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# Hybrid Face recognition using Fusion of DTCWT and FDCT Features

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**ABSTRACT**

The growth of automation in our daily life needs prime requirement of security. Biometric recognition or identification is one of the most important system for security and surveillance related activities compared to conventional techniques like ID cards, Personal Identification Number (PIN) and password. The biometric system security can be increased by combining multiple feature extraction algorithms rather than considering single feature extractor. The proposed work incorporates multi scale resolution techniques for extracting facial image features. The system independently incorporates Dual tree complex wavelet transform (DTCWT) technique to extract one set of features coefficients and Fast Discrete Curvelet Transform (FDCT) via wrapping to extract another set of face image features. The extracted features from both the techniques are multiplied and normalized to obtain final features. In order to classify the test feature with trained set of features Euclidean distance (ED) classifier is used. The system performance is evaluated for different face databases like FERET, L-space k, NIR and JAFFE. The values of False Acceptance Rate (FAR), False Rejection Rate (FRR), Total Success Rate (TSR) and Equal Error Rate (EER) were measured and it is found that the proposed system yields better recognition rate with minimal Equal Error Rate when compared to existing techniques.

**Key words:** Face recognition, FDCT, DTCWT, Success rate, Recognition rate, Euclidean distance.

## 1. INTRODUCTION

As there is rapid growth in technologies like internet, cell phones and digital cameras, there requires increased demand on security since the communication between each users and between several organizations is rapidly increasing through the digital devices. Biometric [1] traits gains more importance because of its high recognition accuracy, resistant to spoofing attack, avoids inter class similarity, reduce intra class variations when compare to password or Personal Identification Number (PIN).Face recognitions has become one of the important biometric trait because of its vast range of applications like credit card, banking, security etc.

Many biometric authentication system like iris, fingerprint, vein and DNA fingerprint systems suffers the problem of data acquisition. For example, for iris recognition system the concerned person should capture his/her iris template by using a special expensive device called ophthalmoscope and in case of fingerprint the concerned person should keep his/her finger in proper position and orientation. But, the face recognition overcomes these problems since the face acquisition is non-intrusive and less expensive. Face recognition system has become very important because of its potential capability in solving other complex applications like object recognition. However, obtaining the high accuracy or the recognition rate for the face biometric trait is still a challenging, since there is wide range of variations in human face due to pose, illumination, view point, expression changes etc.

For a Face recognition system, the extracted features from a feature extractor should provide discriminant features that are not sensitive to environmental changes like scale, pose and expression variations [2]. The edges, textures and lines can be considered as features in an image. A given feature is characterized by scale, direction, position and other different parameters. A robust face representations and substantial features can be obtained irrespective of facial expressions, pose variations and illumination changes by using Multiscale algorithms as these algorithms makes low computational complexity. The most well-known methods are Wavelet [3], Curvelet [4] and Contourlet [5] transforms.

The proposed work consists of four steps (i) Capturing of input face image and its storage: The face images from different databases like L-space k, FERET, NIR and JAFFE are considered having certain degree of face orientation and the large variations in the illumination and also the facial expression. (ii)Image preprocessing: Face region is detected using Voila Jones [6] algorithm and the detected region is uniformly resized for a fixed size. Further, the color image is converted into gray scale image. (iii) Face feature extraction: Facial image features can be extracted from both spatial and transform domain. The proposed work uses extraction of features in transform domain. Further, it is also observed that, the performance of the system can be increased by combining both Dual tree complex wavelet transform (DTCWT) [7] and the Fast Discrete curvelet transform (FDCT) [8].Since DTCWT and FDCT both algorithm provides multi resolution and multi directional feature variations of coefficients of an image and combination of these algorithms provides increased system performance. (iv)Matching: The obtained feature vector for the test image are compared with trained set of features using Euclidean distance (ED) classifier.

## 2. LITERATURE REVIEW

Weihong Deng et al., [9] have implemented an algorithm for complete automatic face alignment, representation and recognition. This algorithm is named as Transform-Invariant Principal Component Analysis (TIPCA) in which the eigenface bases were captured automatically based on the intrinsic structure, as these are static with the in-plane transformation of the training images. This algorithm was tested on the FERET database and is found to be effective only for the frontal faces.

Said Elaiwat et al., [10] developed a face identification algorithm where the dimensionality reduction was achieved using PCA, further the 2D and 3D face robust features were extracted using the curvelet transform. This algorithm was tested on the FRGC v2 database for neutral and non-neutral face expressions by computing the recognition rate on 2D, 3D and fusion of 2D-3D face features. It was observed that the identification rate was better in the feature fusion.

S. Elaiwat et al., [11] presented the 3D face recognition technique where the distinctive features were extracted using curvelet transform. The performance was evaluated for illumination variation and facial expression by using the FRGC v2 dataset.

Marek Loderer et al., [12] have presented the significance of face parts for efficient recognition and to reduce data complexity. Here simulated annealing algorithm was applied on face image to optimize the selection of significant face components like eyebrow, cheeks, chin etc,.The features of the selected face components are extracted using LBP and Non Redundant Local Binary Patterns (NRLBP). The recognition rate of this technique was evaluated on the standard FERET and JAFFE databases.

P. Jahnavi et al.,[13] have introduced a method for detecting the facial expression for different emotions like happy, neutral, angry etc,. In this method softmax classifier was introduced in which face features and emotion features are combined using convolutional neural network. They have used the COHN-KANADE database to evaluate the accuracy.

Poonam Sharma et al., [14] have introduced the technique for recognizing the pose -invariant faces, in which the statistical coefficients of invariant features captured by applying the curvelet transform are fed into the curvelet neural network. The performance of this method was tested on the FERET, CMU-PIE and LFW databases.

Dr.A.Usha Ruby and Dr.J.George Chellin Chandran [15] proposed a descriptor for extraction of face features to test the performance of face recognition. In this technique Dominant Local tetra pattern is computed, which encodes the relationship between the referencedpixel and its neighbors, based on the nth order local derivatives in vertical and horizontaldirections.The effectiveness of the descriptor is measured using Yale B and ORL database. The descriptor efficiency was also analyzed by combining it with the Different of Gaussian.

Zongguang Lu et al., [16] have built an algorithm for face retrieval by fusing shape and texture information. In this method, face shape was captured using supervised descent method (SDM) and the texture information was extracted from the GoogleNet, these features were fused using PCA. It was tested on CASIA-WebFand, MSRA-CFW and LFW databases.

Pengcheng Wei et al., [17] have described the K-mean algorithm to extract face features. In this technique the face biometric features such as cheek, nose, mouth etc., are extracted and clustered by k-mean method. SVM was used to classify and identify the captured facial feature. The experiment was conducted on cas-Peal database to particularly for illumination, expression and scar, with the conclusion that expression has lot of influence on the recognition accuracy.

Ravi J and K B Raja [18] have presented the hybrid model for face recognition. In this model, face features are extracted by applying Dual-Tree Complex Wavelet Transform (DTCWT) to get the DTCWT co-efficient. This co-efficient matrix is sub divided into 3X3 sub-matrixes. Local binary pattern is performed on each of these sub divided matrix to get the final features. The performance is evaluated on L Spacek, NIR and JAFFE databases by measuring False Rejection Rate (FRR), False Acceptance Rate (FAR) and Total Success Rate (TSR) using ED for classification of features.

Alina L. Machidon et al., [19] have used the geometrical approximated PCA (gaPCA) to determine the eigenface rather than standard PCA to reduce the computation cost. Eigenfaces of the datasets Yale, Cambridge and LFW are computed by applying gaPCA on the face images. The performance of Yale and Cambridge dataset was evaluated using the inverse Euclidean Distance measure, whereas LFW dataset were compared using neural networks.

## 3. PROPOSED MODEL

The proposed work consists of two independent multi scale resolution techniques for extracting facial image features. The system incorporates DTCWT technique to extract one set of features coefficients and Fast Discrete Curvelet Transform (FDCT) via wrapping to extract another set of face image features in different angular orientations. The extracted features from both the techniques are multiplied and normalized to obtain final features. In order to classify the test feature with trained set of features Euclidean distance (ED) classifier is used. The block diagram of the proposed model is as shown in Figure. 1.

### 3.1 Training Face Database

#### 3.1.1 L-Space k Database

The L-space K database is considered for algorithm development because of its large variations in lightning, different orientations and expression. The database has 113 persons containing 20 face images for each person. The system is trained for first 63 persons out of 113 considering first 10 images per person for recognition. The recognition rate is calculated by testing the system with eleventh image of the 63 persons.

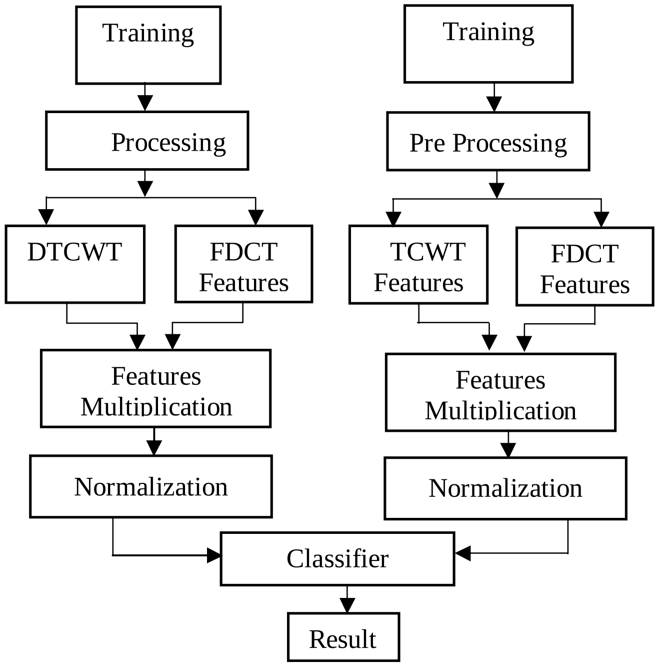


**Figure. 1** The block diagram of the proposed model

**3.1.2 Near Infrared Database (NIR)**

The NIR database is considered for testing the algorithm because of its variations in intensity, illumination change and blurring effect, different pose and facial expressions. The database has total 115 persons with 14 images for each person. The training data has been organized for first 20 persons from total 115 persons by considering first 6 images for each person. The recognition rate is calculated by testing the system with seventh image of the same 20 persons.

**3.1.3 JAFFE Database**

JAFFE Database is considered because of its identical/similar face images of all the persons. The database has 10 persons containing 22 images per person making 220 images. The system is trained for initial 6 people out of 10 people and considering first 10 images of each person for recognition and to calculate the recognition rate.

**3.1.4 FERET Database**

FERET Database is used because of its larger size and contains face images having pose and light variations. The database contains a total of 200 persons having seven images per person. We use the first four image from each individual as training set. Hence the total images in the training set is 800. The remaining sixth image from each individual we used for testing. So the size of test images is 200.

**3.2 Preprocessing**

The proposed work adopts Viola Jones algorithm to detect the face from the complex background. This method uses Haar like features to extract features of both face and non-face regions. Haar features are small kernels having different shapes and scales which are used to detect the presence of the feature in the given image. Any redundancies of the obtained features were eliminated using Adaboost learning algorithm. Adaboost is machine learning algorithm which identifies best among all the features, but these features are called weak classifier, and to construct strong classifier by linearly combining weak classifier. Finally the cascade classifier contains strong classifier at different stages are used to detect the face in the given image. The Region of Interest (Face) is obtained by cropping and resized to 100x100 for all database.

**3.3 Facial image Feature Extraction**

**3.3.1 Dual Tree Complex Wavelet Transform**

A parallel development of two classical wavelet trees (approximately Hilbert pairs) having real filters are formed. The Complex wavelet $\Psi c(t)$ has two parts namely real and imaginary and the wavelets can be interpreted as the two trees of the DTCWT. The real part of the transform is generated from the first tree and the imaginary part of the transform is generated from the second tree. The low pass ($h_0$), high pass ($h_1$) are from real part and the low pass ($g_0$), high pass ($g_1$) are from imaginary part.

The DTCWT has the potential to distinguish negative and positive frequencies and creates six sub bands oriented in six directions ±15, ±45 and ±75 which is shown in Figure.2.However, these direction are fixed unlike the Curvelet case, where the wavelets can be oriented in many directions.
The impulse response of the DTCWT is shown in Figure. 3.It is shown that the transform has 6 orientation with 2 scales. Figure. 4 reveals that the DTCWT transformation applied for two sample images. The two level DTCWT is performed for the input image of size 100 × 100. At each level the dimension of the image is minimized to half of the original dimension. At the initial level, the image size is reduced to 50 × 50 and in the second level it is reduced to 25 × 25 respective

**3.3.2 Curvelet Transform by Wrapping**

Fast Discrete Curvelet Transform (FDCT) technique is used to extract the facial features from the preprocessed image in transform domain. The Curvelets via wrapping technique has been used in the proposed work as this technique is simple, faster and less redundant than first generation curvelet transform. The curvelet via wrapping technique is applied on resized images to obtain the coefficients at each wedge. The curvelet coefficients obtained at each wedge is a function of two windows namely radial window $W$ and the angular window $V$.
The Cartesian window $\widetilde{U}_{j,l}$ isolates frequencies near the wedges $(\omega_1, \omega_2)$ is given by

$$\widetilde{U}_{j,l} = W_j(\omega)V_j(\omega), \qquad (1)$$

Where

$$W_j(\omega) = \sqrt{\varphi_{j+1}^2(\omega) - \varphi_j^2(\omega)},\ j \geq 0, \qquad (2)$$

$$\varphi_j(\omega_1, \omega_2) = \phi(2^{-j}\omega_1)\,\phi(2^{-j}\omega_2),\ 0 \leq \phi \leq 1.$$

$$V_j(\omega) = V(2^{j/2}\omega_1/\omega_2) \qquad (3).$$

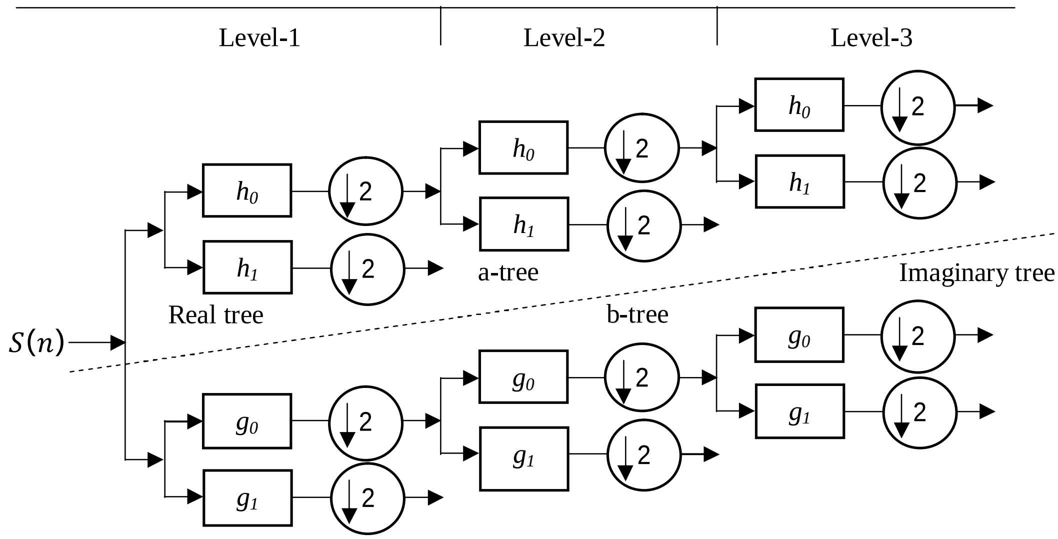


**Figure. 2:** DTCWT Filter Bank

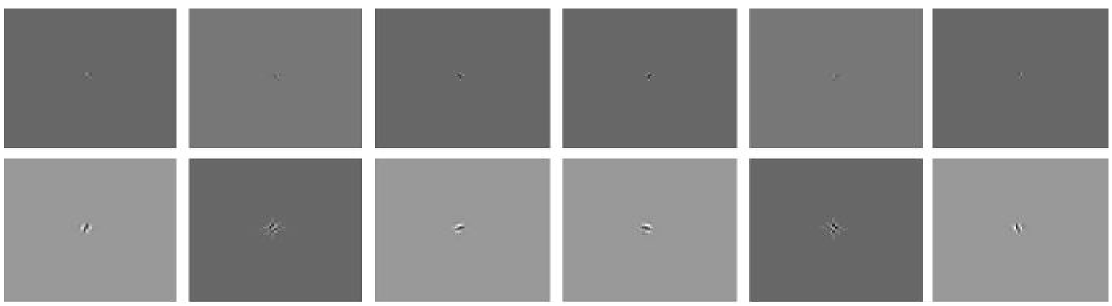

**Figure. 3 :** The Real part of Impulse response of DTCWT at 2 levels and 6 direction

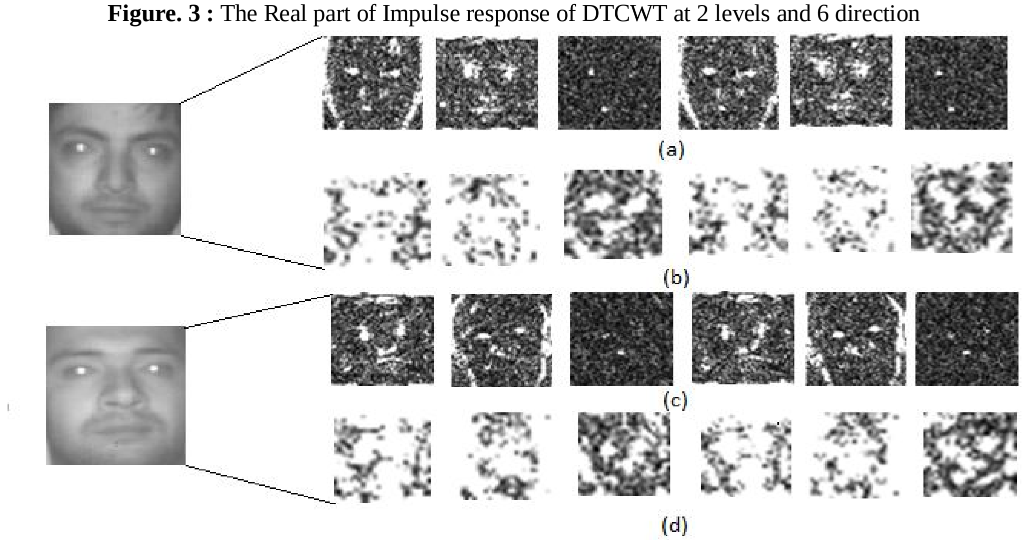


**Figure. 4 :**DTCWT transformation for two sample images (a) and (c) Magnitude of the transformation for the image for Level 1. (b) and (d) Magnitude of the transformation for the image for Level 2

Curvelet via wrapping technique algorithm is developed by considering $f(t_1, t_2)$as an input Cartesian array and $\hat{f}(n_1, n_2)$as a 2D Discrete Fourier Transform as follows:
1. 2D Fast Fourier Transform (FFT) is applied for input Cartesian array $f(t_1, t_2)$ to obtain $f(n_1, n_2)$.

2. For each angle $l$ and scale$j$, the product $\widetilde{U}_{j,l}(n_1, n_2) * \hat{f}(n_1, n_2)$ is calculated, where $\widetilde{U}_{j,l}(n_1, n_2)$ is discrete localizing Cartesian window.

3. This product is wrapped around origin to obtain $\hat{f}_{j,l}(n_1, n_2) = W(\tilde{U}_{j,l}\hat{f})(n_1, n_2)$, where $0 \leq n_1 < L_{1,j}$ and $0 \leq n_2 < L_{2,j}$ and $L_{1,j} \sim 2^j$ and $L_{2,j} \sim 2^{j/2}$

4. Perform 2D inverse FFT to each $\hat{f}_{j,l}$, to obtain the discrete curvelet coefficients.

The input face image of size 100 x 100 with different intensity maps are considered. The different intensity images are thus obtained by quantizing the image pixels with quantization parameter like 1, 16 and 64. Then curvelet is applied for each quantized image for different scales till scale = 5. This results in 5 (scales) x 3 (quantized images) = 15 (feature vectors) and the obtained feature vector is considered as secondary feature vector for matching. Figure.5 shows the curvelet via wrapping technique for L-space k face image with scale = 5.

### 3.4 Classification

The features of DTCWT and features of FDCT are combined by means of multiplication and normalizing to obtain the final feature set for matching. In the proposed work Euclidean Distance (ED) classifier is applied to match test features.

*Euclidean Distance (ED)*

Euclidean Distance (ED), is used since its simple and effective. The Euclidean Distance $d$ for the pair of feature vectors is given by

$$d = \sqrt{\sum_{i=1}^{N}(p_i - q)^2} \qquad (4)$$

$p_i$ Feature vector from the Database images

$q$ Feature vector from the Test Image

$N$ Total Images in the Database

**Algorithm**

*Input: Image of Face.*

*Output: Recognized Face of Person.*

*Step 1: Face image has been selected from the database for reading.*

*Step 2: Face region is detected from the input image using Viola Jones Algorithm.*

*Step 3: The detected face image is cropped and resized to 100 × 100 dimensions*

*Step 4: Dual-Tree Complex Wavelet Transform (DTCWT) is performed over the face image obtained from step 3 to extract one set of transform domain features coefficients.*

*Step 5: Curvelet via wrapping is applied on the face image obtained from step 3 to extract another set transform domain feature coefficients.*

*Step 6: The two set of features extracted from DTWCT and FDCT are multiplied and normalized to constitute the final feature vector.*

*Step 7: Repeat the above procedure for all test images from step 1 to 6*

*Step 8: Comparison of features obtained for the Test image with features obtained for the Database images using Euclidean Distance classifier is performed for matching.*

## 4. RESULTS AND DISCUSSION

The proposed face recognition system has been evaluated on different databases such as L-Space k, NIR, JAFFE and FERET. In this proposed work, the Recognition rate, FAR, FRR and TSR are considered as assessment parameters to evaluate the performance.

From the Table 1, it is found that by varying the threshold values from 0.05 to 1, the FRR has been decreased from 100% to 0% with increase in total success rate to 100%. Furthermore, FAR increases with increase in threshold value.

The FAR and FRR as a function of threshold values is shown in the Figure. 6 for the data base L space k. It is found from the figure that FAR is very minimal with a value of 7.67% and FRR is 4.651%. Further, the equal error rate is 5.994% at a threshold value of 0.542. Hence, the threshold value 0.542 is considered as optimum value

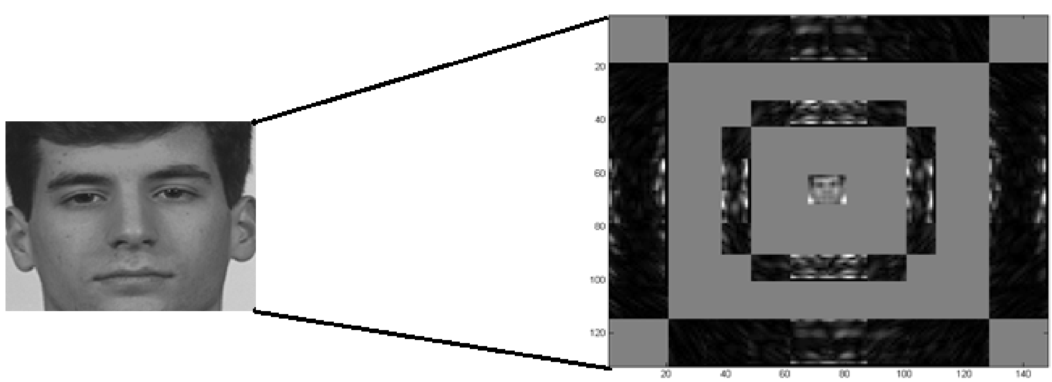


**Figure. 5** Curvelet via wrapping technique for face image with scale = 5

**Table 1:** FAR, FRR and TSR Values with change in Threshold for L space-k Database

| FRR | FAR | Threshold |
|---|---|---|
| 100 | 0 | 0.05 |
| 100 | 0 | 0.10 |
| 100 | 0 | 0.15 |
| 95.35 | 0 | 0.20 |
| 73.26 | 0 | 0.25 |
| 53.49 | 0 | 0.30 |
| 40.70 | 0 | 0.35 |
| 26.74 | 0 | 0.40 |
| 18.60 | 0 | 0.45 |
| 10.47 | 0.41 | 0.50 |
| 4.65 | 7.67 | 0.55 |
| 2.33 | 24.11 | 0.60 |
| 0 | 50 | 0.65 |
| 0 | 64.70 | 0.70 |
| 0 | 85.29 | 0.75 |
| 0 | 92.64 | 0.80 |
| 0 | 95.58 | 0.85 |
| 0 | 100 | 0.90 |
| 0 | 100 | 0.95 |
| 0 | 100 | 1 |

**Table 2:** FAR, FRR and TSR Values with change in Threshold for JAFFE Database

| FRR | FAR | Threshold |
|---|---|---|
| 100 | 0 | 0.05 |
| 100 | 0 | 0.10 |
| 100 | 0 | 0.15 |
| 100 | 0 | 0.20 |
| 100 | 0 | 0.25 |
| 100 | 0 | 0.30 |
| 83.33 | 0 | 0.35 |
| 75 | 0 | 0.40 |
| 66.66 | 0.56 | 0.45 |
| 58.33 | 2.66 | 0.50 |
| 41.66 | 8.50 | 0.55 |
| 33.33 | 10.5 | 0.60 |
| 30.33 | 16 | 0.65 |
| 22 | 20 | 0.70 |
| 8.33 | 38 | 0.75 |
| 0 | 50 | 0.80 |
| 0 | 62.5 | 0.85 |
| 0 | 75 | 0.90 |
| 0 | 87.5 | 0.95 |
| 0 | 100 | 1 |

It has been observed from the Table 2 that the value of FRR decreases from 100% to zero whereas TSR increases to 100%. Further, it is observed that FAR tends to zero till the threshold value was up to 0.45 and later it increases with increase in threshold values. The variation of FRR and FAR as a function of different threshold values is shown in the Figure. 7. It is found from the figure that EER for JAFFE database is 21.135% for a threshold value of 0.72.

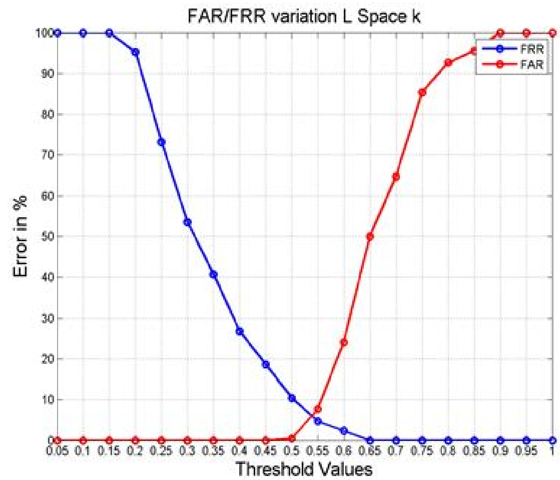


**Figure. 6:** FAR and FRR values with respect to threshold values for the database L space k

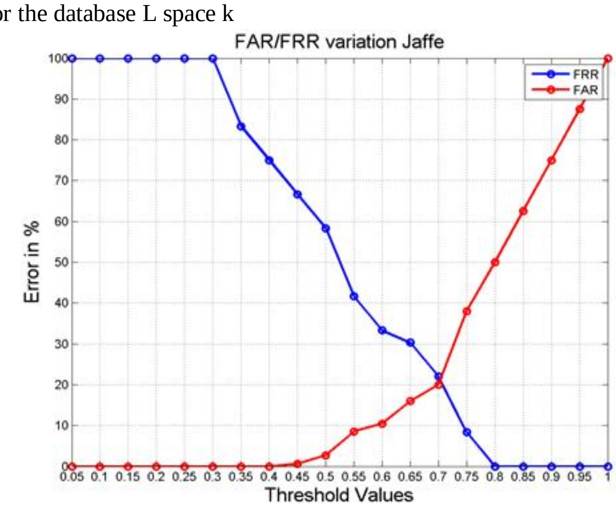


**Figure. 7:** FAR and FRR values with respect to threshold values for the JAFFE database

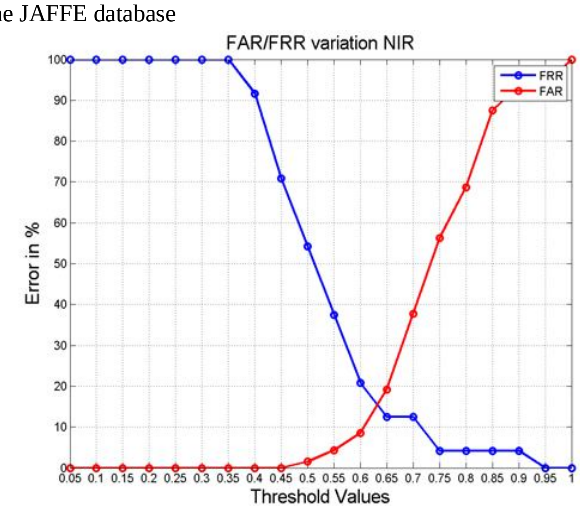


**Figure 8:** FAR and FRR values with respect to threshold values for the database NIR

**Table 3**. FAR, FRR and TSR Values with change in Threshold for NIR Database

| FRR | FAR | Threshold |
|---|---|---|
| 100 | 0 | 0.05 |
| 100 | 0 | 0.10 |
| 100 | 0 | 0.15 |
| 100 | 0 | 0.20 |
| 100 | 0 | 0.25 |
| 100 | 0 | 0.30 |
| 100 | 0 | 0.35 |
| 91.66 | 0 | 0.40 |
| 70.83 | 0 | 0.45 |
| 54.16 | 1.54 | 0.50 |
| 37.50 | 4.34 | 0.55 |
| 20.83 | 8.56 | 0.60 |
| 12.50 | 19.23 | 0.65 |
| 12.50 | 37.75 | 0.70 |
| 4.17 | 56.25 | 0.75 |
| 4.17 | 68.75 | 0.80 |
| 4.17 | 87.50 | 0.85 |
| 4.17 | 93.75 | 0.90 |
| 0 | 93.75 | 0.95 |
| 0 | 100 | 1 |

**Table 4: .**FAR, FRR and TSR Values with change in Threshold for FERET Database

| FRR | FAR | Threshold |
|---|---|---|
| 100 | 0 | 0.05 |
| 100 | 0 | 0.10 |
| 100 | 0 | 0.15 |
| 100 | 0 | 0.20 |
| 98.12 | 0 | 0.25 |
| 92.50 | 0 | 0.30 |
| 85.62 | 0 | 0.35 |
| 60.62 | 0 | 0.40 |
| 48.12 | 0 | 0.45 |
| 33.75 | 2.15 | 0.50 |
| 9.750 | 3.52 | 0.55 |
| 0.875 | 9.27 | 0.60 |
| 0 | 24.4 | 0.65 |
| 0 | 48.92 | 0.70 |
| 0 | 58.60 | 0.75 |
| 0 | 72.58 | 0.80 |
| 0 | 88.70 | 0.85 |
| 0 | 98.38 | 0.90 |
| 0 | 100 | 0.95 |
| 0 | 100 | 1 |

The variation of FAR, FRR and TSR for varying threshold values have been tabulated in the Table 3. The TSR and FAR values are zero and FRR is 100% up to a value of 0.35. After the threshold value of 0.35, the TSR has been increased to 100% with decrease in FRR to 0%. Further, FAR increases to 100% for a threshold value of 1

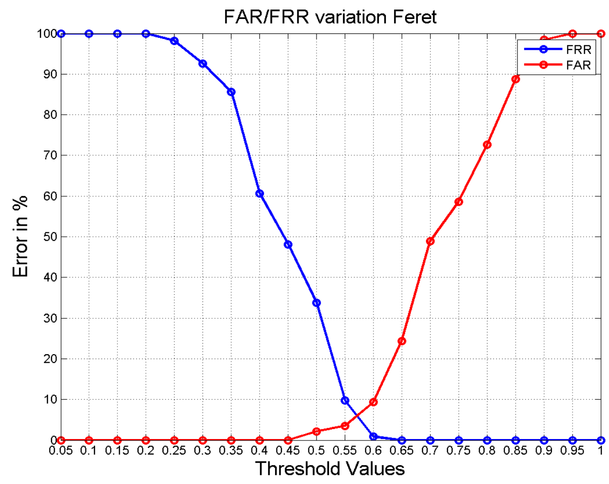


**Figure. 9** FAR and FRR values with respect to threshold values for the database FERET

**Table 5.** Comparison of Recognition rates (%) with previous studies for different database images

| **Methods** | **Recognition rate in %** |
|---|---|
| *FERET Database*[20] | 87.25 |
| *FERET Database*[21] | 72.3 |
| *FERET Database*[22] | 94.18 |
| *NIR Database*[23] | 60 |
| *FERET Database*[Proposed] | 96.01 |
| *NIR Database*[Proposed] | 84.5 |

The variation of FRR and FAR as a function of varying threshold values is depicted in the Figure. 8. The ERR is 15.5% at a threshold value of 0.64.

The variation of FAR, FRR and TSR for different values of the threshold have been tabulated in the Table 4. The TSR and FAR values are zero and FRR is 100% up to a value of 0.2. After the threshold value of 0.2, the TSR has been increased to 100% with decrease in FRR to 0%. Further, FAR increases to 100% for a threshold value of 1. The variation of FRR and FAR as a function of varying threshold values is depicted in the Figure. 9. The ERR is 4% at a threshold value of 0.58.

In the proposed method we got the percentage recognition rate as 96.01 for the FERET database as compared to the existing techniques presented by Meng Pang et al.,[20], Zhijie Tang et al., [21] and Yuqi Pan and Mingyan Jiang [22] as listed in Table 5. Further, for the NIR database the proposed method achieves the percentage recognition rate as 84.5 when compared to the existing method developed by Faten Omri et al.[23], who got the recognition rate as 60 percent.

## 5.CONCLUSION

In this work, Face recognition using the combination of DTCWT and FDCT features in different angular orientations and Euclidean Distance classifier has been proposed effectively for different databases. Here the face region of an image is obtained using Viola and Jones algorithm and resized to uniform dimensions of 100 ×100. The parameters such as FRR, FAR and TSR were measured for different databases by varying the threshold values. It is found that the EER for FERET database is 4% and L space k database is 5.994% whereas the EER for JAFFE and NIR database is little higher and having values 21.135% and 15.5% respectively due to similarity in face variations and lower contrast when compared to the databases mentioned prior.

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