Texture Analytics for Accurate Person Recognition: A Multimodal Approach

Suchetha N V[1], Sharmila Kumari M[2]

Research Scholar-Department of CSE, PA College of Engineering Mangaluru, India and
Department of CSE, Sri Dharmasthala Manjunatheshwara Institute of Technology, Ujire-574240 and
Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India[1]
PA College of Engineering Mangaluru, India[2]

Abstract—**Securing the resources is a most challenging task in the digital era. Traditionally, password and ID card systems were used to provide security. Password and ID cards can be stolen or hacked; to overcome this drawback biometric systems are used to authenticate the user to access the data or resources. Biometric system uses physical and behavioral characteristics of the user. Biological characteristics of the person like face, fingerprint, iris, palm print, voice, hand geometry etc. cannot be stolen and misused. Even though unimodal biometric system is more secure as compared to the traditional approach, it is not able to handle intra-class, inter-class variations, noisy data and spoofing attack. These problems can be solved using multimodal biometrics. In this paper, we discuss unimodal biometric system using Local Binary Pattern (LBP) and Local Ternary Pattern (LTP). We propose a feature level fusion of face and fingerprint biometric traits using LTP. The implementation of the introduced system stands in comparison to the unimodal LBP and LTP for face and fingerprint system. The system is tested on ORL, UMIST, VISA face dataset and FVC fingerprint dataset. Experimental results show that the multimodal biometric system using LTP gives better accuracy as compared to the unimodal biometric system.**

Keywords—Unimodal; Multi-modal; LBP; LTP; intra-class; inter-class; spoofing attack

I. INTRODUCTION

The face and fingerprints are the most widely used biometrics, due to their high availability and universality. Most of the biometric systems use single biometric traits; it has some challenges like intra-class variation, inter-class variation and noise in the sensed data. This problem can be overcome by using multiple biometric traits for person identification. Multimodal biometric system combines more than one biometric trait by fusing at different levels. Fusion methods are mainly split into two types: fusion prior to matching and after matching. Under fusion prior matching, sensor level and feature level fusions and under after matching score and decision level fusion techniques are used. In sensor level fusion raw information from the source images are combined. Fusion at sensor level is having richer set of information. In fusion at feature level, features from multiple biometric traits are extracted individually, and extracted the characteristics of the various biometrics are combined. In matching score level, scores from each biometrics traits are calculated and scores are combined to get resultant score. In decision level fusion decision obtained by individual biometric traits are combined to get final decision.

Section II of this paper deals with a survey of related work, the proposed methodology is outlined in Section III, Section IV presents the results and discussion and finally the Section V presents the conclusion of the work.

II. RELATED WORK

Pabitra Priyadarshini Jena et al.[1] introduced multimodal biometric system utilizing face and fingerprint. The fingerprint and face features are taken using deep learning models such as ResNet50, Xception, FaceNet, EfficientNetB3 and InceptionResNetV2. The extracted features are fused at feature level to authenticate the user. N. Krishnaraj et al.[2] introduced multimodal biometric system using palmprint and fingerprint. Gabor filters and characteristic subset selection is carried on Palmprint and fingerprint. Emphasized characteristic are selected for Gabor features using Correlation based Feature Selection and Hybrid Bacterial Foraging Optimization. P. Sivakumar et.al.[3] proposed multimodal template for fingerprint and finger-vein using deep hashing framework for feature level fusion. Along with providing improved privacy for biometric information to safeguard from the special attacks, it provides unlinkability and cancelability of the templates. It integrates deep hashing, multimodal fusion and biometric security with weightage on structural facts from modalities like fingerprint and finger-vein. Features are extracted using VGG16 model and achieved 95% accuracy. Rupali Kute et al.[4] introduced a strategy to recognize face of the person by using their fingerprint. To acquire skills and improve the transferring subspace, Bregman divergence regularization is used. Here gained knowledge from the training samples are transferred to the testing samples. The difference among the two dissimilar domains is reduced by this regularization. To find a common subspace that boosts the performance. Two methods introduced by Arucha Rungchokanum et al. [5] applies the introduced distance model to the minutiae-triplets generation. In the earlier method, model is applied direct whereas in second method, to handle more distorted fingerprint areas and more curved regions like a singular point, model is combined with ridge flow. The proposed method is evaluated on sixteen public domain fingerprint database using two minutiae triplet matching algorithm. A component-based face recognition approach introduced by Rupali Sandip Kute et al. [6] uses transfer learning to demonstrate the knowledge acquired from face image to categorize face elements like ears, lips and nose. These face components are unaltered by the change of face expression and pose. Since face and face components are from different domain, these are used to transmit the knowledge acquired from distinct domains even though they share common information. To associate between complete and partial faces different half faces like, left, lower diagonal and right upper and left, right, upper half and right upper are considered. This proposed approach can be utilized for components-based face recognition, partial face recognition and full face recognition because of the alliance among face and its components. Sun, Kun et al. [8], this paper presents centre-symmetric local binary pattern and DBN method for face recognition. Initially image is separated into blocks, and feature is extracted from each block using CS-LBP, then texture feature histogram is calculated. This histogram is given as input to DBA for classification. As compared to traditional approaches the proposed approach gave high accuracy by comparing results on Extend Yale B, ORL, and CMU-PIE dataset. Sunil S et al.[9], in this paper, a hybrid solution is presented for face recognition by using SWT, LTP, and DCT. Initially, image is resized and features are extracted using SWT and DCT. Then, LTP is claimed on SWT features and features are combined to obtain final feature vector. Euclidean distance is used for classification. Huilin Ge et al [10], present improved GAN for face recognition. The study uses generator consists of auto encoder and discriminators global descriptor and local descriptor to repair occluded image. To perform image restoration Resnet-50 is used. The proposed method provides improved restoration effect and high recognition rate even in occlusion background. Ashok Kumar Yadav et al. [11], proposed a multi-biometric frame based on DNN using fingerprints, human eye iris and offline signature attribute was introduced. As the first step, fingerprints, signatures and iris of subjects are obtained. At this stage, the client's characteristic is perceived with the help of the multi-modality framework, which is composed of three pre-implemented templates for iris, fingerprints and signatures. The multimodal biometric system using iris, signature and fingerprint shows better performance as compared to unimodal biometrics using fingerprint and iris. Additionally, a different biometric has been developed specifically for offline signing. From that point on, the triple single biometrics solutions are used to construct the provided multi-modal solution. Before integrating these models into a multi-model solution, the correctness of these models is examined after taking into account earlier work on unimodal solutions. The VGG-19 net's performance has improved, according to the results. Using the SDUMLA HMT repository, the model was evaluated. We achieved 99.1% accuracy in score stage merging and 98.4% accuracy in feature level fusing. Nassima Kihal et al. [12] have developed a multimodal ocular biometric system to authenticate. They have used iris texture and the cornea form as a biometric characteristic. Iris texture features are extracted using Log Gabor and cornea features using Zernike polynomials. Once the characteristic of the iris and cornea has been extracted, they carry out a matching operation and scores for iris and cornea are calculated. Later applied fusion to the score and obtained EER 0%, FRR 0% to 0.1% FAR. Aman Kathed et al.[13] proposed 3-level authentication system using the biometric features of the face, iris and voice. Initially, the characteristics of the face and iris features are extracted and merged to form final feature vector. The fused features are stored in database. The subsequent test data is compared to the stored features and if a match is found, the OTP generating system will send OTP to the user. This one-time password is saved as a user’s voice and compared to the voice information stored in the database. If the user’s voice matches, the user is authorized user.

III. Methodology

A. Local Binary Pattern

Local Binary Pattern is rotation and grey invariance which is used to extract textual features. It functions on a 3 * 3 window with the central pixel as a threshold [7]. Threshold pixel value is compared to its adjacent 8 pixel values. The pixel value is marked as 1 when the pixel value exceeds the center pixel value, otherwise it is 0. The central pixel value in the 3 * 3 window is equated with its 8 neighbours to produce an 8-bit binary number, which is converted to LBP code. Overall contrast is standardized using Histogram equalization.

The mathematical expression for LBP operation is:

$$\mathrm{LBP}_{S,P}=\sum_{y=0}^{S-1} 2^{y} g(i_y - i_c) \quad (1)$$

$$\text{Where } g(i_y - i_c) = \begin{cases} 1 & i_y - i_c \geq 0 \\ 0 & i_y - i_c < 0 \end{cases} \quad (2)$$

Where S is the number of neighbors, i_y represents neighbor pixel in radius P and i_c represents centre pixel value. After encoding, histogram is calculated using the Eq. (3).

$$\mathrm{H(m)}=\sum_{i=0}^{I} \sum_{j=0}^{J} f(\mathrm{LBP}_{S,P}(i,j),m) , \; m€ [0,M] \quad (3)$$

$$\text{Where } \; f(x,y)=\begin{cases} 1 & x = y \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

In this case, M represents the maximal LBP pattern value.

50	80	50
90	40	70
20	60	20

⇨

1	1	1
1		1
0	1	0

Fig. 1. LBP operation.

Fig. 1 illustrates LBP operation. It obtains the binary pattern= 11110101 and the corresponding LBP Code is: $1x2^0+1x2^1+1x2^2+1x2^3+0x2^4+1x2^5+0x2^6+1x2^7=245$.

B. Local Ternary Pattern

LTP is advanced version of LBP with 3-valued codes; 0, 1, -1 and more robust to noise[14]. LTP will define a threshold t and works as follows; assigns 1 for any pixel with value above t, -1 in case the pixel value is less than –t and 0 if the pixel value is in between –t and t. To get rid of the negative values, upper and lower patterns are constructed after thresholding step. LTP is the concatenation of upper and lower pattern.

LTP is defined mathematically as Eq. (5) and (6):

$$\mathrm{LBP}_{S,P}=\sum_{y=0}^{S-1} 2^{y} \mathrm{h}(i_y - i_c) \quad (5)$$

Where

$$\mathrm{h(x)}=\begin{cases} 1 & x \geq t \\ 0 & -t < x < t \\ -1 & x < -t \end{cases} \quad (6)$$

Where i_y represents the value of the neighbour pixel of central pixel with radius P, i_c represents central pixel value and S is the number of neighbours. The neighbour is estimated using bilinear interpolation when it is not falling exactly in the centre of the pixel. After this encoding step, using following equation histogram is created using equation (7) and (8).

$$H(m)=\sum_{i=0}^{I}\sum_{j=0}^{J} f(\,LBPS,P(i,j),m)\ ,\ m€\ [0,M] \quad (7)$$

$$\text{Where}\quad f(x,y)=\begin{cases}1 & x=y\\ 0 & \text{otherwise}\end{cases} \quad (8)$$

In this case, M represents the maximal LBP pattern value.

Fig. 2 illustrates operation of LTP, here threshold value is 5; central pixel 34 is compared with 8 neighbour pixel values. If neighbour pixel value is greater than 34+5, then pixel value is defined as 1, if pixel value is less than 34-5, then set the pixel value is set to -1 and if the pixel value is in between 34+5 and 34-5, then set the pixel value is set to 0. The upper and lower pattern are constructed and concatenated to get final LTP code.

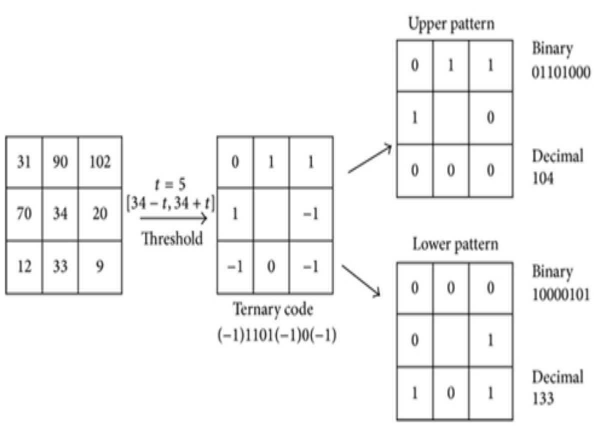

Fig. 2. LTP operation.

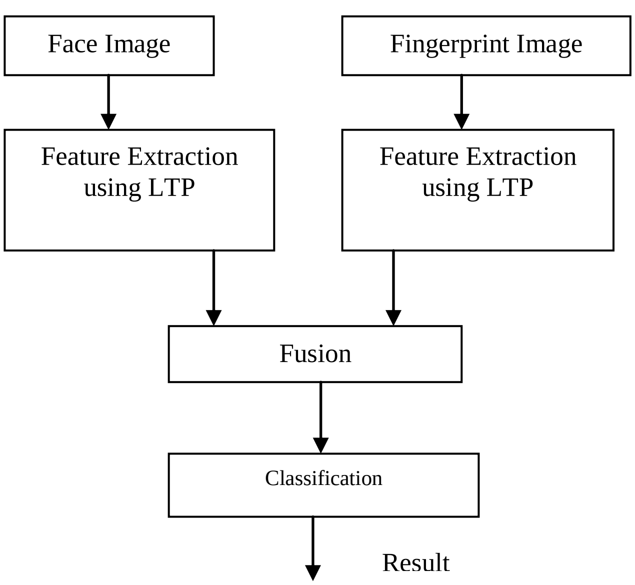

Fig. 3. Architecture of the introduced system.

The Fig. 3 represents proposed method; LTP is a texture descriptor that captures the local texture patterns of an image by comparing the pixel intensities of a central pixel to its neighboring pixels. Initially apply LTP on face image and compute LTP histogram as feature for face. Similarly extract apply LTP on fingerprint and compute LTP histogram as fingerprint feature. Then combine LTP face and fingerprint features to form final feature vector. Then classification is done using Euclidian distance.

IV. Results and Discussion

To evaluate the efficiency of the system implemented, experiments are carried out on ORL, UMIST, VISA standard face dataset and FVC fingerprint dataset. The Fig. 4 is the sample images of ORL dataset. ORL dataset consists of 10 samples of 40 persons, with different pose. The Fig. 5 shows the sample images from UMIST dataset. UMIST dataset consist of 400 images of 20 persons with 20 samples. The Fig. 6 shows sample images of VISA dataset. There are 500 images of 100 people with five samples each in the VISA dataset. The Fig. 7, 8, 9, 10 shows DB1, DB2, DB3, DB4 of FVC dataset respectively. FVC dataset consists of four databases. Each dataset consists of 80 images of 10 persons with eight samples each with different resolution and orientation.

Fig. 4. Sample images from ORL dataset.

Fig. 5. Image samples from UMIST dataset.

Fig. 6. Image samples from VISA dataset.

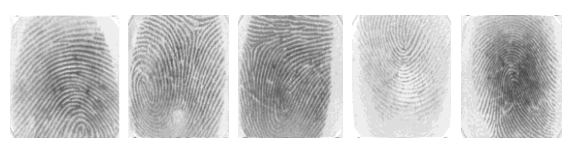

Fig. 7. Image samples from FVC DB1 dataset.

Fig. 8. Image samples from FVC DB2 dataset.

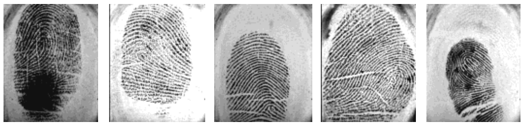

Fig. 9. Image samples from FVC DB3 dataset.

Fig. 10. Image samples from FVC DB4 dataset.

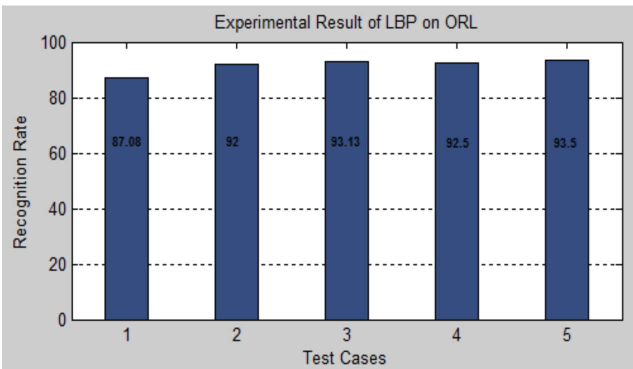

Fig. 11. Recognition rate of LBP on ORL dataset.

The Fig. 11 represents hypothetical outcome of LBP on ORL dataset giving highest accuracy 93.5%. The Fig. 12 shows experimental results of LTP on ORL dataset with highest accuracy 98.13%. Experiment is conducted on different test and training combination. The 1st Experimental setup consists of 1st to 4th indexed samples for training and 5th to 10th samples were used for testing. In the 2nd experimental setup 1st to 5th samples were utilized for training and 6th to 10th samples were considered for testing. Similarly in the 3rd experimental setups, 1st to 6th samples were used for training and 7th to 10th samples are utilized for testing. The fourth experimental setup used odd indexed samples for training and even indexed samples for testing. The last experimental setup was also based on training even indexed samples and testing odd indexed samples. From the above result it is clear that LTP based face recognition gives better accuracy than the LBP based face recognition.

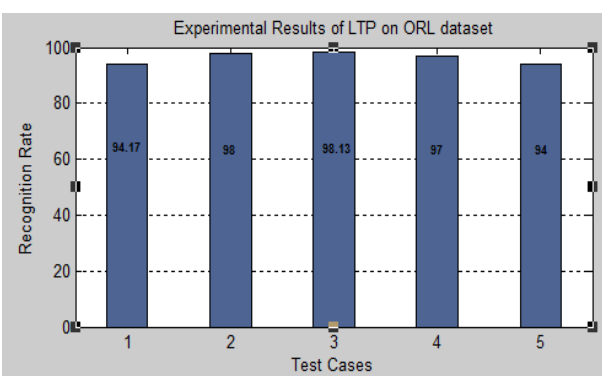

Fig. 12. Recognition rate of LTP on ORL dataset.

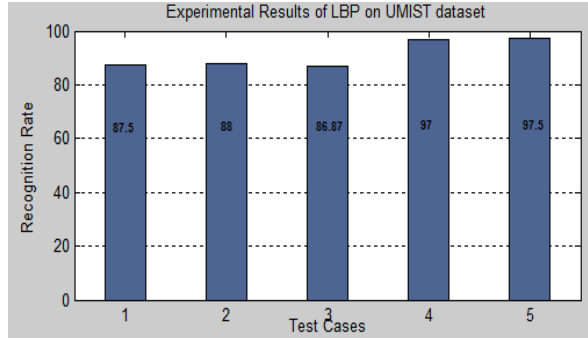

Fig. 13. Recognition rate of LBP on UMIST dataset.

The Fig. 13 represents hypothetical outcomes of LBP on UMIST dataset giving highest accuracy 97.5%. The Fig. 14 shows experimental results of LTP on UMIST dataset with highest accuracy 99%. Experiment is conducted on different test and training combination. The 1st Experimental setup consists of 1st to 8th indexed samples for training and 9th to 20th samples were used for testing. In the 2nd experimental setup 1st to 10th samples were used for training and 11th to 20th samples were considered for testing. Similarly, in the 3rd experimental setups, 1st to 12th samples were utilized for training and 13th to 20th samples are utilized for testing. In the 4th experimental setup odd indexed samples were utilized for training and even indexed samples were utilized for testing. Likewise, in the last experimental setup even indexed samples were used for training and odd indexed samples were used for testing. An experimental result on UMIST dataset shows that LTP based face recognition is best as compared to LBP based face recognition.

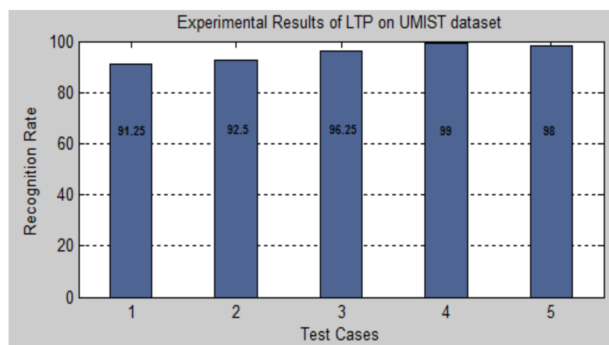

Fig. 14. Recognition rate of LTP on UMIST dataset.

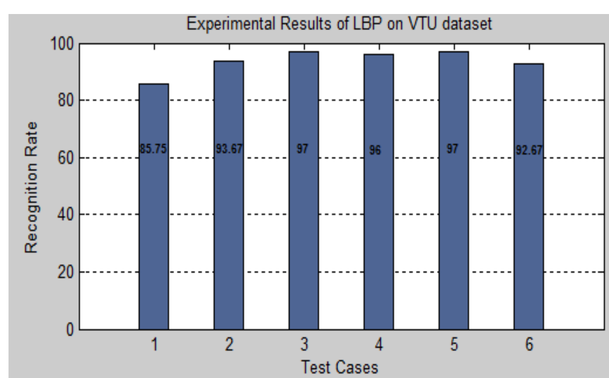

Fig. 15. Recognition rate of LBP on VISA dataset.

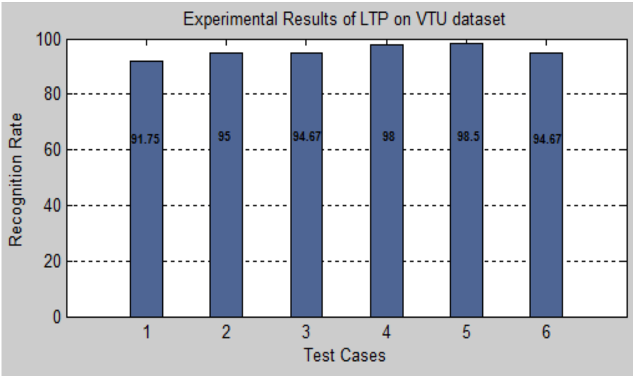

Fig. 16. Recognition rate of LTP on VISA dataset.

Fig. 15 and 16 show experimental results of LBP and LTP on VISA dataset with 97% and 98% accuracy respectively. The experimental setup 1 consists of index 1 sample in training set and 2, 3, 4, 5 indexed samples in testing set. Experimental setup 2 contains index 1 and 2 sample in training set and 3, 4, 5 indexed samples in testing set. Experimental setup 3 contains index 1, 2, 3 in training set and 4 and 5 in testing set. Similarly, experimental setup 4 consists of 1, 2, 3, 4 in training set and 5 in testing set. Experimental setup 5 contains odd indexed samples in training and even indexed sample in testing. Likewise, experimental setup 6 contains even indexed sample in training set and odd indexed samples in testing set. The experimental results show that LTP based face recognition gives better accuracy than LBP based face recognition.

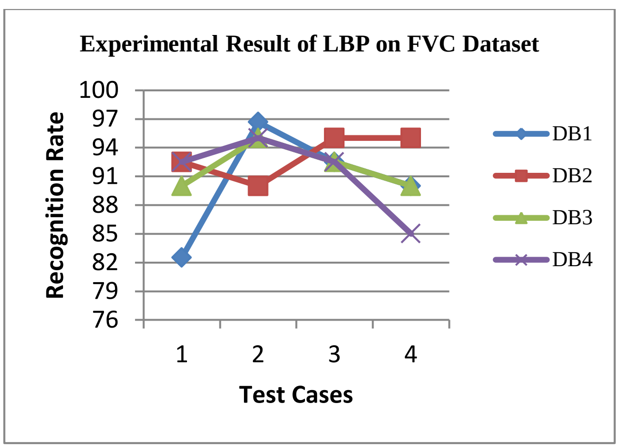

Fig. 17. Recognition rate of LBP on FVC dataset.

Fig. 17 and 18 show experimental results of LBP and LTP on FVC fingerprint dataset with accuracy of 96.6% and 97.5% respectively. FVC dataset contains four different databases DB1, DB2, DB3 and DB4. Experimental setup 1 contains 1st to 4th samples in training and 5th to 8th in testing set. Experimental setup 2 contains 1st to 5th samples in training and 6th to 8th in testing test set. Similarly 4th experimental setup contains odd indexed sample in training and even indexed samples in testing. Last experimental setup contains even indexed samples in training and odd indexed samples in testing set. From the Fig. 17 and 18 we can say that LTP based fingerprint system gives high accuracy as compared to LBP based fingerprint recognition.

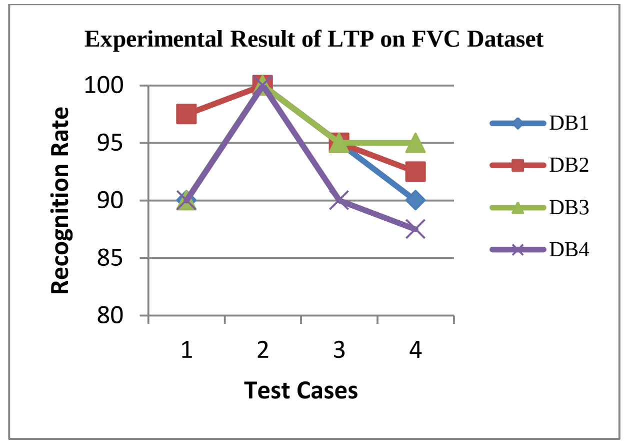

Fig. 18. Recognition rate of LTP on FVC dataset.

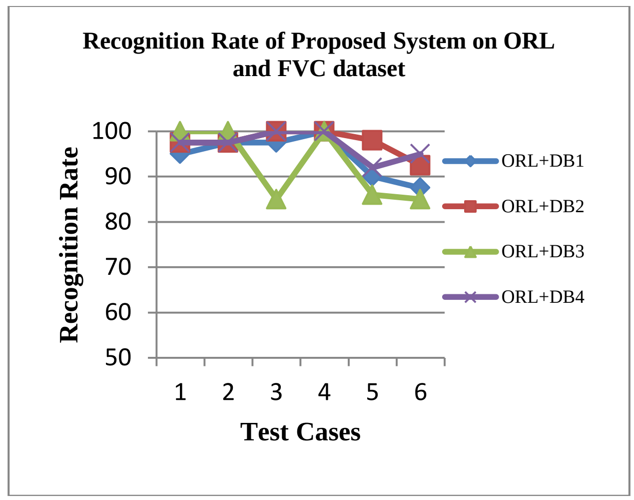

Fig. 19. Recognition rate of proposed system on ORL and FVC dataset.

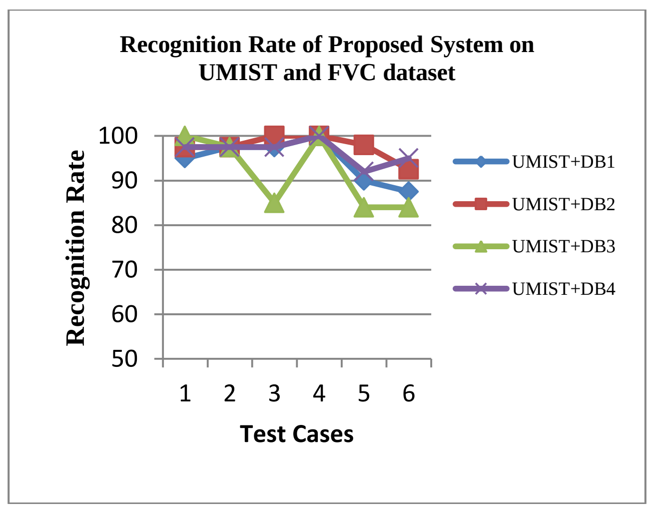

Fig. 20. Recognition rate of proposed system on UMIST and FVC dataset.

The Fig. 19 shows hypothetical outcomes of proposed system on ORL and FVC dataset. The Fig. 20 shows hypothetical outcomes of introduced system on UMIST and FVC dataset. In experimental setup 1, training set consists of even indexed samples and testing set consists of odd indexed samples. Experimental setup 2 contains odd indexed samples in training set and even indexed samples in testing set. In experimental setup 3, index 1 to 4 samples present in training set and 5 to 8 indexed samples present in testing set. Similarly 4th experiment contains 1 to 5 indexed samples in training set and 6 to 8 indexed samples in testing set. Likewise experimental setup 5 contains 1st 3 samples in training set and 4th to 8th indexed samples in testing set. Finally 6th experimental setup containing 5th to 8th indexed samples in training set and 1st to 4th samples in testing set. As compared to unimodal system the proposed LTP based multimodal system performs better.

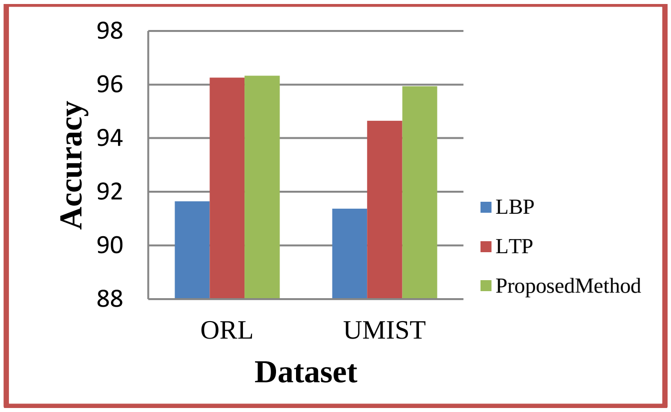

Fig. 21. Comparison of unimodal and multiomodal systems.

The Fig. 21 shows a comparison between the unimodal and multimodal biometric system. In the experiments, it was found that the proposed LTP based multimodal biometric system with face and fingerprints is 96.33% accurate on the ORL_FVC dataset and 95.94% accurate on the UMIST_FVC dataset. The unimodal LBP and LTP based biometric system achieved 91.64% and 96.26% accuracy on the ORL dataset respectively and 91.37% and 94.65% accuracy on the UMIST dataset respectively. Therefore the proposed multimodal biometric system thus provides greater accuracy than a unimodal biometrics using LBP and LTP on different datasets.

V. Conclusion

A multimodal biometric system offers high security than unimodal biometric system. Face and fingerprint are easily available and universally adopted biometric traits. In this paper, we discussed unimodal face and fingerprint recognition system using LBP and LTP as well as compared it with multimodal biometric system using LTP. The proposed approach is invariant to noise in the input image. Also, by the use of two biometric traits it avoids spoofing attack. The experimental results show that the proposed LTP based multimodal biometric system using face and fingerprint performs better than unimodal biometric system. To improve accuracy, hybrid approaches can be introduced in the future.

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