An Efficient Face Recognition System Based On the Hybridization of Pose Invariant and Illumination Process

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Abstract: *In the previous decade, one of the most effectual applications of image analysis and indulgent that attracted significant consideration is the human face recognition. One of the diverse techniques used for identifying an individual is the Face recognition. Normally the image variations for the reason that of the change in face identity are less than the variations between the images of the same face under different illumination and viewing angle. Among several factors that manipulate face recognition, illumination and pose are the two major challenges. Pose and illumination variations harshly affect the performance of face recognition. Considerably less effort has been taken to deal with the problem of mutual variations of pose and illumination in face recognition, while several algorithms have been proposed for face recognition from fixed points. In this paper we intend a face recognition method that is forceful to pose and illumination variations. We first put forward a simple pose estimation method based on 2D images, which uses a proper classification rule and image representation to classify a pose of a face image. After that, the image can be assigned to a pose class by a classification rule in a low-dimensional subspace constructed by a feature extraction method. We offer a shadow compensation method that compensates for illumination variation in a face image so that the image can be predictable by a face recognition system designed for images under normal illumination condition. Starting the accomplishment result, it is obvious that our projected technique based on the hybridization system recognizes the face images effectively.*

Keywords: *Face recognition, Pose, illumination, Edge detection, Shadow compensation*

1. Introduction

The increasing significance of safety and group surrounded by various platforms presently offered credentials and validation methods crooked out to key technology in different areas [1]. In recent times, the exploit of biometrics has improved considerably in personal security and/or right to use control applications [3]. Biometrics technology is likely to replace conventional validation methods that are easily stolen, elapsed and duplicated. Biometrics applied in fingerprints and iris scan deliver extremely steadfast performance, however human face reside as an striking biometric due to its payback over some of the other biometrics. Face recognition is non-intrusive and it needs no support from the test subjects, whereas supplementary biometrics necessitates a subject's cooperation. In favor of case, inside iris or fingerprint recognition, one be supposed to have a fleeting look over an eye scanner or place their finger on a fingerprint reader [4].

In the face of few biometric methods to facilitate the intrinsic worth of both high accuracy and low meddlingness, Face Recognition Technology has varied prospective over applications in the fields of information security, law enforcement and inspection, smart cards, access control and more [5], [2], [6]. Face recognition seems to encompass aspire challenges, while faces of different persons throw in to global shape individuality, whereas face images of a single person is subject to considerable variations, which might overcome the measured inter-person differences

Such variation is owing to the facts to incorporate facial expressions, illumination conditions, pose, presence or absence of eyeglasses and facial hair, occlusion, and aging [7, 8]. The essential consequence of face recognition as a biometric is its throughput, expediency and non-invasiveness. Most of the face recognition investigation done till date uses 2D intensity images as the data format for processing. Success has been achieved at diverse levels over 2D face recognition research [9].

The two major categories of face recognition scenario i.e. Face verification is a conversation match that evaluates a query of face image in counter with a gallery face image (The gallery face images have been stored in the database.) whose exceptionality being uncovered. Face identification is one-to-many matching processes that reflect on a query face image against all the gallery images in a face database to understand the individuality of the query face. The exposure of the query image is delivered by spotting the image in the database that has the maximum resemblance with the query image [10]. Face recognition seems to be the major issue in abundant notorious regions of machine vision for about a decennium. Topical systems have progressed to be reasonably precise in recognition below controlled situation. Conversely extrinsic imaging parameters such as pose, illumination, and facial expression still cause much complication in correct recognition [11]. In general, human face is similar in shape, have two eyes, a mouth and a nose.

Every component makes different distinctive shadows and specularities depending on the direction of the lighting in a fixed pose. By means of such distinctive, the lighting direction can be estimated and illumination variation can be remunerated.
Likewise, in a convenient application environment, the illumination variation is constantly tied with other problem such as pose variation, which increases the convolution of the automatic face recognition problem. Changes in screening conditions or rotations of faces carry difficulties to a face recognition system.

There are two types of face rotations to be considered; first one is the rotation of human face images in the image-plane and the second one is the rotation of faces out of the image plane (in-depth rotation). In the former case, face images can be simply standardized by detecting several pointers in the face after that applying some essential transformations, while in the second case such standardization is inaccessible even as some parts of faces may be occluded. At a halt for the same person, huge variation of look is caused by pose variation. The variation is frequently more important than that warped by different persons under the same pose [21]. Hence the humiliation of conservative appearance-based methods for instance Eigen face etc., humiliates severely when non frontal searches match against the registered frontal faces [20]. Amidst the several methods proposed to address the pose problem the extensively used method are view-based methods [19].

Numeral illuminations constant face recognition looms have been projected in the past years. Presented approaches deal with the illumination variation problem drop into two main categories. The first category is “passive” approaches, as they effort to conquer this problem by studying the visible spectrum images in which face appearance has been changed by illumination variations. The other category contains “active” approaches, in which the illumination variation problem is conquer by employing active imaging techniques to obtain face images captured in steady illumination condition, or images of illumination invariant modalities. The changes stimulated by illumination are frequently larger than the differences between individuals, causing systems based directly on comparing images to misclassify input images. There are four main categories of looms for handling variable illumination: (1) extraction of illumination constant aspects (2) renovation of images with uneven illuminations to a canonical representation (3) modeling the illumination variations (4) exploitation of some 3D face models whose facial shapes and albedos are obtained in advance [7].

One of the most significant troubles in face recognition is the variable illumination. The key fact is that illumination, along with pose variation, is the most important factor that changes the observation (appearance) of faces. Lighting conditions vary mostly between indoor and outdoor environments, but also within indoor environments. Hence, owing to the 3D shape of human faces, a direct lighting source can produce strong shadows that highlight or shrink certain facial aspects. In excess of some previous decades, many face recognition methods have been developed. Frequently used feature extraction methods are chief component analysis (PCA) [12], [13] and linear discriminant analysis (LDA) [14], [15], [16], [17]. Another linear technique identified as Locality Preserving Projections (LPP) [18], [16], which finds an embedding that conserve local information, and expands a face subspace that best detects the essential face diverse structure.

Out of the various factors that involve face recognition Illumination and pose are the two main confronts. Pose and lighting variations significantly deteriorate the utility of recognition. So to undertake this problem, the face is recognized under various lighting conditions by our projected system. The respite of the proposal is ordered as follows: section 2 briefs a few recent related works. Section 3 briefs the face recognition process based on a hybrid approach. Tentative consequences and study of the projected methodology are discussed in Section 4. In conclusion, remarks are provided in Section 5.

2. Literature review

Some of the face recognition schemes, which make use of pattern toning and model based techniques for better performance, have been presented in the literature. Newly, incorporating pose invariant techniques into face recognition schemes to improve its performance and efficiency has expected a great deal of consideration among researchers in face recognition community. A pithy appraisal of a few current researches is presented here.

Wide-ranging hard work have been put into their search toward pose-invariant face recognition in recent years and many prominent approaches have been proposed by Xiao Zheng Zhang and Yong Sheng Gao [22]. Their paper provides a decisive analysis of researches on image-based face recognition across pose. The presented techniques were broadly reviewed and discussed. These techniques were classified into different categories according to the methodologies in handling pose variations. Their approaches, advantages/disadvantages and performances were convoluted. By simplifying diverse strategy in handling pose variations and appraising their performances, several capable directions for future research have been suggested.

Arashloo and Kittler [30] have tackled the problem of face recognition under random pose. A hierarchical MRF-based image identical technique for finding pixel-wise communications between facial images viewed from different angles was planned and used to closely register a pair of facial images. The goodness-of-match between two faces was subsequently measured in terms of the standardized energy of the match which has a combination of both structural differences between faces as well as their texture uniqueness. The method needs no training on non-frontal images and circumvents the need for geometrical normalization of facial images. It was also forceful to moderate scale changes between images.

Dahm and Yongsheng Gao [31] have explained that several Face Recognition techniques have focal point on 2D- 2D comparison or 3D-3D comparison; but only some techniques survey the idea of cross-dimensional assessment. Their paper offered a new face recognition approach that outfit cross-dimensional assessment to solve the problem of pose invariance. Their approach implements a Gabor representation during comparison to allow for variations in texture, illumination, expression and pose. Kernel scaling was used to shrink comparison time during the branching search, which establishes the facial pose of input images. In their paper, they present a novel face recognition approach that utilizes 3D data to conquer changes in facial pose, while remaining non-interfering. To realize this, we use 3D textured head models in the gallery, as gallery data is generally taken from supportive subjects (e.g. identification photos, mug shots). For the query, we use 2D images, which can be taken from submissive cameras such as ceiling mounted surveillance cameras. Together this gives us a cross-dimensional approach, combined with a non-interfering nature.

An efficient novel H-eigenface (Hybrid-eigenface) system for pose invariant face recognition varying from fore to summary view has been offered by Abhishek Sharma *et al* [32]. H-eigenfaces were completely new source for face image representation in different poses and are used for effective fore view separation. The projected method was based on the fact that face samples of same person under different poses are identical in terms of the permutation pattern of facial features. H-eigenfaces develop that fact and thus two H-eigenfaces under different poses capture same features of the face. Thus providing a solid view-based subspace, which can be more used to generate virtual frontal view from inputted non-frontal face image using least square projection technique? The use of their proposed tactic on FERET and ORL face database shows an exciting improvement in recognition accuracy and a discrete reduction in online computation when compared to global linear regression method.

Real-time pose invariant face recognition algorithms from an arcade of frontal images have been projected by Choi Hyun Chul and Oh Se-Young [33]. Initially, they customized the second order minimization method for active appearance model (AAM). That tolerates the AAM to have the ability of correct union with small loss of frame rate. Next, they encompass future pose transforming matrix which can eradicate warping object of the warped face image from AAM fitting. That makes it possible to prepare a neural network as the face recognizer with one frontal face image of each person in the gallery set. Third, they recommend an effortless method for pose recognition by means of neural networks to select suitable pose transforming matrix.

Khaleghian and Rohban [34] have projected an ensemble-based loom to enhance concert of Tied Factor Analysis (TFA) to conquer some of the disputes in face recognition across large pose variations. They used Adaboost to boost TFA which has shown to possess state-of-the-art face recognition performance under large pose variations. They have employed boosting as a discriminative training in the TFA as a generative model. In their model, TFA was used as a base classifier for the boosting algorithm and a biased probability model for TFA was proposed to adjust the importance of each training data. Likewise, a customized weighting and a variety measure are used to produce more diverse classifiers in the boosting process. Experimental results on the FERET data set confirmed the improved performance of the Boosted Tied Factor Analysis (BTFA) in comparison with TFA for lower dimensions when a holistic approach was used.

3. An Efficient Face Recognition System

Let *D* be a database containing N number of images, $\{I_1, I_2, \ldots, I_N\}$ and let *I* be a database image of size $R \times S$. D, After inputting an image from the database D, the user must specify the type of the image i.e., whether it is pose invariant, illumination invariant or both pose and illumination variant. Depending on the image group precise by the user, any one of the following three processes is executed by the system.

3.1 Face Detection

In the recent years face detection have attained to a great extent. Various approaches were offered in excess of previous years in the field of face and eye detection. The position of the art techniques are emergence based methods, which include a lot of ways for object recognition such as neural networks (NN), support vector machines (SVM) etc. The beginning of face detection using neural network, by Rowley et al, in 1996, was an important work by that time [20]. Consequently, there are many other approaches. Interested reader may read the comprehensive survey paper by Yang, et al [21]. Viola and Jones [22] uses boosted cascade of simple Haar-like features introduced by Papageorgiou [24] and enhanced by Viola [22] and Lienhart [23] for object detection. This is one of the most discernible algorithms in face detection.

The Viola-Jones [22] face detection system makes use of a multi-scale multi-stage classifier that functions on image intensity information. This manner of face detection is operated in the existing system that doesn't require any previous calibration process. In general this loom scrolls a window across the image and consigns a binary classifier that discriminates between a face and the background. This classifier is regimented with a boosting machine learning meta-algorithm. It is endorsed as the fastest and most accurate pattern recognition method for faces in monocular grey-level images. They urbanized a real-time face detector comprising of a cascade of classifiers trained by AdaBoost. Every classifier workout with an integral image filter, which hark back of Haar Basis functions and can be processed very fast at any location and scale. This is important to speed up the detector. At each level in the cascade, a division of features is preferred using a feature choice procedure based on AdaBoost.

The process operates on professed primary images: each image element contains the sum of all pixels values to its upper left, allowing for constant-time outline of random rectangular areas [26].

***Integral Image*:-**

For the original image $i(x, y)$, the primary image is defined as follow:

$$ii(x, y) = \sum_{x' \le x} \sum_{y' \le y} i(x', y') \quad (1)$$

Using the following pair recurrence:

$$s(x, y) = s(x, y-1) + i(x, y) \quad (2)$$

$$ii(x, y) = ii(x-1, y) + s(x, y) \quad (3)$$

(Where $s(x, y)$ is the cumulative row sum, $s(x,-1) = 0$ plus $ii(-1, y) = 0$) the primary image can be processed in one pass over the original image. Using the primary image any rectangular sum can be computed in four array references (see Fig. 2).

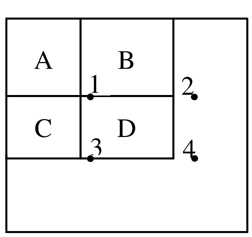

Figure 1. The sum of the pixels within rectangle D can be computed with four array references

The significance of the primary image at location 1 is the sum of the pixel in rectangle A. The value in location 2 is $A+B$, at location 3 is $A+C$, and at location 4 is $A+B+C+D$. The sum within D can be computed as $4+1-(2+3)$.Viola-Jones' modified AdaBoost algorithm is offered in pseudo code [25] as below.Viola-Jones' modified AdaBoost algorithm is offered in pseudo code [25] as below.

The Modified Adaboost Algorithm

- Given sample images $(x_1, y_1), \ldots, (x_n, y_n)$, where $y_1 = 0,1$ for negative and positive examples.
- Initialize weights $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$ for $y_1 = 0,1$, where m and l are the numbers of positive and negative examples.
- For $t = 1, \ldots, T$:
  1. Normalize the weights, $$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$$
  2. Choose the best weak classifier in regard to the weighted error $$\varepsilon_t = \min_{f,p,\theta} \sum_i w_i \left| h(x_i, f, p, \theta) - y_i \right| \quad (4)$$
  3. Define $h_t(x) = h(x, f_t, p_t, \theta_t)$ where f_t, p_t and θ_t are the minimizers of ε_i
  4. Update the weights: $$w_{t+1,i} = w_{t,i} \beta^{1-e_i} \quad (5)$$ Where $e_i = 0$ if example x_i is classified correctly and $e_i = 1$ otherwise, and $$\beta_t = \frac{\varepsilon_t}{1-\varepsilon_t}$$
- The final strong classifier is:

$$C(x) = \begin{cases} 1 & if \quad \sum_{t=1}^{T} \alpha_t h_t(x) \ge \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & otherwise \end{cases} \quad (6)$$

Where $\alpha_t = \log \frac{1}{\beta_t}$.

After detecting the face in the image all further analysis is placed in the upper region of the found face (ROI).

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3.2 Face Recognition

There are three phases of proposed face recognition system namely 1) pose estimation, 2) shadow compensation, 3) face identification. For a face image with multiple variations, the pose of the face image is likely by using the projected pose estimation method. After assigning a face image to an appropriate pose class, the face image is processed by the outline compensation procedure modified for each pose class. These shadow compensated images are used for face identification by a classification rule. The projected method has the following advantages compared to other face recognition methods under clarification and pose variations. Unlike most of 2D image-based methods that contract with individual variation discretely, the proposed method handles both illumination and poses variations. Likewise, the proposed method, which is based on 2D images, does not require to estimate the face surface normals or the albedos, and thus there is no need for any special equipment such as a 3D laser scanner [35-37] or complicated calculation. The proposed shadow compensation method also does not include image deforming or iteration process. These make the proposed recognition system much simpler to implement, and this ease is an important factor for performing a face recognition system in real-time.

3.2.1 Pose Estimation

Within view-based face recognition [38, 39], the pose estimation is to categorize start point of reference into one of several distinct orientation classes, e.g., frontal, left/right profiles, etc. Along with the pose estimation methods based on 2D images such as the geometric methods, detector array methods, appearance template methods and subspace methods [40], we use the subspace method that schemes a check out image into a low-dimensional subspace to estimate its pose. We first divide the pose space into several pose classes from left profile to right profile. In view-based face recognition, the pose estimation stage is essential for face recognition performance since it is at the first stage in face recognition system to verify the pose class of an image. To make pose estimation more consistent against the variations in subjects and ecological alters, it is essential to find the characteristics that are mostly affected by pose variation. We use the geometrical distribution of facial components for pose estimation because the locations of facial components change depending on the pose. Through this information, we can estimate the pose and determine the pose class by a classification rule. In order to remove the redundant information for pose estimation, we transform a face image to an edge image. The block diagram for the whole projected method is offered in Fig. 2.

Edge Detection

In the allocation of facial components edge image is an effective representation. On the converse, in the edge image only the irregular shapes of facial components are present in the edge images, whereas the other information vanishes specifically the positions of facial components are improved in an edge image.raw images contain not only the allocation of facial components however the other information such as texture, gray-level intensity, and appearance variation of subjects, and these can act as noise in estimating pose. Several edge detection algorithms have been proposed in image processing area. Among them, we take on the Sobel edge detector which uses two convolution kernels, one to detect changes in vertical contrast and another to detect changes in horizontal contrast. The Sobel edge detector is effortless and the edges produced by the Sobel edge detector increase only the geometrical distribution of facial components eradicating needless edge shapes.

With pertain a discriminate characteristic mining method to these Sobel edge images from the images of training set, a subspace is raised for each of K pose classes $\{P_k \mid k = 1,2,\cdots,K\}$. The subspace for classification of the pose class is constructed by using a seperate feature extraction method. The pretense of each image projected into the subspace is classified by using the one nearest district rule with the l_2 norm as the distance metric, and a pose class P_k, $k = 1,2,\cdots,K$ is assigned to each image.

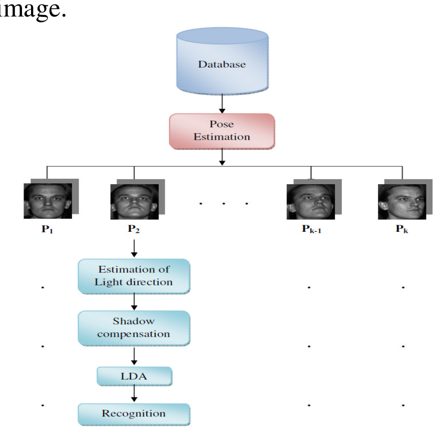

Fig.2: Block diagram of proposed face recognition method

Shadow compensation

On behalf of motion compensation, first we guess the direction of light for the images in each pose class. while the shape of a human face is more convex in azimuth than in elevation, we divide the directions of light into L categories $\{C_l \mid l = 1,2,\cdots,L\}$ from the left side to the right side. We denote the gray-level intensity of a face image of $H(height) \times W(width)$ pixels as $FI_{m,n}^{k,l}(x,y) \in \Re^{H \times W}$, where the subscripts

$m = 1,2,\cdots,M$ and $n = 1,2,\cdots N_{(k,l)}$ denote the n^{th} nth image of the m^{th} individual when the direction of light belongs to category C_l in the pose class P_k. Hence, the superscript (k,l) denotes that the pose class of the image is P_k and the direction of light belongs to C_l. Towards approximation of the direction of light, we make a binary image with a threshold $\frac{1}{HW}\sum_{x=1}^{H}\sum_{y=1}^{W} FI^{(k,l)}(x,y)$ which is the average value of the gray-level intensities, for each face image.

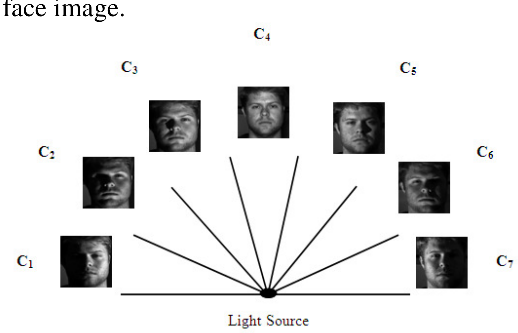

Fig. 3: Light direction categories

By means of these dual images, we consign a category value to the light category C_l. We evaluated this light track classification system with the Yale B database which provides information about the location of the flashlight for each image. In fig. 3 the light group changes from C1 to C7 as the light source moves from left to right. $Diff_{m,n}^{k,l}(x,y) = FI_{m,n}^{k,ref}(x,y) - FI_{m,n}^{k,l}(x,y)$

(7)

As the majority, human faces are comparable in shape, we can imagine that the gloom on facial images in the same pose class and the same illumination category are moreover similar in shape, and the difference image between the images with and without the shadows contains the information on the illumination condition. We select one of the images under the frontal illumination in each pose P_k reference image $FI_{m,n}^{k,ref}(x,y)$. The gray-level intensity $FI_{m,n}^{k,l}(x,y)$ at pixel *(x,y)* varies depending on the light category, and is different from that of. $FI_{m,n}^{k,ref}(x,y)$ We define the intensity difference between the images of $FI_{m,n}^{k,ref}(x,y)$ and $FI_{m,n}^{k,l}(x,y)$ at each pixel *(x,y)* as follows

$$Diff_{m,n}^{k,l}(x,y) = FI_{m,n}^{k,ref}(x,y) - FI_{m,n}^{k,l}(x,y) \quad (7)$$

The strength dissimilarity $Diff_{m,n}^{k,l}$ of one person is inadequate to balance for the strength dissimilarities of another person's images under different illumination environment because $Diff_{m,n}^{k,l}$ contains information about the illumination condition as well as unique features of each individual. So as to compensate for the intensity difference due to illumination variation, we need to eliminate the influence of features that are inherent to each individual. hence, we describe the average intensity difference $Diff_{A}^{k,l}$ for the category C_l in the pose class P_k as follows:

$$Diff_{A}^{k,l} = \frac{1}{MN(k,l)} \sum_{m=1}^{M} \sum_{n=1}^{N(k,l)} D_{m,n}^{(k,l)} \quad (8)$$

$$w_{l_i} = \frac{Dist_{4-i}^{N}}{\sum_{i=1}^{3} Dist_i^N} \quad (9)$$

Note that there is no subscripts *m* or *n* in $Diff_{A}^{k,l}$. Since this typical strength difference signifies the general attribute of the shadow in a face image for the direction of light belonging to category C_l, it can be applied to any face image in compensating for the shadow formed by the light belonging to the category C_l in the pose class P_k. Since the direction of light can change continuously, it is moreover optimistic to expect that one average intensity difference contains enough information for shadow compensation in each pose class and light direction category. Once calculating the distances between the binary image of a test image and the binary images in each category C_l, the three nearest distances and their consequent groups are selected. The weight w_{l_i}, which entails the degree of involvement to the recompense, is determined based on these three nearest distances as the following.

$$w_{l_i} = \frac{Dist_{4-i}^{N}}{\sum_{i=1}^{3} Dist_i^N} \quad (9)$$

Then, we obtain the shadow remunerated image, $FI_{m,n}^{c(k,l)}$ of $FI_{m,n}^{c(k,l)}$ with the typical differences as follows:

$$FI_{m,n}^{c(k,l)}(x,y) = FI_{m,n}^{(k,l)}(x,y) + \sum_{i=1}^{3} w_{l_i} D_A^{k,l_i}(x,y) \tag{10}$$

In general, the shadows can be remunerated by histogram equalization method. For the unprocessed image, the components of the histogram are concerted in the low side of the intensity scale. Even if the components with small strength values extend over a wide range by the histogram equalization, a huge portion still remains in the low side of the intensity scale. In the histogram of the shadow compensated image, pixels are quite evenly dispersed over the entire range of intensity values. It is known that an image, whose pixels be inclined not only to occupy the entire range of gray levels but also to be distributed uniformly, will have an appearance of high contrast and will reveal a large variety of gray tones. Hence, a face recognition system is expected to perform better with the shadow compensated images than the histogram steady images.

4. Results and Discussions

Here in this segment, we have investigated the routine of our planned novel face recognition loom. Our planned loom is executed in Mat lab (7.10) and face recognition was achieved using the large set of Yale Database B under various pose and illumination conditions. The results show that our loom has an hopeful concert.

Database: The concert of illumination invariant face recognition is commonly assessed using the Yale face database B. Nine different poses 10 folks 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 fewer than 576 viewing conditions specifically, a total of 5850 images are present in the database. The steady results accomplished by the projected face recognition system are listed below.

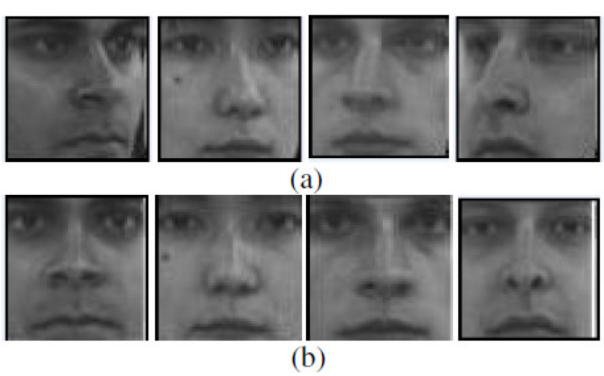

Fig. 4: Sample output obtained from the Posed invariant process a) non frontal face images b) Pose normalized images.

Fig. 5: Sample output obtained from the Illumination invariant process a) images with various illumination conditions b) Shadow remunerated images.

Comparative analysis

This associate segment nearby the proportional analysis of the projected approach. We evaluated the recognition accuracy of the proposed approach with some presented approaches. Computing the false acceptance rate (FAR) and false rejection rate (FRR) is the common way to measure the biometric recognition accuracy. 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 following equation is used to calculate the accuracy measurement of the overall approach,

$$Accuracy = 100 - \left[\frac{(FAR/FRR)}{2}\right] \tag{11}$$

Genuine acceptance rate (GAR) is the general accuracy measurement of the approach. The following table gives the percentage of the recognition rates and the accuracy rates.

Table I: Comparison results of our proposed technique with some existing methods.

Methods	FRR (%)	FAR (%)	Accuracy (%)
Face recognition based on Pose invariant condition	6.82	8.25	93.4
Face recognition based on illumination invariant condition	5.84	7.51	94.2

Proposed Technique	2.87	5.26	97.5

In this table, we study that our projected method has a lower value in both FAR and FRR error rate. Similarly, the proposed system has a higher accuracy compared the other two methods. This can be represented in the following graphs.

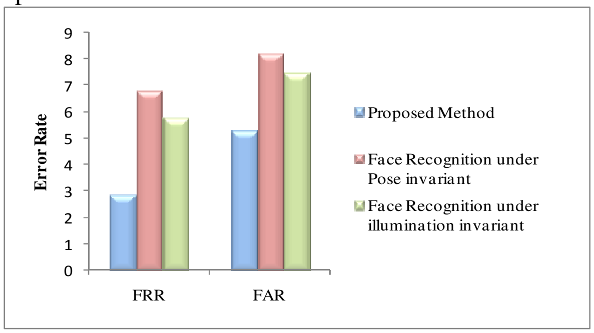

Fig.6: The comparative results of FAR and FRR on proposed technique and some existing techniques.

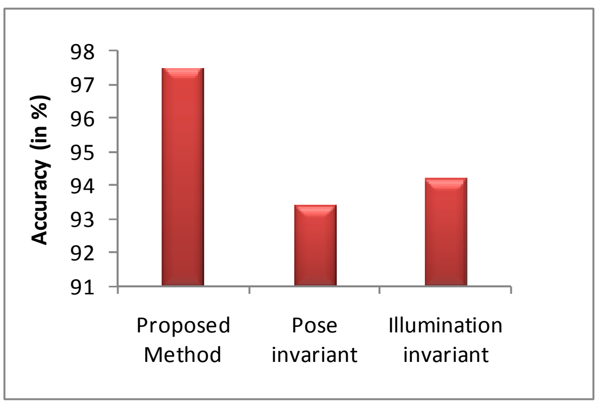

Fig. 7: The comparative results of accuracy on proposed system and some existing systems

Therefore it is evident that the proposed face recognition system resourcefully recognizes the face under various pose and illumination conditions.

5. Conclusion

Here in paper, a proficient face recognition system derived from pose and illumination invariant conditions was projected. In this work, the face images were acknowledged by means of employing a hybridization of both the pose and illumination invariant condition. The effectiveness of the projected system was generally appropriate to the application of a hybrid process for face recognition. In hybrid process, we standardize both pose and illumination of the face image. This can be done by shadow compensation and pose standardization process. The execution results showed that the face recognition process of the proposed method was further efficient than obtainable methods that are moreover pose based or illumination based. The visualization graphs obtained for the recognition results illustrated this.

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