Tetrolet Local Directional Pattern and Optimization-driven 2D-HMM for Face Recognition

Mahendra Singh Meena, Priti Singh, and Ajay Rana

Abstract—Face recognition has achieved more attention in computer vision with the focus on modelling the expression variations of human. However use of a computer system is a challenging task, due to variation in expressions, poses, and lighting conditions. This paper proposes a face recognition system based on Tetrolet, Local Directional Pattern (LDP) and Cat Swam Optimization (CSO). Initially, the input image is pre-processed, where the region of interest is extracted using the filtering method. Then pre-processed image is given to the proposed descriptor, namely Tetrolet-LDP to extract the features of the image. The features are subjected to classification using the proposed classification module, called Cat Swarm Optimization-based 2-Dimensional Hidden Markov Model (CSO-based 2D-HMM) in which the CSO trains the 2D-HMM. The performance is analysed using the metrics, such as accuracy, False Rejection Rate (FRR), & False Acceptance Rate (FAR) and the system achieves high accuracy of 99.45%, and less FRR and FAR of 0.0035 and 0.0025.

Keywords—Face Recognition, Tetrolet, Local Directional Pattern (LDP), Cat Swarm Optimization (CSO), 2-Dimensional Hidden Markov Model (2DHMM).

I. Introduction

THE face of human performs as an essential biometrics because of the characteristics, such as high social acceptability, accessibility, and the nature of non-intrusiveness [1] and having various applications, such as security, surveillance, commerce, forensics, and entertainment [2]. The human face recognition is desirable for the applications, where the biometrics of retinal scans, finger prints, and the iris images are not available due to non-interactive environment [3]. Though, 2D face recognition is gaining interest since last few years, but still remains challenging due to the presence of various factors, such as scale differences, pose, facial expressions, illumination, intensity, and makeup. In addition, at the time of acquisition, the 2D images are subjected to affine transformation that increases the complexity in the recognition of the 2D images [5]. Other than this, due to pose variations, facial makeup, and the variation in lightening conditions, the 3D facial scan becomes very robust [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].

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The face recognition process undergoes three basic steps. The first step is the acquisition of the face, which holds the region of face detection and the localization. The facial data extraction is the second step, where the geometric and the appearance related features are extracted and finally the recognition of face. Features of face can be identified in a local and global manner as per requirements & applications [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 robust even in the presence of the local features, but failed in the detection of nose tip with enough accuracy. Li Ye, et al. [20] 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 cannot be used in partially occluded and non-frontal 3D faces. Jaime A. Martins et al. [23] 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 correct results but accuracy was main concern. Duc My et al. [24] developed the Hierarchical Collaborative Representation-based Classification (HCRC), which was capable of achieving increased recognition rate, and in addition, this method recovered the inadequate solution, but not suitable for some evaluation datasets that contains the face images that were new. Xing Deng et al. [21] designed the expression-robust 3D face recognition method using feature-level fusion and feature-region fusion that was computationally efficient and offered better solution for dimensionally complex problems, but, the dimensionality problem in the presence of occlusion cannot be eliminated effectively.

Yao Peng and Hujun Yin, [25] 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. [26] modelled the 3-D shape representation scheme for automatic face analysis and identification that was able to solve the recognition problem of face with respect to the 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. [27] designed a novel facial coarse-to-fine landmark localization method based on Active Shape Model that 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. [28] 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. [29] developed the Pseudo 2D HMM applied to neural network coefficients that attained 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 simple and accurate algorithm is the nearest-neighbor (NN) algorithm, which is suitable for solving various problems. The drawback associated with this algorithm 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 with the use of two training samples for all the classes for the representation of the face test images further nearest feature plane classifier is a classifier that makes in use of three samples for the representation of the face test image [13], [14]. The classifier known as nearest subspace [15], [16] and the local subspace classifier [17] 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) [18] algorithm was developed with respect to linear regression. The support vector machine (SVM) classifier [19] 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 to be applied to the vectors that defines out samples of the missing entities, which are seen if there presents an occlusion in the face recognition [20], [21].

The variation in the facial expression is considered as the main problem in the recognition of 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 concentrating 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 stability of gradients compared to grey value in the presence of noise and non-monochromatic illumination change. This is the reason that we considered LDP for feature extraction. Performance of Tetrolet transform very 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 initial days. GA is the popular and old technique for optimization. As its faces the local search issue in finding the optimal structure. In order to overcome these 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 which is very effective for intrapersonal variation, change in illumination and change in intensity.

II. Methodology

An automatic face recognition method using the concept of the 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) [30] and Tetrolet transform [31] that engage in 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) [22]. The CSO trains the 2D-HMM, and the performance of the method is analysed through imputing the intrapersonal variations, intensity variations, and illumination variations. Block diagram of proposed face recognition system is shown in Figure 1.

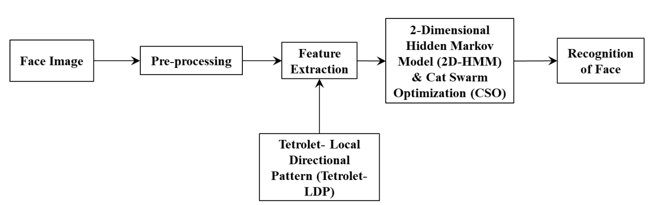

Fig. 1: Block diagram of the proposed face recognition

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. The CVL face database [32] considers the features that are obtained from 114 persons with 7 images of each person. The resolutions of the images of the persons are 640×480 pixels in the jpeg format, which are shoot using the Sony Digital Mavica in the presence of uniform illumination, projection screen at the background and with no flash. The persons selected are around 18 years of old and around 90% of them are male.

B. Feature extraction using the proposed feature Descriptor

The feature extraction process is carried out with the Tetrolet LDP. The proposed descriptor enables the analysis through imputing the intrapersonal variations, intensity variations, illumination variations, and training data variations. Figure 2 depicts the process of feature extraction with the use of the proposed Tetrolet LDP feature descriptor.

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

1) Step 1: Extraction of LDP image: 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 neighboring pixels with Kirsch response greater than k_h is assumed as , and the Kirsch response less thank_h is assumed as . The value of LDP for the pixel (u_i, v_i) is expressed as,

$$L_h(u_i, v_i) = \sum_{n=0}^{7} e\left(k_n, k_n\right).2^n \tag{1}$$

where

$$e\left(k_n, k_n\right) = \begin{cases} 1, & \text{if}\,(k_n, k_n) \geq 0 \\ 0, & \text{else} \end{cases}$$

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

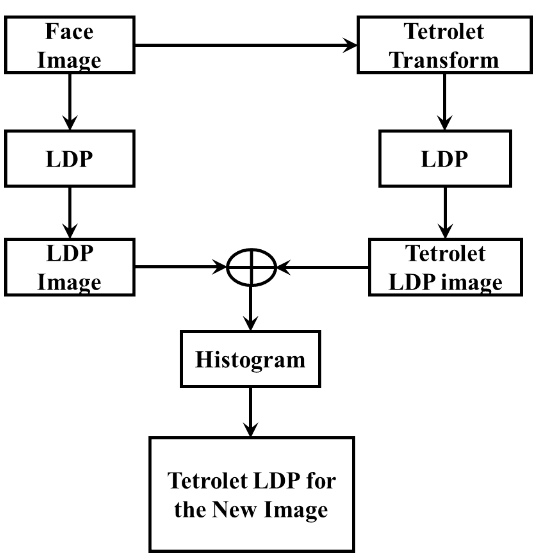

Fig. 2: Feature Extraction using Tetrolet LDP

2) Step 2: Extraction of TetroletLDP image: On the other hand, the pre-processed face image is given to tetrolet transform for obtaining the Tetrolet-LDP image. The tetrolet transform is carried out using the following steps,

a) Partition of the input image: The input image is partitioned into number of blocks of size 4×4.

b) 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.

c) 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 2×2 matrix with the use of the reshape function.

d) 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 acheived with the application of the shrinkage procedure to the coefficients of tetrolet.

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

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

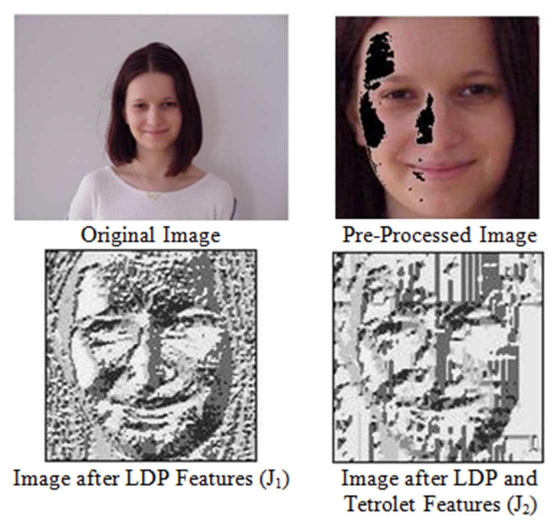

Fig. 3: Feature Extraction Steps

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

The face image that is needed 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.

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

2) Cat Swarm Optimization in the optimal tuning of parameters: The optimal parameters of 2D-HMM are tuned using CSO algorithm to carry out effective face recognition process. The CSO algorithm is the one among the 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 less 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.

a) 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.

b) Tracing mode of cats: The tracing mode represents the chasing phase of cat to catch its prey. 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 dimensional space. The cat informs each of the position 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.

c) 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,

$$P_t = \{P_1, P_2, P_3, ...P_o......P_\eta\} \tag{2}$$

where, P_o is o^{th} cat position. The velocity of the cat, $V^w_{x,y}$ 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.

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

III. Results

We have compared the results of existing methods of face recognition such as, Local Binary Pattern based Hidden Markov Models (HMM & LBP) [28], Local Directional Pattern based Hidden Markov Models (HMM & LDP) [30], and 2-dimension Hidden Markov Models (2DHMM) [29] with our proposed method. The performance is analysed using three metrics, such as Accuracy, FRR, and FAR.

The sample inputs of the proposed method are depicted in figure 4. Figure 4.a depicts the original sample image, and figure 4.b shows the sample image with the illumination variation of 200. Similarly, figure 4.c depicts the sample image with the intensity variation of 0.25, and figure 4.d shows the original image after feature extraction. In the same way, figure 4.e shows the sample image with the illumination variation of 200 after feature extraction, and figure 4.f depicts the sample image with intensity variation of 0.25 after feature extraction.

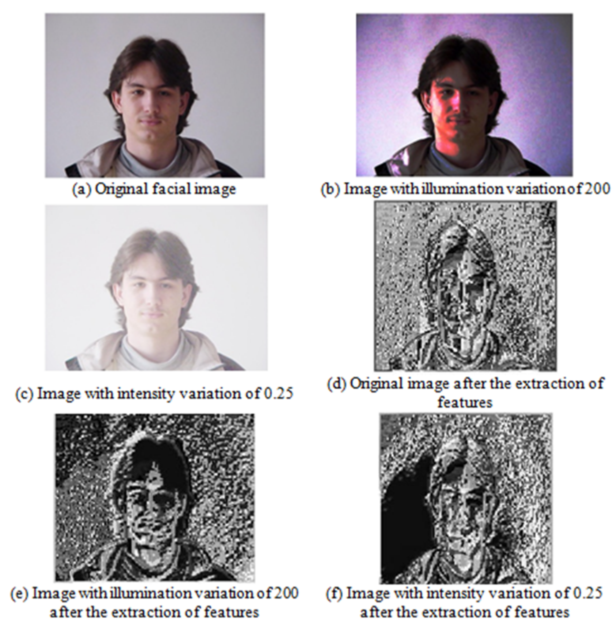

Fig. 4: Simulation results of the proposed method

We have compared the results of existing technique in terms of accuracy; as shown in figure 5. Figure 5(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 5(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, 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.

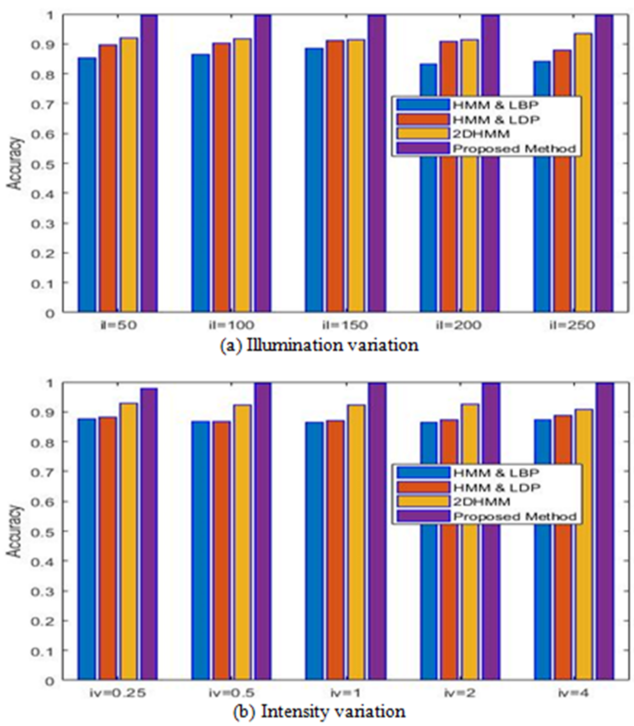

Fig. 5: Comparative analysis based on accuracy

Comparative results of proposed and existing technique in terms of FRR are shown in figure 6. Figure 6(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 0.169, 0.09046, 0.08548, and 0.003509, respectively. Similarly, figure 6(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, 0.07603, and 0.003509, 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 7. Figure 7(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 0.004538, 0.004085, 0.002774, and 0.00263, respectively. Similarly, figure 7(b) shows the FAR in terms of intensity variation. When the intensity variation is 1,

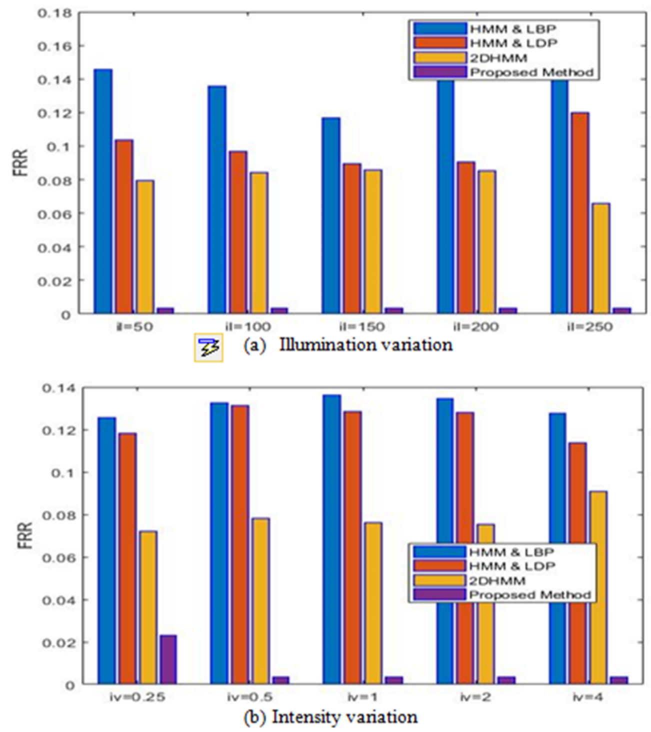

Fig. 6: Comparative analysis based on FRR

the FAR of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.004538, 0.004133, 0.002789, and 0.00269, respectively. Simulation results show that proposed method is better the existing methods.

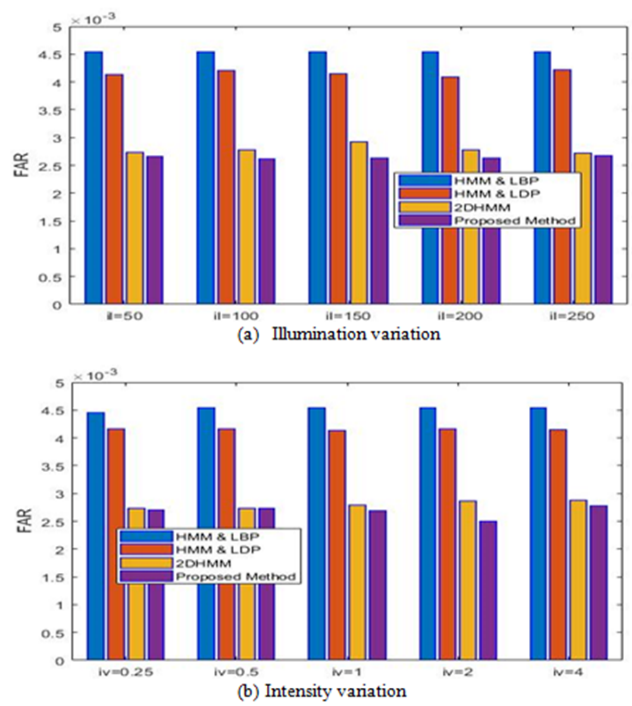

Fig. 7: Comparative analysis based on FAR

TABLE I: Comparative discussion for the methods involved in face recognition

Methods	Metrics		
	Accuracy	FRR	FAR
HMM & LBP	86%	0.1165	0.0045
HMM & LDP	88%	0.0896	0.0041
2D HMM	92%	0.066	0.003
Proposed Method	**99.45%**	**0.0035**	**0.0025**

IV. Discussion

Table I shows the comparative results of simulation of proposed method and existing methods of face recognition in terms of Accuracy, FRR, and FAR. The accuracy of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 86%, 88%, 92%, and 99.45%, respectively. The FRR of the methods, namely HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.1165, 0.0896, 0.066, and 0.0035, respectively. Similarly, the FAR of the methods, such as HMM & LBP, HMM & LDP, 2DHMM and the proposed method is 0.0045, 0.0041, 0.003, and 0.0025, respectively. 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. 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 TetroletLocal Directional Pattern (Tetrolet-LDP) and CSO. The proposed method achieves high accuracy and less FRR and FAR measures of 99.45%, 0.0035, and 0.0025, respectively, which shows the superiority of the proposed method in recognizing the face in an effective manner under interpersonal, intensity and illumination variation. Proposed method can have various applications, such as security, surveillance, commerce, forensics, and entertainment.

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