Comparative Analysis of Face Recognition Approaches: A Survey

Ripal Patel, Nidhi Rathod, Ami Shah
Electronics & Telecommunication Department,
BVM Engineering College,
Vallabh Vidyanagar-388120, Gujarat, India.

ABSTRACT
In recent days, the need of biometric security system is heightened for providing safety and security against terrorist attacks, robbery, etc. The demand of biometric system has risen due to its strength, efficiency and easy availability. One of the most effective, highly authenticated and easily adaptable biometric security systems is facial feature recognition. This paper has covered almost all the techniques for face recognition approaches. It also covers the relative analysis between all the approaches which are useful in face recognition. Consideration of merits and demerits of all techniques is done and recognition rates of all the techniques are also compared.

General Terms
Image Processing, Computer Vision and Pattern Recognition.

Keywords
Still Face Recognition, Video Face Recognition, Biometric System.

1. INTRODUCTION
In recent advance in computer vision, pattern recognition and image processing, face recognition is one of the most popular research topics. The reason behind this is that among the various biometric security systems based on finger print, iris, voice or speech, signature, etc., face recognition seems to be the most universal, non-intrusive, and accessible system. It is easy to use, can be used efficiently for mass scanning which is quite difficult in case of other biometrics, and also increases user-friendliness in human-computer interaction. Moreover, its wide range of surveillance, access control and law enforcement applications and availability of executable technologies after vigorous research in last few decades has made it gain significant attention. This paper provides the techniques used for face recognition in last few decades, its present scenario, and comparison of these techniques. Finally this paper concludes by proposing the possible future advancements.

2. ISSUES/CHALLENGES
2.1 Illumination
The variation in illumination changes the appearance of the face drastically as shown in figure 1. It is found that the difference between two images of the same person taken under varying illumination is greater than the difference between the images of two different persons under same illumination.

2.2 Pose
Pose variations in an image is also a matter of concern in face recognition as shown in figure 2. The changes in the posture strike a serious problem for the identification of the input image. This is because the available image in the database may have only the frontal view of the face which may differ in pose with the input image and so may result in faulty identification.

Fig.1. Variations in illumination.[101]

Fig.2. Variations in pose.[102]

2.3 Expressions
The facial expressions also impose problem in identifying the face as shown in figure 3.

Fig.3. Variations in expressions.[103]

2.4 Ageing
With the increasing age, the appearance of a person also changes which affect the face recognition system as shown in figure 4.

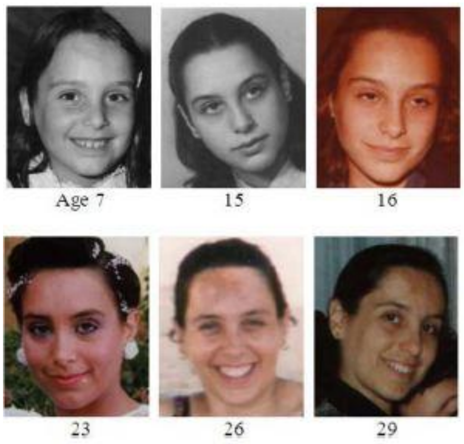

Fig.4. Ageing variations.[104]

2.5 Occlusion
The unavailability of the whole input face is also one of the important challenges as shown in figure 5. This is when some parts of the face are missing for e.g. when an image is captured from a surveillance camera; the face in the image lacks some parts. This is also possible due to glasses, beard, moustache, scarf, etc. Such a problem can severely affect the classification process.

Fig.5. Partial occlusion in images.[98]

2.6 Low Resolution
The images taken from a surveillance camera generally consists of very small face area and so its resolution is very low i.e. it will be smaller than 16 × 16 pixels. Such a low resolution face image consists of very limited information as most of the details are lost. This can drop down the recognition rate drastically.

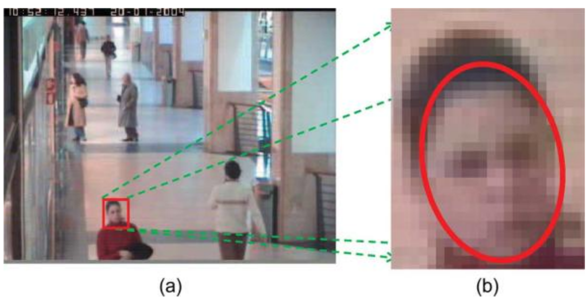

Fig.6. Typical frame from a surveillance video (CAVIAR database).
(a) Surveillance video. (b) Face region. [94]

3. RELATED WORK
Facial recognition has always been a very difficult and challenging task. Its true challenge lies in designing an auto mated system which equals the human ability to recognize faces. But, there is limitation to the human ability when it deals with a large amount of unknown faces. Hence, an automatic computerized system with almost limitless memory and high speed is necessitated.

One of the first researches in this area started in the 1960's by Woodrow W. Bledsoe. Bledsoe along with Helen Chan and Charles Bisson worked on recognition of faces using computer [1]. Later, Bledsoe designed and implemented a semi-automatic system. He mentioned most of the problems which are still faced by the researchers such as variations in illumination, pose, expressions, ageing variations. A. Jay Goldstein, Leon D. Harmon and Ann B. Lesk used the concept of measuring gg features such as ear protrusion, nose length, between-eye distance, etc. to recognize faces using pattern recognition techniques at the Bell Laboratories [2]. Manual computation for measurements was the problem with this method. In 1973, Fischler and Elschanger used local template matching and global measure of fit to measure similar facial features automatically [3]. In the same year, Kanade formulated a fully automated face recognition system. He used an algorithm which extracted sixteen facial features automatically and achieved performance rate of 45-75 % [4]. In 1980's, Mark Nixon introduced geometric measurement for spacing between the eyes [5]. He also worked on automatic gait recognition and was the first to consider ageing in biometrics. Some researchers proposed algorithms which used artificial neural networks. Then after, the technique which proved to be a milestone in facial recognition which used eigenfaces was brought in by L. Sirovich and M. Kirby in 1986 [6][7]. Their methods were based on Principal Component Analysis (PCA) and they showed that PCA is an dimensional reduction system that minimizes the mean squared error between the original images and the image can be reconstructed for any given level of compression. The goal of this technique was to reduce the dimensionality of the data while retaining as much as possible of the variation present in the dataset. But its performance degraded when it encountered higher changes in illumination and pose. Eigenface approach use Karhonen-Loeve (KL) transform for feature extraction. Kirby and Sirovich used PCA to represent faces [6][7] which was then extended by Turk and Pentland to recognize faces [8].In PCA, the data is dealt in its totality without paying attention to its underlying structure whereas in Linear Discriminant Analysis (LDA) or Fisherface [9], the differences between-classes as well as within-classes are considered. Then after, using these scatter matrices, a set of projection vectors is formed to minimize within-class scatter and to maximize between-class scatter.

The LDA technique required computation to a greater extent and so Incremental Linear Discriminant Analysis (ILDA) [10] was formulated. Independent Component Analysis (ICA) [11] is the generalization of PCA.Bartlett and Sejnowski showed its use for face recognition. The advantages of ICA are that it considers the higher-order statistics and the vectors determined by ICA are not necessarily orthogonal and therefore the performance rate is increased. Experiments show that this approach works better than PCA under most of the conditions. The Gabor filters are used to extract features from the images using texture component. The feature-based method proposed by Wiskott i.e. Elastic Bunch Graph Model (EBGM) [12] which is based on Gabor wavelets has good performance in general. Moreover, the illumination and pose variation problems are almost eliminated using this approach. The Support Vector Machines (SVM) method is a binary classification method

[13]. The Hidden Markov Model for face recognition was first conceptualized by Samaria [14][15]. It was later extended for 2D Discrete Cosine Transform (DCT) & Karhunen-Loeve transform by Nefian [16][17][18]. Active Shape Models (ASM) and Active Appearance Models (AAM) are proposed by Cootes [19][20][21][22] for face representation. KPCA [23][24],KFA [25],Neural networks [18][26],Hidden Markov Model, LFA, Laplacianfaces [27] are also the methods which are implemented for face recognition by different researchers in this area. The 2D images created problems in face recognition due to the changes in illumination, pose and expressions and so 3D face recognition was proposed. The first work based on 3D face data usage for identifying humans was published by Cartoux [28].

3.1 Principal Component Analysis (PCA)

The input in a PCA based algorithm is a training set, $t_{1,\ldots,}t_N$ of N facial images such that the ensemble mean of the training set is zero i.e. $\sum_i t_i = 0$.Here, each image is interpreted as a point in $R^{n\times m}$ where each image is n × m pixels. The PCA representation is characterized by a set of N-1 eigenvectors (e_1, …,e_{N-1}) and eigenvalues (λ_1, …,λ_{N-1}). The principal components features of faces are the eigenfaces or the eigenvectors of the covariance matrix of set of training sample images. Normalization of the eigenvectors leads to orthonormality and eigenvectors ordered so that $\lambda_i > \lambda_{i+1}$[29].

The λ_is are equal to the variance of the projection of the training set onto the i^{th} eigenvector. Thus, the low-order eigenvectors encode the larger variations and the higher-order eigenvectors encode the smaller variations in the training set. Thus, they represent redundant part and hence are excluded. Faces are represented by their projection onto a subset of M ≤ N-1 eigenvectors, which is face space. Each face can be exactly represented by the linear combination of eigenfaces. The “best” eigenvectors that has the largest eigenvalues are used to construct an M-dimensional space. Thus, an image is represented as a point in an M-dimensional face space. This method had correct identification rate of 96%, 85%, 64% [8]. Their database consisted of 2500 images of 16 individuals. This method has an advantage of being simple and fast but its performance degrades with changes in lighting condition, expressions, and poses.

3.2 Linear Discriminate Analysis (LDA)

This technique is generally supposed to be better than PCA. But this is not true for small training set. In PCA and ICA, the distance between the face weights of same person is greater than the distance between different people. So to rectify this, the fisherfaces method which is based on LDA was proposed which finds vectors that best discriminate between classes of data along with describing the data. Then, a “within-class” scatter matrix and a “between-class” scatter matrix is calculated. LDA creates a set of projection vectors by using these scatter matrices to maximize the between-class measure while simultaneously minimizing the within-class measure [10].

3.3 Independent Component Analysis (ICA)

ICA is the generalization of PCA and in most of the cases outperforms PCA. ICA attempts for a linear transformation to express a set of random variable as linear combinations of statistically independent source variables [28]. PCA lacks information on higher order statistics as it considers only the second order moments and it uncorrelates data, whereas ICA considers the higher order statistics and it identifies the independent source components from their linear mixtures. Thus it provides a more powerful data representation than PCA [31].

3.4 Normalized Cross Correlation (NCC)

Normalized cross correlation is used extensively in applications which require matching parts of image or the whole image. If there are only translation or small rotation and scale changes between the two images traditional matching methods based on normalized cross-correlation can easily handle the situation.

Normalize cross correlation (NCC) can be defined by,

$$f * g = \frac{1}{n-1}\sum_{x,y}\frac{(f(x,y)-fm)(g(x,y)-gm)}{\sigma_f \sigma_g}$$

The equation can be defined cross-correlation of a template, f(x ,y) with a subimage g(x ,y) where n is number of pixels for both images, *fm* and *gm* are mean of image *f* and *g*, σ_f and σ_g are standard deviation of images *f* and *g*.

4. RECENT APPROACHES

As considered in traditional methods there are so many problems that would occur in face recognition such as dimensionality, pose variation, change in illumination, etc. So there are some recent approaches that may solve these kinds of problems at some extent, which are explained below.

4.1 Gabor Image Representation

It increases dimensionality by incorporating Gabor filters with different scales and orientations, is characterized by spatial frequency, spatial locality, and orientational selectivity for coping with image variability such as illumination variations [25]. This method is fast and robust. It represents the adapted version of original Viola-Jones face detector [32]. It gives better accuracy .Even expression recognition can be achieved by a novel local Gabor filter bank. It depends on frequency and orientation parameters [33].It is basically a feature extraction method but its recent approaches used with PCA and LDA are also use for feature matching. In this method the recent work is carried out by Jamie Cook, VinodChandran, Shridhhashridharan and Clinton Fookes in the year of 2005.

4.2 Discrete Cosine Transform

DCT[34] decompose image in to summation of different cosine function having different frequencies. DCT concentrate energy at upper left corner and also provide reduce in data reduction. Jing Shao[35] has presented new algorithm which combine advantage of DCT and LDA for face recognition. DCT features coefficients are extracted from face training face images and LDA applied for further dimension reduction. Ziad M Hafed[36] has proposed DCT based face recognition scheme. By extracting DCT coefficient from test image preprocessing task are applied for making it suitable for illumination and facial geometry invariant. DCT based FR Hexagonal: Azam, M. [37] has presented test image in to hexagonal image then converting it in to logarithmic space. Feeding it to DCT for extracting features and matching of feature is done by ANN. It is costlier than other methods. RandaAtta[38] have decompose image in to approximations sub bands using DCT. This method results in to dimensionality reduction hence consumes low memory requirement as well giving efficient recognition rate. Statistical features are calculated from sub bands of DCT of image which are used for classification of image.

4.3 Kernel Fisher Analysis [multi-class]

The KFA method first performs nonlinear mapping from the input space to a high-dimensional feature space, and then implements the multiclass Fisher discriminant analysis in the feature space. The advantage of the KFA[25] method is that it increases the discriminating power of the, which is linear in the feature space but nonlinear in the input space. Liang and Shi [39] developed a kernel uncorrelated discriminant vectors technique which describes that this method works quite same as the GDA method. The difference between KFA[25] method from other is that it extends the two-class kernel Fisher methods [40], [41] by addressing multiclass pattern classification problems and it improves upon the traditional Generalized Discriminant Analysis (GDA) method [42] by deriving a unique solution. Yang [43] discussed a technique which was dependent on GDA and kernel Fisherfaces method for face recognition. Zheng et al. [44] had given a modified algorithm for the GDA method for the problems occurred such as several eigenvectors associating with the same eigenvalue. Here the recent work done in this field is carried out by the authors Yu-JieZheng, Jing Yu Yang, Jian Yang, Xio-Jun Wu and Wei DongWang in the year of 2006.

4.4 Enhanced Side-face image [ESFI]

It is a Video-Based technique. In this method a higher resolution image compared with the image directly obtained from a single video frame, is constructed, which integrates face information from multiple video frames [45] .It works for side faces [46] so it can improve the pose variation problem. This is one of the most recent approaches for face recognition which has been proposed by Xiaoli Zhou and BirBhanu in the year of 2008.The latest work done in this direction is carried out by Brad Reed in the year of 2012.

4.5 Frontal View-Face (VFF) approach

In this method, author has applied the generic 3-D facial model in computer graphics into face recognition application. Since 3Dmodel approach [47] is quite expensive, frontal view face approach can be used which was suggested by Pentland et al. [48].Also Beymeret al. [49], [50] suggested to construct a “virtual-view” for recognition based on the theory that any two-dimensional(2-D) views of a face can be represented by a linear combination of the other 2-D views [51].Then after Osunaet al. presented an SVM-based approach for frontal view face detection [52]. Based on the 3-D model, we have developed a 3-D SBM to construct the VFF image. The Pose Variations can be handled by Virtual Frontal-View Face (VFF) Approach and it requires only one VFF image. It requires only Three Facial Landmarks. The Spectroface Method is applicable to VFF images and the results are very good i.e. Accuracy is high (best match:84.7%).The Recognition capacity of VFF images by Spectroface method is 5% more than Eigenfaces [53]. Combination of image wrapping and shape from shading generates virtual viewsand this approach is proposed by Zhao and Chellappa [54]. This approach is used for authentication of face images and recognition is also done by this method. Recognition based on VFF images is the most Efficient and Reliable. In fact, most of the existing face recognition algorithms such as eigenface [48], Jet can be applied to recognize the virtual frontal-view images. Only the disadvantage of this method is that it is based on computer graphics so it is little complex. It is a memory based technique [55]. This information is given by the author G. C. Feng and Pong C. Yuen in the year of 2000.

4.6 Optical Flow-based approach

It uses integrated face recognition system that is robust against facial expressions by combining information from the computed intrapersonal optical flow and the synthesized face image in a probabilistic framework [53].It is a 2-D expression-invariant face recognition system based on integrating the optical flow information and image synthesis. It requires only one neutral image. The proposed algorithm combines the face image comparison and optical flow prior information in a probabilistic MAP framework. Good Recognition accuracy is achieved for expressional faces. But it gives the demerit of high cost [53]. It takes only one of Syn operator in our previous work [56] and now there is no need of image synthesis in the weighted optical flow algorithm [57].

4.7 Fractional Power polynomials method

It improves performance of the proposed pattern recognition framework. Experiments on face recognition using both the FERET database and the FRGC (Face Recognition Grand Challenge) databases show the feasibility of the proposed framework [25].Here the advantage of applying the nonlinear mapping is that it increases the discriminating ability of a pattern classifier [58].

4.8 A 3D Facial Aging Model and Simulation Method

As we know accuracy of face recognition is also dependent on the Age-Variation of the humans [59]. Ling et al. [60] has provided that as the person is getting older the features of the face also changes which will affect the accuracy of recognition. It is used to compensate for the age variations to improve the face recognition performance. The aging modeling technique accepts view invariant 3D faces which is provided by 2D images [61]. Here this approach is quite robust against pose variation and illumination problems due to 2D to 3D domain. For ages under 19,we rescale the overall size of 3D shapes according to the average head width found in [62].The use of 3D model provides more powerful modeling capability than 2D age modeling proposed earlier because the change in human face configuration occurs in 3Ddomain. This method is capable of handling both growth (developmental) and adult face aging effects. A 2D Method is not that efficient as 3D Method. Age estimation is crucial if a fully automatic age-invariant face recognition system is needed. Nixon and Galassi [63] had worked on this method in which it contains collection of photos of four sisters taken at the time span of every 33 years. This method is carried out by Unsang Park, Yiying Tong, and Anil K. Jain in 2010 and improvised in 2012.

4.9 Gait Energy Image (GEI)

In this Method a spatio-temporal compact representation of gait in video, is used to characterize human-walking properties which can be approximated by frequency [64]. The fusion of side-face and gait biometrics is done at the match score level by obtaining synthetic match scores and using different fusion schemes. It has good Performance Rate and Recognition Rate. GEI is affected by the shape of human body to some extent [45].It is sensitive to noise as well as facial expressions because the side face contains less information compared with the frontal face. Features of face and gate can be obtained by using PCA [8]with the help of ESFI and GEI [45]respectively[65].Little and Boyd [49]describe the shape of the human motion with scale-independent features from moments of the dense optical flow, and recognize individuals by phase vectors estimated from the feature sequences. Sundaresanet al. [66] suggested a hidden-Markov models-based framework for individual recognition by gait. Huang et al. [67] extend the template matching method to gait recognition. Tao et al. [68] introduce a set of Gabor-based human-gait appearance models and propose a general tensor discriminant analysis (GTDA) to solve the carrying status in gait recognition.

4.10 3-D Morphable Model

The Morphable Model of 3D faces [51],[52],[69] is a vector. From training image examples 3Dmorphable model is created using 3D shapes and surface textures, which is used to capture variations found within this dataset. It works even if there are variations in Illumination and Pose and give promising results of 95% and 95.9% correct identification respectively [70]. This model is versatile and efficient for facial representation. This system ignores glasses, breads or strand of hair covering the face which can improve 3D representation and identification. If the textures and shape of the images are matched on the regions then optic flow will be produced and result will be degraded. Here the recognition of the face image is done at the faster rate. These Algorithms work on Normalized Local Data[70].In 3D method, pose variations are mostly unaffected but in 2D are affected by the pose variations which can be solved by multiple pose database [71].Good Noise Variation Handling. Other geometric methods such as local Gabor Wavelet filters [72] would however give more accurate results than this method. This method is carried out by Volker Blanz and Thomas Vetter in the year of 2003 ad its improved version is proposed in 2006.

4.11 Local Feature Analysis (LFA)

Local feature analysis is described object using statistical measure which is derived from local features and their positions. LFA define locally geographic representations of face in terms of face feature points. Face feature points or fiducial points can be eyes, nose, eyebrow, chine and lips etc.

4.12 Elastic Bunch Graph Matching (EBGM)

EBGM is a feature-based face recognition method. By manual interaction, some of the features are selected on face. Based on this features, a bunch graph is produced. Node of the bunch graph represent facial landmark. Displacement between test image features and closest train image features is measured by comparing it to all test images and by finding closest measure within it. Face graph is calculated for each test image and train image by extracting landmark features from face. The graph contains location of node and value of those nodes of graph which is created from facial landmark feature.

4.13 Kernel Principal Component Analysis (KPCA)

Techniques of kernel methods are used as an extension of PCA known as KPCA which was proposed by Scholkopf [23].It is able to extract the non-linear features from the image. Using kernel methods, linear PCA exhibit non-linear characteristic i.e. non-linear mapping of data.

4.14 Correlation Filters

The matched spatial filter (MSF) is the most introductory correlation filter, obtained by correlating a known test image, or *template*, with an unknown test image to detect the presence of the authenticate person in the unknown test image. This filter is sufficiently work when image is suffered by Gaussian additive noise but this filter is not giving good results under variation like pose, illumination etc. Correlation filters are shift invariant and can handle multiple visual aspect of the reference image in the test image [73].

To overcome the problems regarding MSF synthetic discriminant function (SDF) filter is proposed by Hester and Casasent et al [74]. SDF is linear combination of MSF and weights are chosen such that for training images peak values get as pre-specified value and for test image it should be one so it's also called equal correlation peak (ECP) SDF filter. But in this technique at correlation output main lobe with so many side lobs acquired.

A. Mahalanobis et al [75] proposed side lobs reduction technique unaffected to main lob. Minimum Average Correlation Energy (MACE) filter is proposed and on account of that resultant correlation output has maximum output respected with training image and all side lobs related with misclassification minimize. For highly secure authentication Peak to Side Lobe Ration (PSR) [76] is found.

$$\text{PSR} = \frac{peak - mean}{\sigma}$$

For authentic image PSR should be high compare to non-authentic images. PSR is also invariant to constant illumination changes [34].

B. V. K. Vijaya Kumar et al [77] proposed biometric system considering face, fingerprint, and iris based on advance correlation filter. Same author has proposed in [78] more highly secure biometric system based on correlation filter. In that user enter the PIN number and base on that PIN number random kernel generated. Training images are convolved with random kernel which is used to generate single biometric filter and finally Peak to Side Lobe Ration (PSR) is found from convolution output which is used to authentic person in camera.

Above algorithm based on Correlation filters are working on still to still face recognition system but ChunyanXie et al [79] have proposed still to video face recognition based on correlation filter. Proposed system considered mainly three part cropping face image from series of training images, establishing multiple correlation filter from each cropped face image which derive part of manifest from each image. Finally, all manifest are summarized and build score for authentication.

4.15 Laplacian Faces

The earlier methods which used Eigenfaces and Fisherfaces algorithms used linear projection to subspace preserving the global structure of the face. On the other hand, the Laplacianfaces [80] method uses optimal linear approximations to the eigenfunctions of Laplace-Beltrami operator preserving the local structure of the face. The unwanted variations resulting from the changes in the illumination, facial expressions, and pose can be reduced or eliminated in this manner. The error rate of this approach is less than that of Eigenface approach and Fisherface approach.

4.16 Active Shape Model (ASM)

Active Shape Model is based on PCA technique and represents shape variations and synthesizes novel shapes similar to those in a training set [81].The advantage of this model is that the instances of models can only deform in ways found in a training set [82], which is suitable for the representation of deformable objects such as face.

4.17 Active Appearance Model (AAM)

Shape information is not sufficient for complete image representation as in the case with ASM. AAM not only seeks to match the position of the model points, but also match the representation of the texture over the object i.e. it represents the shape and texture variations of the training set and correlations between them [20].It is demonstrated that AAM is extraordinarily fast for head tracking. AAM can accurately tell the face motion in real time. An alternative to AAM is the direct appearance model which uses the texture information to linearly predict the shape [83].

5. CLASSIFIER METHODS

After the feature extraction process, the next step is to classify images. For this, we need classifier techniques. At times, two or more classifier methods are combined for improving results.

5.1 SVM

The Support Vector Machines (SVM) method views the problem in difference space. This method was formulated to solve two-class face recognition problem. The classes are: dissimilarities between images of the same person and the dissimilarities between images of different persons [13]. These classes are the input to a SVM algorithm. A decision surface is found for pattern recognition between the two classes that has maximum distance to the closest points in the training set which are called support vectors. The two classes are separated by a hyperplane such that the distance to the support vectors is maximized. SVM is basically a binary classification method and to apply it to multi-class face recognition problem, combination of SVMs is to be used. But as the classes in face recognition is generally very large, large number of SVMs has to be used and hence, the Bayesian SVM method [80] was developed. The Bayesian method converts the multi-class face recognition problem to two-class problem effectively and so SVM can be used directly.

5.2 HMM

HMMs are used for stochastic modeling of time varying signals. In face recognition, the HMM method is based on approximating the blocks taken from the face image with a chain of states of a stochastic model.HMM consists of two interrelated processes: (1) an underlying, unobservable Markov chain with a finite number of states, a state transition probability matrix and an initial state probability distribution and (2) a set of probability density functions associated with each state. In case of pseudo 2D HMM, the image blocks are extracted by scanning the face from top to bottom, left to right with an overlap both in vertical and horizontal direction. Pixel intensities are susceptible to illumination changes and other variations. The 2D Direct Cosine Transform attenuates these distorting effects which improves the performance. For the recognition, the Baum-Welch algorithm is used for training of each class. Given the class model, the class that gives the highest value for the probability of the observation sequence of the testing image, is regarded as the probable identity of the testing face. HMM computations converge speedily which makes it practical for real time applications. This method is generally used along with other algorithms for face detection.

5.3 Neural Networks

Neural networks are algorithms which are inspired by the types of computational structures found in the brain, enabling computers to learn from experience. Such networks incorporate processing elements known as "units", which are analogous to neurons. These are sorted as input units, hidden units, and output units. One unit connected to another implies that activity of one unit directly influences the activity of the other; the tendency of activity in one unit to induce or inhibit activity in the other is called the "weight" of the connection between these units. Networks learn by modifying these connection strengths or "weights". Principal Component Neural Network (PCNN)[84] is a single layer feed-forward network of linear neurons. It uses Hebbian algorithm for extracting eigenface features and is also easy for hardware implementation. The feature extraction algorithms extract relevant features which are fed to neural networks. Other approaches include Radial basis neural network [85] and other neural networks [86][87][24].

5.4 SOM

It is also known as Kohonen's SOM. This is the type of single layer Nueral network which follow unsupervised learning and reduce dimensionality data need to be classify. Self-organization capacity in [88] approach is proposed based on SOM which mapped image samples in to a topological space in which input mapping is same for original and output space. So, it encapsulates dimensional reduction as well unvarying to minor changes in image sample. Victor emilNeagoe[89] has presented concurrent SOM for face recognition. Concurrent SOM is assembling of small SOM in which each SOM is developed individually for efficient and good result for one class[90]. A.S.Raja has proposed face recognition algorithm based on SOM following supervised learning approach. Gregoire Lefebvre and Christophe Garcia[91] have aimed probabilistic approach for face recognition. Local feature is extracted from Region of interest then feed in to SOM Nueral Network then face recognition is executed using probabilistic approach.

5.5 Probabilistic Reasoning Model (PRM)

It is based on Bayesian classifier which assumes that the covariance matrix is diagonal [92].

5.6 Naive Bayesian Classifier

Bayesian classifier is a statistical classifier based on Bayes theorem. It divides the difference vectors between pairs of face images into two classes: one representing intrapersonal differences (i.e. differences in a pair of images representing the same person) and extra-personal differences [93].

6. Comparative analysis

The comparative analyses of the different approaches which are used for face recognition have been shown in fig.7. Different types of methods are considered in this analysis like Gabor + ICA [92], Kernel associated Memory Model (KAMM)[93], Kullback-Leibler divergence (KLD)-based local Gabor binary patterns (LGBP)[98], Hybrid Colour and Frequency Features (CFF)[99], Gabor Image Representation (GIR)[49], Kernal Fisher Analysis + Fractional Power Polynomial Models (KFA-FPPM)[49], Enhanced side-faceImage (ESFI)[45], Virtual Frontal-View Face (VFVF)[100], 3D Facial Aging Model And Simulation Method (3D Ageing Model)[61], Gait Energy Image (GEI) [25], 3D Morphable Model (3DMM)[52]. Comparative analysis of the graph show that Gabor + ICA, Kernel associated Memory Model

Table 1 Comparative Analysis of Face Recognition Approaches

Algorithm	**Image-based/Video-based**	**Database**	**Performance rate**	**Advantage**	**Disadvantage**
PCA[107]	Image	AR-Faces	70	Reduces dimensionality	Class seperability remain same
LDA[107]	Image	AR-Faces	88	Reduce dimensionality Increase class seperability	
ICA[108]	Image	FERET	89	Exploits higher order statistics	
Laplacianfaces[27]	image	MSRA Yale PIE	91.8 88.7 95.4	Lower error rate compared to eigenfaces and fisherfaces approach	Problem occur in estimating intrinsic dimensionality of non-linear manifold images
PCNN [95]		FRGC version 2 and Yale	85	Facilitates efficient hardware mapping	
SVM [13]	image	FERET	77-78		
Gabor + ICA [96]		FERET (180 features) ORL (88 features)	98.5 100	Automatic implementation	
Kernel associated Memory Models [97]		FERET ORL XM2VTS	91.6 98 84	Low computational complexity	Huge storage space
Kullback-Leibler divergence (KLD)-based local Gabor binary patterns (LGBP) [98]	image	Alex-Martinez-Robert (AR)	80	Partially occluded faces High precision & stability	High dimensionality
Hybrid Colour and Frequency Features (CFF) [99]	image	FRGC version 2	80.3		
Scale invariant feature transform (SIFT) and multi-scale local binary patterns (MLBP)	Image	MORPH album 2 FG-NET	83.9 47.5	Age-invariant face recognition	It fails when encounters large pose changes
Gabor Image Representation [25]	Image	FRGC version 2	76	Better performance	High dimensionality
Kernal Fisher Analysis + Fractional Power Polynomial Models [25]	Image	FERET	95	Increases discriminant power	
Enhanced side-face Image [45]	Video/ Image	-	80	High resolution	Contains less information as side faces are considered
Virtual Frontal-View Face [100]	Image	MIT face database	84.7	Pose variations can be handled more efficiently High performance rate	Somewhat complex
3D Facial Aging Model And Simulation Method	Video/ Image	FG-NET(82,82) MORPF-Album1++(612,612) BROWNS(4,4)	37.4 66.4 28.1	Works with both growth and adult face aging effects	Age estimation is crucial
Gait Energy Image [52]	Video/ Image	-	82.2	Recognition is done by walking properties and Good recognition performance at a distance in a video	Sensitive to nose and facial expressions
3D Morphable Model	Video/ Image	Real-time(live faces)	97	Good performance even with pose and illumination variation Better noise handling	Complexity is high

Polynomial Models (KFA-FPPM), 3D Morphable Model (3DMM) encapsulate high accuracy and high efficiency.

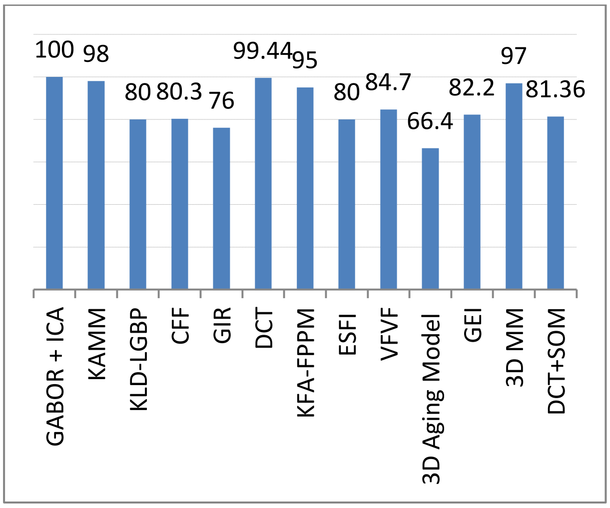

Fig 7. Accuracy Vs Method

6. FUTURE EXTENSION

Face recognition is taking place in many sectors nowadays because it works well under constrained conditions. But there can be many advances in this direction because there are vast scopes of improvement and development.

As considered above, all current face recognition the algorithms fail under the vastly varying condition under which humans need to and able to identify other people. So, future work can be done in the direction that people can recognize the images in 'Real-Time' in less constrained condition. Almost all traditional and recent methods of face recognition are facing the problems such as change in illumination, pose variation, and change in expressions, aging factors and alignment. So, one of the promising future in face recognition approach is 'Enhancement' so as it will be applicable to even low resolution conditions. There may be advances in the direction of natural environment. But in future we can work with 'Smart Environment' which allows low power consumption, small size and can be easily integrated. Even a good quality model of each face built at enrollment time can be achieved. Here a single query image is to be compared with detailed model for each enrolled faces. So the future work can be done for 3D model to 2D query face.

High resolution can improve the accuracy rate for face recognition. So the improvements can be done. For this one of the approaches is 'facial feature localization' which gives better alignment. Another approach is to use skin markings such as unique identifiers and 3D sensors. Now, researchers are beginning to demonstrate that obstructive audio-video based person identification system can achieve high recognition rate without requiring user to be in highly controlled environment.

7. REFERENCES

[1] Proyecto Fin de Carrera, Face Recognition Algorithms.

[2] A. Golstein, L. Harmon, and A. Lest. Identification of human faces.Proceedings of the IEEE, 59:748–760, 1971.

[3] M. Fischler and R. Elschlager. The representation and matching ofpictorial structures. IEEE Transactions on Computers, C-22(1):67 –92, 1973.

[4] T. Kenade. Picture Processing System by Computer Complex and Recognition of Human Faces. PhD thesis, Kyoto University, November 1973.

[5] M. Nixon. Eye spacing measurement for facial recognition. Proceedings of the Society of Photo-Optical Instrument Engineers, SPIE,575(37):279–285, August 1985.

[6] L. Sirovich and M. Kirby, "Low-dimensional procedure for the characterizationof human faces," Journal of the Optical Society of America A - Optics, Image Science and Vision, 4(3):519–524, March 1987.

[7] M. Kirby and L. Sirovich,"Application of the karhunen-loeveprocedurefor the characterization of human faces," IEEE Transactions on Pattern Analysis and Machine Intelligence, 12(1):103–108, 1990.

[8] M. Turk and A. Pentland, "Eigenfaces for recognition," Journal of Cognitive Neurosicence, 3(1):71–86, 1991.

[9] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman,"Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection," in *IEEE TPAMI*. vol. 19, 1997, pp. 711-720.

[10] M. S. Bartlett, J. R. Movellan, and T. J. Sejnowski,"Face recognition by independent component analysis,"IEEE Transactions on Neural Networks, Vol.13, pp.1450-1464, 2002.

[11] T. K. Kim, S. F. Wong, B. Stenger, J. Kittler, and R.Cipolla, "Incremental Linear Discriminant Analysis Using Sufficient Spanning Set Approximations," in *IEEE CVPR*, 2007, pp. 1-8.

[12] L. Wiskott, J. M. Fellous, N. Kruger, and C. von der Malsburg, "Face recognition by elastic bunch graph matching," *IEEE Trans. Pattern Anal.MachineIntell.*, vol. 19, pp. 775–779, July 1997.

[13] P. Jonathon Phillips, "Support Vector Machines Applied to Face Recognition", a technical report NISTIR 6241 appeared in *Advances in Neural InformationProcessing Systems 11*, eds. M. J. Kearns, S. A. Solla, and D. A. Cohn, MIT Press,1999.

[14] F. Samaria, "Face Recognition Using Hidden Markov Models", PhD dissertation,Trinity College, University of Cambridge.

[15] F. Samaria and A. Harter, "Parametrisation of a Stochastic Model for Human FaceIdentification", Proc. 2nd IEEE Workshop on Applications of Computer Vision, pp. 138-142, Dec. 1994.

[16] Aria V. Nefian, and Monson H. Hayes, "Hidden Markov Models for face detectionand recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, April 1999.

[17] Aria V. Nefian, and Monson H. Hayes, "Hidden Markov Models for FaceRecognition", IEEE International Conference on Acoustic, Speech and Signal Processing 98, vol. 5, p. 2721-27224

[18] Cottrell, G.W., Fleming, M.K., 1990. Face recognition using unsupervisedfeature extraction. In: Proc. Intell. Neural Network Conf., pp. 322–325.

[19] T. Cootes, C. Taylor, Statistical models of appearance for computer vision, Technical Report, University of Manchester, Imaging Science and Biomedical Engineering, Manchester M13 9PT, United Kingdom, September 1999.

[20] P.N. Belhumeur, J. Hespanha, D.J. Kriegman, Eigenfacesvs. Fisherfaces: recognition using class specific linear projection, IEEE European Conference on Computer Vision, 1996, pp. 45–58.

[21] R. Brunelli, T. Poggio, Face recognition: features versustemplates, IEEE Trans. Pattern Anal. Machine Intell. 15 (10) (1993) 1042–1052.

[22] J. Cohn, A. Zlochower, J.J. Lien, T. Kanade, Featurepointtracking by optical flow discriminates subtle differences in facial expression, Proceedings of the Third IEEE International Conference on Automatic Face and Gesture Recognition, April 1998, pp. 396–401.

[23] B. Scholkopf, A. Smola, K. Muller, Nonlinear componentanalysis as a kernel eigenvalue problem, Neural Computation 10 (5) (1998) 1299–1319.

[24] Z. Q. Zhao, D. S. Huang, and B. Y. Sun, "Human face recognition based on multi-features using neural networks committee," *Pattern Recognit. Lett.*, vol. 25, no. 12, pp. 1351–1358, Sep. 2004.

[25] Chengjun Liu, "Capitalize on Dimensionality Increasing Techniques for Improving Face RecognitionGrand Challenge Performance": IEEE transactions on pattern analysis and machine intelligence, vol. 28, no. 5, may 2006.

[26] Lawrence S., Giles C. L., Tsoi A. C., ands Back A. D., 1998. Face recognition: A convolutional neural network approach. *IEEE Transactions on Neural Networks*, Vol. 8, pp. 98–113.

[27] Xiaofei He, Shuicheng Yan, Yuxiao Hu, ParthaNiyogi, and Hong-Jiang Zhang, "Face Recognition Using Laplacianfaces," IEEE transactions on pattern analysis and machine intelligence, vol. 27, no. 3, march 2005.

[28] Cartoux J. Y., Lapreste J. T., AND Richetin M. 1989. Face authentication or recognition by profile extraction from range images. In *Workshop on Interpretation of 3D Scenes*, pp. 194–199.

[29] Hyeonjoon Moon and P Jonathon Phillips, 'Computational and performance aspect of PCA based face recognition algorithms', Perception,2001,volume 30, pages 303-321.

[30] P. Comon, "Independent component analysis, a new concept?," *SignalProcessing*, vol. 36, pp. 287–314, 1994.

[31] J. Karhunen, E. Oja, L. Wang, R. Vigario, and J. Joutsensalo, "A classof neural networks for independent component analysis," *IEEE Trans. Neural Networks*, vol. 8, pp. 486–504, Mar. 1997.

[32] DanijelaVukadinovic and MajaPantic"Fully Automatic Facial Feature Point Detection UsingGabor Feature Based Boosted Classifiers" 2005 IEEE International Conference on Systems, Man and CyberneticsWaikoloa, Hawaii October 10-12, 2005

[33] Hong Bo Deng, Lian Wen Jin, Li-Xin Zhen, Jian-Cheng Huang "A New Facial Expression Recognition Method Bassed on Local Gabor Filter Bank and PCA plus LDA"International Journal of Information Technology Vol. 11 No. 11 2005.

[34] J. Nagi, S. K. Ahmed, F. Nagi. A MATLAB based Face Recognition System using Image Processing and Neural Networks, in Proc. of the 4th International Colloquium on Signal Processing and its Applications (CSPA), Mar. 7-9, 2008, Kuala Lumpur, Malaysia, pp. 83–88.

[35] Jing Shao, Jia-fu Jiang, Xiao-wei Liu, 'Biomimetic Pattern Face Recognition Based on DCT and LDA', Artificial Intelligence and Computational Intelligence Lecture Notes in Computer Science Volume 7004, 2011, pp 170-177

[36] ZIAD M. HAFED AND MARTIN D. LEVINE, 'Face Recognition Using the Discrete Cosine Transform', International Journal of Computer Vision 43(3), Pages:167–188, 2001

[37] Azam, M. and Javed, M.Y.," Discrete Cosine Transform (DCT) Based Face Recognition in Hexagonal Images", Proceedings of 2nd International Conference on Computer and Automation Engineering (ICCAE 2010), 26-28, February 2010 (ISBN: 978-1-4244-5585-0), Singapore, pp. 168-170.

[38] Randa Atta and Mohammad Ghanbari, 'Low-Memory Requirement and Efficient Face Recognition System Based on DCT Pyramid', IEEE Transactions on Consumer Electronics, Vol. 56, No. 3, August 2010

[39] M. Lades, J.C. Vorbruggen, J. Buhmann, J. Lange, C. von derMalsburg, R.P. Wurtz, and W. Konen, "Distortion Invariant ObjectRecognition in the Dynamic Link Architecture," IEEE Trans.Computers, vol. 42, no. 3, pp. 300-311, Mar. 1993.

[40] S. Mika, G. Ratsch, J. Weston, B. Scholkopf, and K.R. Miller,"Fisher Discriminant Analysis with Kernels," Neural Networks for Signal Processing IX, Y.H. Hu, J. Larsen, E. Wilson, and S. Douglas, eds., pp. 41-48, 1999.

[41] T. Cooke, "Two Variations on Fisher's Linear Discriminant forPattern Recognition," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 24, no. 2, pp. 268-273, Feb. 2002.

[42] G. Baudat and F. Anouar, "Generalized Discriminant AnalysisUsing a Kernel Approach," Neural Computation, vol. 12, no. 10,pp. 2385-2404, 2000.

[43] M.H. Yang, "Kernel eigenfaces vs. Kernel Fisherfaces: FaceRecognition Using Kernel Methods," Proc. Fifth Int'l Conf.Automatic Face and Gesture Recognition, May 2002.

[44] W. Zheng, L. Zhao, and C. Zou, "A Modified Algorithm forGeneralized Discriminant Analysis," Neural Computation, vol. 16, no. 6, pp. 1283-1297, 2004.

[45] Xiaoli Zhou and BirBhanu "Integrating Face and Gait for Human Recognition at a Distance in Video":IEEE transactions on systems, man, and cybernetics—part b: cybernetics, vol. 37, no. 5, october 2007.

[46] S. Periaswamy and H. Farid, "Elastic registration in the presence of intensityvariations," IEEE Trans. Med. Imag., vol. 22, no. 7, pp. 865–874,Jul. 2003.

[47] K. Okada, J. Steffens, T. Maurer, H. Hong, E. Elagin, H. Neven, and C.v.d. Malsburg, "The Bochum/USC face recognition system and how it fared in the FERET phase III test," in Face Recognition from Theoryto Application, H. Wechsler et al., Eds. New York: Springer-Verlag,1998, pp. 187–205.

[48] A. Pentland, B. Moghaddam, and T. Starner, "View-based and modulareigenspaces for face recognition," in *CVPR'94*, 1994, pp. 84–91.

[49] D. J. Beymer, Face recognition under varying pose, in A.I. Memo, MITAI Lab, no. 1464, 1993.

[50] D. Beymer, A. Shashua, and T. Poggio, Example based image analysisand synthesis, in A.I. Memo, Artificial Intelligence Laboratory, MIT, no.1431, 1993.

[51] T. Vetter and T. Poggio, "Linear object classes and image synthesis from a single example image," IEEE Trans. Pattern Anal. Machine Intell., vol.19, no. 7, pp. 733–742, 1997.

[52] V. Blanz and T. Vetter. A morphable model for the synthesisof 3D faces. In Computer Graphics Proc. SIGGRAPH'99,pages 187.194, 1999.

[53] Chao-Kuei Hsieh, Shang-Hong Lai and Yung-Chang Chen "An Optical Flow-Based Approach to Robust Face Recognition Under Expression Variations" :IEEE transactions on image processing, vol. 19, no. 1, january 2010.

[54] E. Osuna, R. Freund, and F. Girosi. Training support vectormachines: An application to face detection. In Proc.Computer Vision and Pattern Recognition'97, pages 130–136, 1997.

[55] AshwiniKanade, AkhilKhare "A Hybrid Nueral Network Approach for Face Recognition" International Journal of Modem Engineering Research(IJMER), Vol 2,Issue. 3 May-June 2012 pp-574-578.

[56] C.-K. Hsieh, S.-H. Lai, and Y.-C. Chen, "Expression-invariant facerecognition with accurate optical flow," in Proc. PCM, Hong Kong,Dec. 11–14, 2007.

[57] A. M. Martinez, "Recognizing expression variant faces from a single sample image per class," presented at the IEEE Conf. Computer Vision and Pattern Recognition, Jun. 2003.

[58] S. Haykin, Neural Networks—A Comprehensive Foundation, second ed. Prentice Hall, 1999.

[59] P.J. Phillips, W.T. Scruggs, A.J. O'Toole, P.J. Flynn, K.W. Bowyer, C.L.Schott, and M. Sharpe, "FRVT 2006 and ICE 2006 Large-Scale Results," Technical Report NISTIR 7408, Nat'l Inst. of Standards and Technology,Mar. 2007.

[60] H. Ling, S. Soatto, N. Ramanathan, and D. Jacobs, "A Study of FaceRecognition as People Age," Proc. IEEE Int'l Conf. Computer Vision, pp. 1-8,2007.

[61] Unsang Park, Yiying Tong, and Anil K. Jain "Age-Invariant Face Recognition": IEEE transactions on pattern analysis and machine intelligence, vol. 32, no. 5, may 2010.

[62] Anthropometry of the Head and Face, L.G. Farkas, ed. Lippincott Williams &Wilkins, 1994.

[63] N. Nixon and P. Galassi, The Brown Sisters, Thirty-Three Years. The Museumof Modern Art, 2007.

[64] J. Han and B. Bhanu, "Individual recognition using gait energy image,"IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 2, pp. 316–322,Feb. 2006.

[65] Xiaoli Zhou and BirBhanu "Feature Fusion Of Side Face And Gait for Video Based Human-identification" Volume 41, Issue 3, March 2008, Pages 778–795.

[66] A. Sundaresan, A. Roy-Chowdhury, and R. Chellappa, "A hiddenMarkovmodel based framework for recognition of humans from gait sequences,"inProc. Int. Conf. Image Process., 2003, vol. 2, pp. 93–96.

[67] P. S. Huang, C. J. Harris, and M. S. Nixon, "Recognizing humans bygait via parametric canonical space," *Artif. Intell. Eng.*, vol. 13, no. 4,pp. 359–366, Oct. 1999.

[68] D. Tao, X. Li, X. Wu, and S. Maybank, "Human carrying status in visualsurveillance," in Proc. IEEE Conf. Comput. Vis. and Pattern Recog., 2006,vol. 2, pp. 1670–1677.

[69] V. Blanz and T. Vetter. Face recognition based on _tting a3d morphable model. IEEE Trans. on Pattern Analysis andMachine Intelligence, 25(9):1063. 1074, 2003.

[70] Karl B. J. Axnick1 and Kim C. Ng1 "Fast Face Recognition"

[71] A.Pentland, B. Moghaddam, T. Starner, O. Oliyide, and M. Turk., "View-Based and ModularEigenspaces for Face Recognition", Technical Report 245, MIT Media Lab, 1993.

[72] S. Da-Rui and W. Le-Nan, "A local-to-holisticface recognition approach using elastic graphmatching" Proc. International Conference onMachine Learning and Cybernetics, Vol. 1,Page(s):240 - 242, 4-5 Nov. 2002.

[73] B.V.K. Vijaya Kumar, A. Mahalanobis and Richard Juday, *Correlation Pattern Recognition*, Cambridge University Press, November 2005.

[74] C. F. Hester and D. Casasent, "Multivariant technique for multiclass pattern recognition," *Appl. Opt*. 19, pp.1758-1761 (1980).

[75] Mahalanobis, B.V.K. Vijaya Kumar, and D. Casasent, "Minimum average correlation energy filters," *Appl. Opt*. 26, pp. 3633-3630 (1987).

[76] M. Savvides, B.V.K. Vijaya Kumar and P. Khosla, "Face verification using correlation filters," *Proc. Of Third IEEEAutomatic Identification Advanced Technologie*s, Tarrytown, NY, pp.56-61 (2002)

[77] B. V. K. Vijaya Kumar, MariosSavvides, ChunyanXie, KrithikaVenkataramani, Jason Thornton, and AbhijitMahalanobis, "Biometric Verification with Correlation Filters," Appl. Opt. **43**, 391-402 (2004)

[78] Savvides, M. Vijaya Kumar, B.V.K. ; Khosla, P.K. " Cancelable biometric filters for face recognition" Pattern Recognition, 2004. ICPR 2004Page(s): 922 - 925 Vol.3

[79] ChunyanXie, B. V. K. Vijaya Kumar, S. Palanivel and B. Yegnanarayana, ' A Still-to-Video Face Verification System Using Advanced Correlation Filters ,' in International Conference on Biometric Authentication, pp. 102-108, 2004.

[80] Elias Rentzeperis,Thesis on A Comparative Analysis of Face RecognitionAlgorithms: Hidden Markov Models, Correlation Filters and Laplacianfaces Vs. Linear subspace projection and Elastic Bunch Graph Matching.

[81] T.F. Cootes, A. Hill, C.J. Taylor, J. Haslam, The use ofactive shape models for locating structures in medicalimages, IPMI, 1993, pp. 33–47.

[82] G. Hamarneh. Active shape models, modeling shape variations and graylevel information and an application to image search and classification.Technical report, The Imaging and Image Analysis Group, Departmentof Signals and Systems, Chalmers University of Technology, Gothenburg,Sweden, 1998.

[83] X. Hou, S. Li, H. Zhang, Direct appearance models,Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2001, pp. 828–833.

[84] K. I. Diamantaras and S. Y. Kung, Principal Component Neural Networks:*Theory and Applications*. New York: Wiley, 1996.

[85] M. J. Er, S. Wu, J. Lu, and H. L. Toh, “Face recognition with radialbasis function (RBF) neural networks,” *IEEE Trans. Neural Netw.*, vol. 13, no. 3, pp. 697–710, May 2002.

[86] J. Lu, X. Yuan, and T. Yahagi, “A method of face recognition based on fuzzy c-means clustering and associated sub-NNs,” *IEEE Trans. Neural Netw.*, vol. 18, no. 1, pp. 150–160, Jan. 2007.

[87] P. Melin, C. Felix, and O. Castillo, “Face recognition using modularneural networks and the fuzzy Sugeno integral for response integration,” *Int. J. Intell. Syst.*, vol. 20, no. 2, pp. 275–291, Feb. 2005.

[88] Face Recognition Using Self-Organizing Maps, Qiu Chen, Koji Kotani, Feifei Lee and TadahiroOhmi, Tohoku University, Japan.

[89] Neagoe, V.-E., 'Concurrent self-organizing maps for pattern classification' , Cognitive Informatics, 2002. Proceedings. First IEEE International Conference on 2002, Page(s): 304 - 312

[90] A.S.Raja and V. JosephRaj ,'neural network based supervised self organizing maps for face recognition', International Journal on Soft Computing (IJSC) Vol.3, No.3, August 2012

[91] Gregoire Lefebvre and Christophe Garcia, 'A probabilistic Self-Organizing Map for facial recognition ', 19th International Conference on Pattern Recognition, (ICPR) 8-11 Dec. 2008 Page(s): 1 - 4

[92] C. Liu and H. Wechsler, Probablistic reasoning models for face recognition, in Proc. of Computer Vision andPattern Recognition, 827-832, 1998.

[93] Moghaddam, B., Nastar, C., Pentland, A.: A Bayesian similarity measure for direct image matching. In: 13th International Conference on Pattern Recognition. (1996) II: 350–358.

[94] Wilman W. W. Zouand Pong C. Yuen, “Very Low Resolution Face Recognition Problem,” IEEE transactions on image processing, vol. 21, no. 1, January 2012.

[95] N. Sudha, A. R. Mohan, Pramod K. Meher, “A Self-Configurable Systolic Architecture for Face Recognition System Based on Principal Component Neural Network,” IEEE transactions on circuits and systems for video technology, vol. 21, no. 8, august 2011.

[96] Chengjun Liu and Harry Wechsler, “Independent Component Analysis of Gabor Features for Face Recognition,”IEEE transactions on neural networks, vol. 14, no. 4, july 2003.

[97] Bai-Ling Zhang, Haihong Zhang and Shuzhi Sam Ge, ”Face Recognition by Applying Wavelet Subband Representation and Kernel Associative Memory,”IEEE transactions on neural networks, vol. 15, no. 1, january 2004.

[98] Wenchao Zhang, Shiguang Shan, Xilin Chen and Wen Gao, ”Local Gabor Binary Patterns Based on Kullback–Leibler Divergence for Partially Occluded Face Recognition,” IEEE signal processing letters, vol. 14, no. 11, november 2007.

[99] Zhiming Liu and Chengjun Liu, “A Hybrid Color and Frequency Features Method for Face Recognition,” IEEE transactions on image processing, vol. 17, no. 10, october 2008.

[100] G. C. Feng and Pong C. Yuen, “Recognition of Head-&-Shoulder Face Image Using Virtual Frontal View Image” IEEE transactions on systems, man, and cybernetics—part a: cybernetics, vol. 30, no. 6, november 2000.

[101] Stan Z. Li,RuFeng Chu, ShengCai Liao, and Lun Zhang, “Illumination Invariant Face Recognition Using Near-Infrared Images” IEEE transactions on pattern analysis and machine intelligence, vol. 29, no. 4, april 2007.

[102] Richa Singh, MayankVatsa, ArunRoss,andAfzelNoore,” A Mosaicing Scheme for Pose-Invariant Face Recognition” IEEE transactions on systems, man, and cybernetics—part b: cybernetics, vol. 37, no. 5, october 2007

[103] Dirk Smeets, Peter Claes, JeroenHermans, Dirk Vandermeulen, and Paul Suetens, “A Comparative Study of 3-D Face RecognitionUnder Expression Variations” IEEE transactions on systems, man, and cybernetics part c: applications and reviews, vol. 42, no. 5, september 2012.

[104] Zhifeng Li, Unsang Park, and Anil K. Jain *“*A Discriminative Model for Age Invariant Face Recognition*”*- IEEE transactions on information forensics and security, vol. 6, no. 3,september 2011.

[105] Kim K. I., Jung K. and Kim H.J. 2002. Face recognition using kernel principal component analysis. IEEE Signal Processing Letters, Vol. 9, pp. 40–42.

[106] A. Nefian, “A Hidden Markov Model-Based Approach for Face Detection andRecognition”, PhD dissertation in Electrical Engineering, Georgia Instituteof Technology

[107] Martinez, A.M., Kak, A.C., 2001. PCA versus LDA. IEEE Trans. PatternAnal. Machine Intell. 23 (2), 228–233.

[108] Bartlett Marian, Stewart, Movellan Javier, R., Sejnowski Terrence, J.,2002. Face recognition by independent component analysis. IEEE Trans. Neural Networks 13 (6), 1450–1464.

[109] Chirag Patel and RipalPatel,'Gaussian mixture model based Moving object detection from video sequence',International Conference and Workshop on Emerging Trends in Technology (ICWET 2011) – TCET, Mumbai, India

[110] Chirag I Patel and Sanjay Garg,' Robust Face Detection using Fusion of Haar and Daubechies Orthogonal Wavelet Template ' *International Journal of Computer Applications (0975 – 8887) Volume 46– No.6, May 2012* 38

[111] Chirag. I. Patel and Ripal Patel, "Contour Based Object Tracking," *International Journal of Computer and Electrical Engineering* vol. 4, no. 4, pp. 525-528, 2012.

[112] Chirag. I. Patel and Ripal Patel, "Object Counting in Video Sequences," *International Journal of Computer and Electrical Engineering* vol. 4, no. 4, pp. 522-524, 2012.

[113] Chirag I. Patel, Ripal Patel and Palak Patel, 'Goal Detection from Unsupervised Video Surveillance',Advances in Computing and Information Technology Communications in Computer and Information Science Volume 198, 2011, pp 76-88

[114] Chirag Patel, Ripal Patel and Palak Patel . Handwritten Character Recognition using Neural Network, *International Journal of Scientific and Engineering Research*, Volume 2, Issue 4, April 2011.