A Robust Illumination and Intensity invariant Face Recognition System

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Abstract: Face recognition has achieved more attention in computer vision with the focus on modelling the expression variations of human. However, in computer vision system, face recognition is a challenging task, due to variation in expressions, poses, and lighting conditions. This paper proposes a facial recognition technique based on 2D Hybrid Markov Model (2D HMM), Cat Swam Optimization (CSO), Local Directional Pattern (LDP), and Tetrolet Transform. Skin segmentation method is used for pre-processing followed by filtering to extract the region of interest. Resultant image is fed to proposed feature extraction method comprising of Tetrolet Transform and LDP. Extracted features are classified using proposed classifier "CSO trained 2D-HMM classification method". To prove the superiority of method, four face datasets are used, and comparative results are presented. Quantitively results are measured by False Acceptance Rate (FAR), False Rejection Rate (FRR) and Accuracy and the values are 0.0025, 0.0035 and 99.65% respectively

Keywords: Signal Processing, Image Processing, Face Recognition, 2D Hybrid Markov Models, Cat Swam Optimization, Local Directional Pattern, Tetrolet Transform

I. INTRODUCTION

The non-intrusiveness is the major reason behind success of facial recognition systems as a biometric system along with other properties like accessibility and high social acceptability [1]. Facial recognition systems have various applications, such as surveillance, commerce, security, entertainment, and forensics [2]. Human facial recognition techniques become important and handy where the biometrics of fingerprints, iris image and retinal scans are not available or not possible owing to a non-interactive environment [3]. Facial recognition has studied for almost three decades but there are still some unsolved issues such as pose variation, makeup, illumination variation, intensity variation, facial expressions, and scale differences. One more issue with face recognition comes at the time of image acquisition, it suffers from affine transform which increases complexity of the facial recognition system. [4, 5]. Other than this, due to pose variations, facial makeup, and the variation in lightening conditions, the 3D facial scan becomes very difficult [6]. The facial scan represents the 3D geometry, which is capable of providing the new clue for obtaining the exact face recognition. Thus, the 3D face recognition is capable of reducing the drawbacks associated with the 2D face recognition, and acts as a complementary or substitute solution for the existing 2D face recognition methods [7, 8].

Any image in facial recognition system goes through three basic processes. First process is face acquisition from the compound image and holds information about localization and region for face detection. Facial feature or facial data extraction is next process where appearance and geometry related data are extracted. Last process is classification of face. Depending on application and requirement identification of face can be done using global or local features [2, 5]. The algorithms for the existing 3D face recognition system are of two classes, such as holistic-based and the local feature-based algorithms [2]. The common examples of the holistic algorithms are the extended Gaussian images [9], spherical harmonic features [10], Iterated Closest Point (ICP) based surface matching algorithms [3], and the canonical forms [11]. The main drawback of the holistic algorithms is the need for the exact normalizations of the 3D faces, and the more sensitiveness in case of the facial occlusions and the expressions [1, 12].

Yulan Guo *et al.* [8] designed the local feature-based shape matching algorithm, which was capable of providing the global similarity information among the faces using the face recognition process. In addition, this method was capable to perform well even in the presence of the local features but failed in the detection of nose tip with enough accuracy. Li Ye, *et al.* [13] designed the 3D face recognition method using multiple subject-specific curves that offered the necessary and stable features of the facial surface to recognize the face but fails in partially occluded and non-frontal 3D faces. Jaime A. Martins *et al.* [14] modelled the expression-invariant face recognition system in which the data about the 3D structure accompanied the data of luminance that increased the system robustness. Author simulated good results, but accuracy was main concern. Duc My *et al.* [15] developed the Hierarchical Collaborative Representation-based Classification (HCRC). The proposed system has been capable of achieving an increased recognition rate, and recovered the inadequate solution, but not suitable for some evaluation datasets that contains the face images that were new. Xing Deng *et al.* [16] designed the expression-robust 3D face recognition method using feature-level fusion and feature-region fusion that was computationally efficient and offered a better solution for dimensionally complex problems, but, the dimensionality problem in the presence of occlusion cannot be eliminated effectively. To eliminate the misalignment problem of facial features, D. L. Li et. al. [17] proposed facial alignment method based on regression tree and geometric analysis of facial expression to locate facial feature points. E. J. Li et. al. [18] proposed feature extraction using two layer CNN and sparse representation to improve performance of SRC via a precisely selected feature exactor.

Yao Peng and Hujun Yin, [19] modelled the classification and a robust expression-invariant face recognition method. The main drawback of this method was the failure in the assessment of the real-time facial expression and face recognition methods for video sequences. Wei Quan, *et al.* [20] modelled the 3-D shape representation scheme for automatic face analysis and identification to solve the recognition problem of face with respect to change in pose of the face without loss of information but execution time of the system was the main drawback of this system. Xing Deng, *et al.* [21] designed a novel facial coarse-to-fine landmark localization method based on active shape model. The proposed method created increased power of discrimination to reduce the effect of facial expression variation and enhance the recognition accuracy, but the selection of the robust feature was tedious. Mejda Chihaoui *et al.* [22] modelled the 2D face recognition approach called HMM-LBP feature extraction that made the identification and the verification of a specific person possible. The main limitation of this method was the consideration of the face images, non-face images, and the multi-face images as the images and finally classified all images as the faces. Vitoantonio Bevilacqua *et al.* [23] developed Pseudo 2D HMM and it applied with neural network coefficients that attained a better recognition rate, but this system was not robust.

To perform the act of facial recognition, various classifiers have been developed. The most commonly used algorithm is the nearest-neighbor (NN) suitable for solving various problems due to its simplicity and accuracy. However, the main drawback is the usage of a single training sample for the representation of the face image under test. Thus, the classifier called nearest feature line was developed. It used two training samples for all the classes for the representation of the face test images. Further modification to nearest feature line was nearest feature plane classifier, which uses three samples for the representation of the face test image [24, 25]. The classifier known as nearest subspace [26, 27] and the local subspace classifier [28] are used for the representation of the test image with the training samples of classes. As the samples of certain object class has the possibility to fail in linear subspace, the linear regression classification (LRC) [29] algorithm was developed with respect to linear regression. The support vector machine (SVM) classifier [30] is the important classifier that works on the basis of structural risk minimization theory in statistical learning. The SVM classifier is capable of performing the classification of components, which are non-linear in an effective manner, and then the inputs are mapped onto the feature space. Then, a large margin hyper-planes are obtained among the classes that are solved using the quadratic programming algorithm. However, the SVMs are not capable of discriminating between vectors that define out samples of missing entities. These entities are generated due to occlusion present on the face [13, 16]. J. Dalal *et al.* [31, 32] addressed face recognition under variation in lighting conditions using histogram equalization, skin segmentation, principal component analysis to reduce dimensionality of image and neural network for recognition. Authors also presented face identification technique in a group photograph using histogram equalization and SURF technique [33]. D. L. Li *et. al.* proposed a appearance based facial recognition scheme using NWFE to enhance separability of different subjects, approach performed well but scheme is not computationally cost effective for high dimensionality of trained linear projection matrix [34].

The variation in the facial expression is considered as the main problem in the recognition of the face, due to the effect of it in the performance of recognition. The shape of certain surface of the face, like nose, can be stored accurately, even after the deformation of the 3D shape by the variation in facial expression [8]. To perform the holistic matching based on scale, illumination and pose the accurate normalization odd face is needed as this disturbs the feature extraction and affects the accuracy of face recognition [1].

The reason behind using HMMs is its ability to classify faces into meaningful regions which can be converted to probabilistic characteristics. So the concentration of specific facial features can results in person identification. Texture methods are widely applied for face recognition. As we know that, LBP and Gabor pattern played a major role in face recognition. After that, LDP proved that it is very effective for invariant facial recognition due to the stability of gradients compared to the grey value in the presence of noise and non-monochromatic illumination change. This is the reason that we considered LDP for feature extraction. The performance of Tetrolet transforms very well good in recovering shape of edges and directional details. Also, it was very effective in image fusion. For optimizing the HMM structure, genetic algorithm (GA) was applied initially. GA is the most popular and old technique for optimization. As it faces the local search issue in finding the optimal structure. To overcome such issues in structure optimization, we are using Cat Swarm Optimization (CSO); which proved to be efficient and effective in searching.

In this paper we are introducing an automatic face recognition method based on Tetrolet LDP along with 2D HMM optimized by CSO for face recognition. The proposed method can effectively deal with:

- Intrapersonal variation,
- Change in illumination and
- Change in intensity.

II. METHODOLOGY

An automatic face recognition method using modified Hidden Markov Model has been introduced. The three basic steps involved in the automatic face recognition are pre-processing, feature extraction, and face recognition. At first, the image from the input database is fed to the pre-processing module, where pre-processing is carried out using the filtering method. The pre-processed image is then allowed to the feature extraction process using Tetrolet-Local Directional Pattern (Tetrolet-LDP). The proposed Tetrolet-LDP is obtained with the combination of the Local Directional Pattern (LDP) [35] and Tetrolet transform [36] used for extracting the features. These facial features are used in the recognition of the face with the proposed classification model, which is obtained from the modification of the 2-Dimensional Hidden Markov Model (2D-HMM) and the Cat Swarm Optimization (CSO) [37]. The CSO trains the 2D-HMM. The performance of the proposed method is analysed by through intrapersonal variations, intensity variations, and illumination variations. Figure 1 shows block diagram of proposed face recognition system.

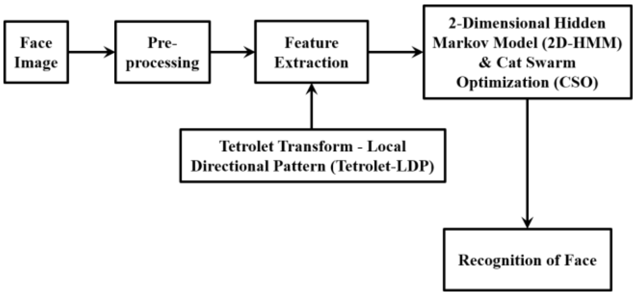

Fig. 1. *Block diagram of the proposed face recognition*

A. Pre-processing of the input facial image

The image from the input database is subjected to pre-processing using the filtering method in order to remove the background of the input sample image *J*. For filtering we use skin segmentation to get only facial region in the image. Figure 2 shows the steps of pre-processing.

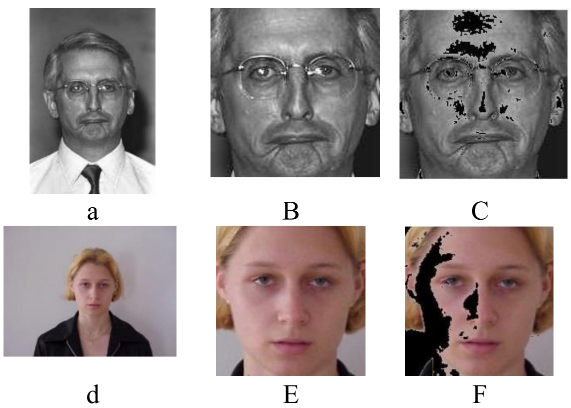

Fig. 2. *Pre-processing steps (a) Original Gray Image (b) Region of Interest in Gray Image (c) Pre-procesed Gray Image (d) Original Colour Image (e) Region of Interest Colour Image (e) Pre-procesed Colour Image*

B. Proposed Feature Extraction Method

Combination of Tetrolet Transform and LDP are used to carry out feature extraction. Proposed method enables study of intrapersonal variations, illumination variations, intensity variations, and training data variations. Feature extraction is fully automatic and without user intervention. Figure 3 shows the step by step process of proposed feature extraction method.

The steps involved in the extraction of the features using the proposed descriptor are as follows:

Step 1: LDP Image Extraction: The pre-processed image is fed to LDP, which is an effective local pattern descriptor that accomplishes a directional component using the Kirsch compass kernels. Consider the image *R*, with the intensity S_i at the pixel (u_i, v_i), and S_n be the intensity of the neighbouring pixel in the absence of the center pixel S_i, with $n = 0, 1, 2... 7$. The eight responses of the Kirsch masks are termed as k_n, and k_h is the h^{th} highest Kirsch activation. The neighbouring pixels with Kirsch response greater than k_h is assumed as *1*, and the Kirsch response less than k_h is assumed as *0*. The value of LDP for the pixel (u_i, v_i) is expressed as,

$$L_n(u_i, v_i) = \sum_{n=0}^{7} e(k_n - k_h).2^n \qquad (1)$$

where, $e(k_n - k_h) = \begin{cases} 1, & if\ e(k_n - k_h) \geq 0 \\ 0, & if\ e(k_n - k_h) < 0 \end{cases}$

The binary image J_1 is obtained as the output of this step.

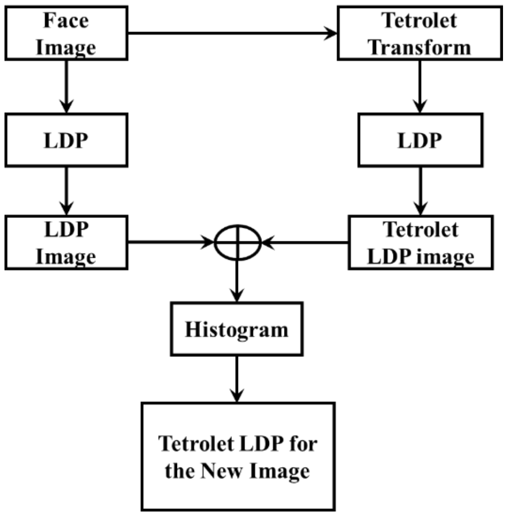

Fig. 3. *Feature Extraction using Tetrolet LDP*

Step 2: Tetrolet–LDP image Extraction: One copy of pre-processed image is passed through Tetrolet Transform followed by LDP to obtain Tetrolet-LDP image. The Tetrolet Transform is carried out using the following steps:

i) Input Image Partition: The input image is partitioned into number of blocks of size *4X4*.

ii) Evaluation of sparsest tetrolet representation: The sparsest tetrolet representation for each block is found. In each block, 117 admissible tetromino coverings *b = 1, 2, ..., 117* are considered, and for each *b*, Haar wavelet transform is applied. Thus, for each *b*, 12 tetrolet coefficients and four low pass coefficients are obtained. For each block, the optimum tetrolet decomposition is obtained with the consideration of minimum of 12 tetrolet coefficients, using which the representation of the sparse image is obtained.

iii) Rearrangement of low pass and the high pass coefficients: In order to continue the further processes of the tetrolet decomposition algorithm, the entities are rearranged into *2X2* matrix with the use of the reshape function.

iv) Storage of Tetrolet coefficients: After the sparse representation in all the blocks, the low pass and high pass matrix are stored. The sparse image representation is achieved with the application of the shrinkage procedure to the coefficients of tetrolet.

v) Termination: Repeat steps from (i) to (iv) for all the low pass image. The binary image J_2 is obtained as the output of this step.

Step 3: Development of Histogram features: Image J_1 and J_2 are EX-ORed to obtain the Tetrolet-LDP image J_n, from which the histogram features are extracted. These histogram features are feed as the input to the 2D-HMM, which is then trained using the CSO in order to perform the task of face recognition.

a b c d

Fig. 4. *Feature Extraction steps (a) Input Image (b) Skin Segmented Image (c) LDP Feature Image (J_1) (d) LDP and Tetrolet Feature Image (J_2)*

C. Face Recognition using 2D-Hiden Markov Model (2D-HMM)

The face image to be classified is partitioned into various blocks in the 2D-HMM model, and the feature vectors are obtained as the block statistics. The image is then classified based on the feature vectors, which are assumed to be produced using the Markov model that changes its state from one block to the other. During classification, the classifier finds the classes of optimal combination for large number of blocks at the same time.

D. Optimal tuning of the 2D-HMM parameters

The parameters of the 2D-HMM are tuned optimally using the CSO to perform the task of face recognition with increased accuracy and effectiveness. The size of the 2D-HMM parameters decides the size of the solution.

D.1 Solution Encoding: The size of solution encoding is similar to that of HMM parameters and are optimally selected using CSO. Let, the set $\delta = \{1, 2, \ldots, S\}$ be the solution vector in the presence of S number of solutions, which are found using CSO.

D.2 Cat Swarm Optimization in the optimal tuning of parameters: The optimal parameters of 2D-HMM are tuned using the CSO algorithm to carry out an effective face recognition process. The CSO algorithm is a recent Swarm Intelligence (SI) based optimization algorithms developed on the basis of the characteristics of the cats. The cat takes maximum time to rest, but provides more concern and sharpness on the objects that moves in their surroundings. This sharp characteristic of the cats motivates them in catching their prey with the conservation of very little time. The CSO is developed based on two modes, namely 'seeking mode' depending on the resting time of cats, and the 'tracing mode' depending on the chasing time of the cats.

i) Seeking mode of cats: The cat watches the surroundings even when it is in resting mode. If there is an indication of the availability of prey, the cat moves with very care and slow manner. The cat observes the Z dimensional space to take a decision about the next move.

ii) Tracing mode of cats: The chasing phase in catching the prey is represented by tracing mode. The cat decides about the movement, direction and speed on the basis of velocity and position of the prey. The new position of each cat depends on their movement in y dimensional space. The cat informs each of the positions that it crosses, and when the velocity is greater than that of the maximum velocity, then the velocity of the cat is assumed to be the maximum velocity.
The termination criterion, such as number of iterations, running time, and the amount of improvement evaluates the termination of the algorithm.

iii) Algorithmic steps of the CSO algorithm:

The algorithmic steps of the CSO algorithm are,
Step 1: Initialization of parameters: The first step involved in the CSO algorithm is the initialization of the solutions and parameters. In the CSO algorithm, let η be the total number of cats involved in the process of optimization, and the Solution vector is obtained as,

$$P_\tau = \{P_1, P_2, \ldots, P_O, \ldots, P_\eta\} \quad (2)$$

where, P_O is O^{th} cat position.
The velocity of the cat, $V_{x,y}^{w}$ and the self-position consideration (SPC) are initialized.
Step 2: Fitness Evaluation: The fitness measure of the CSO is obtained using fitness function.
Step 3: Update the cat position: The cats are sorted on the basis of their fitness value and the cat with minimum fitness is selected as the best solution P_y^*. The steps are repeated for all the cats. If the value of SPC is '1', then the cat is found in the seeking mode and the position of the cat is updated accordingly of the seeking mode, and if the value of SPC is '0', then the cat is found in the tracing mode, and the position of the cat is updated accordingly of the tracing mode.

Step 4: Re-estimation of the fitness to obtain the best solution: The fitness value is calculated again to find the best position of the cats.

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Step 5: Terminate: Repeat steps (ii) to (iv) until the optimal values are obtained.

Algorithm 1: Pseudocode for CSO algorithm

	Weight calculation using CSO Algorithm
1	Input: Solution vector $\rightarrow P_\tau$
2	Output: Best solution $\rightarrow P_y^*$
3	**Start**
4	Parameter initialization
5	η : Maximum cats $\rightarrow$ total cats
6	$V_{x,y}^{w}$: Velocity
7	α_1 and β_1: training samples
8	Population initialization P_O; $1 \leq O \leq \eta$
9	Calculate the objective function *Min (F)*.
10	**While** $P_x < P_{max}$
11	Calculate the fitness of each cat and order them based on fitness function
12	Find the best position of Cat
13	**For τ = 1: η**
14	**If** *SPC = 1*
15	Perform the seeking mode
16	**Else**
17	Perform the tracing mode
18	**End If**
19	**End While**
20	**Stop**

III. EXPERIMENTAL RESULTS

The results of the proposed method has been compared with the existing methods of face recognition such as, Local Binary Pattern based Hidden Markov Models (HMM & LBP) [22], Local Directional Pattern based Hidden Markov Models (HMM & LDP) [35], and 2-dimension Hidden Markov Models (2DHMM) [23]. The performance is analysed using three metrics, such as accuracy, False Rejection Rate (FRR), & False Acceptance Rate (FAR).

A. Dataset

Experiments are performed using three face databases namely Grimaces, Faces95, ORL and CVL. To prove the superiority of proposed method we have compiled the results of existing methods on CVL database and compared with our proposed method. We have also compared the results of proposed method for different databases.

Following three face databases are taken for experimentation of proposed system:

- Grimaces [38] face database has 20 images per individual for 18 individuals using fixed camera, with image resolution 180X200 pixels and contains male and female subjects. The background of images is kept plain. The Database has small head scale variation and considerable variation in head turn, tilt & slant. The Database also include major variations in expressions of the subject. From the point of view of testing a face recognition system. Grimaces face database is small but effective as there are a lot of intrapersonal variations.
- Faces95 [38] face database has 1440 images of 72 individuals subjects using a fixed camera. The Subject moves one step forward towards the camera, to introduce head variation between images and lighting changes on the face. The Database contains 20 images per subject and has male and female subjects. Image resolution for all the images is 180X200 pixels. Background of the image is red and variation is caused by shadow of moving subject.
- The ORL Face Database [39] consists of 10 different images each of 40 distinct subjects. Image are taken at different times, different facial expression like with and without smile, open and closed eyes, with or without glasses. All images are with a dark background and frontal position. The image resolution is 92x112 pixels, with 256 grey levels per pixel.
- The CVL face database [40] considers the features that are obtained from 114 persons with 7 images of each person. The resolutions of the images of the persons are 640X480 pixels in the jpeg format, which are shoot using the Sony Digital Mavica in the presence of uniform illumination, projection screen in the background and with no flash. The persons selected are around 18 years old and around 90% of them are male.

B. Results

The sample inputs of the proposed method are depicted in figure 5. Figure 5(a) depicts the original sample image, and figure 5(b) shows the sample image with the illumination variation of 200. Similarly, figure 5(c) depicts the sample image with the intensity variation of 0.25, and figure 5(d) shows the original image after feature extraction. In the same way, figure 5(e) shows the sample image with the illumination variation of 200 after feature extraction, and figure 5(f) depicts the sample image with intensity variation of 0.25 after feature extraction.

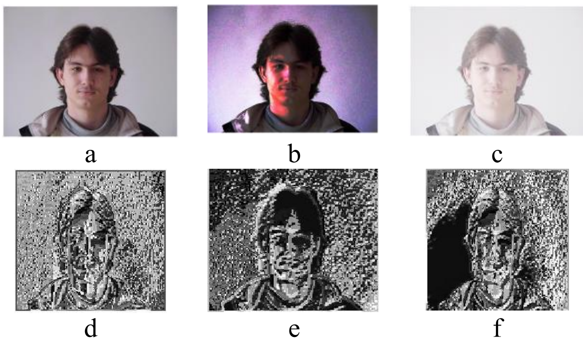

Fig. 5. *Simulation results of the proposed method **(a)** Original facial image **(b)** with illumination variation of 200 **(c)** Image with intensity variation of 0.25 **(d)** Original image after the extraction of features **(e)** Image with illumination variation of 200 after the extraction of features **(f)** Image with intensity variation of 0.25 after the extraction of features*

We have compared the results of existing technique in terms of accuracy; as shown in figure 6. Figure 6(a) shows the accuracy with respect to variation in illumination. When the illumination variation is 200, the accuracy of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.831, 0.9095, 0.9145, and 0.9965, respectively. Similarly, figure 6(b) shows the accuracy in terms of intensity variation. When the intensity variation is 1, the accuracy of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.8637, 0.8716,

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0.924, and 0.9965, respectively. Proposed method is performing better in terms of accuracy compared to existing methods not only for variation in illumination but also for variation in intensity.

Comparative results of proposed and existing technique in terms of FRR are shown in figure 7. Figure 7(a) shows the FRR with respect to variation in illumination. When the illumination variation is 200, the FRR of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.1690, 0.0905, 0.0855, and 0.0035, respectively. Similarly, figure 7(b) shows the FRR in terms of intensity variation. When the intensity variation is 1, the FRR of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.1363, 0.1284, 0.0760, and 0.0035, respectively. Performance of proposed method based on FRR is much better when variation in illumination and intensity are considered.

The comparative results based on FAR are shown in figure 8. Figure 8(a) shows the FAR with respect to variation in illumination. When the illumination variation is 200, the FAR of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.0045, 0.0041, 0.0028, and 0.0026, respectively. Similarly, figure 8(b) shows the FAR in terms of intensity variation. When the intensity variation is 1, the FAR of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.0045, 0.0041, 0.0028, and 0.0027, respectively. Simulation results show that proposed method is better the existing methods.

IV. DISCUSSION

Although the individual methods used in the proposed system are not novel but the method such as Tetrolet Transform and LDP for feature extraction is new to the face recognitions systems. Table I shows the comparative results of simulation of proposed method and existing methods of face recognition under illumination variation in terms of Accuracy, FRR, and FAR. The accuracy of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 85%, 90%, 92%, and 99.65%, respectively. The FRR of the methods, namely HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.1452, 0.1001, 0.0802, and 0.0032, respectively. Similarly, the FAR of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.0045, 0.0042, 0.0028, and 0.0025, respectively.

Table II shows the comparative results of simulation of proposed method and existing methods of face recognition under intensity variation in terms of Accuracy, FRR, and FAR. The accuracy of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 87%, 88%, 92%, and 99.65%, respectively. The FRR of the methods, namely HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.1312, 0.1239, 0.0784, and 0.0074, respectively. Similarly, the FAR of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.0045, 0.0042, 0.0028, and 0.0027, respectively.

Table I: Comparison of proposed and existing methods of face recognition under illumination variation

Methods	Accuracy	FRR	FAR
HMM & LBP	85%	0.1452	0.0045
HMM & LDP	90%	0.1001	0.0042
2D HMM	92%	0.0802	0.0028
Proposed Method	**99.65%**	**0.0032**	**0.0026**

Table II: Comparison of proposed and existing methods of face recognition under intensity variation

Methods	Accuracy	FRR	FAR
HMM & LBP	87%	0.1312	0.0045
HMM & LDP	88%	0.1239	0.0042
2D HMM	92%	0.0784	0.0028
Proposed Method	**99.65%**	**0.0074**	**0.0027**

Table III shows the comparative results of simulation of proposed method for Grimaces, faces95, ORL and CVL face databases in terms of Accuracy, FRR, and FAR under illumination variation. The accuracy of the proposed method is 95%, 98%, 98% and 99.65%, respectively. The FRR of the proposed method is 0.0517, 0.0234, 0.0152, and 0.0032, respectively. Similarly, the FAR of the methods, the proposed method is 0.0124, 0.0032, 0.0084 and 0.0026, respectively.

Table III: Comparison of proposed method over various databases under variation in illumination variation

Face Database	Accuracy	FRR	FAR
Grimace	95%	0.0517	0.0124
Faces95	98%	0.0234	0.0032
ORL	98%	0.0152	0.0084
CVL	99.65%	0.0032	0.0026

Table IV shows the comparative results of simulation of proposed method for Grimaces, faces95, ORL and CVL face databases in terms of Accuracy, FRR, and FAR under intensity variation. The accuracy of the proposed method is 95%, 98%, 98% and 99.65%, respectively. The FRR of the proposed method is 0.0894, 0.0192, 0.02, and 0.0074, respectively. Similarly, the FAR of the methods, the proposed method is 0.0124, 0.0032, 0.0088 and 0.0027, respectively. Results from table III and IV shows that proposed method performs very well for different face databases. We have done comparative study with deep learning techniques and comprehended that for medium size databases deep learning is not cost effective economically as well as computationally.

Table IV: Comparison of proposed method over various databases under variation in intensity variation

Face Database	Accuracy	FRR	FAR
Grimace	95%	0.0894	0.0124
Faces95	98%	0.0192	0.0032
ORL	98%	0.02	0.0088
CVL	99.65%	0.0074	0.0027

Thus, from the analysis, it is clear that the proposed method produces high accuracy, and less FRR and FAR measures, which shows the effectiveness of the proposed method in face recognition under illumination and intensity variations. Experiments were also conducted using limited training samples and results proved that proposed method is robust for face recognition [41]. Proposed method can be utilized in the area of criminal identification, advertising, and finding missing persons were variation in lighting conditions are huge.

V. CONCLUSION

The accurate face recognition is performed using the Tetrolet–Local Directional Pattern (Tetrolet-LDP) and CSO. The proposed method achieves high accuracy and less FRR and FAR measures of 99.65%, 0.0035, and 0.0025, respectively, which shows the superiority of the proposed method in effectively recognizing the face under interpersonal, intensity and illumination variation. The reasons behind high accuracy are accurate feature extraction using Tetrolet-LDP and optimization of 2D HMM parameters using CSO. The system was tested on three databases and results shows consistent performance over the various databases. Implementation and computation cost are the major advantages of the proposed system over recent methods like deep learning. Proposed method can have various applications, such as security, surveillance, commerce, forensics, and entertainment.

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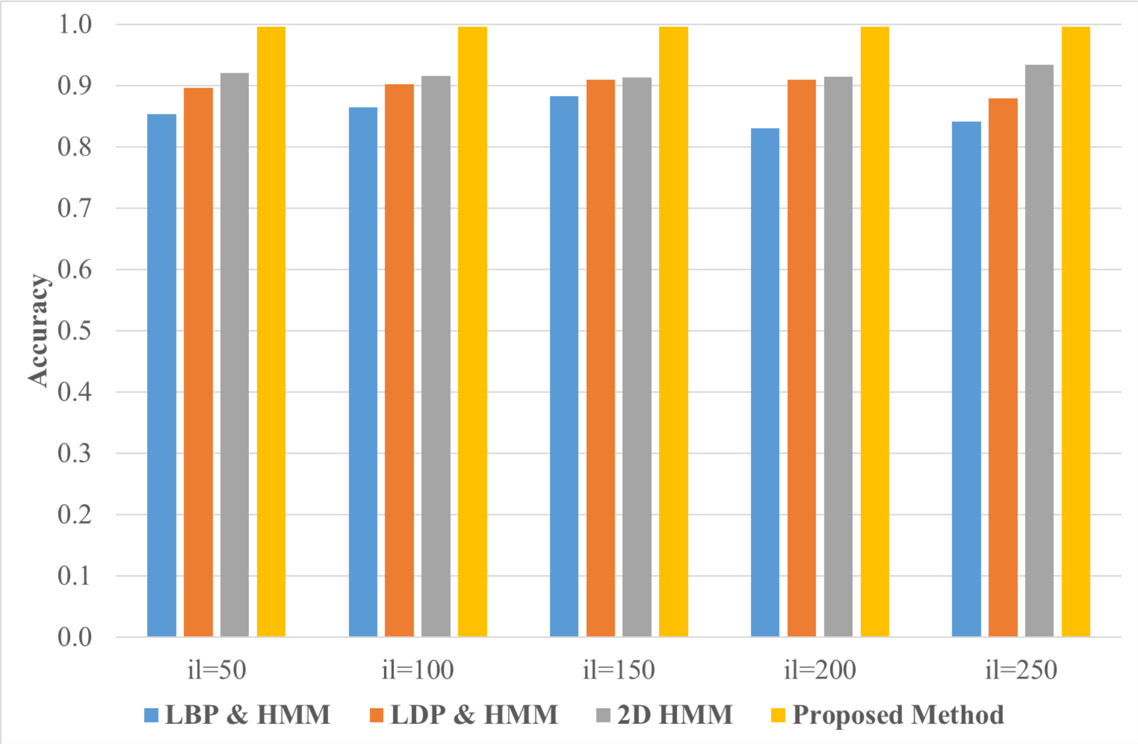

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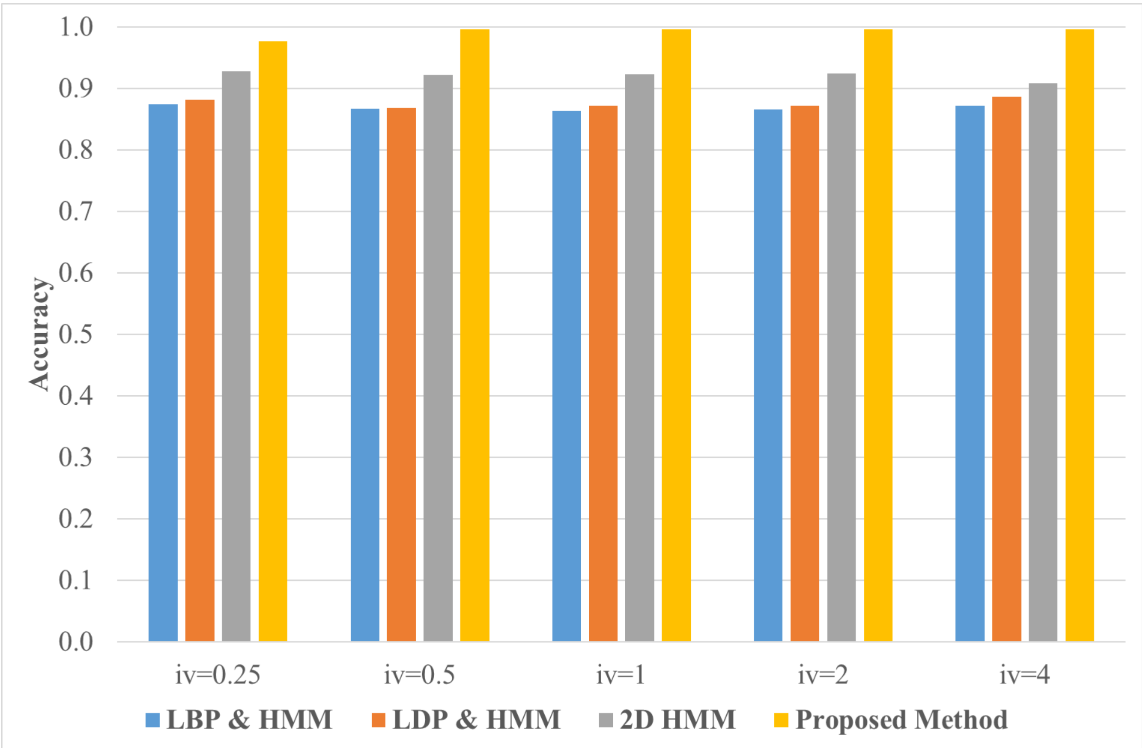
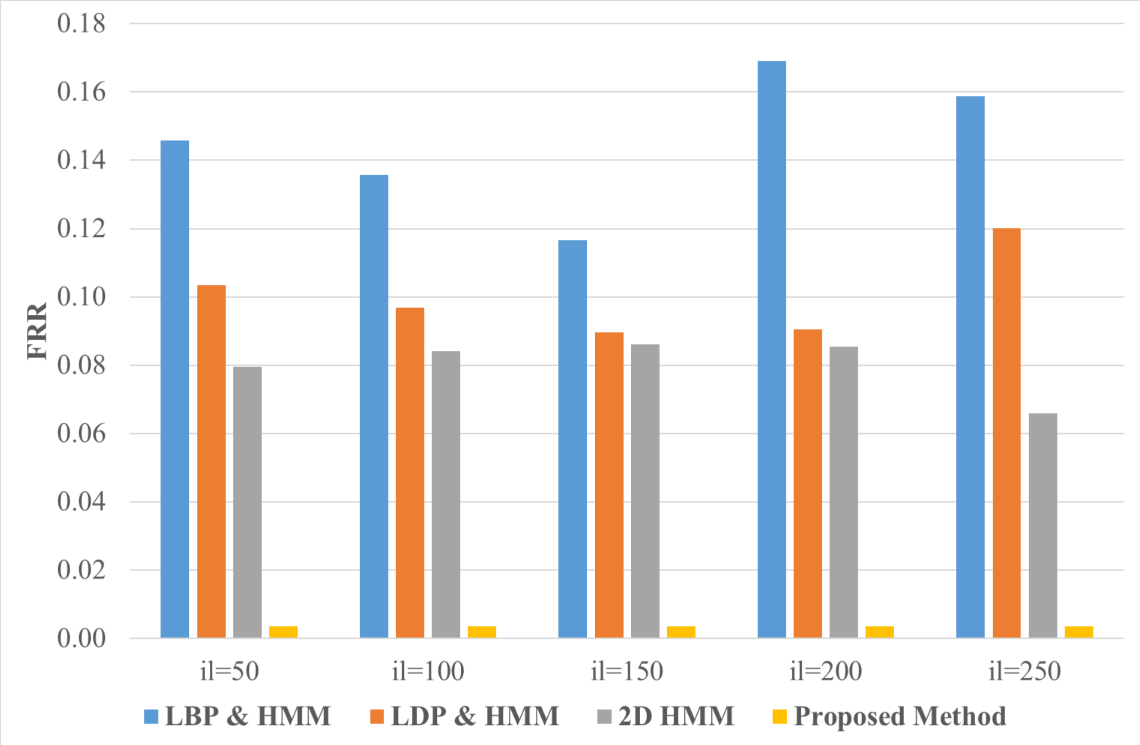


b

Fig. 6. *Comparative analysis based on accuracy **(a)** Illumination variation **(b)** Intensity variation*



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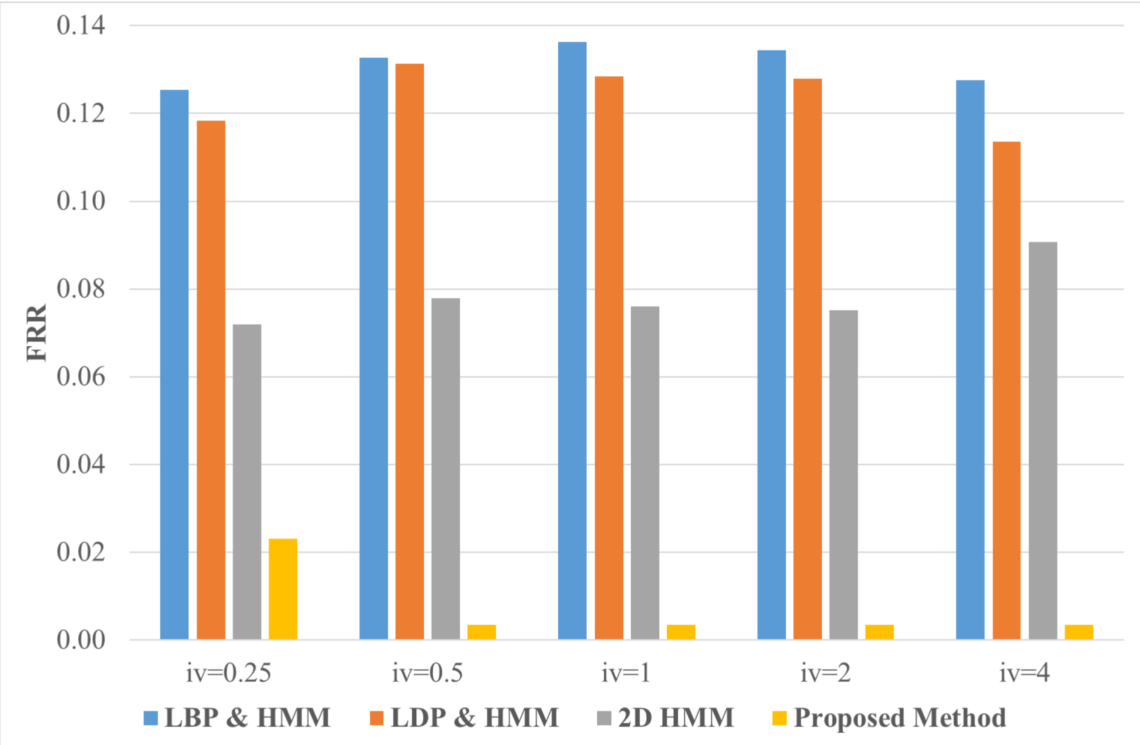
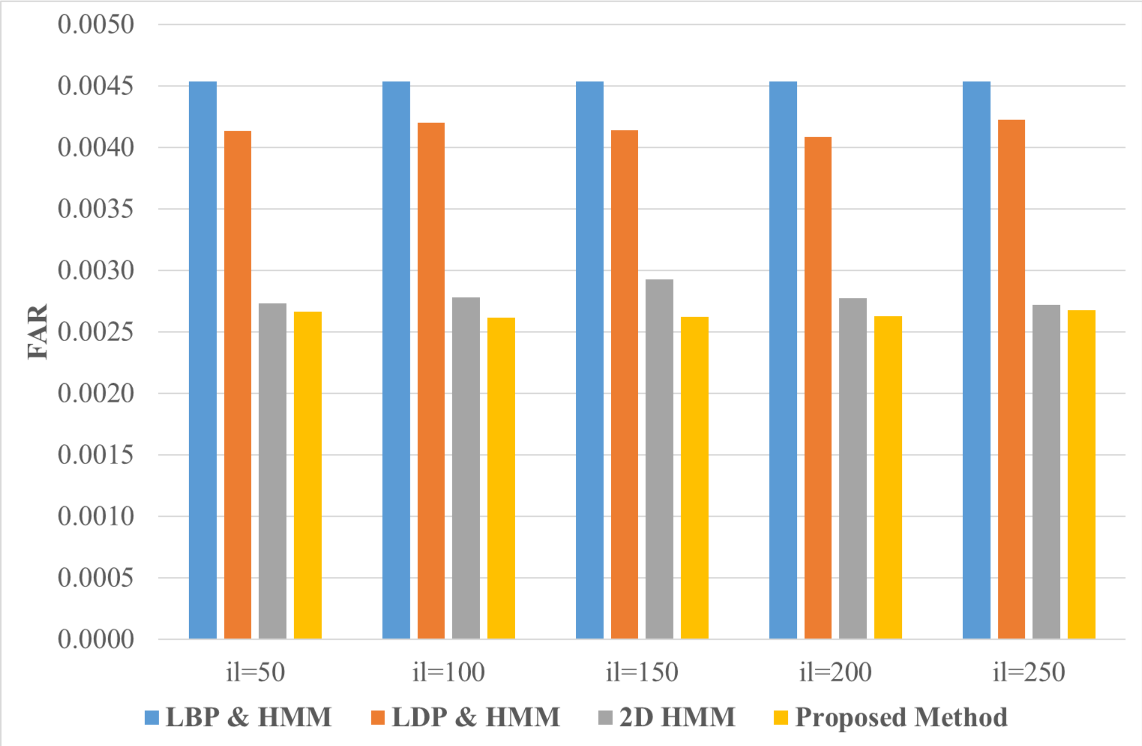


b

Fig. 7. *Comparative analysis based on FRR* ***(a)*** *Illumination variation* ***(b)*** *Intensity variation*



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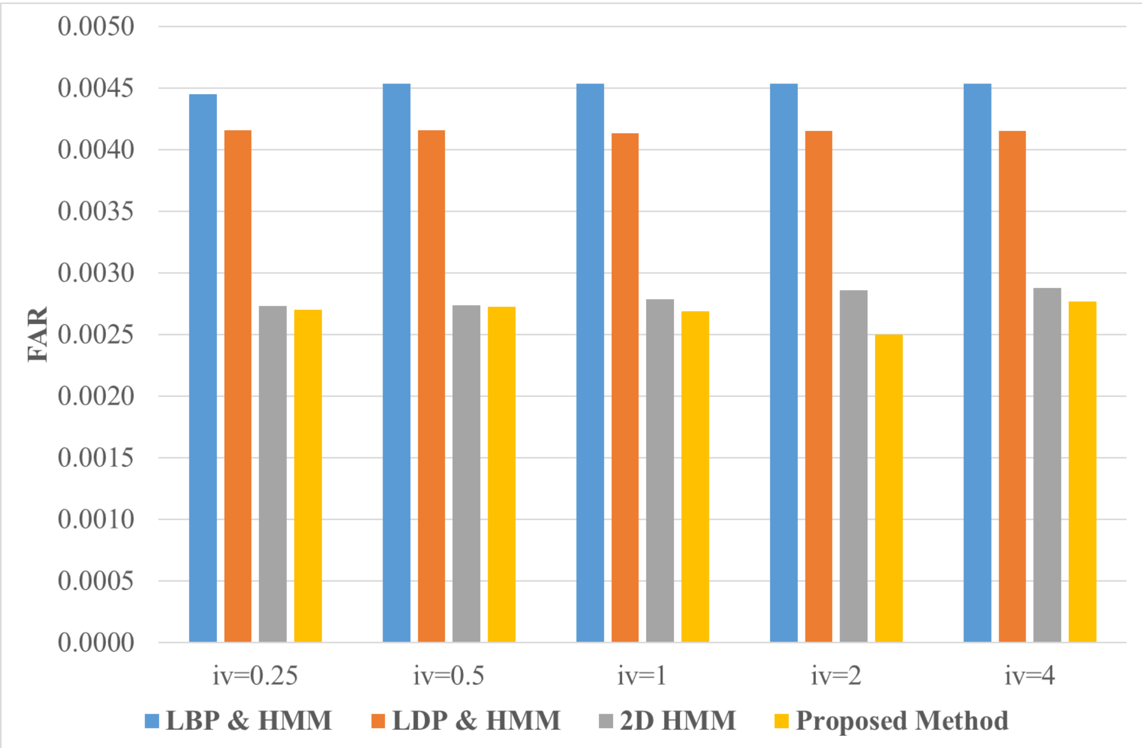

b

Fig. 8. *Comparative analysis based on FAR* ***(a)*** *Illumination variation* ***(b)*** *Intensity variation*