ISSN (e): 2250 – 3005 || Volume, 07 || Issue, 07|| June – 2017 ||
International Journal of Computational Engineering Research (IJCER)

Face Recognition under Varying Illuminations Using Local Binary Pattern And Local Ternary Pattern Fusion

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ABSTRACT
Combining information from two illumination invariant descriptors can provide more discriminative features and high recognition accuracy. In this paper, an illumination invariant face recognition algorithm is proposed based on the combination of gradient based illumination normalization and fusion of two illumination invariant descriptors. The ratio of the gradient amplitude and original image intensity provides the illumination invariant face representation. Illumination insensitive descriptor Local Binary Pattern and its noise resistant version Local Ternary Pattern are used to extract the image features. The feature sets obtained from the LBP and LTP are consolidated into a single feature set by using feature normalization and feature selection. Artificial neural network is used in the classification stage. The efficiency of the proposed hybrid technique is tested on Extended Yale B and AR face database and the recognition rates of 100% and 99.0741% are achieved.
Keywords: Face Recognition, Local Binary Pattern, Local Ternary Pattern, Illumination, Feature Extraction

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Date of Submission: 08-07-2017 Date of acceptance: 20-07-2017

I. INTRODUCTION

Automatic Face recognition is a prominent research area in the current era of the research. Among the various forms of biometric such as iris, fingerprint and voice, face recognition is the most frequently used technology due to its low computational cost and real time applications. Face recognition is extensively used in the fields of security and surveillance systems, law enforcement, telecommunications, human computer interaction and access control. Identification or verification of the individuals is carried out on the basis of their physiological or behavioral characteristics in a biometric system.

Face recognition algorithms mainly perform the task of verification and identification. In the verification process, a face image and its claimed identity are given to the system and the system either accepts or rejects the claim. However in the identification process, some images of the known individuals are used to train the system. When the test image is given to the system, the system identifies which individual the image belongs to. The Face recognition process consists of following stages:

- Image acquisition – The face images are first acquired using any digital device. The images used for face recognition are static images or image sequences. Grey-scale images are most frequently used for face recognition.
- Pre-processing – The face images are preprocessed prior to the feature extraction stage. The preprocessing stage may include various forms of signal conditioning such as normalization, noise removal, image segmentation or locating various parts of the face such as eyes, ears, mouth etc.
- Feature extraction – Feature extraction algorithms are applied on the normalized face images to extract the salient feature vectors which contain useful information for distinguishing various faces. The pixel data is converted into a higher level representation of shape, color, motion, texture and spatial configuration of facial skin and its components.
- Classification – In the classification stage, the features extracted from the input face images are matched to the features of the enrolled face images in the database. It basically involves the process of identifying to which person in the face database, the face image belongs to. The classifier result is based on the set of training data used in the training phase [6].

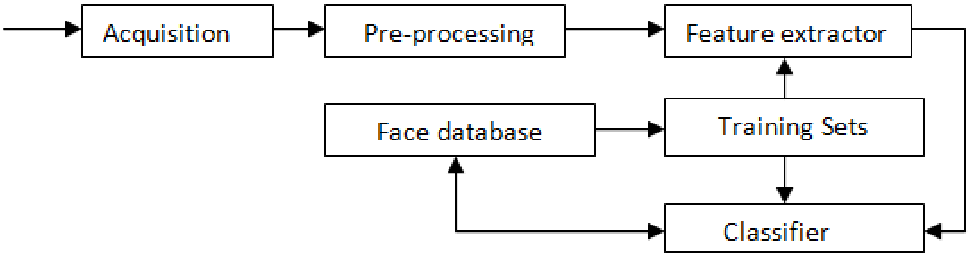


Figure 1 Block diagram for face recognition process [24]

Illumination is the most crucial factor affecting the recognition accuracy of many of the existing face recognition systems. The pixel values are intensively changed due to lighting variations. The image variations due to changing illumination conditions are sometimes more critical than the variations due to distinctive individual identities, thereby leading to misclassification of the input images. Thus illumination is the most important factor determining the success or failure of a face recognition system. The illumination variations affect the feature extraction phase due to the generation of redundant shapes and shadows by the ditches and knobs of a particular face under changing lighting conditions. Moreover, the preprocessing is required by the images which are too dark or too bright partially even in the cases where the lighting angle is not too wide [12].

Figure 2 Face images with different illumination conditions [11]

An ample amount of work has been done in the past few years to develop various face recognition techniques which are robust against illumination variations. The approaches developed for addressing the illumination variation problem are broadly classified into two main categories [11]:

Passive approaches – The illumination problem is overcome by analyzing the visual spectrum images in which the appearance of face has been changed by variations in illumination.

Active approaches – They use active imaging techniques to obtain the images of the face captured under uniform illumination conditions.

II. RELATED WORK

Illumination variations adversely affect the performance of most of the existing face recognition systems. The feature extraction algorithms have to be robust against changing illumination conditions in order to improve the accuracy of the face recognition systems. In the past few years, various techniques have been proposed to overcome the illumination variations:

In [19] Chengjun Liu et al. presented a novel Gabor–Fisher Classifier (GFC) method for face recognition. GFC method worked by applying the Enhanced Fisher linear discriminant Model (EFM) to an augmented Gabor feature vector derived from the Gabor wavelet representation of face images. The method is proved to be robust against changes in illumination and facial expressions. In [18] Chengjun Liu et al. proposed an independent gabor features (IGFs) technique for face recognition. The IGF technique works by the derivation of a Gabor feature vector from a collection comprising of downsampled Gabor wavelet representations of facial images followed by the reduction of dimensionality of the vector by the method of principal part analysis, and finally the independent gabor features are defined based on the independent component analysis (ICA). These gabor features possess an independency property that facilitates the application of the PRM method for the classification purpose. In [13] Timo Ahonen et al. proposed a new technique of face recognition in which both the shape and texture information is considered for the representation of face images. The face area is divided into small regions followed by the extraction of Local Binary Pattern (LBP) histograms and the histograms are concatenated into a single, spatially enhanced feature histogram which represents the face image efficiently. For the recognition purpose, the nearest neighbor classifier is used in the computed feature space with a dissimilarity measure as Chi Square. In [14] Lei Zhang et al. proposed new technique Sparse Representation based classification which works by firstly coding a test sample in the form of sparse linear combination of all the training samples and then the test samples are classified by evaluating which class has the minimum representation error. SRC can be made robust to face occlusion by coding the occluded portions of face images using an identity occlusion dictionary. But the l_1 norm minimization and more number of atoms in the dictionary make SRC computationally expensive. In [22] Meng Yang et al. proposed a Gabor feature based robust representation and classification technique. Gabor features increases the discrimination power and also have less number of atoms than identity occlusion dictionary. The use of l_2 norm in place of the l_1 norm to regularize the coding coefficients also reduces the computational cost. In [1] Soodeh nikan et al. presented a hybrid approach for face recognition which involved the use of two common illumination invariant descriptors multi-resolution Local Binary Pattern and Local Ternary Pattern for feature extraction. The fusion of the distance measurements of Chi-Square classifier is carried out at score level to find the best match and then decision level fusion is used to combine the results of two matching techniques.

III. PROPOSED WORK

The proposed system comprises of a hybrid feature extraction technique which is a combination of an illumination invariant descriptor Local Binary Pattern and its noise resistant version Local Ternary Pattern. The overall architecture of the proposed system is given in Figure 3. The various modules used in the system are preprocessing, feature extraction, feature fusion and classification. The two illumination invariant feature extraction techniques multi-resolution LBP and LTP are used in the feature extraction stage. The feature level fusion of the features extracted from both the techniques is carried out in the next step. In the classification stage, Artificial Neural Network classifies whether the given face matches the database images or not.

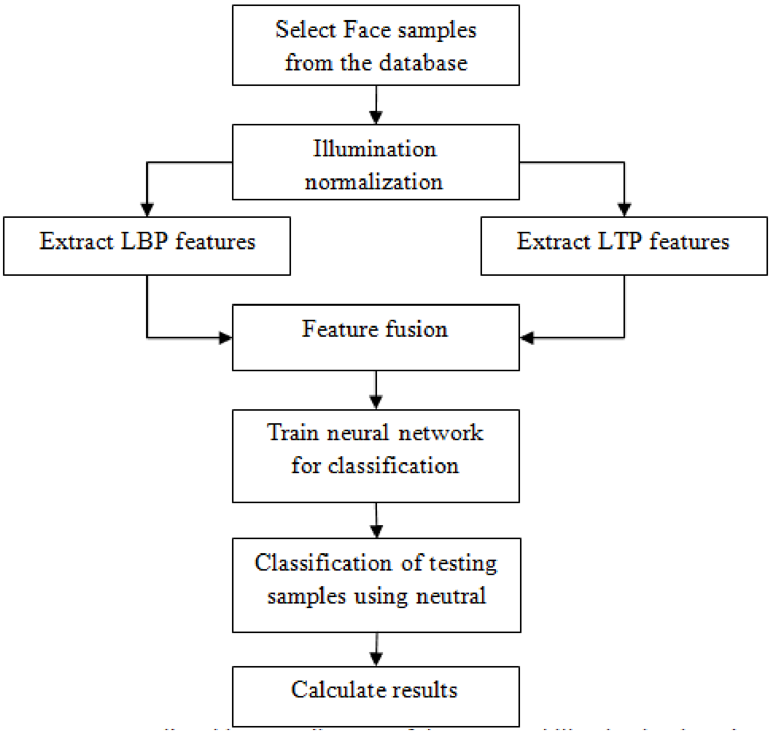


Figure 3 Overall architecture diagram of the proposed illumination invariant approach

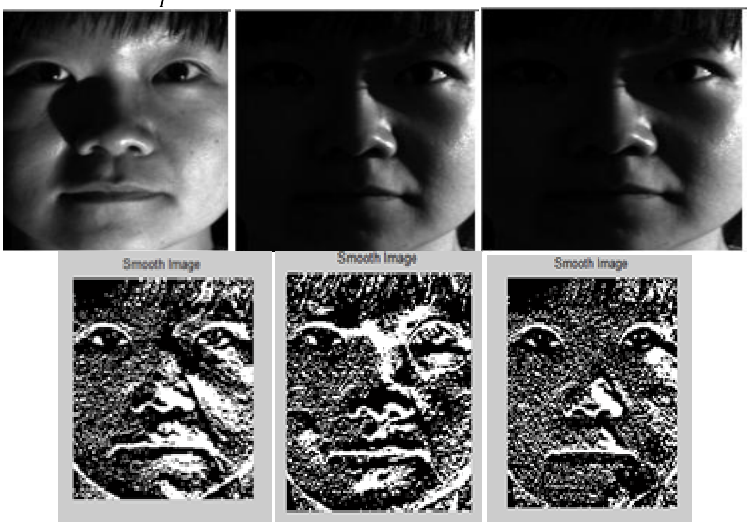
A. Illumination normalization

Different methods of image normalization are used to minimize the influence of the illumination variations on the face recognition system. In the proposed work, a method based on gradient domain processing is used to obtain the illumination insensitive image representation [1]. The gradient domain processing takes into consideration the dependency between the pixels and hence the image representation so obtained is more discriminative. The illumination effect is suppressed significantly if the ratio of the gradient amplitude to the original image intensity is taken.

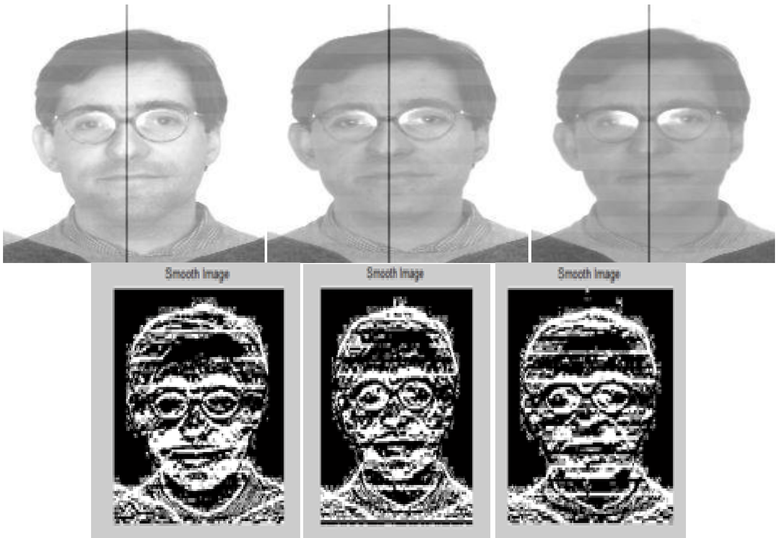
$$\frac{GA}{I} = \frac{L(x,y)\sqrt{(\frac{\partial R(x,y)}{\partial x})^2+(\frac{\partial R(x,y)}{\partial y})^2}}{L(x,y).R(x,y)} = \frac{\sqrt{(\frac{\partial R(x,y)}{\partial x})^2+(\frac{\partial R(x,y)}{\partial y})^2}}{R(x,y)} \quad (1)$$

where L(x,y) is the illumination component and R(x,y) is the reflection component of the image. To avoid the ambiguity due to zero values of image intensity in the above ratio, we take tan−1 of the ratio i.e.

$$\rho = tan^{-1}(\frac{GA}{I}) \quad where \quad 0 \leq \rho \leq 2\Pi \quad (2)$$



(a)



(b)

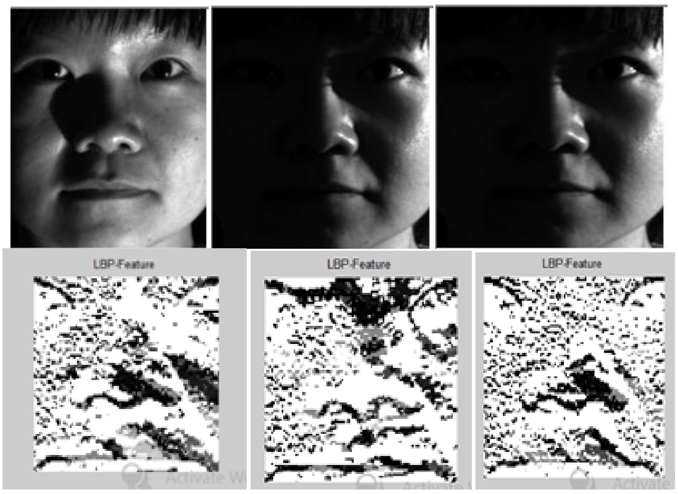
Figure 4 Results of illumination normalization on (a) Extended Yale B database (b) AR database

B. Feature extraction

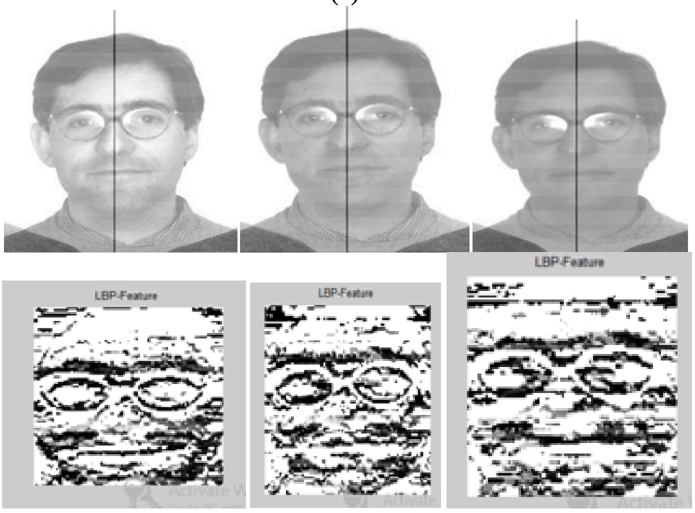
1) *Local binary pattern* – The Local Binary Pattern[12] feature vector is generated in the following manner:

- The examined window is divided into cells (e.g. 16x16 pixels for each cell).
- Each pixel in a cell is compared to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). The pixels are followed along a circle, i.e. clockwise or counter-clockwise.
- A pixel is assigned value '1'if it is greater than center pixel and '0' if it is less than center pixel value thus giving an 8-bit binary pattern which is usually converted into decimal form for convenience.
- This gives the facial feature of the given face image.
- The value of LBP code for a pixel say (x_c, y_c) is obtained as :

$$LBP_{P,R}=\sum_{P=0}^{P-1} s(g_p - g_c)2^p \qquad s(x)=1 \text{ if } x\geq 0; \quad s(x)=0 \text{ otherwise.}$$



(a)



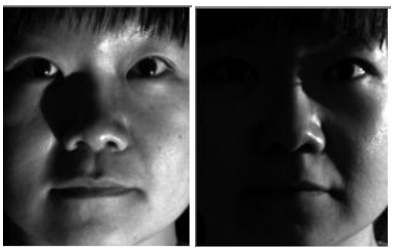
(b)

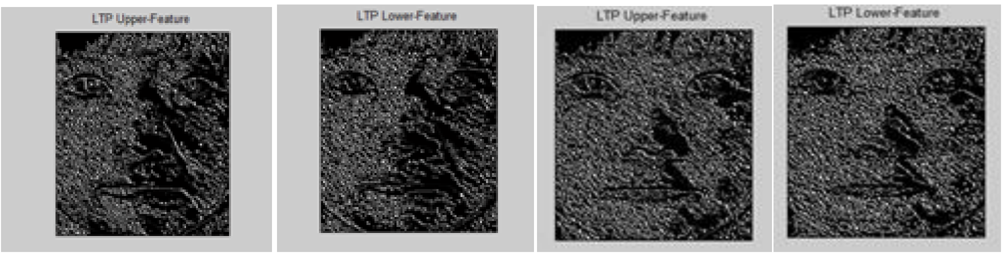
Figure 5 Results of LBP feature extraction on (a) Extended Yale B database (b) AR database

2) *Local Ternary Pattern* – Local ternary patterns (LTP) [9] are the extended form of Local binary patterns (LBP). While LBP thresholds the pixels into 0 and 1 by comparing with the center pixel but a threshold constant is used in LTP technique to threshold pixels into three values i.e. 0,1 and -1. Considering c as the value of center pixel, k as the threshold constant and p as the neighboring pixel , the result of thresholding is:

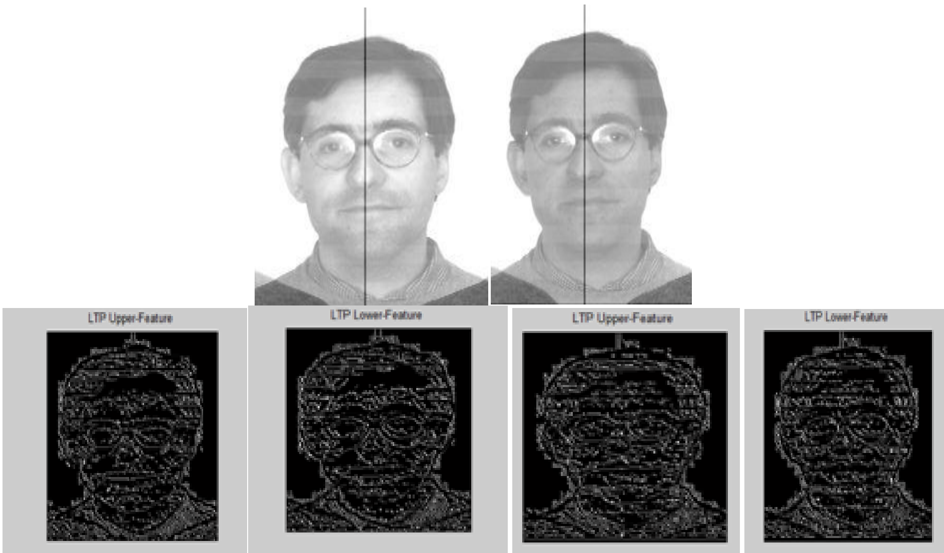
$$s'(x)=\begin{cases} 1 & p > c + k \\ 0 & p > c - k \text{ } and \text{ } p < c + k \\ -1 & p < c - k \end{cases} \tag{3}$$

In this way, one of the three values are assigned to each of the threshold pixel by LTP. A ternary pattern is obtained by combining the neighboring pixels after thresholding. If the histogram of these ternary values is computed, it will result in a large range, so the ternary pattern is split into two binary patterns. A descriptor double the size of LBP is obtained by concatenating the histograms of these two binary patterns for each cell.





(a)



(b)

Figure 6 Results of LTP upper and lower feature extraction on (a) Extended Yale B database (b) AR database

C. Feature fusion

The features extracted from the two feature extraction techniques are fused to form a feature vector for the classification purpose. In the fusion at feature level, the feature sets obtained from multiple feature extraction algorithms are integrated into a single feature set by making use of the techniques like feature normalization, feature selection etc[8]. Firstly, the correlated feature values generated by the different feature extraction techniques are detected and then a salient set of features are identified which can improve the recognition accuracy of the system. The main motive of feature normalization is to adjust the scale and location of the feature values obtained from the two techniques so that their contribution to the final match score becomes comparable. Min-Max technique is used for feature normalization. The max-min normalization is performed as follows:

$$x' = \frac{x - \min(F_x)}{\max(F_x) - \min(F_x)}$$

where F_x denotes the function that generates x, and max (F_x) and min (F_x) represents the maximum and minimum values respectively for all possible x. In the feature selection process, a limited set of relevant features which contain most of the discriminatory information are selected while the redundant features are discarded.

D. Classification

Artificial Neural Networks are somewhat unrefined form of electronic networks of neurons which are based biological neural structure of the brain. The records are processed one at a time and the Artificial Neural Network learns by comparing its own classification of records to the actual known classification of records. The neural network is basically the organization of neurons into three layers: input layer, hidden layer and output layer. The input layer of the network comprises of record values that are to be given as inputs to next hidden layer of neurons. The next layer after input layer is hidden layer. A neural network may contain several hidden layers. The next is the output layer which has one node for each class. The values are assigned to each output node even in a single sweep forward through the network and the class node with the highest value is assigned the record.

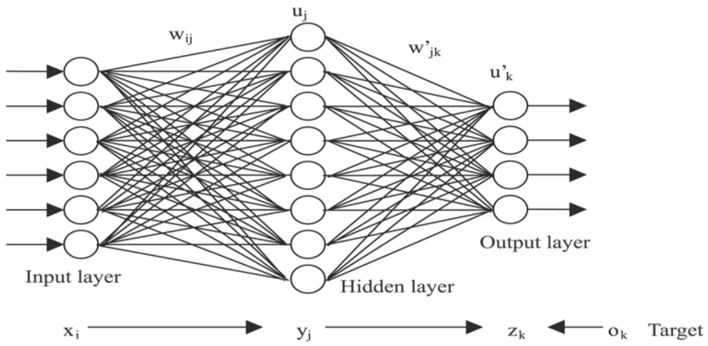


Figure7 Artificial Neural Network Architecture [25]

In the training stage, the actual class of each record is known and the correct values can be assigned to the output nodes i.e. '1' is assigned to the node belonging to the correct class and '0' is assigned otherwise. The network's calculated values are compared with these correct values and an error term is calculated for each node. The weights in the hidden layer are adjusted using these error terms so that for the further iterations the network's calculated values can be closer to the correct values.

IV. EXPERIMENTAL RESULTS

Experiments are conducted on two popular face databases Extended Yale B and AR database in order to check the strength of the proposed method against illumination variations. The robustness of the algorithm is tested under severe illumination variations under uncontrolled conditions. The proposed method is compared with other existing techniques and the recognition accuracies of various techniques on the Extended Yale B and AR database are shown in the Table I and II respectively. The proposed method gives better results than the existing techniques in terms of recognition accuracy.

Extended Yale B database

The Yale B database consists of 5760 images having size 192 ×168 pixels for 10 persons with 9 different poses and 64 illumination conditions for one pose. The Extended Yale B database is an extended form of Yale B database with 10 to 38 subjects having 21 888 single light images with the same viewing conditions as in Yale B. The frontal pose images of 20 persons with 26 different illumination conditions per person are used in this work to evaluate the performance and illumination insensitivity of the proposed algorithm. The method achieves 100% accuracy on the Extended Yale B Database [1].

AR database

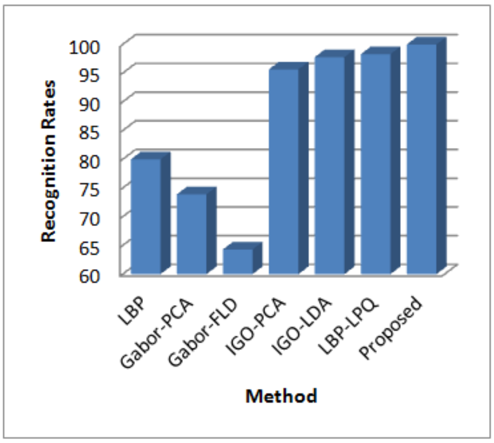
The AR face database consists of 3536 facial images of 136 people out of which 76 are men and 60 are women. The images are frontal view face images with different illumination conditions, facial expressions and occlusions. The frontal view face images of 9 persons under 12 different illumination conditions are used in this work for evaluating the performance of the algorithm. The proposed work achieves 99.071 % accuracy on the AR database [1].

METHOD	RECOGNITION ACCURACY(%)
LBP[3]	80
Gabor-PCA[18]	73.9
Gabor-FLD[19]	64.3
IGO-PCA[16]	95.65
IGO-LDA[16]	97.80
Multi-resolutionLBP-LPQ[1]	98.30
Proposed method	100

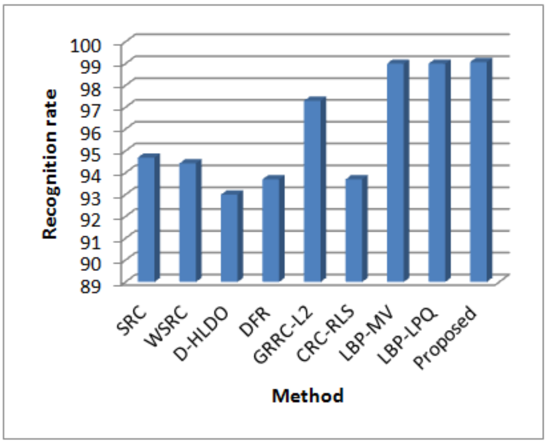
Table 1 Accuracy Percentage of various techniques on Extended Yale B database

METHOD	RECOGNITION ACCURACY(%)
SRC[14]	94.7
WSRC[20]	94.43
D-HLDO[17]	93
DFR[21]	93.7
GRRC-L2[22]	97.3
CRC-RLS[23]	93.7
LBP-MV[15]	99
Multi-resolution LBP-LPQ[1]	99
Proposed method	99.0741

Table 2 Accuracy Percentage of various techniques on AR database



(a)



(b)

Recognition rates of various FR techniques on (a) Extended Yale B (b) AR database

V. CONCLUSION

Illumination variations affect the performance of face recognition systems by altering the face appearance and thereby reducing the recognition rates. The proposed system uses the gradient based illumination normalization to remove the luminance component superiorly. The illumination insensitive local histograms are extracted using Local Binary Pattern which is insensitive to monotonic grayscale variations and its noise resistant version Local Ternary Pattern. The features extracted from the two techniques are consolidated into a single feature set using feature level fusion and classified using Artificial Neural Networks. The proposed algorithm is evaluated on two famous face databases Extended Yale B and AR database and the better accuracies are achieved using the proposed method as compared to the existing techniques.

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International Journal of Computational Engineering Research (IJCER) is UGC approved Journal with Sl. No. 4627, Journal no. 47631.

Swati Manhotra. "Face Recognition under Varying Illuminations Using Local Binary Pattern And Local Ternary Pattern Fusion." International Journal of Computational Engineering Research (IJCER) 7.7 (2017): 69-77.