 by varying the number of training and probe images in each. Particularly, D1 has 1 training and 9 probe images, D2 has 3 training and 7 probe images, D3 has 5 training and 5 probe images and D4 has 7 training and 3 probe images.

All above mentioned face recognition techniques were tested on all these four datasets. Accordingly we obtained ROC, CMS and DET curves for all the cases. Hence a total of (6x4x3) 72 curves we have obtained. But, due to page constraints, we could not include all curves in this paper. However, the necessary plots are included in this paper. These curves are important by means of recognition and authentication rates to illustrate the performance of face recognition techniques.

RESULTS AND DISCUSSION

As we are interested in studying the characteristic of different FR approaches with respect to size of database and percentage FAR, results were tabulated accordingly as given in tables 1-3. While, table 1, shows the impact of database size on verification rate with constant FAR equal to 1%. As seen from table 1, highest verification rate is obtained with dataset D4 for all approaches. Highest verification rate of all approaches is listed in table 4. GPCA and Gabor KPCA approaches achieve superior performance (equal to 100%) with data set D3 and D4. Table 2 presents the comparison of approaches with 0.1% FAR for different datasets. Little reduction in false acceptance rate did not affect verification rate much. As seen in table 5, highest verification rate (100%) in this case, was achieved for GPCA and GKPCA approaches with dataset D4. However, further reduction in percentage FAR has affected verification rate greatly and shows a poor performance for all the approaches. Table 3 lists verification rate of mentioned approaches with 0.01% (i.e. 1 false subject is accepted out of 100 correct subjects). In this case, the highest verification rate was achieved for PCA (64.5%) and KPCA (52%) with data set D3 only. In all other cases, verification rate is being very poor. From these results, it is clear that, to achieve better verification rates, a minimum of 5 different types of images per subject are required.

Table 2. Recognition rate at 0.1% FAR.

Algorithm	Recognition Rate	Dataset
GPCA	100%	D3
GKPCA	100%	D3
PCPCA	87.5%	D4
PCA	84.17%	D4
PCKPCA	78.75%	D4
KPCA	75.83%	D4

Table 3. Recognition rate at 0.01% FAR.

Algorithm	Recognition Rate (%)	Dataset
PCA	64.5%	D3
KPCA	52.0%	D3
GPCA	2.5%	D3
GKPCA	2.5%	D3
PCPCA	1.25%	D4
PCKPCA	1.25%	D4

Figure 3 shows rank-1 recognition rate of all approaches on four datasets. It is observed that, for dataset D1, GPCA approach achieves highest recognition rate. But GKPCA achieves highest recognition rate for remaining datasets. KPCA method achieves low recognition rate among all methods. Figure 4 shows a bar graph of equal error rate versus dataset. Among all methods, KPCA shows poor performance and GPCA and GKPCA shows very good performance.

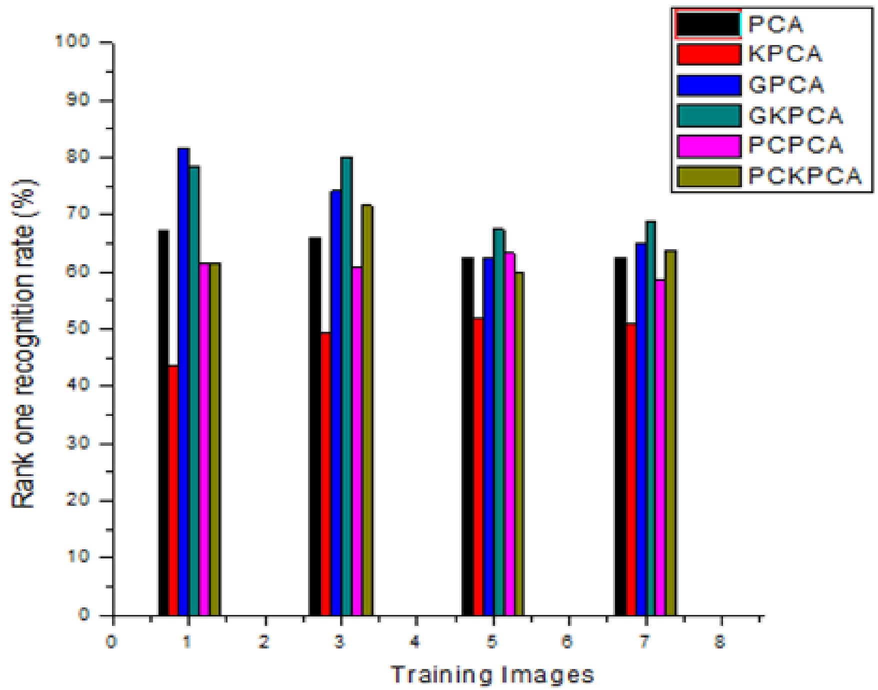


Fig. 3. Percentage rank-one recognition rate.

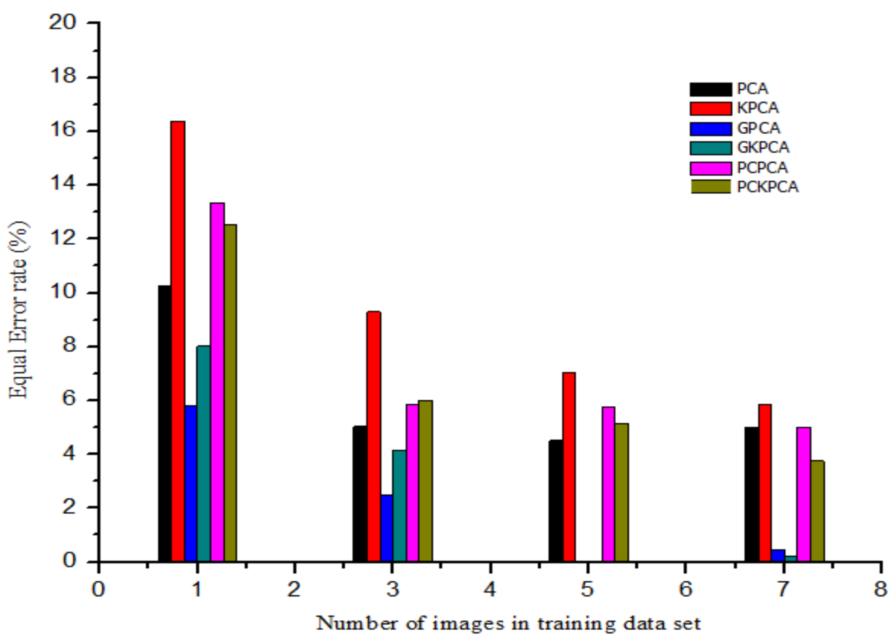


Fig. 4. Percentage equal error rate.

Table 4. Verification rate at 1% FAR.

Data set	Face recognition Technique					
	PCA	KPCA	PCPCA	PCKPCA	GPCA	GKPCA
D1	70.83	41.39	64.17	64.17	83.33	80.83
D2	86.79	69.29	85.83	86.67	97.50	95
D3	87.50	77.50	88.33	85	100	100
D4	94.17	85.83	95	95	100	100

Table 5. Verification rate at 0.1% FAR.

Data set	Face recognition Approach					
	PCA	KPCA	PCPCA	PCKPCA	GPCA	GKPCA
D1	50.56	18.61	43.33	46.67	66.67	60.83
D2	66.79	51.43	75	78.3	92.50	92.50
D3	78.00	62.50	72.5	75.83	100	100
D4	84.17	75.83	87.5	78.75	97.5	98

Table 6. Verification rate at 0.01% FAR.

Data set	Face recognition Approach					
	PCA	KPCA	PCPCA	PCKPCA	GPCA	GKPCA
D1	12.22	4.72	0.83	0.83	0.83	0.83
D2	45	27.14	0.83	0.83	0.83	0.83
D3	64.5	52	0.83	0.83	2.50	2.50
D4	0.83	0.83	1.25	1.25	2.50	1.25

CONCLUSION

We have analyzed performance of different methods of PCA based face recognition with respect to percentage of authentication rate, rank one recognition rate and equal error rate. Certain methods achieve good rate with different datasets. However Gabor-PCA and Gabor-KPCA methods outperforms among all the methods for all datasets. Hence both these methods can be used for authentication applications where in only few images of a subject will be available in database. As a continuation to this work, we will implement accurate authentication system based on Gabor-PCA method.

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Received: Sept 12, 2014: Accepted: Nov 1, 2014