

A Novel Approach to Face Recognition with Pose and Illumination Variation Using Support Vector Machine as Classifier

R.Rajalakshmi, M.K.Jeyakumar

Abstract-Human face recognition has attracted significant consideration as one of the most effective applications of image analysis and understanding. Face recognition is one among the diverse techniques used to identify an individual. Pose and Illumination are the two major challenges, among the several factors that influence face recognition. The objective of this paper is to implement an automated machine supported Face recognition System that recognizes well the identity of a person in the images that were not used in a training phase That is an initialization and training by representative sample of images precede an evaluation phase. Pose and illumination variations severely affect the performance of face recognition. Feature Extraction and Dimensionality Reduction is applied using Principal Component Analysis(PCA) and Linear Discriminant Analysis(LDA). During Recognition phase different classifiers such as ANFIS(Adaptive Neuro Fuzzy Inference Engine), NN(Neural Network), SVM (Support Vector Machine), K-NN(K-Nearest Neighbourhood) algorithms are used to the analyze and evaluate the Recognition Rate.

Keywords : Eigen Vector, Recognition Rate, Training Sets, Testing Set

I.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 detection 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 labeling of facial parts, facial region retrieval, partial face matching, face mesh reconstruction, face texturing and relighting, face synthesis, and face motion capture and animation. The recognition performance thoroughly degrades with pose and lighting variations, though the recognition performance has been improved substantially under frontal pose and optimal lighting conditions [1].

Manuscript published on 30 September 2013.

*Correspondence Author(s)

R.Rajalakshmi, Research Scholar, Department of Computer Application
Noorul Islam University, Kumaracoil, TamilNadu, India

Dr.M.K.Jeyakumar, Professor, Department of Computer Application,
Noorul Islam University, Kumracoil, Tamil Nadu, India.

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an [open access](http://creativecommons.org/licenses/by-nc-nd/4.0/) article under the CC-BY-NC-ND license <http://creativecommons.org/licenses/by-nc-nd/4.0/>

Sources of errors in automated face recognition algorithms are usually ascribed to the well considered dissimilarities in pose, illumination, and expression, collectively known as PIE. Extra factors such as image quality (e.g., resolution, compression, blur), time lapse and occlusion also add to face recognition errors [2]. First, it requires matching facial identities despite changes in lighting and viewpoint and thus requires processing identity rather than simple image matching [3]. Furthermore, global features are susceptible to variations in facial expressions, poses and occlusions. Another inherent difficulty of all holistic approaches is their belief to the training databases since information about the face discrimination is in discriminated by machine learning from the face samples. A representative training database is necessary, which, however, is not available in many applications [4].

Principal Component Analysis (PCA)-based face recognition method was proposed in (Turk), 1991 and became very popular. Face recognition is performed by comparing these feature vectors using different distance measures. Using the PCA-based face recognition method we calculate the eigenvectors and eigenvalues of the covariance matrix of the training data. If this matrix is large, calculation of eigenvectors becomes complicated. In order to solve this problem we can use the decomposition of the covariance matrix [4]. Face-based approach attempts to capture and define the face as a whole. The face is treated as a two-dimensional pattern of intensity variation. Under this approach, face is matched through identifying its underlying statistical regularities. Principal Component Analysis (PCA) has been proven to be an effective face-based approach. However, common PCA-based methods suffer from two limitations, namely, poor Discriminatory power and large Computational Load. It is well known that PCA gives a very good representation of the faces[5]. Eigen face [7] method is the most popular linear techniques for face recognition. Eigen face applies Principal Component Analysis (PCA) to project the data points along the directions of maximal variances. Eigen face method is unsupervised, ability to learn and later recognize new faces. There is another popular technique, Linear Discriminant Analysis (LDA) which is a supervised algorithm and this approach projects the face images along the directions optimal for discrimination. But the eigenface is better because it provides for the ability to learn and later recognize new faces in an unsupervised manner.

KNN classifier is best suited for classifying persons based on their images due to its lesser execution time and better accuracy than other commonly used methods which include Hidden Markov Model and kernel method.



Although methods like SVM and Adaboost Algorithm are proved to be more accurate than KNN classifier, K-NN classifier has a faster execution time and is dominant than SVM in sparse datasets [8]. While research towards automatic face recognition began in the late 1960's, progress has been slow. Recently there has been renewed interest in the problem due in part to its numerous security applications ranging from identification of suspects in police databases to identity verification at automatic teller machines [1]. Though automatic face recognition systems exhibit higher FAR (False Acceptance Rate), the probability that a sample falsely matches the presented face identification record or feature sets, and FRR (False Rejection Rate), the probability that a sample of the right person is falsely rejected, than other successful biometric systems like fingerprint or iris recognition, it is attractive because of its wide-spread acceptability, universality and easier acquisition. Recognition is a step by step process and quite time-consuming in case it has to deal with a large problem domain. In applications like surveillance system, airport and banking security, database search time is significantly huge. Thus, development of real-time application is a challenging task. Neural networks have emerged as a field of study within AI and engineering via the collaborative efforts of engineers, physicists, mathematicians, computer scientists, and neuroscientists. Although the strands of research are many, there is a basic underlying focus on pattern recognition and pattern generation, embedded within an overall focus on network architectures [10]. Artificial Neural Networks (ANN) and Linear Discriminant Analysis (LDA) are used to increase the generalization accuracy in face recognition. ANN is a powerful technique, which can predict not only for seen data, but also for unseen data[9].

Although many face recognition techniques has been proposed, there exists still the pose and illumination variation difficulties. In this paper we developed a novel approach for face recognition using different classifiers to achieve the better recognition rate and to overcome the above mentioned problems. The outline of this paper is as follows. In Section II overview of the proposed system is presented . Section III presents an Methodology of the Proposed work. Section IV presents the Result and Discussion which illustrates the Experimental results and evaluates the performance of the proposed system. Then the Section V gives the Conclusion, Finally the paper ends with the References.

II. OVERVIEW OF THE PROPOSED SYSTEM

In our proposed system there are two phases, enrollment phase and Recognition phase in turn consist of Preprocessing, Feature Extraction and Classification as depicted in Fig 1. It consists of several modules which are image acquisition, Training, Testing and Recognition/verification.

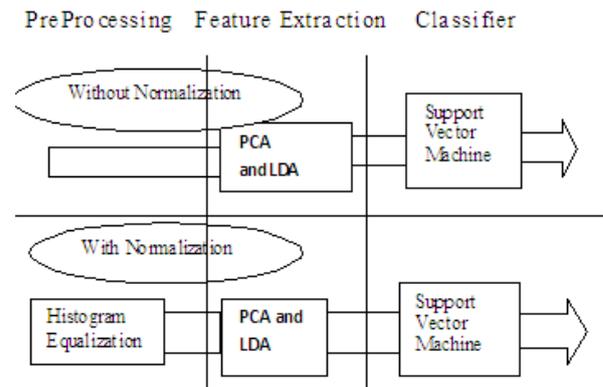


Fig.1 Method and Classifiers in different Phases of the system

III. FACE RECOGNITION SYSTEM WITH POSE AND ILLUMINATION VARIATION

A. Normalization Phase

During the Enrollment phase, the face image is taken using web camera and stored into database. CMU-PIE database Next different subset of face are features data are extracted and used for training. During training, the face image is preprocessed using geometric and [10] photometric Normalization. The features are extracted by feature extraction techniques. The feature data is stored together with the user identity in a database. Preprocessing is applied for both training and testing dataset. (i) In preprocessing phase Histogram equalization is applied and edges are detected using Sobel operator,(ii) Face Features are extracted using LDA(Linear Discriminant Analysis) (Principles is Component Analysis) at feature extraction phase, and (iii) Classification phase done using ANfis Adaptive Neuro Fuzzy Inference , NN Neural network .SVM (Support Vector Machine), system, K-NN (K-Nearest Neighborhood). Using different dataset as listed below the Accuracy ,Precision, Recall and F-measure are evaluated in terms of Recognition rate.

B. Feature Extraction Phase

Feature extraction (or dimensionality reduction) is an important research topic in computer vision and pattern recognition fields, since (i) the curse of high dimensionality is usually a major cause of limitations of many practical technologies; (ii) the large quantities of features may even degrade the performances of the classifiers when the size of the training set is small compared to the number of features [1]. In the past several decades, many feature extraction methods have been proposed, in which the most well-known ones are PCA and LDA. Fisherface (LDA) method outperforms the eigenface [3] method in case of large variation of lighting condition, different face poses, and different facial expression. Linear Discriminant Analysis (LDA) has been one of the popular techniques employed in the face recognition.

C. LDA(Linear Discriminant Analysis)

The objective of LDA is to find the subspace that best discriminates different face classes by maximizing between class scatter, while minimizing the within-class scatter[13].



The eigenvectors chosen by LDA provide the best separation among the class distributions, while PCA selects eigenvectors which provide best representation of the overall sample distribution. The eigenvectors for LDA can be obtained by computing the eigenvectors of $S_w^{-1}S_b$. Here, S_b and S_w are the between-class and within-class scatter matrices of training Samples and are defined in equation (1) and (2) as:

$$S_w = \sum_{i=1}^c \sum_{x_k \in C_i} (x_k - m_i)(x_k - m_i)^T, \quad (1)$$

$$S_b = \sum_{i=1}^c n_i (m_i - m)(m_i - m)^T, \quad (2)$$

Where m_i is the mean face for class, n_i is the number of training samples in i^{th} class. LDA subspace is spanned by a set of vectors W , which maximizes the criterion, J , defined in Equation (3) as:

$$J = \frac{tr(S_b)}{tr(S_w)} \quad (3)$$

W can be constructed by the eigenvectors of $S_w^{-1}S_b$. In most of the image processing applications, the number of training samples is usually less than the dimension of the sample space.

D. Principal Component Analysis

PCA, which is a Maximum Expression Feature (MEF) extraction and used for data reduction and reconstruction. The idea behind PCA [12, 13] is to find the best set of projection directions in the sample space that maximizes total scatter across all images. This is accomplished by computing a set of eigenfaces from the

eigenvectors of total scatter matrix S_t defined in Equation (4) as:

$$S_t = \sum_{i=1}^N (x_i - m)(x_i - m)^T, \quad (4)$$

Where m is the mean face of the sample set. For dimensionality reduction, K (where $K < M$) eigenvectors $U = [u_1, u_2, \dots, u_k]$ corresponding to first K largest eigenvalues of S_t are selected as eigenfaces. Reduced dimension training samples, $Y = [y_1, y_2, \dots, y_N]$ can be obtained by the transformation $Y = U^T X$.

Now, when a probe image is presented for identification/verification, it is projected on U to obtain a reduced vector $y_y = U^T x_t$. A response vector of length C , $R(x_t) = [r_1, r_2, \dots, r_c]$ is calculated by measuring distances from the probe to the nearest training samples from each class. The distance function between two vectors can be expressed in the following Equation (5)

$$d = (y_i, y_j) = \|y_i - y_j\|^2 \quad (5)$$

The desired class label for the probe image can be obtained by minimum membership rule in equation (6).

$$L(x_t) = \arg \min_c r_c \quad (6)$$

PCA also known as Karhunen-Loeve (KL) transformation or eigenspace projection, a frequently used statistical technique for optimal lossy compression of data under least square sense, provides an orthogonal basis vector-space to represent original data.

IV. RECOGNITION/VERIFICATION PHASE

The face recognition module contains preprocessing, feature extraction and classification sub-modules. The face image is preprocessed using photometric normalization and during feature extraction normalized images are represented as feature vectors. The result of classification for recognition purpose is determined by matching training and testing set data [17].

The purpose of the classification sub module is to map the feature space of a test data to a discrete set of label data that serve as template. The classification techniques used are ANFIS, NN, SVM, K-NN. The performance of a classifier depends on the amount of sample images, number of features and classifier complexity. One could think that the false positive ratio of a classifier does not increase as the number of features increases. However, added features may degrade the performance of a classification algorithm. This may happen when the number of training samples Table-1 Training and Testing Dataset

is small relative to the number of the features. This problem is called “curse of dimensionality” or “peaking phenomenon”. A generally accepted method of avoiding this phenomenon is to use at least times as many training samples per class as the number of features. This requirement should be satisfied when building a classifier. The more complex the classifier, the larger should be the mentioned ratio. This “curse” is one of the reasons why it’s important to keep the number of features as small as possible. The other main reason is the speed. The classifier will be faster and will use less memory. Moreover, a large set of features can result in a false positive when these features are redundant. Ultimately, the number of features must be carefully chosen. Too less or redundant features can lead to a loss of accuracy of the recognition system.

A. Support Vector Machine

Support vector machines (SVMs), also support vector networks are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the input, making it a [18]non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

In addition to performing linear classification, SVMs can efficiently perform non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

IV.RESULTS AND DISCUSSION

The purpose of the experiment is to evaluate the performance of the face recognition system by applying the Feature extractions PCA and LDA with support vector machine as the classifier to verify the recognition rate. The face images are non frontal and illuminated ,which are taken from CMU-PIE face database. The CMU-PIE consists of 45 persons with PIE variation.

We test the proposed algorithms on a face dataset(d1,d2,d3,d4) from the CMU-PIE face databases. The experiments were made with “closed” image set, so we did not have to deal with issues like detecting people who are not in the training set. On the other hand, we worked with real-world face images; our database contains images of the same subjects that often differ in different Poses and Illumination variation.

As comparison, we also did experiments with the traditional NN (Nearest Neighbor) algorithm[15], K-NN (K-nearest neighborhood),ANfis Adaptive Neuro-Fuzzy Inference system , , and proposed method was SVM (Support Vector Machine)[19]. Accuracy, F-Measure, Recall, Precision were some of the performance metric used in terms of Recognition Rate. If there are a total of t test images from all subjects and c images out of these t images can be correctly recognized then a recognition rate is c/t. some experimentation were conducted to the effectiveness of the proposed system. For evaluating the Recognition and Authentication performances, the different datasets were used. The Table-1 shows the different dataset for Training and Testing dataset (d1,d2,d3,d4) used to evaluate the recognition rate.

Table-1. Different Dataset and its Training set and Testing Set sizes

Dataset	Image Size	Training Samples	Testing Samples	Total face Images
13x24(d1)	128x128	4x24	8x24	312
16x24(d2)	128x128	8x24	12x24	256
20x24(d3)	128x128	10x24	10x24	480
25x24(d4)	128x128	12x24	18x24	625



Fig.2 Dataset of 24 Poses and Illuminated Face Images per subject

The First experimental results shows the feature extraction using LDA with three different classifiers and proposed SVM without normalizing the Datase(d1,d2,d3,d4).

Fgdhfgdfgdf

Table-.2 Without Normalization using LDA

Testing set	Trainin g Set	classifiers	Accuracy	Precision	Recall	F- measure
8x24	4x24	An fis	0.70139	0.55556	0.52083	0.53763
		NN	0.71181	0.62745	0.33333	0.43537
		K-NN	0.73958	0.57047	0.88542	0.69388
		Proposed SVM	0.80417	0.98039	0.52083	0.68027
12x24	8x24	An fis	0.72105	0.19701	0.34375	0.25047
		NN	0.75417	0.94048	0.41146	0.57246
		K-NN	0.72292	0.67879	0.58333	0.62745
		Proposed SVM	0.84375	0.7931	0.71875	0.7541
16*24	12*24	An fis	0.75298	0.744	0.64583	0.69145
		NN	0.78125	0.70674	0.83681	0.7663
		K-NN	0.79613	0.78927	0.71528	0.75046
		Proposed SVM	0.8631	0.78655	0.93403	0.85397
20*24	16*24	An fis	0.78819	0.74453	0.79688	0.76981
		NN	0.70023	0.6392	0.7474	0.68908
		K-NN	0.69444	0.60638	0.89063	0.72152
		Proposed SVM	0.87847	0.81922	0.93229	0.87211

In the second experiment, the Table-3 results in using PCA without Normalization.

Table-3. Without Normalization using PCA

Testing set	Training set	classifiers	Accuracy	Precision	Recall	F-measure
8x24	4x24	Anfis	0.88889	0.79091	0.90625	0.84466
		NN	0.84375	0.7931	0.71875	0.7541
		K-NN	0.80903	0.71134	0.71875	0.71503
		Proposed SVM	0.90972	0.78689	1	0.88073
12x24	8x24	Anfis	0.90417	0.85437	0.91667	0.91667
		NN	0.87917	0.98551	0.70833	0.82424
		K-NN	0.90	0.9186	0.82292	0.86813
		Proposed SVM	0.92113	0.97189	0.84028	0.90139
16*24	12*24	Anfis	0.91071	0.97107	0.81597	0.88679
		NN	0.87	0.99519	0.71875	0.83468
		K-NN	0.91518	0.89965	0.90278	0.90121
		Proposed SVM	0.94792	0.87156	0.98958	0.92683
20*24	16*24	Anfis	0.93519	0.88318	0.98438	0.93103
		NN	0.91204	0.92541	0.8724	0.89812
		K-NN	0.88889	0.9586	0.78385	0.86246
		Proposed SVM	0.9513	0.91837	0.9375	0.92784

Table-4. With Normalization using LDA

Testing set	Training Set	classifiers	Accuracy	Precision	Recall	F-measure
8x24	4x24	Anfis	0.75347	0.68657	0.47917	0.56442
		NN	0.74653	0.57516	0.91667	0.70683
		K-NN	0.64931	0.41379	0.125	0.192
		Proposed SVM	0.90278	0.90476	0.79167	0.84444
12x24	8x24	Anfis	0.88542	0.91018	0.91018	0.8468
		NN	0.84583	0.75431	0.91146	0.82547
		K-NN	0.80417	0.72685	0.81771	0.76961
		Proposed SVM	0.90833	0.87	0.90625	0.88776
16*24	12*24	Anfis	0.8895	0.87166	0.84896	0.86016
		NN	0.84375	0.73123	0.96354	0.83146
		K-NN	0.79167	0.98684	0.52083	0.68182
		Proposed SVM	0.91458	0.82969	0.98958	0.90261
20*24	16*24	Anfis	0.8898	0.8474	0.90625	0.87584
		NN	0.87054	0.89105	0.79514	0.84037
		K-NN	0.89468	0.80973	0.9974	0.89382
		Proposed SVM	0.93452	0.89869	0.95486	0.92593

In third experiment, Table-3 and Table-4 are tabulated using with normalization before the extracting the features of the training and testing set of face image data and with different classifiers.

Table:5 With normalization using PCA

Testing set	Training set	Classifiers	Accuracy	Precision	Recall	F-measure
8x24	4x24	Anfis	0.92361	0.93023	0.8333	0.87912
		NN	0.92014	0.86139	0.90625	0.88325
		K-NN	0.90972	0.82407	0.92708	0.87255
		Proposed SVM	0.94792	0.90099	0.94792	0.92386
12x24	8x24	Anfis	0.92917	0.92473	0.89583	0.91005
		NN	0.91369	0.95635	0.83681	0.89259
		K-NN	0.90923	0.88215	0.90972	0.89573
		Proposed SVM	0.95417	0.99419	0.89063	0.93956
16*24	12*24	Anfis	0.94196	0.9308	0.93403	0.93241
		NN	0.91815	0.90877	0.89931	0.90401
		K-NN	0.89732	0.93281	0.81944	0.87246
		Proposed SVM	0.96429	0.92308	1	0.96
20*24	16*24	Anfis	0.95833	0.98066	0.92448	0.95174
		NN	0.92477	0.97612	0.85156	0.9096
		K-NN	0.90856	0.83814	0.98438	0.90539
		Proposed SVM	0.96528	0.96825	0.95313	0.96063



The Table-4 and Table-5 represents the Accuracy Rate of the Face Recognition System with Normalization included in the preprocessing phase and LDA and PCA applied in the Feature Extraction Phase and evaluated using Anfis, NN,K-NN and proposed SVM in the Classification Phase. Among all the experiments Tabulated in Table-1.,2,3,4 ,the Proposed Classifier SVM gives the best recognition Rate with the feature Extraction using PCA as 96.5% when the size of the training set increases with the increase of Accuracy.

The Fig.3 and fig.4 depict the bar graph of the Recognition Rate(Accuracy) in (%) for different Classifiers with the proposed classifier Support Vector Machine(SVM) with out Normalization Phase.

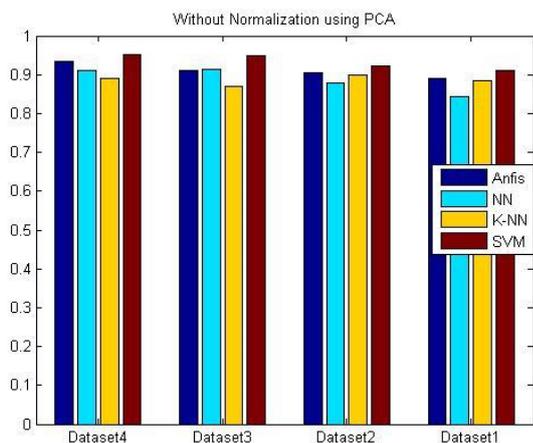


Fig.3 LDA without Normalization

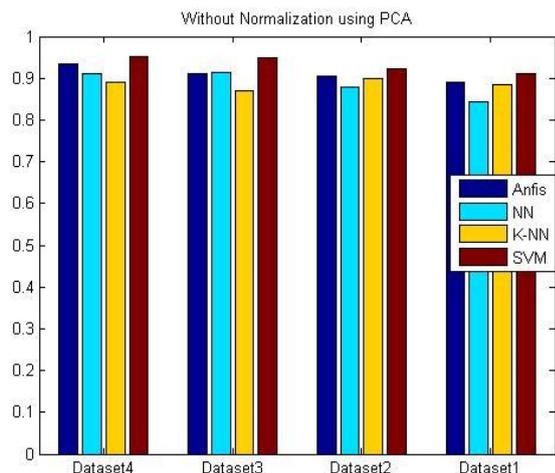


Fig.4 PCA without Normalization

The Fig.5, Fig.6 depict the bar graph of the Recognition Rate(Accuracy) in (%) for different Classifiers with the proposed classifier Support Vector Machine(SVM) with our Normalization Phase.

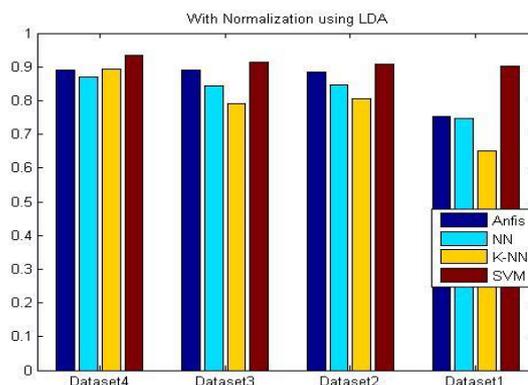


Fig 5. LDA with Normalization

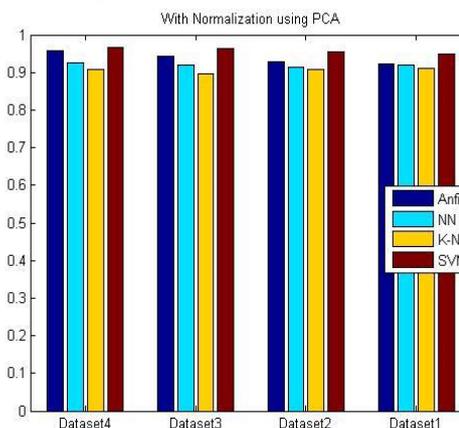


Fig.6 PCA with Normalization

V.CONCLUSION

A Novel face recognition algorithm is proposed through the methodology of identifying the Recognition rate using training and testing dataset. Classification problem can be easily handled by Support Vector Machines (SVM) hence a classification algorithm that has successfully been used in this framework is the all-known Support Vector Machines (SVM) [20], which can be applied to the original appearance space or a subspace of it obtained after applying a feature extraction method. advantage of SVM classifier over traditional neural network is that SVMs can achieve better generalization performance. For experimental purpose three classifiers were used along with SVM and the results were tabulated and represented using the Bar graph.

- (i) LDA and PCA are feature extractors given best accuracy rate when support Vector Machine is used as classifier.
- (ii) Among the two Feature Extractors LDA and PCA , with Normalization gives the best Recognition rate of 96%.
- (iii) When the dataset size is increased the Recognition Rate also increased.
- (iv) Classifier with Supervised Learning method such as SVM is better when compared to Unsupervised method such as K-NN.
- (v) LDA can handle very high resolution image efficiently and robust against noise and take very low computational cost.
- (vi) Similarly PCA has more advantage over LDA, which can handle very low resolution images gives best performance result when the face is normalized and even very small training sets.



REFERERENCES

1. J. Shermina and V. Vasudevan , "An Efficient Face Recognition System Based on the Hybridization of Invariant Pose and Illumination Process , "European Journal of Scientific Research, Vol. 64 , pp. 225-243, 2011.
2. Klare, B.F. Burge , M.J , Klontz, J.C , Vorder Bruegge , R.W. and Jain, A.K , "Face Recognition Performance: Role of Demographic Information , "IEEE Transactions on Information Forensics and Security , Vol. 7, pp. 1789-1801, 2012.
3. Adélaïde de Heering , Bruno Rossion and Daphne Maurer , "Developmental changes in face recognition during childhood: Evidence from upright and inverted faces , "Cognitive Development , Vol. 27, pp. 17-27, 2012.
4. Cong Geng and Xudong Jiang , "Face recognition based on the multi-scale local image structures , "Pattern Recognition , Vol. 44, pp. 2565-2575, 2011.
5. Mr. Hamid M. Hasan , Prof. Dr. Waleed A. ALJouhar and Dr. Majid A. Alwan , "Face Recognition Using Improved FFT Based Radon by PSO and PCA Techniques , "International Journal of Image Processing (IJIP) , pp. 26-37, 2012.
6. Shaohua Kevin Zhou and Rama Chellappa , "Image-Based Face Recognition under Illumination and Pose Variations , "Journal of the Optical Society of America A , Vol. 22, pp. 217-229, 2004.
7. V. Blanz , S. Romdhani , and T. Vetter , "Face Identification across Different Poses and Illuminations with a 3D Morphable Model , "Fifth IEEE International Conference on Automatic Face and Gesture Recognition , pp. 192-197, 2002.
8. Jen-Mei Chang, Michael Kirby, and Chris Peterson , "Set-to-Set Face Recognition Under Variations in Pose and Illumination , "Biometrics Symposium , pp. 1- 6 , 2007.
9. Ying-Nong Chen, Chin-Chuan Han, Cheng-Tzu Wang And Kuo-Chin Fan, "A Novel Scheme for Face Recognition and Authentication Against Pose, Illumination and Expression Changes , "Journal Of Information Science And Engineering , Vol. 27, pp. 369-380, 2011.
10. Roy-Chowdhury , A. & Xu , Y, " Pose and Illumination Invariant Face Recognition Using Video Sequences. Face Biometrics for Personal Identification , " Multi-Sensory Multi-Modal
11. Sushma Jaiswal, Dr. Sarita Singh Bhadauria, Dr. Rakesh Singh Jadon, "Evaluation Of Face Recognition Methods", Journal of Global Research in Computer Science, vol 2, No. 7, July 2011.
12. Yuchun Fang, Tieniu Tan, Yunhong Wang, "Fusion of Global and Local Features for Face Verification",
13. M. Sifuzzaman, M.R. Islam and M.Z. Ali, "Application of Wavelet Transform and its Advantages Compared to Fourier Transform", Journal of Physical Sciences, Vol. 13, 2009, 121-134
14. Sang-Il Choi, Chong-Ho Choi and Nojun Kwak, "Face recognition based on 2D images under illumination and pose variations", Pattern Recognition Letters, Vol. 32, pp. 561-571, 2011
15. Ralph Gross, Simon Baker, Iain Matthews and Takeo Kanade, "Face Recognition Across Pose and Illumination", Vol. 12, no. 1-2, pp. 193-216, Handbook of Face Recognition, 2005.
16. Kailash J. Karande and Sanjay N. Talbar, "Face Recognition under Variation of Pose and Illumination using Independent Component Analysis", ICGST-GVIP, Vol. 8, No. IV, pp. 1-6, December 2008
17. Fatih Kahraman, Binnur Kurt and Muhittin Gokmen, "Robust Face Alignment for Illumination and Pose Invariant Face Recognition", IEEE Conference on Computer Vision and Pattern Recognition, pp. 1-7, 2007.
18. Manjunath, Chellappa and von der Malsburg, "A feature based approach to face recognition," In Proc. of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR '92), pp. 373-378, June 1992.
19. Sushma Jaiswal, Dr. Sarita Singh Bhadauria, Dr. Rakesh Singh Jadon, " Evaluation of face recognition methods", Journal of Global Research in Computer Science, Volume 2, No. 7, July 2011
20. Sujata G. Bhele and V. H. Mankar, "A Review Paper on Face Recognition Techniques", International Journal of Advanced Research in Computer Engineering & Technology , Volume 1, Issue 8, October 2012

R. Rajalakshmi was born in Pudhukkotai, Tamilnadu, India on 18th January 1971. She studied her Masters in Computer Science at Avinashilingam Deemed University, Coimbatore, Tamilnadu, India in 1999. She received her Master of Philosophy in Computer Science from Mother Theresa University, Kodaikanal, Tamilnadu, India in 2003. Presently, she is a research scholar at the Department of Computer Applications, Noorul Islam Center for Higher Education, Noorul Islam University, Tamilnadu, India. She is currently working as Assistant Professor at the Department of Computer Science, Noorul Islam College of Arts and Science, Kumarakoil, Tamilnadu, India. Her research interests include Soft Computing and Image Processing Applications.

Dr. M. K. Jeya Kumar was born in Nagercoil, Tamilnadu, India on 18th September 1968. He received his Masters in Computer Applications degree from Bharathidasan University, Trichirappalli, Tamilnadu, India in 1993. He fetched his M.Tech degree in Computer Science and Engineering from Manonmaniam Sundarnar University, Tirunelveli, Tamilnadu, India in 2005. He completed his Ph.D degree in Computer Science and Engineering from Dr.M.G.R University, Chennai, Tamilnadu, India in 2010. He is working as a Professor in the Department of Computer Applications, Noorul Islam University, Kumaracoil, Tamilnadu, India since 1994. He has more than seventeen years of teaching experience in reputed Engineering colleges in India in the field of Computer Science and Applications. He has presented and published a number of papers in various national and international journals. His research interests include Mobile Ad Hoc Networks and network security, image processing and soft computing techniques.