A REVIEW ON CLASSIFIERS USED IN FACE RECOGNITION METHODS UNDER POSE AND ILLUMINATION VARIATION

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Abstract:

Face recognition and authentication are two significant and vigorous research issues in computer vision applications such as military, secure control and crime prevention systems. There are many factors that should be accounted for face Recognition; among them Pose and Illumination invariant are two major challenges.Pose and illumination variations harshly influence in the performance of face recognition. In order to improve the performance, several research methods have been developed to perform the face recognition process with pose and illumination conditions. In this paper we review and compare such recently developed face recognition methods with 2D face Images with Pose and Illumination. The comparison results shows that all existing methods have good performance in the face recognition process but on Pose and Illumination variation with different Classifiers gives different results based on the measurement of FAR, FRR and Accuracy. To improve the performance in face recognition methods there is a need to develop an effective face recognition technique under pose and illumination conditions.

Index Terms: *Eigen Faces, False Acceptance Rate, False Rejection Rate, Gallery set, Probe faces.*

I. INTRODUCTION

Today's needs to maintain information or external property protection practices and challenges in the universe are interconnected.Security and the rising importance of various platforms available in identification and authentication methods are the major technical change in different areas [4].Some of the common physiological properties, Which are used for personal identification, include fingerprints, palm prints, hand geometry, retinal patterns, facial patterns, iris patterns, etc. Behavioral properties include signature, voice pattern, keystroke dynamics etc. A biometric system is capturing and storing biometric data and comparing the data with the database. Biometric technology will focus on areas such as high-level security systems and law enforcement market. The core concentration of biometric technology is its ability to identify and monitor the safety of human [3]. Compared to other biometrics such as fingerprints and iris, human faces have the clear advntages of being natural and non-intrusive. As a result, face recognition has attracted considerably improved attention from both academic and industrial communities in last decade. It has been used in many applications, such as credit card verification, criminal identification, seizure control, security, user logon face recognition, human-computer interaction, face to find a system, AFRS, album, etc. In order to robust in practice, face recognition system has been successfully achieved in uncontrolled environmental conditions, such as variable lighting, a variety of expressions, age, cause, etc [5]. Face recognition is a vital part of the domain object recognition in which the scientific community has shown a growing attention in the past so many decades. Since then, the rapid development of technology and the commercialization of technological achievements, face detection became more and more popular [6].

One of the greatest challenges in face recognition systems is to recognize faces around different poses and illuminations [13]. The first step of face recognition is the identification of an efficient method to reduce the dimensionality, Feature Extraction and Classifier,finally Classification.

Face recognition across pose refers to recognizing face images in diverse poses by computers. It is of much attention in many face recognition applications, more particularly those using indifferent or un-cooperative subjects, such as surveillance systems. Consider an example, face recognition is attempting in airport security is to recognize terrorists and prevent them from boarding plane. Ultimately, the terrorist's faces are collected and piled up in the database against which travelers faces will be compared. Every one's faces undergoing the security check point will get scanned. When a match is found, the cameras will be pointed on to surveil people with a live video feed, and then the authorities will authenticate the match and decide whether to stop the individual whose face matches one in the database. The most natural solution for this task might be to collect multiple gallery images in all possible poses to cover the pose variations in the captured images, which requires a fairly easy face recognition algorithm [14]. Illumination difficulty occurs due to irregular lightening on faces. This irregular lightning generates variations in illumination that distress the classification very much since the facial features that are being used for classification gets effected due to this variation [6]. There are plentiful literatures on illumination invariant feature extraction in the area of face recognition, since variable lighting face recognition is a vital issue for many applications in computer vision. It has been shown that, in face recognition, changes due to different illuminations are more important than the inherent dissimilarities amid face identities. The illumination-invariant feature extraction which only mines discriminative features that are invariant for the same person under various lighting environments and discriminative between various people [15].

Among numerous methods proposed to concentrate on the pose problem the extensively used method are view-based methods [16]. Varied appearance of the 3D shape of human faces under lighting from diverse direction is the central cause for troubles associated with Illumination variation for facial image. Principalomponents analysis [17], discrete wavelets transform [18], and discrete cosine transforms [19] and Gabor wavelet-based representation [20] are some of the several methods for representing face images that have been proposed in the literature. But the success of these methods is not bright because they have got two significant disadvantages. The first one is high computational complexity and the second one is the exceptionally large memory required for storing features. Little effort has been taken to deal with the problem of unified variations of pose and illumination, though several algorithms have been proposed for face recognition from fixed viewpoints [29]. Over past few decades, many face recognition methods have been developed. Often used feature extraction methods are principal component analysis (PCA), [13] and linear discriminant analysis (LDA). Another linear technique identified as Locality Preserving Projections (LPP), which finds an embedding that preserves local information, and gains a face subspace that best detects the essential face manifold structure.

The paper is organized as follows. Section 2 reviews the approaches of Pose and Illumination based methods for face recognition. Section 3 reviews the face recognition process and its subsections are give the detailed descriptions of the various methods that are involved in the face recognition process. Section 4 presents the results and comparison analysis. Finally there is a conclusion in Section 6.

II.RELATED RESEARCHES: APPROACHES OF POSE AND ILLUMINATION VARIATION

Shermina et al. [21] have proposed a face recognition method that was robust to pose and illumination variations. For processing the pose invariant image, the Locally Linear Regression (LLR) method was used to create the virtual frontal view face image from the non frontal view face image. For processing the illumination invariant image, low frequency components of Discrete Cosine Transform (DCT) were used to normalize the illuminated image. In order to recognize the facial images that were both pose variant and illumination variant, the Fisher Linear Discriminant Analysis (FLDA) method and Principal Component Analysis (PCA) methods are used. As a final part the scores of FLDA and PCA were combined using a hybrid technique based on the Feed Forward Neural Network (FFN). Based on the scores obtained in the initial recognition process, a weight was assigned to the image. The image was recognized based on the weight assigned and the combination of the scores. From the implementation result, it was evident that their proposed method based on the hybridization technique recognizes the face images effectively.

Sang-Il Choi et al. [22] Described as a 2D image-based approach that can simultaneously handle illumination and pose variations to enhance face recognition rate. It was much simpler, requires much less computational effort than the methods based on 3D models, and provides a comparable or better recognition rate.

Ralph Gross et al. [23] have discussed that the last decade has seen automatic face recognition evolve from small scale research systems to a wide range of commercial products. Driven by the FERET face database and evaluation protocol, the currently best commercial systems achieve verification accuracies comparable to those of fingerprint recognizers. In these experiments, only frontal face images taken under controlled lighting conditions were used. The two successful appearance-based algorithms for face recognition across pose are used, Eigen light-fields and Bayesian face sub regions. They furthermore show how both of these algorithms can be extended towards face recognition across pose and illumination.

Kailash J. Karande et al. [24] Have addressed that the problem of face recognition under variation of illumination and poses with large rotation angles using Independent Component Analysis (ICA). Face recognition using ICA, based on information theory concepts, seek a computational model that best describes face, by extracting most relevant information contained in that face. ICA approach used here to extract global features seems to be an adequate method due to its simplicity, speed and learning capability. The preprocessing has been done by Principle Component Analysis (PCA) before applying the ICA algorithm for training of images. The independent components obtained by ICA algorithm has been used as feature vectors for classification. The Euclidian distance classifier has been used for testing of the images. The variation in illumination and facial poses up to 1800 rotation angle was used by the proposed method and result have shown that the recognition improved significantly.

Fatih Kahraman et al. [25] have developed AAM based on face alignment method which handles illumination and pose variations. The classical AAM fails to model the appearances of the same identity under different illuminations and poses. From the experimental results, they have showed that the proposed face restoration scheme for AAM provides higher accuracy for face alignment in point-to-point error sense. Recognition results based on PCA and LDA feature spaces showed that the proposed illumination and pose normalization outperforms the standard AAM.

III. FACE RECOGNITION – A REVIEW

Face recognition is one of the biometric methods identifying individuals by the features of face. Research in this area has been performed for more than 30 years; as a result, the current status of face recognition technology is well advanced. As a result, numerous methods have been developed for face recognition in the last few decades. These methods perform the face recognition process under different illuminations and poses by exploiting the classification and feature extraction process. The different classifiers and the features extraction method performs in the face recognition process are discussed in the following subsections.

A. Face Recognition using ICA

The face recognition process by ICA initially performs the preprocessing procedure in the training data set images using the PCA and the features from the ICA are used in the classification process. In classification, the Euclidian distance classifier classifies the testing images based on the features vectors. The proposed face recognition method utilized the images with large rotation angles with poses and variation in illumination conditions. They used the database which has the large rotation angles up to 1800 change between the images of person while looking right and or left. The face images having various orientations of the face are looking front, looking left, looking right, looking up, looking up towards left, looking up towards right and looking down. In this study they have considered the samples of individual person which consist of sufficient number of images having expressions, changes in illumination and large rotation angles. The dimensionality reduced data results from PCA are given to the feature vectors extraction process based on ICA. The ICA based face recognition was presented in [24].

Independent component analysis (ICA) is a method for finding underlying factors or components from multivariate (multidimensional) statistical data. There is a need to implement face recognition system using ICA for facial images having face orientations and different illumination conditions. The independent components are computed from the PCA result Eigen vector matrix and make the matrix as square by reduce the size of the matrix. The feature vectors matrix contains the independent components are further utilized in the classification process. The Euclidian distance classifier finds the distance between the input testing image and the recognized training dataset images. If the distance between these two images is small we say that the two images are same otherwise the images are different.

B. Face Recognition using Pose Estimation and Shadow Compensation

The Face Recognition using Pose Estimation and Shadow Compensation approach based on 2D images for handling illumination and pose variations simultaneously. The proposed method consists of three parts which are pose estimation, shadow compensation and face identification. For a face image with multiple variations, the pose of the face image has been estimated by using the proposed pose estimation method. After assigning a face image to an appropriate pose class, the face image has processed by the shadow compensation procedure customized for each pose class. These shadow compensated images are used for face identification by a classification rule. The detailed procedures of this face recognition process are in [22]. In the face recognition process, they first proposed a simple pose estimation method based on 2D images, which uses a suitable classification rule and image representation to classify a pose of a face image. In order to represent the characteristic of each pose class, they transformed a face image into an edge image, in which facial components such as eyes, nose and mouth in the image has been enhanced. Then, the image can be assigned to a pose class by a classification rule in a low-dimensional subspace constructed by a feature extraction method. Second, they proposed a shadow compensation method that compensates for illumination variation in a face image so that the image can be recognized by a face recognition system designed for images under normal illumination condition. Generally, human faces are similar in shape in that they are comprised of two eyes, a nose and a mouth. Each of these components forms a shadow on a face, showing distinctive characteristics depending on the direction of light in a fixed pose. Furthermore, they extended the compensation method that works not only for the frontal pose class but also for other pose classes as well.

The cast shadow is caused by the blockage of light from a light source by some part of a subject, and projected onto another part of the subject itself. The edge images are effective especially when shadow is present on face images due to illumination variation. These shadow compensated images in each pose class are used for face recognition. The Sobel edge detector is used to eliminate the unnecessary edge shapes in the facial components. By applying a discriminant feature extraction method to these Sobel edge images from the images of training set, a subspace is constructed for each of pose classes. The pose of each image projected into the subspace is classified by using the one nearest neighborhood rule with the distance metric l2.

C. Face Recognition System Based on the Hybridization of Invariant Pose and Illumination process

This face recognition system performs the pose invariant and illumination process individually as well as simultaneously based on the user input. If 'pose invariant' is the user input, then in the initial step, the pose invariant process is executed and the created virtual frontal view of the image is given as input to the illumination invariant process. If 'illumination invariant' is the user input, then in the initial step, the illumination invariant process is executed and the normalized image is given as input to the pose invariant process. If 'both pose variant and illumination variant' is the user input, then both processes are executed concurrently.

This method uses the Locally Linear Regression (LLR) to execute the pose invariant process. Identifying the face images under diverse pose and illumination conditions is the objective of their proposed method. This face recognition system consists of several steps are explained in [21]. First after choosing the im.age from the database, the process to be executed at first is decided on the basis of user input. It creates a corresponding virtual frontal view face image if the given image is a non frontal face image. Then, the Fisher Linear Discriminant Analysis (FLDA) method is used to recognize the face image. In the illumination invariant process, lower frequency component of Discrete Cosine Transform (DCT) is used to obtain the normalized image. The normalized image is then recognized using the Principal Component Analysis (PCA). In the final step, the scores of both the pose and illumination invariant process are combined using a novel hybrid approach. The hybrid approach is a Feed forward Neural Network (FFN) can be used to recognize the face images based on the combinations of the scores. Based on the score acquired by the recognition methods, a weight is assigned to the image. The results are selected from the FFN, if it has a maximum value. If the output of the selected network passes a predefined threshold, it will be reported as the host of the input face. Otherwise it will be reported as unknown and adds this member to the face library.

D. Face Recognition across Pose and Illumination

This Face Recognition process addresses the face recognition by the appearance based algorithm. Different from the other existing algorithms, that paper only focus the pose not illumination i.e. the appearance based algorithm perform the face recognition across pose. The proposed appearance based algorithm of that paper is an Eigen light field estimation algorithm. The Eigen light field algorithm comprised of two steps, namely, vectorization and classification are given in [23]. Their algorithm can use any number of gallery images captured at arbitrary poses, and any number of probe images also captured with arbitrary poses. A minimum of 1 gallery and 1 probe image are needed, but if more images are available the performance of our algorithm generally improves.

Vectorization consists of converting the input images into a light- field vector (with missing elements, as appropriate.). The input to a face recognition algorithm consists of a collection of images (possibly just one) captured from a variety of poses. The Eigen Light-Field Estimation Algorithm operates on light-field vectors (light- fields represented as vectors). Vectorization is performed by first classifying each input image into one of a finite number of poses. For each pose, normalization is then applied to convert the image into a sub-vector of the light- field vector. Before that conversion process the light-field vactors are discretized into pixels. The most natural way to do this is to uniformly sample the light-field angles. Given a set of gallery faces, they obtain a corresponding set of vectors and an index value is allocated over the set of gallery faces. Similarly, given a probe face, they obtain a vector of Eigen coefficients for that face. The vector of Eigen coefficients outputs from the Eigen light-field estimation algorithm are given to the classification process. In classification the nearest neighbor algorithm which classifies the vector with the index.

Their algorithm models the appearance changes of the different face regions in a probabilistic framework. Using probability distributions for similarity values of face sub regions they have computed the likelihood of probe and gallery images coming from the same subject. The intensity values in each of the sub regions are normalized to have zero mean and unit variance. As similarity measure between sub regions they have used SSD (sum of squared difference) values. Since they compute SSD after image normalization it effectively contains the same information as normalized correlation. They currently do not model dependencies between sub regions, so they simply combine the different probabilities using the sum rule and choose the identity of the gallery image with the highest score as recognition result. Since appearance-based methods use image intensities directly they are inherently sensitive to variations in illumination. Drastic changes in illumination such as between indoor and outdoor scenes therefore cause significant problems for appearance-based face recognition algorithms. Hence they describe two different ways of handling illumination variations in facial imagery. The first algorithm extracts illumination invariant subspaces by extending the previously introduced eigen light-fields to Fisher light-fields, mirroring the step from eigenfaces to Fisher faces. The second approach combines Bayesian face sub regions with an image preprocessing algorithm that removes illumination variation prior to recognition. In both cases they have demonstrated the results for face recognition across pose and illumination.

E.Face Recognition by Histogram Fitting and AAM

The AAM based approach producing different poses of unseen person and a non-frontal face is projected to a frontal face. Their primary goal is to eliminate the negative effect of challenging conditions, especially illumination and pose, on the face recognition system performance through illumination and pose-invariant face alignment based on Active Appearance Model are explained in [25]. Active Appearance Models are generative models capable of synthesizing images of a given object class. By estimating a compact and specific basis from a training set, model parameters can be adjusted to fit unseen images and hence perform image interpretation. Training objects are defined by marking up each image with points of correspondence. Relying upon the landmarks, a triangulated mesh is produced for the reference position and orientation of the object. Before modeling variations, all shape vectors are normalized to a common reference shape frame by using Procreates Analysis. After obtaining the reference shape vector, all of the training images are warped to the reference shape by using a piecewise affine warping, which is defined between corresponding triangles to obtain normalized texture vectors.

AAM uses principal component analysis (PCA) to model the variations of the shapes and textures of the images. Usage of PCA representation allows AAM to model and represent a certain image with a small set of parameters. After that the illumination normalization process is applied to the faces captured under different illumination conditions. The illumination normalization process improves the accuracy of the solution. They have utilized a new histogram fitting algorithm for taking the structure of the face into account in face illumination normalization. The algorithm is to fit the histogram of the input face image to the histogram of the mean face. The face is first divided into two parts (left/right) and then the histogram of each window is independently fitted to the histogram of mean face.

Pose normalization is required before recognition in order to reach acceptable recognition rates. The variation in pose imposes effect on the face appearance for all individuals. Deformation mostly occurs on the shape whereas the texture is almost constant. Therefore they change pose, only wireframe triangles undergo affine transformation but the gray level distribution within these translated and rotated triangles remains the same. Appearances are also obtained through warping in AAM framework, using synthetically generated landmarks. Moreover, the AAM model trained by using only frontal faces can only fit into frontal faces well and fail to fit into non-frontal faces. They have enriched the training database by inserting synthetically generated faces at different poses so that AAM model trained by frontal faces can now converge to images at any pose. The trained AAM generate pose variations not govern by any shape ratio vector. Subsequently they obtain the aligned faces with high accuracy based on the proposed AAM-histogram fitting method.

IV. RESULTS AND DISCUSSION

The experimental result of the ICA based face recognition method divided into two parts. Both parts evaluate the face representations using PCA as well as ICA methods. In first part the face images are used that have the pose variation with large rotation angles. In second part the face images are used that have variation in illumination conditions. They also presented the result of traditional method of face recognition using PCA, these results are used for comparison purpose with face recognition using ICA algorithm. Two standard databases are used for evaluation of these results. The first database is an Indian face database, in these database images of 60 persons with 10 sample images with different

IJCSI International Journal of Computer Science Issues, Vol. 9, Issue 6, No 2, November 2012
ISSN (Online): 1694-0814
www.IJCSI.org

orientations and views are available. The second database known as Asian face image database having face images of 56 male persons with 10 samples each; which consist of variation in illumination conditions and different views. The resolution of all images they used in the algorithm is 128 x 128 for computational purpose.

The both ICA and PCA methods face recognition performance results are compared, the comparison results of these methods are in Table 1.

Table 1: Results of the Face Recognition Algorithm using ICA

Conditions of Images Used for Algorithm	***Database Used***	***No of Components Used (PCs & ICs)***	***Recognition Rate Using PCA (%)***	***Recognition Rate Using ICA (%)***
Part I-Pose Variation with Large Rotation Angles	Indian Face Database[24]	50	100	100
		100	100	100
		150	90.33	96
		200	90.5	92.5
Part II-Variation of Illumination Conditions	Asian Face Data Base[24]	50	100	100
		100	97	94
		150	92	89.33
		200	90.5	86.5

The result shows that existing face recognition methods using ICA their algorithm gives better results under various conditions of face images. The performance of the algorithm suggested produces very good recognition rate varying from 86% to 100%. If they observed the results of face recognition using ICA under pose variation with rotation angles up to 180^0, the results are very good and encouraging. The results of the second part with ICA method are also close to the results of first part. This implies that ICA on face images is less sensitive to face orientations as compared to illuminations as shown in results.

Another one face recognition method using post estimation and shadow compensation uses two face database images namely, CMU-PIE and Yale B for evaluate the performance. The CMU-PIE database contains more than 40,000 facial images of 68 individuals, 21 illumination conditions, 13 poses and four different expressions. Among them, we selected the images of 65 individuals with seven pose indices (c22,c02,c05,c27,c29,c14,c34), so that the entire set consists of 21 images in 7 pose classes of 65 individuals (21x7x65 images in total). The training set was constructed by randomly choosing 3 images from each pose for each individual (3x7x65 images), while the test set consisted of all the other images (18x7x65 images). In order to estimate the pose of a face image, each of the seven pose classes was assigned a numerical target value from 1 (left profile) to 7 (right profile). They repeated this test three times by changing the composition of training and test sets, and computed the average classification rate (image indices: ‘02’, ‘08’, ‘17’ for the first training set; ‘05’, ‘08’, ‘14’ for the second training set; ‘03’, ‘07’, ‘18’ for the third training set).

In order to extract useful features for discriminating the pose of a face image, they investigated the performance of feature extraction methods for regression problem such as the Sliced Inverse Regression (SIR) and the Principal Hessian Directions (PHD), along with the conventional LDA which has been very successful for classification problems and LDA-r, which is a variant of LDA to effectively handle classification problems with order relationship between classes. The overall classification rates of PHD and SIR (S = 10), which makes use of order relationship between classes and are good for regression problems, are both below 50.0%. On the contrary, LDA and LDA-r, which are good for classification problems, give the overall classification. The classification rates for SIR and PHD are 79.1% and 81.2%, respectively, which are better by more than 35%. As expected, the Sobel edge detector performs better than the canny edge detector for the pose classification problem. For the edge images produced by the Sobel edge detector, among all the feature extraction methods, LDA-r gives the best classification rate of 93.1%, which is 6.5%, 6.0% and 0.4% more than those of SIR, PHD and LDA, respectively.

The features were extracted from the shadow compensated images by the null space method (NLDA), which is widely used for face recognition.

With the features, the one nearest neighborhood rule was used as a classifier with the Euclidean distance (l_2) as the distance metric. They compared the proposed method with two other shadow compensation methods, which are mLBP (Modified Local Binary Pattern) and SQI (Self-Quotient Image). The methods I_{Raw}, I_{SQI} and I_{mLBP} give the average recognition rates of 91.1%, 96.0% and 98.4% for overall pose indices, respectively, whereas the average recognition rate for the images compensated by the proposed method (I^C) increases by 8.6%, 3.7% and 1.3% compared to I_{Raw}, I_{SQI} and I_{mLBP}, respectively. The average recognition rate over all the poses and illumination categories is 98.9% and the recognition rate does not change much depending on the pose class of the probe image.The comparison results of the methods in two different databases are given in following Tables 2 and 3.

Table 2: Recognition rates of different methods on the CMU-PIE

Method	***Pose of a probe image***		
	Front (c_{27})	***Half Profile (c_{05})***	***Profile (c_{22})***
3d MM	99.9	99.3	89.4
Spherical basis MM	96.5	96.7	80.6
Face recognition under illumination and pose variations	97	88	52
Face Recognition using Pose Estimation and Shadow Compensation[22]	99.5	99.4	99

Table 3: Recognition rates of different methods on the Yale B database

Method	***Pose of a probe image***		
	Front (Pose1)	***12^0 (Pose2-6)***	***24^0 (Pose7-9)***
Correlation	70.9	24.2	12.8
Cone Appox.	100	34.7	18
Correlation with Planar Transformations	62.4	53	36.4
Cone Approx. with Planar Transformations	99.3	84.5	51.9
Cone Approx. with Full Pose	99.1	97.3	94.5
Face Recognition using Pose Estimation and Shadow Compensation	95.8	94.8	92.3

The proposed method gave recognition rates of 92.3%–95.8% for all of the poses. That paper demonstrates that the face recognition system based on 2D images can be more efficient and effective under pose and illumination variations. Similar to the previous method, the Face Recognition System Based on the Hybridization of Invariant Pose and Illumination Process also uses Yale Database B for evaluate the performance of face recognition process. Nine different poses 10 individuals is present in the Yale face database B. 64 different illumination conditions exists for each pose. Single light source images of 10 subjects each seen under 576 viewing conditions i.e., a total of 5850 images are present in the database.

This method performance is evaluated by performing the comparison process with other existing approaches. The recognition accuracy of this proposed and existing methods are computed by the two measures are FRR (False Rejection ate) and FAR (False Acceptance Rate). FAR is the percentage of incorrect acceptances i.e., percentage of distance measures of different people's images that fall below the threshold. FRR is the percentage of incorrect rejections - i.e., percentage of distance measures of same people's images that exceed the threshold. The formula for this accuracy computation process is as follows, $Accuracy= 100-[FAR/FRR]/2$ (1)

The comparison results of the proposed and existing face recognition methods performance in terms of their FAR, FRR and Accuracy are shown in Table 4.

Table 4: Comparison results of Face Recognition System Based on the Hybridization of Invariant Pose and Illumination Process

Methods	***Database***					
	Yale Database B			***Yale Database***		
	FRR (%)	***FAR (%)***	***Accuracy (%)***	***FRR (%)***	***FAR (%)***	***Accuracy (%)***
Face Recognition based on Pose Invariant condition	6.82	8.25	93.4	5.73	7.48	95.4
Face Recognition based on Illumination Invariant condition	5.84	7.51	94.2	4.24	6.72	96.2
Face Recognition System Based on the Hybridization of Invariant Pose and Illumination Process	2.87	5.26	97.5	2.07	4.84	98.1

As can be seen in Table 4, that Face Recognition System Based on the Hybridization of Invariant Pose and Illumination Process has a lower value in both FAR and FRR error rate in both the databases. At the same time, the proposed system has a higher accuracy compared with the other two methods. The face recognition process across pose and illumination by using appearance based algorithms used two databases in face recognition process. The two databases are CMU Pose, Illumination, and Expression (PIE) database and the FERET database. Each of these databases contains substantial pose variation. In the pose subset of the CMU PIE database, the 68 subjects are imaged simultaneously under 13 different poses totaling 884 images. In the FERET database, the subjects are imaged non-simultaneously in 9 different poses. They used 200 subjects from the FERET pose subset giving 1800 images in total. If not stated otherwise they used half of the available subjects for training of the generic eigenspace (34 subjects for PIE, 100 subjects for FERET) and the remaining subjects for testing. In all experiments (if not stated otherwise) they retained a number of eigenvector sufficient to explain 95% of the variance in the input data.

They compared Eigen light-fields algorithm with eigenfaces and FaceIt. Eigen light-fields perform far better than other methods. Next the similar comparison process is carried out with the FERET database. Also the performance of the Bayesian face sub region method compared with the eigenfaces and FaceIt. In this comparison the Bayesian face sub region method gives good performance than other methods. The aforementioned eigen light fields and Bayesian face sub region are extended to the face recognition across both pose and illumination by using fisher light fields. The fisher light fields face recognition has been compared with the eigen light field and FaceIt. The both fisher light field and eigen light field methods provides better performance than FaceIt in different face recognition across pose and illumination are given in Table 5.

Table 5: A comparison of the performance of Eigen light-fields and Fisher light-fields with FaceIt on three different face recognition across pose and illumination scenarios

	Eigen Light	***Fields Fisher Light***	***Fields FaceIt***
Same pose, Different illumination	-	81.1	41.6
Different pose, Same illumination	72.9	-	25.8
Different pose, Different illumination	-	36.0	18.1

The face recognition method AAM combines the shape and texture model in one single model. The alignment algorithm (also called AAM searching) optimizes the model in the context of a test image of a face. The optimization criterion is the error occurring between a synthesized face texture and the corresponding texture of the test image. In this approach, they normalize the corresponding texture in the test image just before they compute the error. This AAM method is tested on the Yale-B face dataset. The total number of images under different lighting conditions for each individual is 64. The database is portioned into four sets identified as Set 1-4. Set 1contains face images whose light direction is less than ±20 degrees. Set 2 contains face images whose light directions are between ±20 and ±50 degrees. Set 3 contains face images whose light directions are between ±50 and ±70 degrees. Set 4 contains face images whose light directions are greater than ±70 degrees.To establish the models, 73 landmarks were placed on each face image; 14 points for mouth, 12 points for nose, 9 points for left eye, 9 points for right eye, 8 points for left eyebrow, 8 points for right eyebrow and 11 points for chin. The warped images have approximately 32533 pixels inside the facial mask.

The first one is called point-to-point error, defined as the Euclidean distance between each corresponding landmark. The other distance measure is called point-to-curve error, defined as the Euclidean distance between a landmark of the fitted shape. These errors are calculated for all images in the datasets (from Set 1 to Set 4). They conducted an experiment to see how close they fit into unseen faces at different poses. They perform 10 experiments for each test image with different initializations and took the average error. Moreover, there are two feature spaces are utilized to analyze the AAM method. To perform the training process, 25 images of each person are randomly selected from Set 1 dataset. All datasets (Set 1 through Set 4) contain faces of all poses. The remaining faces in Set 1 dataset are used as test data. Two feature spaces LDA and PCA are used for the experimental purpose. The recognition rates obtained when the original images are used as input to the classifier are denoted as ORG-PCA and ORG-LDA. The recognition rates obtained when the images restored by RI are used as input and are denoted as RI-PCA and RI-LDA. Finally, the recognition rates obtained when the images restored by HF are used as input and are denoted as HF-PCA and HF-LDA. ORG-PCA reaches to 74.36% at most, while ORG-LDA reaches to 91.26% at most in Set 1. This performance drops to 30.99% for ORG-PCA and to 41.13% for ORG-LDA in Set 4. On the other hand, HF-PCA reaches to 76.20% at most and HF-LDA reaches to 82.68% at most.

A. Comparison of Classifiers used in Pose and llumination variation

In comparative analysis process the aforementioned five face recognition methods performance is compared with one another. The comparison performed based on pattern matching classification task i.e. the given facial image is transformed into features, after which a classifier trained on example faces decides whether that particular facial image is present in the database or not. This section briefly discusses about the classifiers that have been used successfully in face recognition domain. Classifiers that are discussed in this paper are Euclidian distance [24], nearest neighbor classifier [22], Feed Forward Network[21], Eigenlight-field Estimation Algorithm[23], and AAM Histogram Fitting Method[25] which combined both Pose and Illumination Variation.

Eucldian distance classifiers test the distance between the key points of an face image and ICA generate 25 feature vectors for classification, the variation in illumination and facial poses up to 180 degree rotation angle having the testing with gallery image. In Nearest neighborhood classifier feature vectors are generated in terms of eigen light field vectors, the algorithm is used to find the index vector which is available in a given set of gallery of poses with merely Right profile and Left Profile.In Feed forward Neural Network (FFN) classifier used to recognize the face images based on the combinations of the scores. Based on the score acquired by the recognition methods, a weight is assigned to the image.This has been achieved consistently high performance, without a priori assumptions about the distributions from which the training images are drawn.In distance classifier method, to extract useful features, several feature extraction methods in Regression problem such as Sliced Inverse Regression ,Principal Hessian Direction, Conventional LDA,LDA-r are taken for pose estimation. Among this LDA, LDA-r gives 84% to 88%.AAM provides higher accuracy for face alignment in point-to-point error sense. With the help of histogram Fitting Align the Face. Recognition results based on PCA and LDA feature spaces showed that the proposed illumination and pose normalization outperforms the standard AAM.

Euclidian Distance Classifier and Nearest Neighborhood method depend on the feature vectors generated by ICA, PCA, and Eigen, with good performance with maximum 180 degree rotation. But Feed Forward Neural Network and Distance Classifier works better than above methods with the recognition rate less than the first two methods. AAM with Histogram Based Approximation is better than Distance Classifier method.

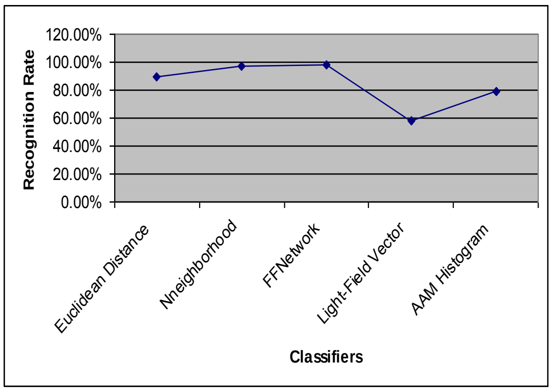

Figure 1: Classifiers Versus Recognition Rate

However these high performance methods also have drawback in their face recognition process as well as the conditions are utilized during the performance analysis. Hence the methods to be enhanced for attain the higher performance in the face recognition process and the drawbacks are presented in the existing face recognition methods.

V.CONCLUSION

In this paper, a comparative analysis of exiting face recognition methods was presented to examine the performances of such existing methods in terms of their face recognition rates. The comparative analysis shows that the existing methods are need to enhance to attain the higher recognition rates. This lower performance in comparative analysis process has motivated to do a new effective face recognition method under face and illumination with higher face recognition rate. The new developed face recognition method under pose and illumination process utilized most renowned method to perform the face recognition process. The performance of the most renowned method provided higher face recognition rates than the methods are discussed in the comparative analysis.

VI. REFERENCES

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