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Procedia Computer Science 54 (2015) 809 – 817

Procedia Computer Science

Eleventh International Multi-Conference on Information Processing-2015 (IMCIP-2015)

FRDF: Face Recognition using Fusion of DTCWT and FFT Features

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Abstract

Face recognition is a physiological Biometric trait widely used for personal authentication. In this paper we have proposed a technique for face recognition using Fusion of Dual Tree Complex Wavelet Transform (DTCWT) and Fast Fourier Transform (FFT) features. The Five Level DTCWT and FFT are applied on the pre-processed face image of size 128×512. The Five Level DTCWT features are arranged in a single column vector of size 384×1. The absolute values of FFT features are computed and arranged in column vector of size $65,536 \times 1$. The DTCWT features are fused with dominant absolute FFT values using arithmetic addition to generate a final set of features. The test image features are compared with database features using Euclidean distance to identify a person. The face recognition is performed for different database such as ORL, JAFFE, L-SPACEK and CMU-PIE having different illumination and pose conditions. It is observed that the performance parameters False Acceptance Rate (FAR), False Rejection Rate (FRR) and True Success Rate (TSR) of proposed method FRDF: Face Recognition using Fusion of DTCWT and FFT are better compared to existing state of the art methods.

Peer-review under responsibility of organizing committee of the Eleventh International Multi-Conference on Information Processing-2015 (IMCIP-2015)

Keywords: Biometrics; Face recognition; DTCWT; FFT; Fusion.

1. Introduction

Biometrics is an automatic recognition of a person using distinguished traits. An expansive definition is automatically measurable, distinctive physical characteristics or behavioural characteristics that can be used to identify an individual or verify the claimed identity of an individual. In information technology, biometrics is used as a form of identity access management and access control. It is also used to identify individuals in groups that are under surveillance. Biometrics can be classified into two classes: (i) Physiological characteristics such as face, fingerprints, hand geometry and iris etc are related to body parts and these characteristics remain unchanged throughout the life time. (ii) Behavioral characteristics which include signature, speech, keystroke and these parameters change with environment, mood and age. Biometric selection depends on characteristics like (i) *Uniqueness:* the collected biometric data should be distinct and unique. (ii) *Universality:* It should be available with each individual (iii) *Permanence:* the biometric data should be robust and invariant to any environmental changes (iv) *Collectability:* data should be easy to collect and store (v) *Performance:* data should give better performance with less errors.

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Peer-review under responsibility of organizing committee of the Eleventh International Multi-Conference on Information Processing-2015 (IMCIP-2015)
doi:10.1016/j.procs.2015.06.095

Biometric System acquires data from an individual and extracts required features from a data set which will be stored as template in database. The individual who wants to claim his/her identity is subjected to a process of Enrolment and Feature Extraction as similar to database creation. Finally the authentication of an individual is carried out under verification and identification process. In verification, the claimed individual template is compared against his/her own template which is already stored in database and this requires one to one comparison and prevent multiple comparison with other database templates whereas in a identification the claimed individual is tested with all the stored template database using one to many comparison resulting in more computation time. The Performance of an efficient biometric system are measured by plotting Region of Operating Characteristics (ROC) which plots False Acceptance Ratio and False Rejection Ratio against threshold which is a classifier selected based on Feature Extraction Method. Face recognition is a visual pattern recognition wherein a three dimensional face images of different pose, expressions and illumination variations are to be recognized using a two dimensional image captured from a camera as a intensity valued pixel matrix. Face images are subjected to filtering and histogram equalization to denoise and remove the illumination variations which are associated with face images because of varying optical axis of a camera while capturing images. The features are extracted from these pre-processed face images which help in identification and verification of claimed individual based on a threshold set in a matching classifier. Face Recognition has become a prominent biometric system due to its naturality and non invasive process of collecting the data. The efficient face recognition system can be developed using robust face recognition algorithm which are invariant to different facial expressions and poses.

Motivation: The motivation to design and develop an effective biometric algorithms based on physiological and behavioral characteristics of a human being is to overcome the disadvantages of a traditional authentication systems which uses a password, Personal Identification Number, ID badges to recognize a person which are not secure as these can be shared, forgotten with other individuals leading to hacking of a biometric system. In the proposed work we are motivated to select a face recognition based biometric system which has to face a challenges of recognizing an individual against illumination and background variations of face images occurring due to difference in camera angular position, direction of lightening ,image orientation and its conditioning.

Contribution: In this paper, FRDF algorithm is proposed to authenticate a person efficiently. Two sets of features are extracted using, DTCWT and FFT. The final feature vector is arithmetic addition of DTCWT and FFT features. The Euclidean Distance is used to compare features between test and database images to identify a person.

Organization: The paper is organized into the following sections. Section 1 gives introduction to biometrics. Section 2 is an overview of related work and Background is given in Section 3. Face recognition model is described in Section 4. Section 5 contains the algorithm of face recognition system with methodology and feature extraction. Performance Analysis and results are discussed in section 6.Conclusions are presented in section 7.

2. Literature Survey

Song and Min[1] have proposed a method for face recognition which combines two dimensional Principal Component Analysis and two dimensional Discrete Wavelet Transforms. Nearest neighbor classifier is used for the face classification. Experimental results show that the combination of 2DPCA and 2DWT method improve the recognition rate effectively in comparison with PCA, Wavelet + PCA and 2DPCA.

Ravi *et al.*,[2] proposed the method in which the original face image is pre-processed and five level DT-CWT is applied in ordered to get DT-CWT coefficients. The 3×3 matrix is considered, for each of these matrix local binary patterns is applied to get the final features and comparison of features of test image with database image is done using Euclidean Distance. Rangaswamy *et al.*[3,6] proposed face recognition using texture features obtained from a Dual tree complex wavelet transform and Overlapping Local Binary pattern. DTCWT is applied on high frequency bands of DWT coefficients to capture directional variations of face images. Texture features of face images are obtained using local binary pattern operator (OLBP). Euclidean Distance is used as a classifier for matching Zhongxi *et al.*,[4] have introduced a face recognition by combining DT-CWT and two dimensional inverse Fisher Discriminant Analysis. DT-CWT is applied to extract features at different scales and orientations. 2DIFDA is applied for dimensionality reduction and feature selection. Raja and Ramesha[5] have presented performance evaluation of face recognition based on DT-CWT using multi-matching classifiers. A 2D DWT is applied along with DT-CWT to get the coefficients. Nick Kingsbury[7] has discussed a method to design a filters for DT-CWT. The filters are designed such that both the filers are of even length and also time-reverse of each other. The filters have additional property that the group delay between the filter is one quarter of the sample period. Ivan[8] has discussed a method of filter designing such that the two filters are Hilbert transform of each other. Spectral factorization technique is used for filter designing.

Uzair *et al.*,[9] proposed a hyper spectral face recognition algorithm based on spatio spectral covariance for band fusion and PLS regression for classification. The algorithm was tested on three standard databases and compared with 18 existing state of the art algorithms including seven image set classification, six gray scale/RGB and five hyper spectral face recognition algorithms. Gao Zhirong *et al.*,[10] proposed a robust face recognition algorithm using transform domain based multiple feature fusion and linear regression. Transform domain based feature fusion provide comprehensive face information and decrease the effect of variations in illumination and pose. The linear regression classifier is used for recognition.

Yue Long *et al.*,[11] proposed a recognition method based on sparse representation on down sampled input image to locate un occluded face parts. Linear Discriminant Analysis is performed on occluded face parts to obtain local stastical local features for better recognition Rate. Jun Huang *et al.*,[12] proposed a face recognition algorithm based on both the Multilinear Principal Component Analysis (MPCA) and Linear Discriminant Analysis (LDA). This approach treats face images as multidimensional tensor in order to find the optimal tensor subspace for dimension reduction. The LDA is used to project samples to new discriminant feature space and K Nearest Neighbor (KNN) classifier is used for matching. Zhang *et al.*,[13] proposed a face recognition based on singular value decomposition features which reduces and remove redundancy in a data using a nearest orthogonal matrix representation of each subspace in a face images. The nearest neighbor classifier is used for matching Ali and Moeini[14] proposed a face recognition method which is invariant to pose and expression variations of face images. A 2D frontal image with different facial expressions are converted into a 3D modeled face images using Probabilistic Facial Expression Recognition Generic Elastic Model (PFER-GEM). A Feature Library Matrix (FLM) is generated using DTCWT features for each face image in database. Iterative scoring classification is used to recognize face images.

3. Background

3.1 Dual tree complex wavelet transform (DTCWT)

Dual Tree Complex Wavelet Transform is a recent enhancement technique of DWT. It is an effective method for implementing an analytical wavelet transform[7]. The complex coefficients generated by DTCWT introduce limited redundancy and allows the transform to provide shift invariance and directional selectivity of filters.

(i) **Structure of DTCWT:** DTCWT can be implemented using 2D separable two real wavelet transform in parallel. The first real wavelet transform can be implemented using low pass and high pass filter coefficients $h_0(n)$ and $h_1(n)$ applied along row and column dimension of 2D data which forms Upper Filter bank structure of DTCWT. The second Real wavelet transform which represents Lower Filter bank of DTCWT can be implemented using low pass and high pass filter coefficients $g_0(n)$ and $g_1(n)$ which are approximately analytic to upper filter bank coefficients resulting in perfect reconstruction of input image data.

(ii) **Real Oriented 2-D Dual-Tree Wavelet Transform:** The Real 2-D Dual-Tree Wavelet Transform based on six oriented wavelets can be implemented using two real separable 2-D wavelet transform in parallel. To obtain a real 2-D wavelets oriented at ±15, ±45, ±75 a 2-D separable wavelet transform is applied on image along row and column dimensions using six complex oriented wavelets as given in Equations (1) and (2)

$$\psi_i(x, y) = \frac{1}{\sqrt{2}}(\psi_{1,i}(x, y) - \psi_{2,i}(x, y)) \tag{1}$$

$$\psi_{i+3}(x, y) = \frac{1}{\sqrt{2}}(\psi_{1,i}(x, y) + \psi_{2,i}(x, y)) \tag{2}$$

For $i = 1, 2, 3$, where the two separable 2-D wavelet are defined as given in Equations (3), (4) and (5)

$$\psi_{1,1}(x,y) = \phi_h(x)\psi_h(y), \quad \psi_{2,1}(x,y) = \phi_g(x)\psi_g(y) \tag{3}$$

$$\psi_{1,2}(x,y) = \psi_h(x)\phi_h(y), \quad \psi_{2,2}(x,y) = \psi_g(x)\phi_g(y) \tag{4}$$

$$\psi_{1,3}(x,y) = \phi_h(x)\psi_h(y), \quad \psi_{2,3}(x,y) = \psi_g(x)\psi_g(y) \tag{5}$$

(iii) **Complex 2-D Dual-Tree Wavelet Transform:** The complex 2-D dual-tree DWT is obtained by converting a 2D real wavelet transform into a complex wavelet transform of unidirectional spectrum. The real and imaginary part of this complex wavelet contains sum of two separable wavelets, the spectrum of theses separable wavelets are unidirectional avoiding checkerboard artifacts in frequency plane. The six angular directions $\pm 15°$, $\pm 45°$ and $\pm 75°$ can be obtained by considering real and imaginary part of this complex wavelets. The Equations (6)–(11) gives six complex wavelets for these six directions where h and g indicates upper and lower tree filter coefficients respectively

$$\psi_1(x,y) = [\psi_h(x)\psi_h(y) - \psi_g(x)\psi_g(y)] + j[\psi_h(x)\psi_g(y) + \psi_g(x)\psi_h(y)] \tag{6}$$

$$\psi_2(x,y) = [\psi_h(x)\psi_h(y) + \psi_g(x)\psi_g(y)] + j[\psi_h(x)\psi_g(y) - \psi_g(x)\psi_h(y)] \tag{7}$$

$$\psi_3(x,y) = [\phi_h(x)\psi_h(y) - \phi_g(x)\psi_g(y)] + j[\phi_g(x)\psi_g(y) + \phi_h(x)\psi_h(y)] \tag{8}$$

$$\psi_4(x,y) = [\phi_h(x)\psi_h(y) + \phi_g(x)\psi_g(y)] + j[\phi_g(x)\psi_g(y) - \phi_h(x)\psi_h(y)] \tag{9}$$

$$\psi_5(x,y) = [\psi_h(x)\phi_h(y) - \psi_g(x)\phi_g(y)] + j[\psi_g(x)\phi_g(y) + \psi_h(x)\phi_h(y)] \tag{10}$$

$$\psi_6(x,y) = [\psi_h(x)\phi_h(y) + \psi_g(x)\phi_g(y)] + j[\psi_g(x)\phi_g(y) - \psi_h(x)\phi_h(y)] \tag{11}$$

3.2 Fast fourier transform

Fast Fourier Transform is a fast computation algorithm for Discrete Fourier Transform (DFT). DFT is used in signal processing applications like Linear Filtering, Correlation analysis and spectrum analysis that involves more computation time resulting in less efficient algorithms. In FFT, data sequence is decomposed into small sequences till we get single-point sequences. For $N = 2^{\upsilon}$, this decomposition can be performed $\upsilon = \log_2 N$ times. Thus, the total number of complex multiplications is reduced to $(N/2)\log_2 N$ against N^2 complex multiplication of direct computation of DFT. Similarly, the number of complex additions is reduced to $N \log_2 N$ compared to $N^2 - N$ complex additions of direct DFT computation. In the FRDF algorithm the two dimensional FFT is applied on $128 * 512$ face images and the resulting complex coefficient vector of size 65, 536 which forms the FFT features.

4. Proposed Model

In this section, the proposed FRDF model is discussed. The transform domain features are fused to generate final feature set in the Proposed Model to enhance the recognition rate. The block diagram of proposed FRDF is shown in Fig. 1.

4.1 Pre-processing

The face database such as ORL, JAFFE, L-Speck and CPU-PIE are used for the Performance analysis. The different face databases has different dimensions in the face, hence the images are resized into uniform size. Each image is resized to $2^m \times 2^n$ where m and n are integers. The face images are resized to $2^7 \times 2^9$ i.e., 128×512. DTCWT is applied to these resized images.

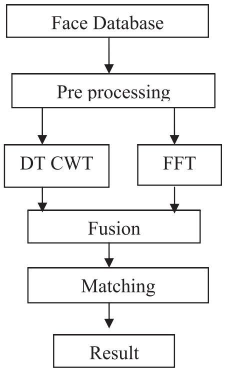

Fig. 1. Block diagram of proposed face recognition using fusion of DTCWT and FFT feature

4.2 Feature extraction by DTCWT

The Feature Extraction of 2D DTCWT consists of following three steps.

(i) An input image is decomposed using 2D DWT. In the proposed model 5 level DT-CWT is applied on face image, which provides sixteen sub bands at each level, 4 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 image size. i.e., after 5 levels the image size is reduced to 4×16.
(ii) In the second step, every two corresponding sub bands which have the same pass bands are linearly combined by averaging and differencing. As a result, the sub bands of 2D-CWT at each level are obtained as $(LH_a+LH_b)/\sqrt{2}$, $(LH_a - LH_b)/\sqrt{2}$, $(HL_a + HL_b)/\sqrt{2}$, $(HH_a - HH_b)/\sqrt{2}$, $(HH_a + HH_b)/\sqrt{2}$.
(iii) Magnitudes of real and imaginary bands are used as features for face recognition.

The 2D separable DWT on each decomposition produces three high frequency bands HL, HL and HH which gives a directional information along 0°, ±45°, and 90°. DTCWT implemented using 2D real wavelet transform produces six complex wavelets producing directional information along ±15°, ±45° and ±75° directions by taking real and imaginary part of each of these complex wavelets. The magnitude of real and imaginary part of a set of six complex wavelets are calculated using Equation (12) and Equation (13). Final magnitude coefficients are obtained by concatenating using Equation (14)

$$m_{ac} = \sqrt{m_a^2 + m_c^2} \tag{12}$$

$$m_{bd} = \sqrt{m_b^2 + m_d^2} \tag{13}$$

$$M = [m_{ac}; m_{bd}] \tag{14}$$

where m_a, m_b and m_c, m_d are corresponds DTCWT high frequency coefficient vectors of size 1×192 at 5-Level DTCWT. The Final feature vector M of size 1×384 is obtained by concatenating magnitude of m_{ac} and m_{bd}.

4.3 Final feature extraction

The two dimensional FFT is applied on Pre-processed face image of size 128×512 to generate FFT coefficients using Equation (15). The absolute FFT coefficient values are sorted in the descending order. The top dominant 384 coefficients are considered as FFT features. The DT-CWT features are fused with dominant FFT features using arithmetic addition to generate final features, for better recognition of a person. Final fusion futures are obtained using Equation (16). The 5-Level DTCWT and FFT is applied on test images to get test image features. The Features of test

Table 1. Algorithm for face recognition using Fusion of DTCWT and FFT features.

Input: Face images of ORL, L-Space k, JAFFE, CMP-PIE
Output: Face image identification
Step 1: The Face database is created.
Step 2: The face image is resized to 128×512
Step 3: The 5-Level DTCWT is applied to extract DT-CWT 384 coefficients.
Step 4: The FFT is applied on pre processed image to generate absolute coefficient values and converted into 1-dimestional column vector of size $65,536 \times 1$.
Step 5: The absolute coefficients are sorted in descending order and top 384 coefficients are considered as FFT features.
Step 6: The FFT and DT-CWT features are fused using arithmetic addition to generate final set of features.
Step 7: The features of test image are compared with features of database images using Euclidian distance to compare performance parameters

images are compared with features of database images using Euclidean distance to compute FRR, FAR, EER and TSR values. The Euclidean distance is given in the Equation (17)

$$F(u, v) = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} f(x, y) e^{-j2\Pi\left(\frac{ux}{N} + \frac{vy}{M}\right)} \tag{15}$$

where $F(u, v)$ and $f(x, y)$ represents FFT coefficients and input image

$$\text{Final Feature} = \sum_{i=1}^{384} (\text{DTCWT}_i + \text{FFT}_i) \tag{16}$$

DTCWT_i and FFT_i gives Dual Tree Complex wavelet and Fast Fourier Transform coefficients

$$d(p, q) = \sqrt{\sum_{i}^{n} (p_i - q_i)^2} \tag{17}$$

where

$$p_i = \text{the feature value of the database images.}$$
$$q_i = \text{the feature value of the test image.}$$

5. Algorithm

Problem Definition: Given face images to verify the authentication of a person using fusion of DTCWT and dominant FFT features. *The objectives are*: (i) To increase the Total Success Rate (TSR) (ii) To reduce the False Rejection Rate (FRR) (iii) To reduce the False Acceptance Rate (FAR). The Proposed algorithm for face recognition is given in Table 1.

6. Performance Analysis

In this section, the performance analysis of proposed algorithm is discussed. The face databases ORL, L-space K, and JAFFE and CMU-PIE are considered for performance analysis. The results are compared with the existing techniques.

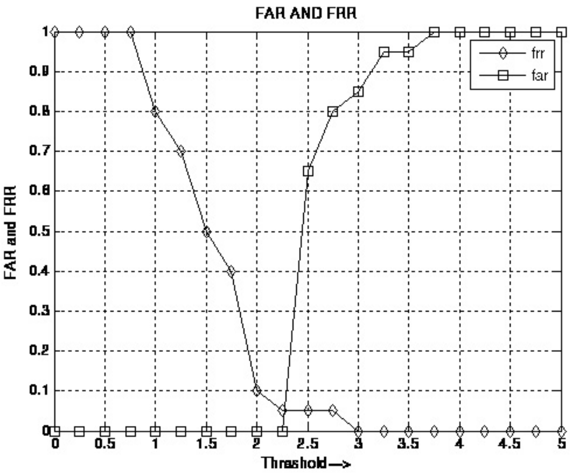

Fig. 2. Graph of FRR and FAR with threshold value for ORL.

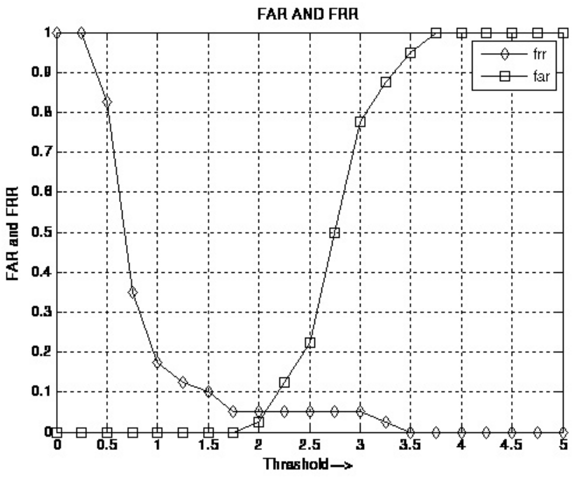

Fig. 3. Graph of FRR and FAR with threshold value for L-speck.

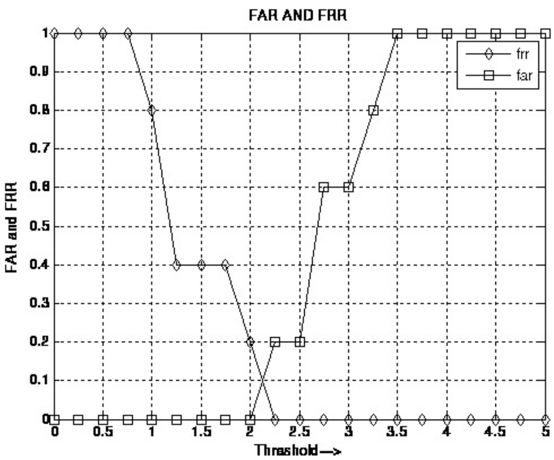

Fig. 4. Graph of FRR and FAR with threshold value for JAFFE.

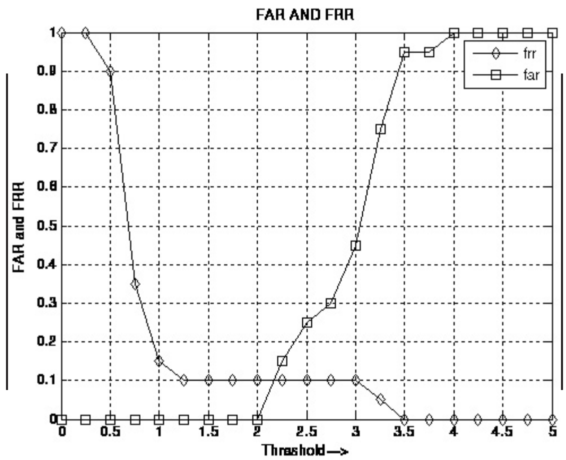

Fig. 5. Graph of FRR and FAR with threshold value for CMU-PIE.

6.1 Results of percentage variations of FAR, FRR and TSR for different face databases

FRR and FAR variations with threshold for ORL, L-SPECK, JAFEE and CMU-PIE database are plotted in Fig. 2 to Fig. 5. The FRR values decrease from maximum value to zero and FAR values increase from zero to maximum values as threshold is increasing from zero to maximum value. FRR and TSR decreases with increase in threshold whereas FAR increases with increase in threshold. Figure 2 shows variations of FAR and FRR for ORL database. The TSR for ORL database obtained at a threshold value of 2.25 is 95.3% and Equal Error Rate obtained at 2.25 threshold value is 4%.

Figure 3 shows Equal Error Rate of 5% and TSR of 90% obtained at 2.1 threshold value for L-speck database. Figure 4 shows Equal Error Rate of 10% and TSR of 80% obtained at a threshold value of a 2.5 for JAFEE database. Figure 5 shows for CMU PIE database Equal Error Rate of 10% and TSR of 90.25% is achieved at a threshold value of 2.1. The Recognition Rate of FRDF Algorithm for different database against threshold values is shown in Fig. 6.

From the graph it is observed that Recognition Rate linearly varies for all considered database within the threshold range of 0 to 2 and Recognition Rate reaches a saturation values of 95, 97.5, 80 and 90.25 for ORL, L-Speck,

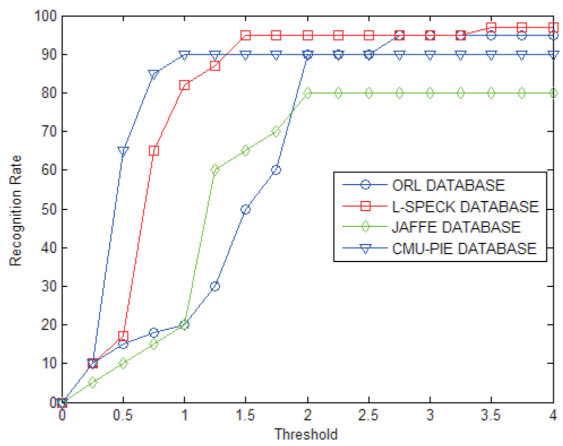

Fig. 6. Graph of recognition rate of FRDF algorithm.

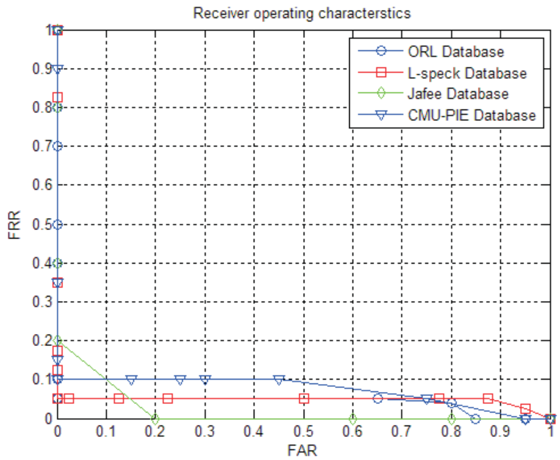

Fig. 7. Receiver operating characterstics of FRDF.

Table 2. Comparison recognition rate of FRDF with other algorithms for ORL database.

Sl. No.	Authors	Techniques	Recognition rate
01	GaoZhirong *et al.*,[10]	HL_LRC	93.5%
02	Li YueLong *et al.*,[11]	DSRC-LDA	88.0%
03	Jun Huang *et al.*,[12]	MPCA+LDA	92%
04	Proposed FRDF algorithm	DTCWT+FFT	95.3%

Table 3. Comparison recognition rate of FRDF algorithm for CMU-PIE database.

Sl. No.	Authors	Techniques	Recognition rate
01	Jian Zhang *et al.*,[13]	NOMR	82.31%
02	Proposed FRDF algorithm	DTCWT+FFT	90.25%

JAFEE and CMU-PIE database respectively within a threshold ranging from 2 to 4. The Receiver Operating Characteristics for different features of FRDF Algorithm is shown Fig. 7. The ROC consists of plot of FRR versus FAR against threshold. The ROC Characteristics helps in selecting a optimum threshold value which gives good Recognition Rate with less FAR and FRR values.

6.2 Comparison of recognition rate of proposed method with existing algorithms

The percentage recognition of FRDF algorithm is compared with existing algorithms presented by Gao *et al.*,[10] Li *et al.*,[11] and Huang *et al.*,[12] is given in Table 2 for ORL database. It is observed that the percentage recognition rate is high i.e., 95.3% compared to low value of existing algorithms[10–12] for the ORL database. The percentage recognition rate of FRDF is 90.25% compared to existing algorithm presented in Zhang *et al.*,[13] for CMU-PIE database. The FRDF algorithm performs better for the following reasons: (i) The feature extracted by DTCWT are shift invariant and capture directional variations (ii) The pose and illumination variations are converted into frequency domain using FFT and features are computed by considering absolute values of FFT coefficients. (iii) The features of DTCWT and FFT are fused using arithmetic addition to obtain final features to identify face images accurately. Table 2 gives Comparison of Recognition Rate of FRDF algorithm with other Existing Algorithms[10–12] for ORL Database. Table 3. gives the comparison of Recognition Rate of FRDF algorithm in comparison with Zhang *et al.*[13]

7. Conclusions

The physiological biometric trait face is used to identify a person effectively without cooperation from a person we have presented the FRDF algorithm for face recognition using fusion of DTCWT and FFT features. The face images are resized to 128×512 and a 5-level DTCWT is applied on face images to generate 384 DTCWT coefficients. The FFT is applied on face images to generate 65, 536 absolute FFT coefficients. The DTCWT coefficients are fused with dominant absolute FFT coefficients using arithmetic addition to generate final features. The test features are compared with database features using Euclidean distance for matching. It is observed that the performance parameters are better in case of proposed FRDF techniques in comparison with the state of the art techniques. Future work can be directed at improving the fusion techniques at matching level.

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