Robust face recognition system Using multiple face model of hybrid fourier feature under uncontrolled illumination and partial occlusion

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***Abstract*— Automatic face recognition is an important vision task with many practical applications such as biometrics, video surveillance, image retrieval, and human computer interaction Accurate face recognition can be problematic when the face images used for recognition contain partial occlusion (e.g. the presence of beard, scarf or sunglasses not seen in the training images). Existing work used face recognition system for large-scale datasets taken under uncontrolled illumination variations. This system used illumination insensitive preprocessing method, a hybrid Fourier-based facial feature extraction, and a score fusion scheme for recognization process. However face images with partial occlusion are not recognized. To deal with this, the proposed framework uses combined method of uncontrolled illumination variations and partial occlusion for face recognition. First, in the preprocessing stage, a face image is transformed into an illumination-insensitive image, called an \integral normalized gradient image," by normalizing and integrating the smoothed gradients of a facial image. Features such as clean local features (i.e. `recognition by parts') and hybrid Fourier features are extracted from different Fourier domains in different frequency bandwidths. Then PUM posterior union model is proposed for selecting the extracted features for recognition to improve robustness to partial occlusion. These selected features are efficiently classified by linear discriminant analysis (LDA). The proposed method shows an average of 89.49% verification rate on 2-D face images .**

***Index Terms*— Face recognition, face recognition grand challenge, PUM feature, feature extraction, preprocessing, score fusion.**

I.INTRODUCTION

Face recognition is becoming primary biometric technology because of rapid advancement in the technology such as digital cameras, the internet and mobile devices which in turn facilitates its acquisition[1]. Artificially simulating face recognition is required to create intelligent autonomous machines. Face recognition by machine can contribute in various application in real life such as electronic and physical access control , biometric authentication , surveillance , human computer interaction , multimedia management to name just a few. Also, it has many advantages over other biometric traits as it requires least co-operation , non-invasive , easy to acquire and use. Automated face recognition is a relatively new concept. Developed in the 1960s, the first semi-automated system for face recognition required the administrator to locate features (such as eyes, ears, nose, and mouth) on the photographs before it calculated distances and ratios to a common reference point, which were then compared to reference data. In the 1970s, Goldstein, Harmon, and Lesk used 21 specific subjective markers such as hair color and lip thickness to automate the recognition. The problem with both of these early solutions was that the measurements and locations were manually computed. recognition problem. This was considered somewhat of a milestone as it showed that less than one hundred values were required to accurately code a suitably aligned and normalized face image.

In 1991, Turk and Pentlands discovered that while using the eigenfaces techniques, the residual error could be used to detect faces in images. A discovery that enabled reliable real-time automated face recognition systems. Although the approach was somewhat constrained by environmental factors, it nonetheless created significant interest in furthering development of automated face recognition technologies.

The technology first captured the public’s attention from the media reaction to a trial implementation at the January 2001 Super Bowl, which captured surveillance images and compared them to a database of digital mug shots. This demonstration initiated much-needed analysis on how to use the technology to support national needs while being considerate of the public’s social and privacy concerns. Today, face recognition technology is being used to combat passport fraud, support law enforcement, identify missing children, and minimize benefit identity fraud.

II. RELATED WORK

A. *Face Recognition: Structure And Procedure*

The following system shows the general process of face recognition framework is as follows: Given a picture taken from a digital camera, we'd like to know if there is any person inside, where his/her face locates at, and who he/she is. Towards this goal, we generally separate the face recognition procedure into three steps: **Face Detection**, **Feature Extraction**, and **Face Recognition.**

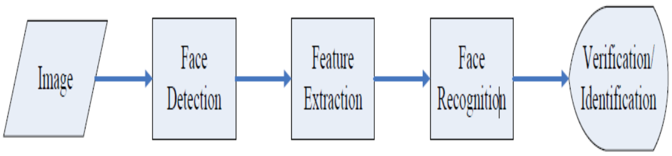

Figure 1: Configuration of a general face recognition structure

1) Face Detection

The main function of this step is to determine (1) whether human faces appear in a given image, and (2) where these faces are located at. The expected outputs of this step are patches containing each face in the input image. In order to make further face recognition system more robust and easy to design, face alignment are per-formed to justify the scales and orientations of these patches. Besides serving as the pre-processing for face recognition, face detection could be used for region-of-interest detection, retargeting, video and image classification, etc.

2) Feature Extraction

After the face detection step, human-face patches are extracted from images. Directly using these patches for face recognition have some disadvantages, first, each patch usually contains over 1000 pixels, which are too large to build a robust recognition system. Second, face patches may be taken from different camera alignments, with different face expressions, illuminations, and may suffer from occlusion and clutter. To overcome these drawbacks, feature extractions are performed to do in-formation packing, dimension reduction, salience extraction, and noise cleaning. After this step, a face patch is usually transformed into a vector with fixed dimension or a set of fiducial points and their corresponding locations. In some literatures, feature extraction is either included in face detection or face recognition.

3) *Face Recognition*

After formulizing the representation of each face, the last step is to recognize the identities of these faces. In order to achieve automatic recognition, a face database is required to build. For each person, several images are taken and their features are extracted and stored in the database. Then when an input face image comes in, we perform face detection and feature extraction, and compare its feature to each face class stored in the database. There have been many researches and algorithms pro-posed to deal with this classification problem, and we'll discuss them in later sections. There are two general applications of face recognition, one is called identification and another one is called verification. Face identification means given a face image,[2] we want the system to tell who he / she is or the most probable identification; while in face verification, given a face image and a guess of the identification, we want the system to tell true or false about the guess. In fig. 2, we show an example of how these three steps work on an input image

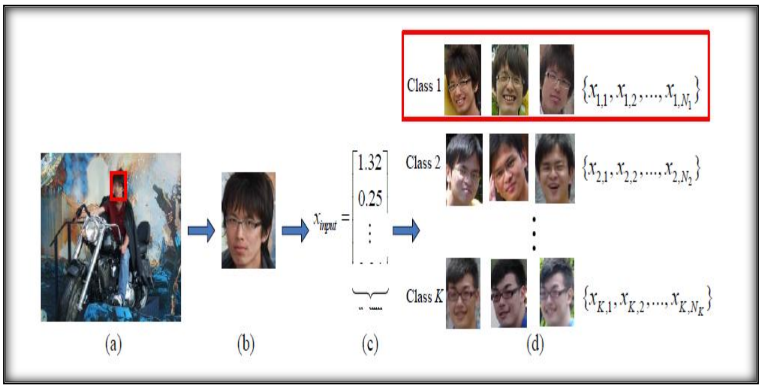

Figure 2: An example of how the three steps work on an input image. (a) The input image and the result of face detection (the red rectangle) (b) The extracted face patch (c) The feature vector after feature extraction (d) Comparing the input vector with the stored vectors in the database by classification techniques and determine the most probable class (the red rectangle).

III. PROBLEM DEFINITION

Accurate face recognition can be problematic when the face images used for recognition contain partial occlusion (e.g. the presence of beard, scarf or sunglasses not seen in the training images). This problem can be further compounded by different lighting conditions between the training and test images, and by the shortage of training samples. Previously, little research has dealt simultaneously with partial occlusion, illumination[3] variation and limited training data. One major problem for face recognition system is how to ensure recognition accuracy for a large data set captured in various conditions. The following are the problems found in the face recognition is listed below:
Less recognition accuracy is achieved in face recognition systems in a large-scale data set, particularly focused on verification of the person rather than identification.
Mismatching occurs when two face images of the same person under different conditions such as varying illumination and partial occlusion of face images.[4]

IV. PROPOSED SYSTEM

In proposed system, the combination of illumination variation and partial occlusion face has been recognized. Partial occlusion face includes beard, scarf or sunglasses etc., initially the Illumination insensitive preprocessing has been done. Features to be used for person classification are extracted to identify any invariance in the face images against environmental changes[5]. The Hybrid Fourier features and clean local features are extracted [6].

The proposed framework consist of Preprocessing, Feature extraction, PUM based feature selection and similarity-based formulation for limited training data and classification using LDA.

In preprocessing Input face image can be pre-processed by using illumination-insensitive preprocessing method .In this process a face image is transformed into an illumination-insensitive image, called an "integral normalized gradient image," by normalizing and integrating the smoothed gradients of a facial image[15].

Then, for feature extraction of complementary classifiers, multiple face models based upon hybrid Fourier features[13] and clean local features are extracted. The hybrid Fourier features are extracted from different Fourier domains in different frequency bandwidths and then each feature is individually classified by linear discriminant analysis. Clean local features represent the recognition by parts of face image. Then posterior union model (PUM) is used for investigates face recognition with partial occlusion, illumination variation and their combination, assuming no prior information about the mismatch, and limited training data for each person. Finally, LDA Classifier is used to classy the selected facial features for recognition of face respectively[11].

A. Preprocessing

In this section, the illumination-insensitive image integral normalized gradient image (INGI)[12] method is proposed to overcome the unexpected illumination changes in face recognition with limited side effects such as image noise and the halo effect. Based upon intrinsic and extrinsic factor definitions, we first normalize the gradients with a smoothed image and then integrate the division results with the anisotropic diffusion method. the unexpected illumination changes in face recognition with limited side effects such as image noise and the halo effect.

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The grayscale intensity image $\chi_{(i,j)}$of a 3-D object is represented by

$$\chi_{(i,j)} = \rho(i,j)\, n^{T}_{(i,j)}.s$$

where ρ(i,j) is the surface texture associated with point (i,j) in the image, $n_{(i,j)}$is the surface normal direction (shape) associated with point (i,j) in the image, and s is the light source direction whose magnitude is the light source intensity.

1) Integral Normalized Gradient Image (INGI)

The following assumptions such as: 1) most of the intrinsic factor is in the high spatial frequency domain, and 2) most of the extrinsic factor is in the low spatial frequency domain. Considering the first assumption, one might use a high-pass filter to extract the intrinsic factor, but it has been proved that this kind of filter is not robust to illumination variations. In addition, a high-pass filtering operation may have a risk of removing some of the useful intrinsic factor. Hence, an alternative approach, namely employing a gradient operation is used. The gradient operation is written as

$$\begin{aligned}\nabla_\chi &= \nabla(\rho \textstyle\sum_i n^T.s_i)\\ &= \nabla(\rho) \textstyle\sum_i n^T.s_i + \rho\nabla(\sum_i n^T.s_i)\\ &\approx \nabla(\rho) \textstyle\sum_i n^T.s_i = \nabla(\rho)W\end{aligned}$$

where the approximation comes from the assumptions that both the surface normal direction (shape) n and the light source direction vary slowly across the image, whereas the surface texture ρ varies fast. The scaling factor W is $\sum_i n^T.s_i$

The extrinsic factor of our imaging model

Smoothed image is obtained by using approach to estimate the extrinsic part

$$\widehat{W} = \chi * K$$

Where K is a smoothing kernel and * denotes the convolution. To overcome the illumination sensitivity, we normalized the gradient map$\nabla_\chi = \{\frac{\partial_\chi}{\partial_x}, \frac{\partial_\chi}{\partial_y}\}$ with the following equation:

$$N = \nabla_\chi/\widehat{w} \approx \nabla(\rho)\, W/\widehat{w} \approx \nabla(\rho)$$

Because $\widehat{w}$ can be taken as the estimation of the extrinsic factor; the illumination effect could be reduced from the gradient map after this normalization.

B. Feature extraction

1) Hybrid Fourier feature

Three different Fourier feature domains, namely, the real and imaginary component (RI) domain, Fourier spectrum domain Γ, and phase angle domain ϕ.

We apply the three frequency band selections, B1, B2 and B3 to the three Fourier features domains. The RI domain has more powerful descriptions to distinguish faces than other domains, so we apply $RI_{B1} \sim RI_{B1}$ to it.

On the other hand, the Γ and ϕ domains do not make use of the highest frequency region because the discriminating power of the highest frequency parts in these Fourier domains are small. Moreover, the higher frequency information of the phase angle is sensitive to small spatial changes and, thus, only ϕ_{B1} is adopted.

In this respect, this selection procedure in phase information is a kind of compensation for the susceptible phase coefficients. Consequently, Γ_{B1}, Γ_{B2} and ϕ_{B1} are additionally used to describe the face model with domain features.

All Fourier features are independently projected into discriminative subspaces by PCLDA theory. For example, one output of RI_{B1} is derived by

$$YRI_{B1} = W^{T}_{RI_{B1}}(RI_{B1} - mRI_{B1})$$

Where $W_{RI_{B1}}$ is the transformation matrix of PCLDA learned by a given training set and $mRI_{B1}$is its mean vector. In sequence, three outputs of different frequency bands are concatenated as follows

$$\mathbf{yRI} = [\mathbf{y}^{\mathbf{T}}_{\mathbf{RI_{B1}}}\ \mathbf{y}^{\mathbf{T}}_{\mathbf{RI_{B2}}}\ \mathbf{y}^{\mathbf{T}}_{\mathbf{RI_{B3}}}]^{\mathbf{T}}$$

In other domains, the outputs are also calculated

$$\mathbf{y}\ \boldsymbol{\Gamma} = [\mathbf{y}^{\mathbf{T}}_{\boldsymbol{\Gamma}_{\mathbf{B1}}}\ \mathbf{y}^{\mathbf{T}}_{\boldsymbol{\Gamma}_{\mathbf{B2}}}\ ]^{\mathbf{T}}$$

$$\mathbf{y}\ \boldsymbol{\phi} = [\mathbf{y}\boldsymbol{\phi}_{\mathbf{B1}}]$$

The final augmented feature consists of three different complementary features, and the notation is given by

$$\mathbf{F} = [\mathbf{y}^{\mathbf{T}}_{\mathbf{RI}}, \mathbf{y}^{\mathbf{T}}_{\boldsymbol{\Gamma}}, \mathbf{y}^{\mathbf{T}}_{\boldsymbol{\phi}}]$$

2) Local features

Let $\Omega = (w_1, w_2 . . . w_C)$ denote C distinct person classes of interest, and let X represent a test face image. The aim is to find a person class from V that best matches X. Assume that X can be divided into N local images

$$\mathbf{X} = (\mathbf{x_1}, \mathbf{x_2}, \ldots, \mathbf{x_N}),$$

where x_n is the feature vector for the nth local image. By unknown partial distortion we mean that some of the local image features x_n are distorted (which may be caused, e.g. by a partial occlusion in the test image not shown in the training images), but knowledge about the distortion, including the number and location of the distorted x_n and the characteristics of the distortion, is not available. When restoring the distorted local images/features becomes impractical, one may alternatively ignore the distorted local features and so perform recognition based only on the 'clean' local features. This is the 'recognition by parts' principle, for improved image recognition with local mismatches.[7]

3) PUM posterior union model for feature selection

In the PUM approach, the problem of finding the person class given a test image is formulated $X = (x_1, x_2, \ldots, x_N)$ with unknown partial distortion as a maximum posterior probability problem, which can be expressed as

$$[\hat{w}, \mathbf{X}_{\hat{\mathbf{I}}}] = \mathbf{argmax}_{w,I}\, \boldsymbol{P}(\boldsymbol{w}|\boldsymbol{X_I})$$

where X_I is a subset in X indexed by $I \subseteq \{1, 2, \ldots, N\}$, and $P(w|X_I)$ is the posterior probability of class $w \in \Omega$ given X_I. The expression seeks to find the most-probable class $\hat{w}$ by jointly maximising the posterior probability $P(w|X_I)$ over all classes w and all possible local feature subsets X_I, where ˆI contains the indices of the optimal local features for the most-probable class $\hat{w}$. Since clean features produce large likelihoods for the correct class, maximising the probability of the correct class over the given features is likely to locate the clean features. Therefore the joint maximisation in above equation effectively maximises the posterior probability of the correct class by choosing clean or optimal local features. This joint maximisation removes the requirement for the prior knowledge of the clean features.

The PUM approach further generalises the problem by removing the requirement that an exact set of optimal features, $X_{\hat{I}}$, be found. Instead, for $X_{\hat{I}}$ containing a given number of features Q, denoted as $X_{\hat{I}Q}$ where $\hat{I}_Q$ is the set of the Q indices for the Q optimal features, PUM makes the following assumption

$$\mathbf{P}(\mathbf{X}_{\hat{\mathbf{I}}_{\mathbf{Q}}}|\mathbf{w}) \approx \textstyle\sum_{I \in I_Q^N} \boldsymbol{p}(\boldsymbol{X_I}|\mathbf{w})$$

Where I_Q^N is the collection of all possible combinations of Q distinct indices chosen from the full N indices {1, 2, . . . , N}. In other words, it is assumed that the sum over all $p(X_I|w)$ for a given number of Q features is dominated by the subset of the Q optimal features which has the maximum likelihood. This reduces the problem of finding the set of optimal local features to the problem of finding the number of optimal local features but not the exact set. The generalised problem can be expressed as

$$[\hat{\boldsymbol{w}}, \hat{\boldsymbol{Q}}] = \mathbf{argmax}_{w,Q} \frac{P\left(X_{\hat{I}_Q}\middle|w\right)P(w)}{\sum_{w' \in \Omega} P\left(X_{\hat{I}_Q}\middle|w'\right)P(w')}$$

where $P\left(X_{\hat{I}_Q}\middle|w\right)$ is calculated, and ˆQ is an estimate of the number of the optimal local features.

4) PUM with limited training data – a similarity-based formulation

PUM is used as a similarity-based likelihood function in the PUM formulation. The new likelihood function is a transformation of the cosine similarity. The cosine similarity for comparing a test vector $X = (x_1, x_2 \ldots x_N)$ and a reference vector $Y = (y_1, y_2, \ldots, y_N)$, each being expressed as N local vectors, can be written

$$\mathbf{S}(\mathbf{X},\mathbf{Y}) = \frac{\boldsymbol{X}.\boldsymbol{Y}}{||\boldsymbol{X}||\,||\boldsymbol{Y}||}$$

$$= \textstyle\sum_{n=1}^{N} \boldsymbol{S}(\boldsymbol{x_n}, \boldsymbol{y_n})\boldsymbol{w_n}$$

where $S(a, b) = a \cdot b/||a||\,||b||$ is the inner product between vectors a and b normalised by their respective norms.
For X with partial distortion, we intend to perform recognition based on the similarity based only on the clean local features (i.e. 'recognition by parts')

$$\mathbf{S}(\mathbf{X_I}, \mathbf{Y_I}) = \textstyle\sum_{n \in I} \boldsymbol{S}(\boldsymbol{x_n}, \boldsymbol{y_n})$$

where $I \subseteq \{1, 2, \ldots, N\}$ contains the indices of the clean x_n in X.

5) Classification using LDA

LDA is a supervised learning method that finds the linear projection in subspaces; it maximizes the between-class scatter while minimizing the within-class scatter of the projected data[8][9][14]. According to this objective, two scatter matrices S_B the between class scatter matrix and the within-class scatter matrices S_W are defined as

$$\mathbf{S_B} = \textstyle\sum_{c=1}^{C} \boldsymbol{M_c}(\mathbf{m_c} - \mathbf{m})(\mathbf{m_c} - \mathbf{m})^{\mathbf{T}}$$

$$S_W = \sum_{c=1}^{C} \sum_{x \in x_c} (m_c - m)(m_c - m)^T$$

where the set of training data $X = \{x1, x2 \ldots Xm\} = \cup_{c=1}^{C} X_c$ have total C classes, m is the sample mean for the entire data set, m_c is the sample mean for c^{th} class, $M_c = |X_c|$ is the number of samples of a class c , and $M = \sum_{c=1}^{C} M_c$. To maximize the between-class scatter and minimize the within-class scatter, the transformation matrix, w_{opt} , is formulated as

$$w_{opt} = \mathrm{argmax}_W \frac{|W^T S_B W|}{W^T S_W W|} = [w_1, w_2 \ldots\ldots w_n]$$

In face recognition, when dealing with high-dimensional image data, the within-class scatter matrix is often singular. To overcome this problem, PCA is first used with the sample data often called a PCLDA to reduce its dimensionality. The extracted feature f is projected to PCLDA in order to reduce the dimensionality of the augmented feature $y \in R^K$.

6) Score Fusion Based Upon Weighted Sum Method

One way to combine the scores is to compute a weighted sum as follows

$$S = \sum w_i s_i$$

where the weight w_i is the amount of confidence we have in the i-th classifier and its s_i score[10] .
In this .1/EER is used as a measure of such confidence. Thus, a new score is as follows

$$S = \sum s_i / EER_i$$

V. RESULTS AND OBSERVATIONS

A) Experimental Results

The system is implemented using MATLAB programming language. For this purpose MATLAB 13a is installed.

1) Dataset Description

In this experiment databases such as FRGC Evaluation Protocol, XM2VTS and AR were used in the experiments:

a) FRGC Evaluation Protocol:

FRGC provides three components as an evaluation framework: image data sets, experimental protocols, and the infrastructure. The FRGC data corpus contains high-resolution 2-D still images taken under controlled lighting conditions and with unstructured illumination as well. The still images were taken with a 4-mega-pixel digital camera, and the resolutions are either 1704 ×2272 or 1200 × 1600. The data corpus is divided into training and validation partitions. The data in the training partition was collected in the 2002–2003 academic year. The training set consists of 12,776 images from 222 subjects, with 6,388 controlled still images and 6,388 uncontrolled still images. Images in the validation partition were collected during the 2003–2004 academic year with time elapse. The validation set contains images from 466 subjects.

b) XM2VTS

First, experiments were conducted on the XM2VTS database. As preprocessing, we first manually localised the face in each image, so that the resulting images were aligned horizontally with the eyes and each face was centred vertically within each image. Then we resized each face image to 100 × 100 pixels. We have run four recognition experiments on the database. Each experiment included 100 persons selected randomly from the database, with four images for each person. Of the four images, one and two images, respectively, were used for training, and the remainder were used for testing. The test set contains clean images and corrupted images with simulated partial distortion by adding four different occlusions to each test image: (i) sunglasses, (ii) beard (for male) or scarf (for female), (iii) combined sunglasses/beard/scarf and (iv) hands.

c) AR Database

The AR database contains the realistic distortions of images. The AR database consists of frontal images of 126 persons. For each person, 26 pictures were taken in two separate sessions with variable partial occlusion, facial expressions and facial disguises. The following comparative graph shows the Verification rate obtained for proposed system is shown below:

2) Performance Metrics

The verification performance is characterized by two statistics: the verification rate (VR) and false acceptance rate (FAR). The FAR is computed from comparisons of faces of different people, defined as “non-match.” On the other hand, the VR is computed from comparisons of two facial images of the same person, defined as “match.”

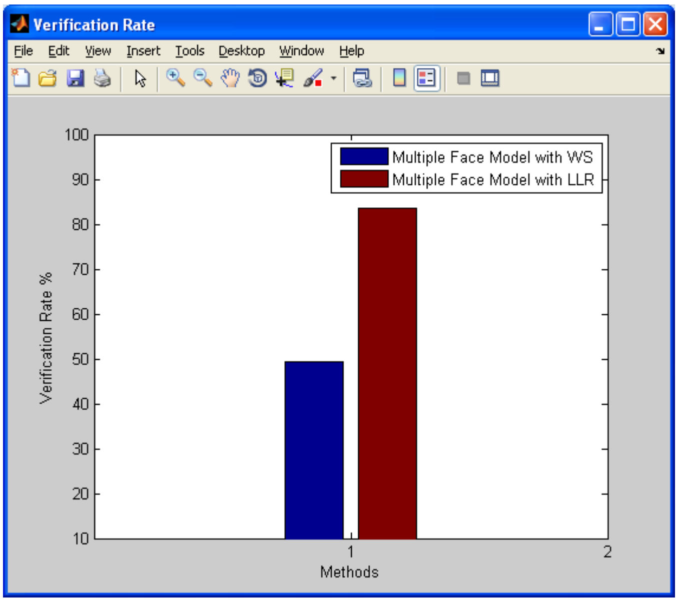

Figure 5.1: Face recognition verification rate comparison graph under uncontrolled illumination variations

The above graph in figure 5.1 and figure 5.2shows the verification performance obtained for existing system and proposed system of framework. Existing system recognizes the face under uncontrolled illumination variations whereas proposed system recognizes face under uncontrolled illumination variations and partial occlusion. All parameters of the LLR and weighted sum methods are calculated in advance by training samples, respectively for face recognition purpose. Thus the proposed system provides higher verification rate in terms of LLR and weighted sum methods than the existing methods of frameworks

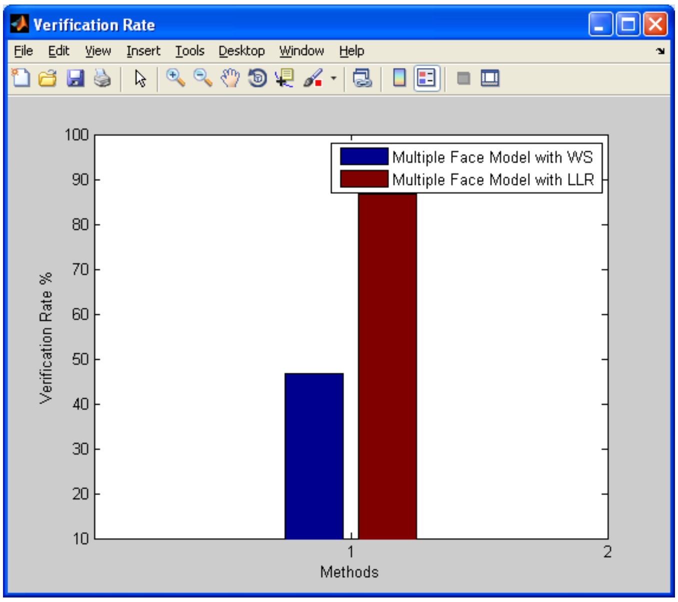

Figure 5.2: Face recognition verification rate comparison graph under uncontrolled illumination variations and partial occlusion .

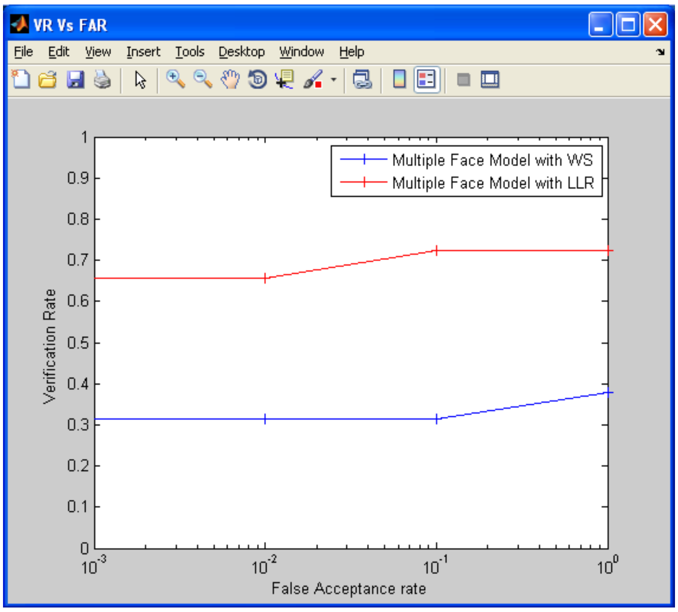

Figure 5.3: Verification curves for face recognition under uncontrolled illumination variations fused by the weighted sum and by LLR

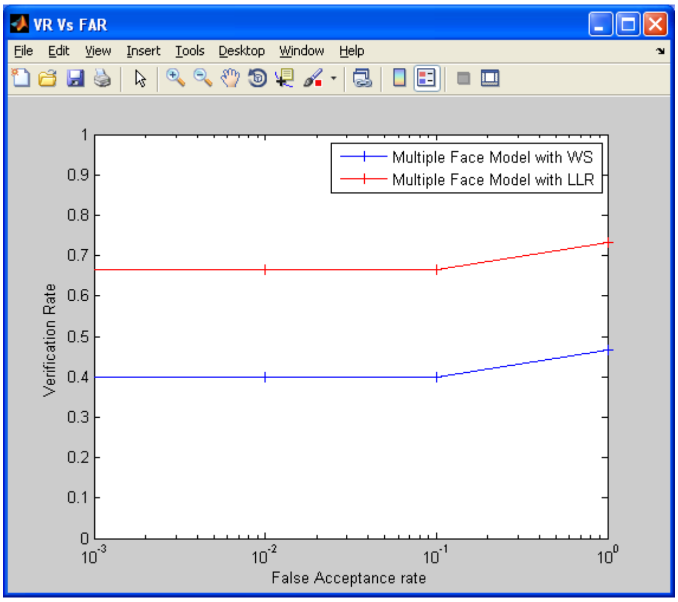

Figure 5.4: Verification rate for face recognition under uncontrolled illumination variations and partial occlusion fused by the weighted sum and by LLR

The above graph in Figure 5.3 and Figure 5.4 shows the verification rate for existing system and proposed system of framework. Existing system recognizes the face under uncontrolled illumination variations whereas proposed system recognizes face under uncontrolled illumination variations and partial occlusion. The above graph in Figure 5.3 is constructed based on Hybrid Fourier feature and Figure 5.4 is constructed based on Local feature and Hybrid Fourier feature for better accuracy of the face recognition respectively.
In Figure 5.3 verification rate obtained for Hybrid Fourier feature is 0.32 for weighted sum methods and 0.65 for LLR. In Figure 5.4 verification rate obtained for Hybrid Fourier feature is 0.45 for weighted sum methods and 0.65 for LLR .All parameters of the LLR and weighted sum methods are calculated in advance by training samples, respectively for face recognition purpose. Thus the proposed system provides higher verification rate in terms of LLR and weighted sum methods than the existing methods of frameworks.

The below ROC graph in Figures from 5.5 and 5.6 shows the performance improvement of face recognition accuracy by using local features and hybrid Fourier features respectively. A ROC graph is a plot with the false positive rate on the X axis and the true positive rate on the Y axis.

The TP value is measured in % at Y-axis and FP value in X axis. From the graph, TPR is improved for proposed method when compare with the existing methods. From the graph, TPR is improved for proposed method when compare with the existing methods. The proposed method will be useful for the scenarios where the input images have small resolution and it has the benefits of lower computational complexity compared to the local feature-based methods

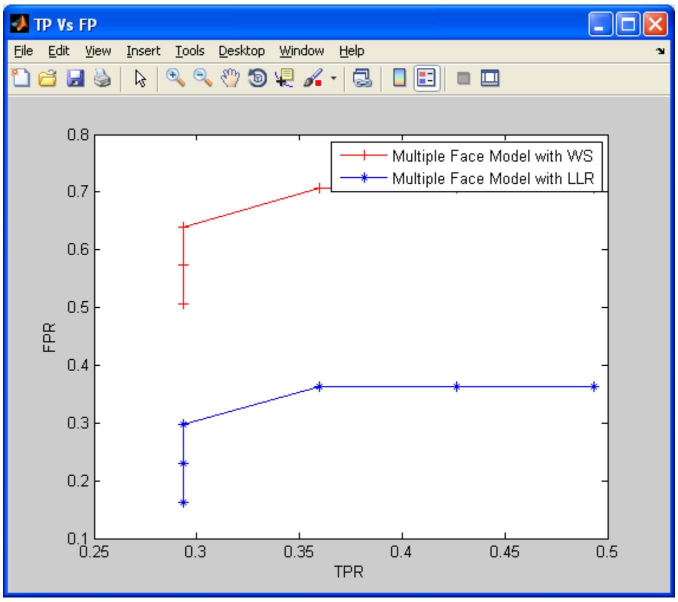

Figure 5.5 ROC curve for face recognition under uncontrolled illumination variations fused by the weighted sum and by LLR

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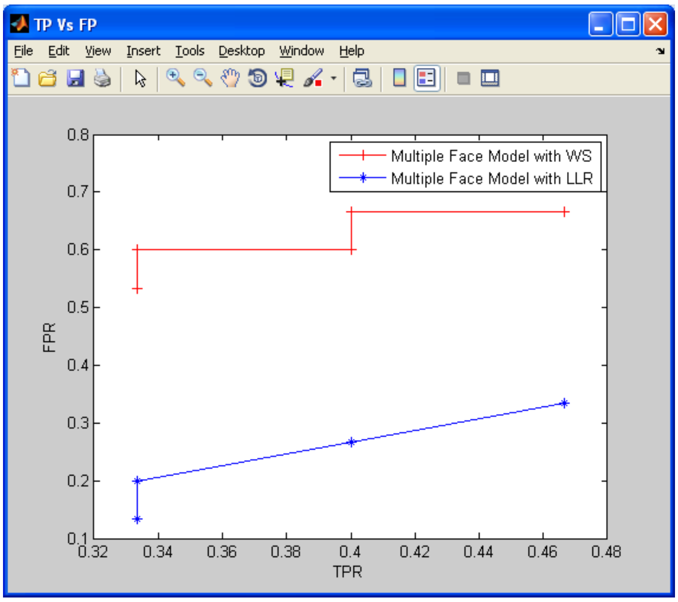

Figure 5.6: ROC curve for face recognition under uncontrolled illumination variations and Partial occlusion fused by the weighted sum and by LLR

VI .CONCLUSION AND FUTURE WORK

The present work proposes face recognition approach using combined method uncontrolled illumination variations and partial occlusion for face recognition. First, a preprocessing method is proposed based upon the analysis of the face imaging model with the definitions of intrinsic and extrinsic factors of a human face and proposed the INGI method as an illumination insensitive representation for face recognition. Then Features of hybrid Fourier features and Local features are extracted. Hybrid Fourier features includes three Fourier domains, concatenated real and imaginary components, Fourier spectrum, and phase angle. Local features are extracted from small local images each contain only a little information about the face. Optimal features are selected by using PUM which provide robustness both to partial occlusion and to illumination variation. For limited training data, similarity-based formulation is used by extending the PUM. Finally the selected feature of each domain within its own proper frequency bands, and to gain the maximum discriminant power of the classes, each feature is projected into the linear discriminative subspace with the PCLDA scheme. Experimental result provides better result when compare with the existing system.

As a future work, it is of interest to extend our approach to address face recognition under general occlusions, including not only the most common ones like sunglasses and scarves but also like beards, long hairs, caps, extreme facial make-ups , etc. Automatic face detection under severe occlusion, such as in video surveillance applications, is also far from being a solved problem and thus deserve thorough investigations.

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