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Hybrid Domain Based Face Recognition System

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ABSTRACT

Automation in every field of daily life is required the need of mechanized human identification and verification for ensuring the security. The study of physiological or the behavioural information is referred to as biometrics. Face recognition is a highly active research area with a wide variety application. In this paper, we propose Hybrid Domain Based Face Recognition System (HDFRS) for different databases. The original face image is resized to uniform dimensions of 2^p x 2^q. The DT-CWT of a signal *x (n)* is constructed using two critically-sampled DWTs in parallel with same data. The five levels Dual-Tree Complex Wavelet Transform (DT-CWT) is applied on face image to obtain DT-CWT coefficients. The matrix of DT-CWT coefficients is segmented in to 3x3 matrixes. The Local Binary Pattern (LBP) algorithm is applied on each 3x3 matrix to get final features. The Euclidean Distance (ED) is used to compare features of test face image with data base images. It is observed that the values of False Rejection Rate (FRR), False Acceptance Rate (FAR) and Total Success Rate (TSR) are better in the proposed model compare to existing method.

Keywords - **DT-CWT, Euclidean Distance, Face Recognition, LBP**

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I. INTRODUCTION

Biometric authentication is the primary and prevalent system for security and surveillance activities in the past several years. The automation in every field of daily life has made human identification and verification is a prime issue for ensuring the security. The biometric techniques are relates to the parts of human body which are unique, cannot be stolen and is not easily transferable compared to traditional methods such as Identification badges, Personal Identification Number (PIN), password, smartcards etc. The choice of biometric techniques depends on user acceptability, universality, distinctiveness, permanence, accuracy, implementation time and cost. Biometrics can be classifieds under two categories based on the characteristics such as (i) *Physiological characteristics* and (ii) *Behavioral characteristics.* The physiological characteristics such as face, fingerprint, and palm print, iris etc., and behavioral characteristics such as signature gait, speech and keystroke etc. Biometric recognition based on fingerprint, iris, voice and other attributes all suffer from a series of drawbacks, because they need of high precision image acquisition and good recording instruments.

Face recognition is one of the primary biometric technologies and one of the active research fields that recognize a person using facial characteristics of human beings. It has received a significant interest because of its wide range of applications in credit card verification, airports, banks, government offices, criminal screening and surveillance etc. Every face recognition system commonly consists of Face image acquisition and storage, Preprocessing, Features extractions and matching. Several existing face recognition and verification techniques use single feature extraction process in spatial domain itself or transformation domain of an image. The features are extracted in spatial domain are counting the pixel density, width of the lips, pixel mean, variance and standard deviation etc. The features extracting in transformation domain are the coefficients of Fast Fourier Transformation (FFT), Discrete Cosine Transform (DCT), Short-Time Fourier Transform (STFT), Discrete Wavelet Transform (DWT) and Dual-Tree Complex Wavelet Transform (DT-CWT).

The biometric techniques such as information from single feature extraction method either in spatial domain or transformation domain of an image has some limitations in terms of Total Success Rate (TSR), higher values of False Rejection Rate (FRR) and False Acceptance Rate (FAR). These limitations can be eliminated by considering hybrid domain based recognition system by using spatial and transformation domain features to ensure a higher level of security and improved performance.

Contribution: In this paper HDFRS model is proposed. Five level DT-CWT is applied on face image to obtain real and imaginary bands to generate DT-CWT coefficients. The LBP algorithm is applied on each 3x3 matrix of DT-CWT coefficients to obtain final features. The Euclidean Distance is used to compare features of test image with data base images.

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Organization: The paper is organized as follows. Section II presents related work. Section III explains the proposed model. Section IV explains the algorithm. Section V gives the results and performance analysis and Section VI gives the conclusion.

II. LITERATURE SURVEY

Yongsheng GAO and Maylor K.H. Leung [1] proposed a faces reorganization using line edge mapping technique for different lighting condition, images with varying facial expression and poses. The proposed method gives improved performance. Guillaume Heusch et al., [2] have proposed a preprocessing algorithm based on Local Binary Patterns for face authentication. The LBP operator provides texture representation and is resulting from the input face image before being forwarded to two different classifier of holistic and feature based. The efficiency is improved in the proposed approach. Yue-Hui Sun and Ming-Hui Du [3] proposed DT-CWT spectral histograms and support vector machine for face detection. Laplacian of Gaussian filter and DT-CWT filter are applied to capture spatial and frequency properties of human faces at different scales and different orientations. The responses convolved with the filters are summarized to multi-dimensional histograms. Finally, the histogram matrix is fed to the trained SVM for classification. The experimental results show that spectral histogram representation is a good choice for face detection. Marios Kyperountas et al., [4] proposed a face recognition algorithm using discriminant analysis. Projected face data is portioned using face classes and clustering algorithm to form a set of discriminant clusters. This process iterates until one final cluster is selected that consists of a single face class, whose identity is set to be the good match to the identity of the test face. Praseeda Lekshmi.V and M.Sasikumar [5] proposed method Radial Basis Function for face recognition by separating skin and non- skin pixels. The face region is extracted from skin region. The facial expression is analyzed using Gabor wavelet transform and discrete cosine transform on face images and finally RBF network is used to identify a person. G. R. S. Murthy and R.S.Jadon [6] proposed a method to examine the facial expression recognition based on the static image using Eigen spaces. The proposed system is tested for Cohn-Kanade facial expression database and JAFFE database. The experimental results show better recognition rate.

Yee Wan Wong et al., [7] presented novel dual optimal multiband features method for face recognition. Image decompose is carried out to generate frequency sub bands using wavelet packet transform and optimal multiband feature sets are selected using multiband feature fusion technique. Then parallel radial basis function neural networks are employed to classify the two sets of feature. The generated scores are combined and processed by an adaptive fusion mechanism. The proposed technique gives better performance. S. Anila and N. Devarajan [8] proposed a fast face detection system based on edges. The method consists of three steps, initially the median filtering method is applied to remove the noise and for contrast adjustment histogram equalizer is used and sobel operator is used to detect edges. Edge tracking algorithm is used to obtain the sub windows from the enhanced image. Edges and features are obtained and these feature values are passed into a trained back propagation neural network to sort the sub-window as either face or non-face. The result of the proposed method gives better performance in terms of processing time in testing and training. Bongjin Jun et al., [9] developed a code selection method to obtain a compact LBP using the maximization of mutual information between features and class labels for better classification performance with smaller number of codes. An experimental result shows that the CLBP outperforms other LBP variants such as LBP, ULBP and MCT in terms of smaller number of codes and better recognition performance. Zhen Lei et al., [10] presented a face recognition technique by considering information in image space, scale and orientation domains. The face image is decomposed as an orientation and scale responses by convolving multi scale and multi orientation Gabor filters. Local binary pattern is used to describe the neighboring relationship in image space, different scale and orientation responses. Linear discriminant analysis technique is used to discriminant classification based upon weighted histogram intersection or conditional mutual information for different databases. Experimental results show that better improvement in the performance. Manish Gupta and Govind Sharma [11] developed a sub-window extraction algorithm, principal component analysis and back propagation algorithm for face recognition in extraction phase and recognition phase. In extraction phase, face images are enhanced using filtering, clipping and histogram equalization and are converted into edge images using Sobel operator and then converted into binary images finally sub windows extraction algorithm is used to extract different features and for recognition phase back propagation algorithm and PCA algorithm is used for different face databases.

III. MODEL

In this section the definitions of performance parameters and the proposed model are discussed.

A. DEFINITIONS

(i) False Rejection Rate (FRR): It is the measure of biometric security system that incorrectly rejects an access attempt by an authorized user and is given in Equation 1.

$$FRR = \frac{Number\ of\ Falsely\ rejected\ images}{Total\ number\ of\ persons\ in\ the\ databese} \quad (1)$$

(ii) False Acceptance Rate (FAR): It is the measure of biometric security system that incorrectly accepts an access attempt by an unauthorized user and is given in Equation 2.

$$FAR = \frac{Number\ of\ Falsely\ Accepted\ images}{Total\ number\ of\ persons\ out\ of\ database} \quad (2)$$

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(iii) Total Success Rate (TSR): is the probability that different images of the same person are matched and is given in Equation 3.

$$TSR = \frac{Number\ \ of\ \ correct\ \ persons\ \ matched}{Total\ \ number\ \ of\ \ persons\ \ in\ \ the\ \ database} \qquad (3)$$

B. PROPOSED MODEL

In the proposed model Dual-Tree Complex Wavelet Transform (DT-CWT) and the Local Binary Pattern (LBP) are used to generate features of face images to identify a person more effectively. The block diagram is as shown in the Figure.1

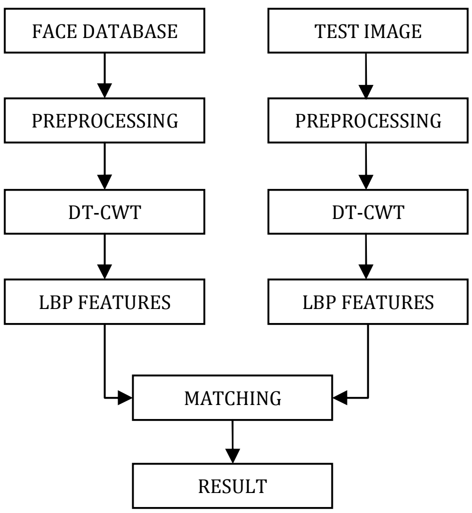

Fig.1. Block diagram of HDFRS

(i) Face Database:

Near Infrared (NIR) Database:

The NIR data base of one person shown in Figure 2 is considered due to its variation of pose, expression, illumination, scale, blurring and a combination of them. The database consists of 115 persons and 14 images per person. The data base is created by considering first 60 persons out of 115 persons and first 10 images per person are considered which leads to 600 images in the database and the thirteenth image from first 60 persons is considered as a test image to compute FRR and TSR. The remaining 55 persons out of 115 are considered as out of database to compute FAR.

Fig.2.Near Infrared Database

L-Spacek:

The database consists of 119 persons. The first 65 persons are considered for database and reaming 54 persons are considered out of database. Each person has 19 images in that first 10 images per person are considered to create data base which leads to a total of 650 images and thirteenth image of the first 65 persons taken as test image to compute the FRR and the TSR and FAR is computed using 54 persons out of data base image. The *L-Spacek* database of single person is as shown in Figure.3

Fig.3. L-Spacek Database

JAFFE Database:

The face database consists of 9 persons with 23 images per person. The database is created by considering first 5 persons out of 9 persons and first 10 images per person are considered to create data base which leads to 50 images in the database and fourteenth image from first 5 persons are taken as test image to compute FRR and TSR. The remaining 4 persons out of 9 are considered as out of database to compute FAR. The JAFFE database of twenty three images of single person is shown in Figure.4

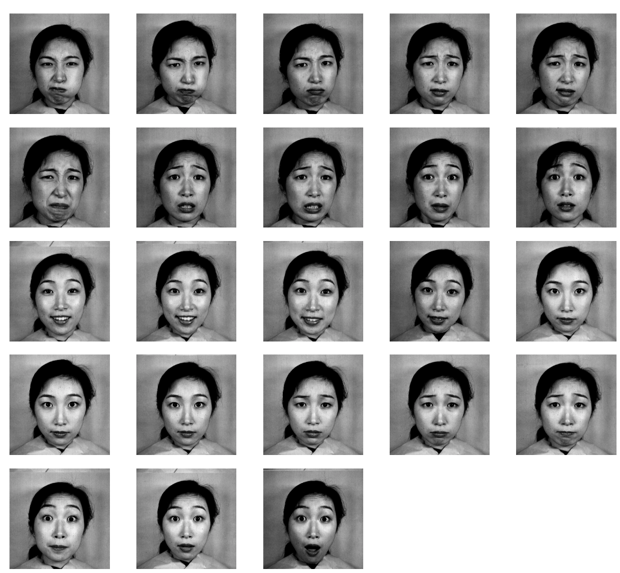

Fig.4. JAFFE Database

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(ii) Face Preprocessing:

The different available face databases such as Near Infrared (NIR) Database, L-Spacek database and JAFFE database has different sizes, hence requires a preprocessing to convert into a suitable size of 2^n dimensions, where n is an integer to apply DT-CWT. In the proposed model for all face data bases, the images are resized to 2^7 x 2^9 i.e. 128X512.

(iii) Dual-Tree Complex Wavelet Transforms (DT-CWT):

The DT-CWT is an effective approach for implementing a wavelet transforms. This technique has been used to incorporate the good properties of Fourier Transformation in the Wavelet Transformation. The important advantages of DT-CWT over the DWT are approximate shift invariance, directional selectivity, limited redundancy and perfect reconstruction and also a good basis for de-noising and de-blurring. The DC-TWT of a signal *x (n)* is constructed using two critically-sampled DWTs in parallel with same data as shown in Figure 5.

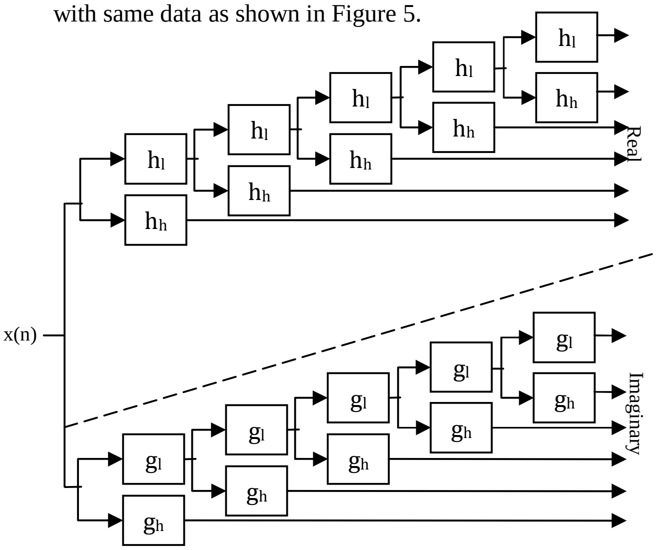

Fig.5. Filter Bank of DT-CWT

The first tree generates the real parts of the transform and the second tree generates the imaginary parts. The real part has low pass (h_l) and high pass (h_h) pair and imaginary part has low pass (g_l) and high pass (g_h) pair of the complex coefficients.

DT-CWT distinguishes positive and negative frequencies and generates six sub bands oriented in $\pm 15^0$, $\pm 45^0$, and $\pm 75^0$ as shown in Figure 6.

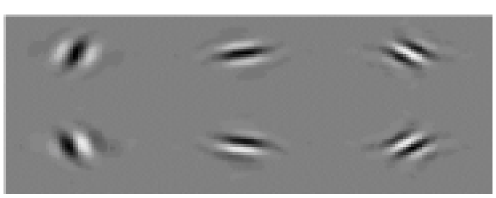

Fig.6. Directional wavelets

Five level DT-CWT is applied on face image, which provides sixteen sub bands at each level with four sub bands of low frequencies and 12 sub bands of high frequencies. At every level the image size is reduced to half of the original size. In the first level the image size 128x 512 is reduced to 64x256 and the second level image size is reduced to half of the first level i.e., 32x128 and third, fourth and fifth level the image size are reduced to 16x64, 8x32 and 4x16 respectively.

(iv) The Local Binary Pattern (LBP):

The texture classification and segmentation with better accuracy and less computational complexity can be achieved using LBP operator. The LBP operator is used for different neighbor sizes such as the operator $LBP_{8,1}$ uses 8 neighbors on a circle with radius 1 where $LBP_{16,2}$ considers the 16 neighbors on a circle with radius 2. In general the LBP operator at a scale can be denoted as $LBP_{P,R}$ where R is the radius of the circle surrounding the center, and P is the number of pixels on the circle. The operator produces 2^P different output values, corresponding to the 2^P different binary patterns that forms the P pixels in the neighbor set. Hence it is possible to use only a subset of the 2^P LBPs to describe the textured images. Ojala et al. [12] proposed these fundamental patterns with bitwise transitions from 0 to 1 and vice versa. For example, 11111111 and 00000000 contain 0 transitions while 00000110 and 01111110 contain 2 transitions and so on. Hence the important properties of LBP features are their tolerance against changes in the illumination and their computational simplicity.

The face image is divided into Small regions of 3x3 matrixes. The textures of the facial images are locally encoded by the LBP patterns from which the features are extracted. These features can be seen as composition of patterns such as Spot, Flat, Line End, Edge and Corner which are invariant with respect to grey scale transformations. Global description of the face image is obtained by combining all these patterns as shown in Figure7.

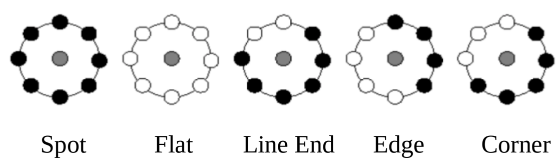

Fig.7. Patterns represented by LBP operator

Spot: In this, the values of all the neighborhood pixels are *less* compared to center pixel value i.e., threshold and the corresponding binary value is 00000000.
Flat: In this, the value of all neighborhood pixels are *more* compared to center pixel value i.e., threshold and the corresponding binary value is 11111111.
Line End, Edge and Corner: In this, few values of neighborhood pixels are greater and few values are lesser compared to center pixel value i.e., threshold and the corresponding binary values are combination of one to zero or zero to one transitions.

The LBP operator is applied on DT-CWT feature to derive LBP coefficients of face image which forms face features using Equation 4

$$LBP_{P,R} = \sum_{p=0}^{7} S\left(g_p - g_c\right) 2^p \qquad (4)$$

Where g_p=Intensity value of neighbourhood pixel.

g_c = Intensity value of central pixel.

$$S\left(g_p - g_c\right) = \begin{cases} 1, & \left(g_p - g_c\right) \geq 0 \\ 0, & otherwise \end{cases}$$

The feature vector set of a face is constructed by considering neighbour sizes of 3x3 cells consisting of 8 neighbours on a circle of radius 1. Central pixel image value is 28 and the neighbour pixel value is 34 which is greater than 28 hence is assigned 1, the next neighbour pixel value is 20 which is less than 28 hence is assigned 0 and so on is shown in Figure 8. The LBP binary values are extracted by dividing an image into several small regions and then converting into decimal values and these values are considered as features for classification process.

$$\begin{array}{|c|c|c|} \hline 34 & 20 & 25 \\ \hline 12 & 28 & 48 \\ \hline 19 & 54 & 47 \\ \hline \end{array} \Longrightarrow \begin{array}{|c|c|c|} \hline 1 & 0 & 0 \\ \hline 0 & c & 1 \\ \hline 0 & 1 & 1 \\ \hline \end{array}$$

Binary sequence =10011100=156

Fig. 8: LBP operator on 3x3 matrix.

(v) Matching

Euclidean distance is used to verify whether the person is in database or not by comparing final features vector set of database image with final features vector set of test image. The Euclidean distance is calculated using Equation 5

$$d(p,q) = \sqrt{\left(p_i - q_i\right)^2 + \left(p_i - q_i\right)^2} \qquad (5)$$

Where p_i = the feature value of database image.
q_i = the feature value of test image.

When Euclidean distance value is minimum compared with threshold value, the person is matching with database otherwise not matching.

IV. ALGORITHM

The proposed algorithm is used to recognize a person effectively based on DT-CWT and LBP features.

The objectives are as follows:

1. To increase Total Success Rate.
2. To reduce FAR and FRR.

The HDFRS algorithm is given in Table 1

Table 1: Proposed Algorithm

Input: Face image
Output: Recognition of a person
Step 1: Face image is read from data base.
Step 2: Colored image is converted in to gray scale.
Step 3: Image is resized to 2^px2^q.
Step 4: DT-CWT is applied.
Step5: The matrix of DT-CWT coefficients is divided into Small regions of 3x3 matrixes.
Step 6: For each matrix LBP is applied.
Step 7: The LBP binary values are extracted then converting into decimal values and these values are considered as features.
Step8: Repeat step 1 to 7 for test image.
Step 9: Test features are compared with database features using Euclidean distance.
Step10: Image with Euclidean distance is less than threshold value is considered as matched image otherwise not matching.

V. RESULT ANALYSIS

The face data base images such as JAFFE, L-spacek and NIR are considered for performance analysis. m

The values of FRR, FAR and TSR variations with threshold for JAFFE face database is tabulated in Table 2. It is observed that values of FRR decreases from100% to 0% as a threshold values increases. The values of FAR and TSR are increased with threshold. The maximum TSR with JAFFE database is 100%.

Table 2: FRR, FAR and TSR variation with Threshold for JAFFE Database

THRESHOLD	FRR (%)	FAR (%)	TSR (%)
0	100	0	0
0.25	100	0	0
0.5	100	0	0
0.75	100	0	0
1.00	100	0	0
1.25	100	0	0
1.5	80	0	20
1.75	80	0	20
2.0	80	0	20
2.25	80	0	20
2.5	20	50	80
2.75	20	50	80
3.0	0	50	100
3.25	0	50	100

The variation of FRR and FAR with threshold is shown in the Figure 9. It is noticed that as threshold value increase the FRR and FAR values decrease and increases respectively. For threshold value of 3.25 the FRR become zero. The FAR is 0.5 at threshold value is 3.25.

The value of FRR, FAR and TSR variations with threshold for L-Spacek face database is tabulated in Table 3. It is observed that values of FRR decreases from100% to 1.54% as a threshold values increases. The values of FAR and TSR values are increased with threshold. The maximum TSR with L-spacek database is 98.46%.

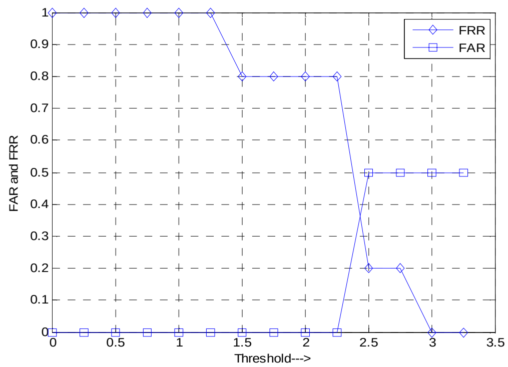

Fig.9. Graph of FAR and FRR with threshold value for JAFFE database.

Table 3: FRR, FAR and TSR variation with Threshold for L-Spacek Database.

Threshold	%FRR	%FAR	%TSR
0.5	100	0	0
0.75	81.54	0	18.46
1.00	61.54	0	38.46
1.5	38.46	0	61.53
1.75	33.85	0	66.15
2.00	20.00	0	80.00
2.25	16.92	0	83.07
2.5	7.69	0	92.30
2.75	4.62	1.85	95.38
3.00	3.08	5.56	96.92
3.25	1.54	18.52	98.46

The variation of FRR and FAR with threshold is shown in the Figure 10. It is noticed that as threshold value increase the FRR values decrease and FAR increases. For threshold value of 3.25 the FRR become 1.54% and FAR is 18.52%.

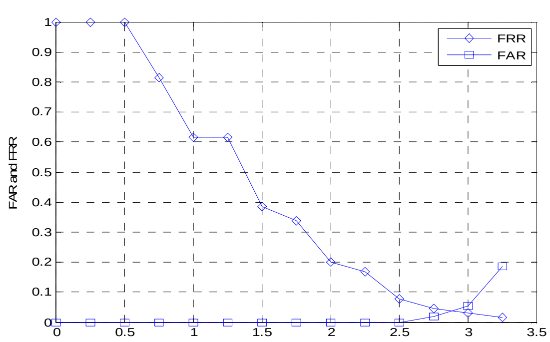

Fig.10: Graph of FAR and FRR with threshold value for L-Space k database.

Table 4 shows the values of FRR decrease from 100% to 3.08% and TSR increase from 0% to 89.23% as a threshold value increases from 0 to 3.8 and FAR is 0% up to the threshold value of 2.2 and it is increases to 94.44% as threshold value increases from 2.4 to 3.8.

Table 4: FRR, FAR and TSR variation with Threshold for NIR Database

Threshold	%FRR	%FAR	%TSR
0	100	0	0
0.2	100	0	0
0.8	100	0	23.07
1.0	76.92	0	23.07
1.4	75.38	0	24.61
1.8	55.38	0	44.61
2.0	40.00	0	60.00
2.2	40.00	0	60.00
2.4	29.23	3.7	70.76
2.6	26.15	11.11	73.84
2.8	21.54	22.22	76.92
3.0	16.92	40.74	81.53
3.2	12.31	62.92	86.15
3.6	7.69	85.19	87.69
3.8	3.08	94.44	89.23

The variation of FRR and FAR with threshold is shown in the Figure 11. It is noticed that as threshold value increase the FRR values decrease and FAR increases. For threshold value of 3.8 the FRR become 3.08% and the FAR becomes 94.44 and TSR is 89.23%.

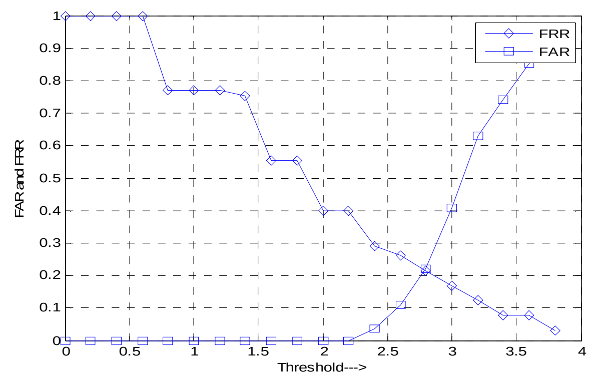

Fig. 11: Graph of FAR and FRR with threshold value NIR database.

The percentage face recognition rate of the proposed algorithm is compared with existing technique *Dual Transform based Feature Extraction for Face Recognition (DTFE)* [13] is given in Table 5. It is observed that the proposed algorithm gives better recognition rate compared to existing technique.

Table 5: Comparison of TSR with existing method of DTFE and proposed HDFRS method

Data base	**Total Success Rate**	
	Existing method [13]	**Proposed method**
JAFFE	90.3%	100%
L - Spacek	87.2%	98.4%

VI. CONCLUSION

Face recognition is a physiological biometric trait. The different face data bases are considered for performance analysis. In this paper, we proposed Hybrid Domain Based Face Recognition System (HDFRS). The original face images are resized to 2^p X 2^q. The Five level DT-CWT is applied on face images to generate coefficients and these coefficients are segmented into 3x3 matrixes. The LBP is applied on each 3X3 matrix to obtain final features sets. The Euclidean Distance (ED) is used for matching. It is observed that the Total Success Rate (TSR) value is better in the case of proposed technique. In future the algorithm is tested using different kinds of transformation and fusion techniques with different levels such as feature level and decision level to improve the performance and to obtain better results.

REFERENCES

[1] Yongsheng Gao and Maylor K.H. Leung, "*Face Recognition Using Line Edge Map,"* IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, pp. 764-779, 2002.
[2] Guillaume Heusch, Yann Rodriguez and Sebastien Marcel, "*Local Binary Patterns as an Image Preprocessing for Face Authentication,"* IEEE International Conference on Automatic Face and Gesture Recognition, pp. 4-6, 2006.
[3] Yue-Hui Sun, Ming-Hui Du, "*Face Detection using DT-CWT on Spectral Histogram,"* IEEE International Conference on Machine Learning and Cybernetics, pp.13-16, 2006.
[4] Marios Kyperounta, S Anastasios Tefas, Ioannis Pitas, "*Dynamic training using multistage clustering for face recognition,"* Elsevier Pattern Recognition, pp. 894 – 905, 2008.
[5] Praseeda Lekshmi.V M.Sasikumar, "*RBF Facial recognition and expression analysis,"* World Academy of Science, Engineering and Technology vol. 32, pp. 589-582, 2008.
[6] G. R. S. Murthy and R.S.Jadon, "*Effectiveness of Eigenspaces for Facial Expressions Recognition,"* International Journal of Computer Theory and Engineering, vol. 1, pp. 638-642, 2009.
[7] Yee Wan Wong, Kah Phooi Seng, Li-Minn Ang, "*Dual optimal multiband features for face recognition,"* Elsevier Expert Systems with Applications, pp. 2957–2962, 2010.
[8] S. Anila and N. Devarajan, "*Simple and Fast Face Detection System Based on Edges,*" International Journal of Universal Computer Sciences, vol.1 pp. 54-58, 2010.
[9] Bongjin Jun, Taewan Kim, Daijin Kim, "*A Compact Local Binary Pattern using Maximization of Mutual Information for Face Analysis,"* IEEE Pattern Recognition, vol. 44, pp. 532–543, 2011.
[10] Zhen Lei, Shengcai Liao, Matti Pietikäinen and Stan Z. Li, "*Face Recognition by Exploring Information Jointly in Space, Scale and Orientation,"* IEEE Transactions on Image Processing, vol. 20, pp. 247-256, 2011.
[11] Manish Gupta, Govind Sharma, "*An Efficient Face Recognition System Based on Sub-Window Extraction Algorithm,*" International Journal of Soft Computing and Engineering, vol. 1, pp. 304-310, 2012.
[12] Timo Ojala, Matti PietikaÈ inen, "*Multi Resolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns,"* IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, No. 7, pp. 971-987, 2002.
[13] Ramesha K, K B Raja, "Dual *Transform based Feature Extraction for Face Recognition,"* International Journal of Computer Science, vol. 8, No 2, pp. 115-121, 2011.

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