Chapter 3

Iris Recognition based on Spatial and Transform Domain Features

3.1 Introduction

In this chapter, the spatial and transform domain techniques for iris recognition are discussed. The iris is considered as one of the most reliable biometric traits. Its reliability is due to the high degree of entropy per unit area as well as the stability of the iris texture patterns with age and health conditions. The iris texture is unique to an individual and it is impossible to modify without the risk to vision. Iris is an internal organ, which is isolated and protected from the external environment. The identification of an individual using iris biometric trait compared to other biometric traits is more efficient, since iris pattern is unique among all biometric traits. Hence iris is the potential biometric trait.

The Iris Recognition using Directional Filter Bank (IRDFB) in spatial domain is used to authenticate an individual effectively. The eye images of CASIA Iris database V1.0 are localized to extract iris portion from an eye image using canny edge detection and circular Hough transform. The iris portion is normalized using Daugman’s rubber sheet model [37] to convert circular iris portion into rectangular shape. The normalized iris of size 128*512 is fragmented into two equal parts of size 64*512. The iris region nearer to pupil is divided into sixty four subblocks and Directional Filter Bank (DFB) is
used to extract features from each subblock. The iris region nearer to sclera is divided into only thirty two subblocks, since it has less information and DFB is used to extract features from this region. The final feature vector is generated by concatenating region 1 and region 2 features. The final feature vector of test eye is compared with final feature vectors of eye images in the database using HD to find decidability index.

In case of Iris Recognition using Discrete Wavelet Transform and Integer Wavelet Transform (IRDIWT) for personal identification, an iris and pupil boundaries of an eye are identified by integro-differential operator. The circular iris is normalized by using Daugman’s rubber sheet model. The features of the normalized iris are extracted using IWT and DWT. The HD is used for matching of two iris feature vectors.

3.2 Iris Recognition using spatial domain technique

In this section, the block diagram of IRDFB shown in Figure 3.1 is discussed in detail.

The iris portions from the eye images are obtained by using localization and normalization techniques. The iris features are extracted using DFB from the fragmented iris regions. The HD is used for the identification of a person based on iris features.
3.2.1 Iris database

The eye image acquired by any image acquisition device includes pupil, iris, sclera, eyelids, eye lashes and other occlusions. The size of iris varies depending on camera to eye distance and lighting conditions. Iris samples from CASIA database version 1.0 are used for performance analysis. CASIA Iris Image database version 1.0 includes 756 iris images from 108 persons. For each person, seven images are captured in two sessions with the CASIA close-up Iris camera, where three samples are collected in the first session and four in the second session [105, 106]. All images of size 320*280 are stored in BMP format. The samples of CASIA Iris database version 1.0 for single person are as shown in Figure 3.2.
The database for the proposed model is created by considering first fifty persons iris images from one hundred and eight persons. The database consists of first six samples per person of fifty person’s that is totally three hundred samples. The seventh sample of every person is considered as test eye image to compute Mean $\mu_G$ Standard Deviation $\sigma_G$ of Intra-class. One sample per person from the remaining fifty eight persons is considered as out of database to compute Mean $\mu_I$ and Standard Deviation $\sigma_I$ of Inter-class. The performance parameter decidability index $d$ is computed using mean and standard deviation of Intra and Inter classes.

### 3.2.2 Iris localization

The circular iris portion between pupil and sclera is detected using localization. The eye image along with iris contains occlusions like eyelashes, eyelids and Pupil. The edge detection technique is applied on eye image to convert grey scale image into binary edged image using canny edge detection technique. The portion of an eye image within the sclera is cropped to obtain iris and pupil. The
circular Hough transform is applied on the cropped image to detect two circles of iris/sclera (outer) and iris/pupil (inner). The iris region between inner and outer circles is considered by omitting pupil and sclera. The localized iris region is shown in Figure 3.3.

![Figure 3.3: Localized iris region](image)

### 3.2.3 Normalization

The localized iris region in the Cartesian form is converted into polar form [9, 37] to obtain rectangular representation of iris. The homogenous rubber sheet model linearly maps the iris texture in the radial direction form pupil boundary to limbus boundary to a pair of dimensionless real coordinates \((r, \theta)\) where \(r\) lies on the unit interval \([0,1]\) and \(\theta\) is the angular quantity over the cyclic interval \([0,2\pi]\). The mapping of the iris image \(I(x, y)\) from Cartesian coordinates \((x, y)\) to the dimensionless non concentric polar coordinates system \((r, \theta)\) is represented by the Equation 3.1.

\[
I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta) \quad \text{----------------} \quad (3.1)
\]

where \(x(r, \theta)\) and \(y(r, \theta)\) given by the Equations 3.2 and 3.3 are defined as linear combinations of pupillary boundary coordinates \((x_p(\theta), y_p(\theta))\) and the limbic boundary coordinates \((x_s(\theta), y_s(\theta))\) along
the $\theta$ direction. The normalized iris obtained is of size 128*512 and is as shown in Figure 3.4.

\[
x(r, \theta) = (1-r)x_p(\theta) + rx_s(\theta)
\]

\[
y(r, \theta) = (1-r)y_p(\theta) + ry_s(\theta)
\]

where

\[
x_p(\theta) = x_{p0}(\theta) + r_p \cos(\theta)
\]

\[
y_p(\theta) = y_{p0}(\theta) + r_p \sin(\theta)
\]

\[
x_s(\theta) = x_{s0}(\theta) + r_s \cos(\theta)
\]

\[
y_s(\theta) = y_{s0}(\theta) + r_s \sin(\theta)
\]

where $r_p$ and $r_s$ are respectively the radius of pupillary and limbic boundaries, $(x_{p0}, y_{p0})$ and $(x_{s0}, y_{s0})$ are the coordinates of pupillary and limbic centers.

![Normalized iris of size 128*512](image)

**Figure 3.4: Normalized iris of size 128*512**

### 3.2.4 Fragmentation

The information in iris patterns is dispersed randomly and non-uniformly. Pereira and Veiga [41] proved that reliability of iris recognition system can be improved by considering the portion an iris, which has majority of the information and hence the decidability index can be improved. By a visual survey of iris samples from CASIA
iris database version 1.0, it is noticed that more variations are concentrated around pupil region. The iris portion near the sclera boundary has less texture variation and often occluded by eyelashes and eyelids.

The normalized iris image of size 128*512 is fragmented into two regions of size 64*512 each as shown in Figure 3.5. The iris region nearer to pupil is fragmented into eight major blocks of size 32*128. Each block of size 32*128 is again fragmented into eight minor blocks of size 16*32, since region 1 has significant information. Therefore region 1 has sixty four blocks. The region 2 of size 64*128 is fragmented into eight major blocks of size 32*128. Each block is again fragmented into only four minor blocks of size 16*64, since region 2 nearer to sclera has less information. The region 2 has 32 blocks.

(a) Region 1

(b) Region 2

Figure 3.5: Normalized iris fragmented into two regions of size 64*512
3.2.5 Feature extraction

The features are extracted using DFB, which is a directionally oriented 2-D filter bank with the property that the individual channels may be critically sampled without loss of information. This filter bank decomposes images into directional components, which can be maximally decimated while still allowing the original image to be exactly reconstructed from its decimated channels. DFB is implemented in a tree-structure composed of two-band systems [50]. The most basic directional decomposition is a two-band split which divides a signal into the two hour glass shaped spectral regions. To maximally decimate the output of the hour glass shaped filters, it is desirable to modulate the signal by \( \pi \) radians in frequency variable.

The subblocks of region 1 and 2 have rich directional information. A three level DFB is used to extract directional information features from each subblock of region 1 and 2. The directional energy \( E_{mn} \) of each subblock is computed using Equation 3.8.

\[
E_{mn} = \sum_{x,y \in S_{mn}} |I_{mn}(x,y) - I_{mn}| \quad \text{(3.8)}
\]

where \( I_{mn} \) is the mean of pixel values of \( I_{mn}(x,y) \) in the subblock \( S_{mn} \),

\( m \) is major block of region 1 and 2 and \( m = 8 \) for both regions

\( n \) is the minor subblock of region and \( n = 8 \) for region 1 and 4 for region 2.

The normalized directional energy for region 1 and 2 are computed using Equations 3.9 and 3.10 respectively.
The feature vector $F_{mn}$ from both the regions is generated by using the Equation 3.11.

$$F_{mn} = \begin{cases} F_{\text{max}} \times M_{mn}, & M_{mn} \geq T_{\text{energy}} \\ 0, & \text{otherwise} \end{cases} \quad (3.11)$$

where $F_{\text{max}}$ is positive normalization constant and is set to 255, $T_{\text{energy}}$ is the threshold energy value between 0 and 1 and is set to 0.13, arbitrarily. The normalized directional energy values with dominant intensity are scaled and quantized to an integer between $F_{\text{max}} \times T_{\text{energy}}$ and $F_{\text{max}}$ and the other values with low intensity are set to 0. Thus the outcome of the feature extraction is binary in nature. The energy threshold of 0.13 implies that directional components with energy ratio of less than 13% in each block are discarded as noise. The region 1 is fragmented to obtain sixty four feature elements and region 2 to obtain thirty two feature elements. Thus totally 96 features are obtained.

**3.2.6 Matching**

Feature vectors of two iris samples, which may belong to the same iris or of different, are obtained using the proposed feature extraction process. The similarity between these two vectors is measured using Weighted Hamming Distance ($HD_w$) and it is defined

$$M_{mn} = \frac{E_{mn}}{\sum_{l}^{8} \sum_{m=1}^{8} E_{mn}} \quad (3.9)$$

$$M_{mn} = \frac{E_{mn}}{\sum_{l}^{8} \sum_{m=1}^{4} E_{mn}} \quad (3.10)$$
as given by Equation 3.12. The HD is used for classification because the output of the previous stage is binary. The HD metric is better compared to ED for binary comparison. The binary features make the processing fast and simple.

\[
HD_W = \frac{1}{N} \sum_{j=1}^{N} X_j \oplus Y_j \quad \text{-------- (3.12)}
\]

where \(X_j\) is the \(j^{th}\) component of the template feature vector, \(Y_j\) is the \(j^{th}\) component of the input feature vector and \(N\) is dimension of the input feature vector. A lower value of \(HD_W (\equiv 0)\) indicates that both the vectors are from same iris. In contrary, a larger value shows that they are from different irises.

### 3.2.7 Proposed IRDFB Algorithm

**Problem Definition**

Consider an eye image of a subject whose identity has to be verified. The objectives are to:

(i) *Localize the iris, transform the circular iris into rectangular representation and fragment the iris into two parts to extract features to verify the authenticity of the person*

(ii) *Obtain better decidability index*

The Iris Recognition using DFB algorithm is given in Table 3.1. The circular portion of the iris is obtained by using circular Hough transform and converted into rectangular rubber sheet model. The rectangular iris is fragmented into two regions to extract features. The features are matched using HD.
Table 3.1: Algorithm of IRDFB

- **Input**: Iris database and test image.
- **Output**: Match/ Mismatch of the test iris

1. Iris region is localized using canny edge detection
   
   *(i)* Circular Hough transform to find iris/sclera and iris/pupil boundary
   
   *(ii)* Linear Hough transform to detect eyelid boundaries

2. Localized iris is remapped into a rectangular grid of size 128*512 using Daugman’s rubber sheet model

3. The rectangular iris is fragmented into two regions:
   
   Region1 of size 64*512
   
   Region2 of size 64*512

4. DFB is applied on region 1 to get 64 blocks and region 2 to get 32 blocks

5. Energy values of all blocks are computed and stored as feature vector

6. The features of test iris are compared with database iris using HD to authenticate the person

### 3.2.8 Performance Analysis

Iris samples from CASIA Iris database version 1.0 are used for performance analysis of the proposed IRDFB model. The directional components with low energy are considered as noise and only
dominant energy values are used as iris features. The recognition performance is measured by decidability index \( d \). It reflects the separability between the intra-class and the inter-class. The larger value of decidability index \( d \) indicates better performance [109]. The decidability index \( d \) [107] is defined by the Equation 3.13.

\[
d = \frac{|\mu_G - \mu_I|}{\sqrt{((\sigma_G^2 + \sigma_I^2) / 2)}}
\]

where \( \mu_G \) - Mean of HD for intra-class

\( \mu_I \) - Mean of HD for inter-class

\( \sigma_G \) - Standard deviations of HD for intra-class

\( \sigma_I \) - Standard deviations of HD for inter-class

For an iris recognition system to be efficient the mean of HDs of irises belonging to same person (intra-class) must be small and the mean of HDs of irises belonging to different persons (inter-class) must be large. Therefore higher decidability index is desired for efficient algorithm.

The mean, standard deviation and decidability index of the IRDFB system for genuine and imposter irises are given Table 3.2. It is observed that the mean and standard deviation values for the genuine iris are less compared to imposter iris.
Table 3.2: Mean and Standard deviation of genuine and imposter distributions

<table>
<thead>
<tr>
<th></th>
<th>Genuine</th>
<th>Imposter</th>
<th>Decidability Index $d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>0.4008</td>
<td>0.4543</td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.0144</td>
<td>0.0233</td>
<td></td>
</tr>
</tbody>
</table>

The comparison of decidability indices of the proposed method with existing methods are given in Table 3.3. The decidability index is high in the case of proposed method compared to existing methods presented by Pereira and Veiga [41], Gil and Hoyle [108] and Peihua Li et al., [109]. The performance of the proposed algorithm is improved for the reasons: (i) the rubber sheet model of iris is fragmented into two regions of size $64^*512$, (ii) the iris region nearer to pupil consisting more information is fragmented into sixty four subblocks to generate sixty four features using DFB. (iii) the region 2 of iris, which is nearer to sclera is fragmented into only thirty two subblocks and features are obtained from each subblock using DFB, since region 2 has less significant information.
<table>
<thead>
<tr>
<th>Method</th>
<th>Preprocessing</th>
<th>Feature extraction technique</th>
<th>Decidability index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pereira and Veiga [41]</td>
<td>Integro Differential Operator</td>
<td>Fragmentation of circular iris, extraction of pixel intensity</td>
<td>1.77</td>
</tr>
<tr>
<td>Gil and Hoyle [108]</td>
<td>Hough transform, Histogram equalization, Canny edge detection, Daugman’s rubber sheet model</td>
<td>LBP, 2-D Dyadic wavelet</td>
<td>1.74</td>
</tr>
<tr>
<td>Peihua et. Al., [109]</td>
<td>Canny edge detection, Hough transform, Daugman’s rubber sheet model</td>
<td>Weighted Co-occurrence Phase Histogram</td>
<td>1.57</td>
</tr>
<tr>
<td>Proposed IRDFB method</td>
<td>Canny edge detection, Hough transform, Daugman’s rubber sheet, fragmentation</td>
<td>Directional Filter Bank</td>
<td>2.763</td>
</tr>
</tbody>
</table>

3.3 Iris Recognition using transform domain technique

In this section, block diagram of Iris Recognition using DWT and IWT (IRDIWT) shown in Figure 3.6 is discussed in detail.

The iris portions of the eye image are obtained by localization, normalization and image enhancement. The DWT and IWT are used
to extract the features from the normalized iris image. Matching between the test iris and the database iris is done using HD.

![Block diagram of IRDIWT system](image)

**Figure 3.6: Block diagram of IRDIWT system**

### 3.3.1 Iris database

The CASIA Iris database version 1.0 is used as input to the system. The database consists of iris images of 108 persons. Each person has seven iris images. There are totally 756 iris images. The database to test the proposed algorithm is created by considering fifty persons with six samples per person for Persons Inside Database (PID) and remaining fifty eight persons with one sample per person
for Persons Outside Database (POD). The FRR is computed using seventh iris image of PID and FAR is computed using POD.

3.3.2 Integro-Differential Operator for image segmentation

The Integro-Differential Operator (IDO) presented by Daugman is used to detect the boundaries and the radii of the iris. It functions as a circular edge detector by searching the gradient image along the boundary of circles of increasing radius. The IDO is defined by the Expression 3.14.

$$\max_{(r, x_0, y_0)} \left| G_\sigma(r) \ast \frac{\partial}{\partial r} \int_{r, x_0, y_0} \frac{I(x, y)}{2\pi r} ds \right|$$

where $I(x, y)$ is the eye image, $r$ is the radius, $G_\sigma(r)$ is a Gaussian smoothing function, and $s$ is the contour of the circle given by $(r, x_0, y_0)$. The operator searches for the maximum change in pixel values along a circular arc $ds$ with respect to increasing radius $r$ and center coordinates $(x_0, y_0)$. The $\ast$ symbol denotes the convolution.

The IDO is applied iteratively with the amount of smoothing progressively reduced in order to attain precise localization and also eyelids are localized with the path of contour integration changed from circular to an arc. The IDO can be seen as a variation of the Hough transform, as it makes use of first derivatives of the image and performs a search to find geometric parameters. The IDO works with raw derivative information and hence it does not suffer from the threshold problems of Hough transform. The segmented iris image is shown in Figure 3.7.
3.3.3 Normalization by Daugman’s Rubber Sheet Model

The localized iris region in the Cartesian form is converted into polar form [9, 37] to obtain rectangular representation of iris. The homogenous rubber sheet model linearly maps the iris texture in the radial direction from pupil boundary to limbus boundary to a pair of dimensionless real coordinates \((r, \theta)\) where \(r\) lies on the unit interval \([0, 1]\) and \(\theta\) is the angular quantity over the cyclic interval \([0, 2\pi]\). The mapping of the iris image \(I(x, y)\) from Cartesian coordinates \((x, y)\) to the dimensionless non concentric Polar coordinates system \((r, \theta)\) is represented by the Equation 3.15.

\[
I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta) \quad \text{----------- (3.15)}
\]

where \(x(r, \theta)\) and \(y(r, \theta)\) given by the Equations 3.16 and 3.17 are defined as linear combinations of pupillary boundary coordinates \((x_p(\theta), y_p(\theta))\) and the limbus boundary coordinates \((x_s(\theta), y_s(\theta))\) along the \(\theta\) direction.

\[
x(r, \theta) = (1-r)x_p(\theta) + rx_s(\theta) \quad \text{----------- (3.16)}
\]
\[ y(r, \theta) = (1-r)y_p(\theta) + ry_s(\theta) \quad \text{(3.17)} \]

where
\[ x_p(\theta) = x_{p0}(\theta) + r_p \cos(\theta) \quad \text{(3.18)} \]
\[ y_p(\theta) = y_{p0}(\theta) + r_p \sin(\theta) \quad \text{(3.19)} \]
\[ x_s(\theta) = x_{s0}(\theta) + r_s \cos(\theta) \quad \text{(3.20)} \]
\[ y_s(\theta) = y_{s0}(\theta) + r_s \sin(\theta) \quad \text{(3.21)} \]

where \( r_p \) and \( r_s \) are respectively the radius of pupillary and limbic boundaries, \((x_{p0}, y_{p0})\) and \((x_{s0}, y_{s0})\).

The conversion of rectangular form of iris to polar form using Daugman’s rubber sheet model is demonstrated in the Figure 3.8.

![Figure 3.8: Daugman’s Rubber Sheet Model](image)

The rubber sheet model takes into account pupil dilation and size inconsistencies in order to produce a normalized representation with constant dimensions. The iris region is modeled as a flexible rubber sheet anchored at the iris boundary with the pupil centre as
the reference point. The segmented iris image is normalized to the size 60 * 250 and is as shown in Figure 3.9.

3.3.4 Image enhancement

In order to obtain best features for iris recognition, polar transformed image is enhanced using contrast-limited adaptive histogram equalization [110]. An iris image before and after enhancement are shown in Figure 3.9.

![Normalized iris before enhancement](image1.png)

![Normalized iris after enhancement](image2.png)

Figure 3.9: (a) Normalized iris before enhancement  
(b) Normalized iris after enhancement

3.3.5 Feature extraction

Feature extraction is the most important step in iris recognition. The Haar wavelet is used to extract the features from the normalized iris image. The normalized iris image of size 60*250 is subjected to DWT and IWT to get approximation band, horizontal band, vertical band and diagonal bands. The horizontal detail band obtained after the first level is further subjected to two levels of decomposition [21, 111]. The approximation band obtained after the third level decomposition consists of the prominent features. The
horizontal band is selected at the first two stages of decomposition, because the normalized iris image shows more details in the horizontal direction *i.e.*, angular dimensions of the actual iris image compared to the vertical direction *i.e.*, the radial dimension of the actual iris image. The two dimensional approximation bands containing the prominent features are converted into a one dimensional array and it is binarized. All the positive features are equated to 1 and the negative features to 0. This finally constitutes a feature vector of size 256 bits. The conceptual model for the three levels wavelet decomposition for feature extraction is as shown in Figure 3.10.

![Figure 3.10: Conceptual diagram for 3 levels 2D Wavelet Decomposition](image)

### 3.3.6 Fusion

The DWT and IWT features obtained form the basis of feature vector are fused to get final feature vector. The final feature vector is formed by concatenation of the DWT and the IWT features. The final feature vector is given in Equation 3.22.
Final Feature Vector = \{DWT features; IWT features\} \quad \text{(3.22)}

### 3.3.7 Matching

The iris feature vector obtained is a binary stream. Therefore the matching between the two iris feature vectors is done using HD. It is a measure of how many bits are the same between two bit patterns. Using the HD of two bit patterns, a decision is made as to whether the two patterns were generated from different iris images or from the same one. In comparing the bit patterns \(X\) and \(Y\), the HD is defined as the sum of disagreeing bits over \(N\), the total number of bits in the feature vectors and is given by the Equation 3.23.

\[
HD = \frac{1}{N} \sum_{j=1}^{N} X_j \oplus Y_j \quad \text{------------------ (3.23)}
\]

Since an individual iris region contains features with high degrees of freedom, each iris region produces a bit-pattern which is independent to that produced by another iris. On the other hand, two iris codes produced from the same iris will be highly correlated. In ideal case, if two bit patterns are completely independent, such as iris templates generated from different iris images, the HD between the two patterns is high. This occurs because independence implies the two bit patterns are totally different. If two patterns are derived from the same iris, the HD between them is close to zero, since they are highly correlated and the bits should agree between the two iris codes. However, because of the presence of noise due to eyelid and eyelashes occlusion, the HD may vary up to 0.4 even for the same iris images captured at different instances. To increase the efficiency, the
iris image under test is compared with all the other images of each group and the mean value of all the HD is used to decide whether the iris image under test belongs to the same group or not. If the average HD obtained is greater than 0.39 then the subject is rejected and if the average HD is lesser than 0.39 then the subject is accepted as genuine.

3.3.8 Proposed IRDIWT Algorithm

**Problem definition:**

Consider an eye image of a subject whose identity has to be verified. The objectives are to:

i) **Segment the iris, transform the circular iris to rectangular shape, enhance the image contrast,**

ii) **Apply DWT and IWT,**

iii) **Verify the authenticity of the subject**

iv) **Obtain the low error rates**

The iris recognition using DWT and IWT algorithm is given in Table 3.4. The circular iris is obtained by using IDO and converted to rectangular rubber sheet model. The contrast of the normalized iris is enhanced. The features are extracted by applying DWT and IWT. The HD is used for matching.
Table 3.4: IRDIWT Algorithm

<table>
<thead>
<tr>
<th>Input</th>
<th>Iris database and test image.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output</td>
<td>Match/ Mismatch of the test iris</td>
</tr>
</tbody>
</table>

i. Segment the iris image using IDO

ii. Normalize the segmented iris image from Cartesian coordinates to the normalized non-concentric polar representation of size 60*250 using Daugman’s rubber sheet model

iii. Enhance the image using contrast limited adaptive histogram equalization

iv. Apply DWT and IWT to the normalized iris image

v. Subject the horizontal detail band to two level DWT and IWT and consider approximation band at level 3

vi. Convert the approximation band obtained into one dimensional array

vii. Binarize the one dimensional array

viii. Fuse the DWT and IWT features by concatenation

viii. The features of the test iris are compared with database iris using HD to authenticate the person

3.3.9 Performance Analysis

The Iris Recognition using DWT and IWT model is tested on the CASIA Iris image database version 1.0. The algorithm is simulated on MATLAB version 7.4. The graph of FAR and FRR obtained for different values of HD threshold to compare the performance of the
The proposed fusion technique are shown in Figures 3.11, 3.12 and 3.13. As threshold HD increases, the value of FRR decreases whereas FAR increases. The value of EER is a point where FAR is equal to FRR. The EER value is 0.165 for DWT method; it is 0.107 for IWT method and 0.08 for the proposed fusion method. Therefore IWT performs better compared to DWT.

Figure 3.11: Graph of FAR and FRR for DWT method

Figure 3.12: Graph of FAR and FRR for IWT method
The average computation time for different steps viz., segmentation, normalization, enhancement, feature extraction and matching involved in IWT and DWT are given in Table 3.5. It is observed that the time required for feature extraction in case of IWT is only 0.16 milli seconds when compared to 0.49 milli seconds for DWT. Thus IWT reduces the computation time for feature extraction by 66%. This shows that the system with IWT features performs better compared to the system with DWT performs.

Figure 3.13: Graph of FAR and FRR for fusion of DWT and IWT features
Table 3.5: Average computation time of the IWT and DWT systems

<table>
<thead>
<tr>
<th></th>
<th>IWT</th>
<th>DWT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time (ms)</td>
<td>% of total time</td>
</tr>
<tr>
<td>Segmentation</td>
<td>12.92</td>
<td>94.72</td>
</tr>
<tr>
<td>Normalization</td>
<td>0.39</td>
<td>2.88</td>
</tr>
<tr>
<td>Enhancement</td>
<td>0.08</td>
<td>0.58</td>
</tr>
<tr>
<td>Feature Extraction</td>
<td>0.16</td>
<td>1.17</td>
</tr>
<tr>
<td>Matching</td>
<td>0.09</td>
<td>0.65</td>
</tr>
<tr>
<td>Total Time</td>
<td>13.64</td>
<td>100</td>
</tr>
</tbody>
</table>

The comparison of FAR, FRR and EER of the proposed IRDIW with other systems is shown in Table 3.6. It is observed that the value of FAR, FRR and EER are better in case of the proposed method compared to existing methods presented by Zhuoshi et al., [112], Jang et al., [113], Peng-Fei et al., [114], Benhammadi et al., [115], Neffisa et al., [116], and Adam et al., [117]. The results in the proposed algorithm are improved because of the following reasons:

(i) In the first two levels of DWT and IWT decomposition, the horizontal detail band is considered, since the variation along the horizontal direction is more in the normalized iris. (ii) At third level, the approximation band coefficients are considered as features of DWT and IWT.
Table 3.6: Comparison of FAR, FRR and EER values of the proposed method with existing methods

<table>
<thead>
<tr>
<th>Method</th>
<th>FAR</th>
<th>FRR</th>
<th>EER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhuoshi et al., [112]</td>
<td>1.4</td>
<td>2.6</td>
<td>0.71</td>
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<tr>
<td>Jang et al., [113]</td>
<td>1.0</td>
<td>0.54</td>
<td>-</td>
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<tr>
<td>Peng-Fei et al., [114]</td>
<td>0.3</td>
<td>1.1</td>
<td>-</td>
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<td>Benhammadi et al., [115]</td>
<td>0.06</td>
<td>1.2</td>
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<td>Nefissa et al., [116]</td>
<td>0.29</td>
<td>0.94</td>
<td>-</td>
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<td>Adam et al., [117]</td>
<td>0.0</td>
<td>2.7</td>
<td>0.9</td>
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<td>DWT method</td>
<td>0.19</td>
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<td>IWT method</td>
<td>0.11</td>
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<td>0.107</td>
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<tr>
<td><strong>Proposed IRDIWTFusion algorithm</strong></td>
<td><strong>0.05</strong></td>
<td><strong>0.043</strong></td>
<td><strong>0.08</strong></td>
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3.4 Summary

The proposed IRDFB method to identify person using fragmentation and DFB is discussed. The Canny edge detection technique is applied on eye images to remove occlusions and portion of the iris is extracted. The circular Hough transform is applied to detect circular iris portion. The Daugman’s rubber sheet model is used to convert circular iris portion into rectangular iris. The rectangular iris is fragmented into two equal regions of size 64*512. The iris region nearer to pupil is divided into sixty four subblocks to
extract features using DFB. The second iris region nearer to sclera, which has less significant information, is divided into thirty two subblocks only and features are extracted using DFB. The features of iris region 1 and 2 are fused by concatenation. The test iris features are compared with database iris features using Hamming distance to authenticate an individual.

The human identity recognition using iris based on IWT and DWT has been proposed. The iris and pupil boundaries of an eye are identified by IDO. The features of the normalized iris are extracted using IWT and DWT. The HD is used for matching of two iris feature vectors. It is found that the iris recognition using IWT is better than DWT. The error rates in the proposed method based on IWT is superior, because IWT rounds off the result of the filter before performing the other operations. Hence the computation time is reduced and efficiency is increased. The error rates are decreased by fusing the DWT and IWT features.