6.1 Introduction

As discussed in earlier chapters, iris recognition system involves four main modules: iris acquisition, iris segmentation and normalization, feature extraction, encoding and finally matching. However, it is noticed that almost all the iris recognition systems proceed without controlling the iris image quality. Naturally, poor image’s quality degrades significantly the performance of the recognition system. Thus, an extra module, measuring the quality of the input iris image, must be added to ensure that only “good image” will be processed by the system. The proposed module is able to detect and discard the faulty images obtained in the segmentation process, which do not have enough information to identify a person. In literature, most of quality evaluation methods have developed indices to quantify occlusion, focus, contrast, illumination and angular deformation. These measurements are sensitive to segmentation errors.

This chapter aims to present, firstly a novel iris recognition method based on Wavelet transform representing local texture information and encoding local variation across different Wavelet coefficients. Proposed method is tested on CASIA-Interval-Version3 and UBIRIS iris databases. The experiments illustrate the effectiveness of the method in extracting rich local and global information of iris texture. Further, selecting good quality iris images from a sequence frames can efficiently depress the False Rejection Rate and False Acceptance Rate of the recognition system. Based on quality, proportionate weights are assigned to different regions of iris image. Further, the iris templates are matched based on a weighted similarity measure. Obtained
results show a performance improvement of iris recognition system due to integration of the proposed quality measures in the typical system.

6.2 Iris image Quality Measures

To select images of good quality, an image quality measure is developed that evaluates the richness of texture. For this purpose, the measure is integrated in the recognition system after the phase of segmentation. Based on generated quality measures, further stage is implemented only for the image that surpasses a certain threshold. The choice of its value depends on the security level of the intended application. Figure 6.1 shows four main images which often degrade iris image quality: defocus, motion blur, eyelash occlusion and eyelid occlusion.

![Defocus](image1)

**a) Defocus**

![Motion Blur](image2)

**b) Motion Blur**

![Eyelash Occlusion](image3)

**c) Eyelash Occlusion**

![Eyelid Occlusion](image4)

**d) Eyelid Occlusion**

**Fig. (6.1):** Four main causes of iris image degradation

The quality of images are expressed in terms of texture clarity, focus degree, occlusion rate, dilation degree, view angle, etc. The techniques which are in use for iris quality evaluation can be classified into 3 categories: those operating in the frequency Domain, those based on 2D wavelets transform and the statistical methods.
Quality measures in the frequency domain:
The choice of quality measurement indices in the frequency domain is justified by the fact that an out-of-focus image can be considered as a result of the filtering of the ideal image by a low pass filter. The main part of information of texture in out-of-focus images is located in the low frequencies. On the contrary, this information is between the low and middle–low frequencies for clear image.

Quality measures based on wavelet transform:
Generally, the algorithms operating in frequency domain are applied on the entire image or on interest region; hence they are sensitive to the noise and give a global sight of the focus degree of the iris texture. To solve these problems, 2D wavelets transform are used to produce a local descriptor of the iris quality.

Quality measures based on statistical measures:
In addition to the techniques described above, several researchers have considered statistical measures to assess the quality of iris images. Detailed literature review on quality measures is taken in chapter 2.

6.3. Proposed Iris Recognition System Integrating Quality Measures

A typical biometric system includes 4 stages as mentioned earlier. A too noisy or poorly segmented iris is processed in all system steps which often lead to false identity recognition. Thus, the proposed system consists of integrating a quality module after the segmentation step.

The objective of this module is to select images to be processed in the system. For this, a quality measure to assess quality of iris image is developed which estimates the richness of texture. Figure 6.2 illustrates different units of the given system and the following sections describe every unit in detail.

In a typical iris recognition system, the eye image is pre-processed to obtain a segmented and normalized image, then its texture is analysed and encoded to form an iris features vector ‘template’. Finally, templates are compared to estimate similarity between irises to decide about authenticity.
Comparative study of iris recognition system using WPNN and Gabor Wavelet

Fig. (6.2) : Proposed iris recognition systems integrating iris quality measures

6.3.1 Iris pre-processing :
Iris pre-processing step includes iris segmentation and normalization. Iris segmentation aims to isolate iris texture from the acquired eye image, with exclusion of any obscuring elements such as eyelids, eyelashes, and reflections from the cornea or possibly from eyeglasses. In the present work, iris and pupil are modelled by two circles not necessarily concentric as shown in figure 6.3-a. Different borders are located by the application of Hough transform. Further, pseudo polar transformation of Daugman is applied to transform the iris arc from raw coordinates \((x, y)\) to a doubly dimensionless and non-concentric coordinate system \((r, \theta)\) (Figure 6.3-b). Since, the result is not well contrasted, it is better to enhance the textured image before analysing its texture (Figure 6.3-c).

6.3.2 Iris image quality assessment :
The quality of iris image is the key point to affect the accuracy of iris recognition system. Selecting good iris images from a sequence frames can efficiently depress the False Rejection Rate and False Acceptance Rate of a recognition system. Considering the texture distribution characteristics on iris images, a novel iris quality assessment
scheme is proposed corresponding to different situations. The experiment results show that the proposed method is efficient and are coincident to the judgment of human eyes.

This module aims to generate a index expressing the richness of iris texture to verify if the region of interest of iris image has enough information to identify a person. This module is integrated into the recognition process after the image segmentation and normalization unit. In order to ensure a good estimation of the texture richness with acceptable computation time, a global quality index is calculated. To estimate the richness of texture, we generated a global quality index $Q_t$ by three generated quality scores: Quality measure for defocus ($Q_d$), Motion blur ($Q_b$) and Occlusion ($Q_o$), related to quality indices for defocus, motion blur and occlusion respectively.

6.3.3 Iris texture analysis:
In an iris recognition system, the feature extraction and encoding aims to represent the details of the iris texture by finding efficient and discriminative descriptors that are resistant to large variation in illumination, rotation, occlusions, deformation and other factors which disturb the iris texture. There are various methods proposed as discussed in chapter 2 and which has shown very good performance because of their
capability to multi-scale representation. Gabor features encode edge information and texture shape of iris texture over a range of multiple narrow-band frequency and orientation components.

In this chapter, a novel method as discussed in chapter 5 is used to extract iris features using wavelet packets to represent spatial texture information. Further, these local signatures representing features are obtained by first dividing each obtained image into non-overlapping blocks having a given size, then computing features within each block to form a vector.

According to result obtained in the segmentation step, it has been observed that the area belonging to \([\pi/6 - 11\pi/6]\) is generally disturbed by the presence of eyelids and eyelashes and consequently, the most discriminating information of texture is in the other portion of the iris. Figure 6.4 (a-b) shows the effect of the presence of occlusion, eyelids and eyelashes. These effects are considered while preparing the noise mask as shown in figure 6.4(c). Moreover, in order to reduce the impact of reflection in this region, we don’t consider texture present in the 1/6 internal portion.

![Eye image](image1)

![Inner and outer Boundaries](image2)

![Mask for the noise present in the iris image](image3)

![Iris Template](image4)

**Fig. (6.4) : Iris code generation process**
For matching, a weight to each feature vector is assigned and weighted similarity measure procedure is used. The main idea is to assign a higher value of weights to a feature which has more significance in the iris part. In most of the cases, upper and lower part of the iris is occluded by the eyelids and eyelashes. To improve the recognition rate and to denoise the information, quantize a coefficient of packets using eq.(5.35) and (5.36). Iris template is formed by encoding this local relationship between measures of vector. This step aims to generate iris template based on representing the features variations. In practice, this iris code facilitates greatly the matching process. Since persons are identified by their templates, the process of person verification needs a comparison between two templates in order to estimate their similarity. Considering that the iris is represented by a bit template, the Manhattan distance is more suitable to estimate the difference between iris patterns with a bit-by-bit comparison.

In our algorithm, rotational invariance is obtained by unwrapping the iris ring at different initial angles. Five initial angle values are used in experiments [-4°, -2°, 0, 2°, 4°]. Thus, five images are defined for each iris class in the data base. While, matching the input feature code with a class, the minimum of the scores is taken as the final matching distance.

6.4 Proposed Scheme of Iris Image Quality Assessment

Selecting good quality iris images from a sequence frames can efficiently depress the False Rejection Rate and False Acceptance Rate of the recognition system. From observation, the bad quality iris images are mainly caused by four factor-oriented abnormalities. Each kind of abnormality has its own distinct characteristics. The following sections discusses the methods proposed for the quality measures for defocus (Qdf), for motion blur (Qb) and quality measure for noise due to eyelids and eyelashes (Qn). Further, the iris quality index is generated by the fusion of these quality measures. If this quality index is more than the threshold decided, then segmented image is passed for the feature extraction stage otherwise it is discarded due to less textural information content.
\[ Q_t = Q_{df} + Q_B + Q_n \] (6.1)

**6.4.1 Quality measures for defocus (\(Q_{df}\)):**

Iris area is very small. To get high resolution iris image, the acquisition system should have a definite zoom in ability. At the same time, a big aperture is required to provide enough illumination condition since the irises are often shadowed by eyelid and eyelash. But bigger aperture leads to the reduction of depth of field, then, defocus often occurs when the head shifts back and forth a little. Defocus is the most popular situation in the abnormal images.

Other iris image assessment methods are based on the analysis of whole iris image after segmentation. But in many cases, the segmented iris always contains some eyelid and eyelash, and using whole iris for assessment cannot reflect the real quality of iris image. From observation and testing, we find that the areas beside the pupil are more stable (Figure 6.5, region 1 and 3) and less suffer by other factors. Then it would be more reliable to take the two areas for defocus assessment. As the captured iris images always vary in size, the detected iris is normalized into a rectangular block.

Then, the two regions are defined for defocus assessment, region 1 \([11\pi/6-\pi/4]\) and region 3: \([3\pi/4, 5\pi/4]\).

![Assessed area segmentation](image1.png)

**Fig. (6.5 a) :** Assessed area segmentation  b) Corresponding rectangular area.

Iris contains abundant texture information. It is known that the texture property can be represented by the coefficients in high frequency domain. The bigger coefficients in high frequency domain are regarded that the textures are clearer. Besides, the textures in iris always distribute along radial direction, and they distribute in vertical direction when the iris is aligned into rectangular coordinate system (as
shown in Figure 6.5). Then, the high frequency energy of corresponding texture should be concentrated in vertical high frequency component, $V$, after the wavelet transform.

Generally, the 2-D wavelet decomposition of $k$ octaves of an image $g(m, n)$ represents it by $3^k+1$ sub images: Where, $A_k$ is a low frequency component of the original image, and $V_i$, $H_i$, $D_i$ are the wavelet sub images containing the image details at different scales and orientations. The wavelet decomposition coefficient $V_i$, $H_i$, $D_i$ correspond to the vertical high frequencies, horizontal high frequencies, and the high frequencies in both directions respectively. The coefficients obtained by applying the 2-D wavelet transform on an image are called the sub images of the wavelet transform. Wavelet packet transform (WPT) can decompose each sub images ($A$, $H$, $V$, $D$) rather than only $A$ is further decomposed in wavelet transform (WT). It indicates that WPT has better capability than WT in the analysis of high frequency components. So we can use WPT to get further decomposition of component $V$ and choose sub images $V$, $VA$, and $VV$ to analyze the iris textures, as shown in Figure 6.6.

![Wavelet packet decomposition](image)

**Fig. (6.6) : 2-level Wavelet packet decomposition**

At the same time, the texture on the iris is not well distributed along the radial direction. The inner regions often provide finer texture than outer regions. So, it is obvious to give larger weights to the inner iris regions than outer as is more similar to the nature of iris texture. Based on the above analysis, a defocus assessment method is presented with localized weighted energy analysis based on wavelet packet transform. The flow of this method is shown in Figure 6.7. a) extract the evaluation areas of a
given iris image (Region 1 and 3, as shown in Figure 6.5); b) decompose these two regions by wavelet packet transform; c) calculate the energy of given high frequency ranges; d) weight at different frequency ranges (WDFR); e) weight at different ring range (WDRR).

Then quality index for defocus assessment criterion $Q_{df}$ is calculated as,

$$Q_{df} = E_f + E_i$$  \hspace{1cm} (6.2)

$$E_i = \sum_{j,k} M_i (j,k)^2$$  \hspace{1cm} (6.3)

where, $E_f$ and $E_i$ are the energy of different frequency ranges and different ring ranges respectively. $M_i$ is the sub image of wavelet packet transform. Give different weights to the sub images $V$, $VV$, and $VA$, and the weights $W_i$ are increasing according to the degree of energy convergence.

$$E_f = E_v X W_v + E_{VA} X W_{VA} + E_{VV} X W_{VV}$$  \hspace{1cm} (6.4)

In this work, weight assignment is considered based on frequency component content as,

$$w = [W_v, W_{VA}, W_{VV}] = [0.1, 0.2, 0.7]$$

Further, these two regions are divided into several concentric rings with a fixed width, and the weights of each ring by are calculated considering the radius. The weights descend along the radial direction.

$$E_f = \frac{1}{T} \sum_{i=1}^{T} (w_i X \log E_i)$$  \hspace{1cm} (6.5)
\[ w_t = \exp\left\{ -\left\| l_t - l_p \right\|^2 / c \right\} \]  

(6.6)

\( T \) is the number of divided rings, \( l_p \) denoting the center of the pupil, \( E_t \) is the energy of the \( T^{th} \) ring, it denotes the mean radius of the \( T^{th} \) ring to \( l_p \), \( w_t \) is the weight of the \( T^{th} \) ring, and \( c \) is constant. In this inner ring provide more information.

### 6.4.2 Quality measures for Motion blur (\( Q_B \))

Motion blur is another case to affect the iris image quality. Since motion blur occurs when the pixels overlap along on the moving direction, it leads to the gray level difference between neighbour points getting smaller. So the gray level difference can be used to evaluate the motion blur. Here a \( 3\times n \) operator is defined as shown in Table 6.1 to measure the average difference between the adjacent rows \( H_{diff} \) to get quality criterion for motion blurred images \( Q_B \).

\[ H_{diff} = \sum_y |I(x, y) * \Delta| \]  

(6.7)

\[ Q_B = \text{mean} (H_{diff}) \]  

(6.8)

Where \( I(x, y) \) is the iris image.

<table>
<thead>
<tr>
<th>( x )</th>
<th>( y )</th>
<th>( z )</th>
<th>( w )</th>
<th>( v )</th>
<th>( u )</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1</td>
<td>-1</td>
<td>.....</td>
<td>-1</td>
<td>1-</td>
<td></td>
</tr>
<tr>
<td>+2</td>
<td>+2</td>
<td>.....</td>
<td>+2</td>
<td>+2</td>
<td></td>
</tr>
<tr>
<td>-1</td>
<td>-1</td>
<td>.....</td>
<td>-1</td>
<td>1-</td>
<td></td>
</tr>
</tbody>
</table>

**Table 6.1** The \( (3\times n) \) operator.

### 6.4.3 Quality measures for Occlusion (\( Q_O \))

Occlusion by eyelid and eyelashes is another problem when capturing iris images. In this kind of images, parts of iris area are covered by eyelid or eyelash. In occluded iris images, there are higher frequency components in the occluded region than good iris images. If the occlusion is getting worse, it affects iris segmentation accuracy and feature extraction which finally leads to the rise of False Rejection Rate. The local noise identification methods described in chapter 3 produce a binary map correspondent to the segmented and normalized iris image where the noisy regions
appear as dark areas and the noise-free regions are represented through white areas (figure 6.8).

Let $I$ be the segmented and normalized iris image and $(x, y) \in \mathbb{N}^2$ be the coordinates of a pixel from the image. Let $n((x, y)) : \mathbb{N}^2 \rightarrow \{0, 1\}$ be the function that classifies as "noisy" or "noise-free" every pixel $(x, y)$ from the image $I$:

$$n(x, y) = \begin{cases} 0, & I(x, y) \text{ noisy} \\ 1, & \text{otherwise} \end{cases}$$

The quality of the feature is:

$$Q_o = \frac{1}{N} \sum_{i=1}^{N} n(I(x_i, y_i))$$

(6.9)

This quality measure $Q_o$ gives the proportion of noise free data considered in the extraction of features. This value has inverse correspondence with the proportion of noisy pixels evolved in the creation of feature. Thus, for completely “noisy” (poorest quality) and “noise free” (optimal quality) features, the quality value will be respectively equal to 0 and 1.

![a) Segmented iris image](image1.png)  
![b) Identification of the noisy regions](image2.png)

**Fig. (6.8) :** Identification of the noisy regions in the normalized iris image

### 6.4.4 Quality Index generation

This module aims to generate a quality index expressing the richness of iris texture to verify if the region of interest of iris image has enough information to identify a person. It estimates a global quality index based on the following index: the occlusion index $Q_o$, the blur index $Q_B$ and the defocus index $Q_{df}$. To estimate the richness of texture, a global quality index $Q_t$ is generated by averaging the three generated quality
scores $Q_o$, $Q_B$ and $Q_{df}$. The validation of these measures on CASIA and UBIRIS datasets shows that they are important for quality assessment also they are uncorrelated.

### 6.5 Experimentation and Discussions

The experiments are based on two iris databases: The public iris database V3.0 of Institute of Automation, Chinese Academy of Sciences (CASIA) and UBIRIS iris database. About 1000 images of 4-5 objects were chosen for the experimentation. In order to enable this analysis, we further divided the selected images in two sub sets, according to their noise characteristics. The 550 less noisy images were included in the data set and the 450 noisier ones in the data set. The sample iris images in figure 6.9 are from CASIA and UBIRIS datasets. Image (a) represents a good quality from CASIA and (c) represents a good quality image from UBIRIS (based on visual evaluation). Images (b) and (d) represent degraded quality images which are affected by occlusion (b) and motion blur in (d).

![Sample Images from CASIA and UBIRIS datasets](image)

*Fig. (6.9): Sample Images from CASIA and UBIRIS datasets*

Table 6.2 lists the estimated factors (factors are between 0 and 1, with 0 implying heavy degradation) for these images and the combined quality for them. The quality column represents the lower bound (minimum value attained of quality index) on image quality.

To evaluate the performance of the proposed scheme, we define a correct recognition Rate (CRR) which is the ratio of correct classified images and the total testing images. The performance evaluation includes three experiments.
Comparative study of iris recognition system using WPNN and Gabor Wavelet

### Table 6.2: Quality measures of figure 6.9

<table>
<thead>
<tr>
<th>Image</th>
<th>Defocus</th>
<th>Motion Blur</th>
<th>Occlusion</th>
<th>Quality Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>0.72</td>
<td>0.81</td>
<td>0.84</td>
<td>2.37</td>
</tr>
<tr>
<td>(b)</td>
<td>0.49</td>
<td>0.57</td>
<td>0.24</td>
<td>1.3</td>
</tr>
<tr>
<td>(c)</td>
<td>0.78</td>
<td>0.77</td>
<td>0.91</td>
<td>2.36</td>
</tr>
<tr>
<td>(d)</td>
<td>0.37</td>
<td>0.20</td>
<td>0.64</td>
<td>1.21</td>
</tr>
</tbody>
</table>

6.5.1 **Experiment 1:** Testing on abnormal subsets

In the first experiment, all the abnormal iris samples are selected out from CASIA database and UBIRIS database, and group them into 4 subsets (defocus, motion blur, eyelid occlusion, and eyelash occlusion) based on our subjective decision. Then, four assessment schemes are carried out in corresponding abnormal subsets. The testing results are listed in Table 6.3. The correct recognition rates of this experiment are near 97% or higher.

<table>
<thead>
<tr>
<th>Abnormal situations</th>
<th>Defocus</th>
<th>Blur</th>
<th>Eyelid occlusion</th>
<th>Eyelash occlusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRR</td>
<td>96.67%</td>
<td>98.34%</td>
<td>97.28%</td>
<td>97.98%</td>
</tr>
</tbody>
</table>

6.5.2 **Experiment 2:** Comparison with other methods

In the second experiment, the whole scheme is tested based on CASIA database and UBIRIS database, and compare the scheme with Daugman’s [2] and Zhang’s [3] method. The testing results are listed in Table 6.4. The correct recognition rates our scheme is 96.27% which is higher than Daugman’s and Zhang’s methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>Zhang</th>
<th>Daugman</th>
<th>Our method</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRR</td>
<td>87.34%</td>
<td>94.25%</td>
<td>96.27%</td>
</tr>
</tbody>
</table>
6.5.3 **Experiment 3**: Comparison between iris quality of CASIA V3 and UBIRIS database:

In the third experiment, image quality assessment on CASIA database and UBIRIS database is presented. The result is shown in Figure 6.10. It states the image quality becomes better along the horizontal direction. From Figure 6.10, we can see that CASIA iris database is good than UBIRIS database. The results agree with the fact which is discussed in detail regarding the noise content in the iris databases. It can be easily embed into real iris recognition system.

![Comparison of iris quality between CASIA and UBIRIS database.](image)

**Fig. (6.10)**: Comparison of iris quality between CASIA and UBIRIS database.

Quality measures $Q_{df}$, $Q_B$ and $Q_O$ are calculated for all segmented images of CASIA and UBIRIS database. It is been observed that quality measure of images varies between 0.5 and 2.8 and most images are well segmented. If quality measure $Q_O$ varies between 1.4 and 2.6, then images contain enough information to be identified. Also it has been observed that the CASIA-v3 images have a medium quality and $Q$ varies between 1.2 and 3. Based on the distribution of the quality score $Q$, we fixed a
number of decision thresholds specifying the minimum quality to exploit the image by the system.

6.6 Feature Extraction and Weight Assignment in Normalised Image:

The feature processing task is followed by two iris pre-processing tasks: iris localization and iris normalization of an input eye image. In this work, consider that normalized eye image is available accurately following the above mentioned pre-processing tasks. The feature processing task consists of two sub tasks namely, feature extraction and feature encoding. In this section, local feature generation using Haar wavelet transform along with noise mask is discussed.

6.6.1. Feature Extraction

Normalised and enhanced iris part of an eye image is obtained with fixed block of size 100 × 360 pixel. This iris part is divided into five sub images and Haar wavelet transform is applied to each sub image up to 3-level. In other words, to extract the characteristic values in the iris image Haar wavelet transform is applied to five sub-images up to three levels successively as explained in fifth chapter. Figure 6.11 shows an example of dividing the UBIIRIS iris image. The Haar wavelet packet decomposition is repeatedly performed in order to reduce information sizes.

The regions I₁ to I₄ contain the information size 50 X 90 data for each sub images. The region I₅ is shown in top part of figure 6.11(b) of size 50 X 360 sub image. Characteristic vector is obtained from these regions using the appropriate energy packet extracted. As mentioned in chapter 5, the code is computed using combination of appropriate packets. For region I₅ three and for region I₁, I₂, I₃ and I₄ two appropriate packets are considered for feature vector generation.

Let $F$ be the characteristic vector and $f^{i}$ be the feature vector of the $i^{th}$ sub image. The $F$ and $f^{i}$ are obtained using Equation (6.10).

$$
F = \{ f^{1}, f^{2}, \ldots, f^{5} \} \\
f^{i} = \{ f_{i1}, f_{i2}, \ldots, f_{i94} \} \text{ for } i = 1, 2, 3, 4 \\
f^{5} = \{ f_{51}, f_{52}, \ldots, f_{545} \} \text{ for } i = 5
$$

(6.10)
The total number of characteristics values obtained for the entire normalized image are 1617.

![Segmentated iris image](image1.png)

![Partitioning of normalised iris image](image2.png)

**Fig. (6.11) Feature extraction using weight assignment**

### 6.6.2 Feature Encoding:

A binary feature vector is generated by quantizing the relevant characteristic values of a characteristic vector from the extracted image including the appropriate components in the third level. In the previous sub section, the characteristics vector of 896 dimensions is obtained. Quantization process similar to Wavelet packet encoding as described chapter 5 is used. It requires 1-bit to encode each characteristic value.

Therefore, the generated feature vector requires less than or equal to 1617 bits. Since the values of feature vectors lie in the range of -1 and +1 both inclusive. It may please to be noted that the proposed third level quantization is sufficient because both sign and magnitude information of wavelet coefficients are considered. Our experimental results show no significant improvement with higher levels of quantization compared to that of third level quantization.
6.6.3 Feature Matching:

In this sub section, proposed approach to feature matching is described. Approach consists of setting rotation invariant feature vectors, assigning weight to a feature vector and finally the decision for a match. All these steps are discussed in following section.

Rotational Invariance: It is observed that usually an iris is rotated within small angle. So, to achieve the rotation invariant feature, we propose circularly shifting the normalized image in five positions (-8, -4, 0, 4, 8 pixel) in y-direction and hence storing the features at five different angles. Shifting -8, -4, 0, 4, 8 pixels in y-direction means rotating the original eye in $-6^\circ, -3^\circ, 0^\circ, 3^\circ, 6^\circ$.

Matching: For matching, assign a weight to each feature vector and also apply a weighted similarity measure procedure in our work. The main idea is to assign a higher value of weights to a feature which has more significance in the iris part. We observed that upper and lower part of the iris is occluded by the eyelids and eyelashes in maximum cases. From our study it also observed that the most discriminating iris features are present in the iris region near to the pupil boundary. Hence apply a weighted matching procedure to compare the two feature vectors. The maximum weight is given to that sub images which are more visible (less noise) and the least weight is given to that sub images which are maximally occluded by eyelids and eyelashes. From figure 6.11 we see that the regions $I_5$ are given maximum weight (1) because these regions are closer to the pupil boundary and are not obstructed by eyelashes or eyelids in majority of the cases. The $I_2$ to $I_4$ regions are far away from the pupil boundary but the chance of blocking by eyelashes or eyelids. A weight to this sub image is assigned by checking its quality measure for occlusion.

The weight assigned to each sub-image is calculated by using the quality of feature corresponding to that sub image which is represented in the normalised form [0:1]. The weight assignment to sub-image is:

$$W_i = \frac{1}{N} \sum_{j=1}^{N} n(I(x_j, y_j) i = 1,2...,4$$

(6.11)

where, N is number of pixels of subimage.
This weight \( W_i \) is the weight assignment for sub-image \( i \). This value has direct correspondence with the proportion of noise-free pixels evolved in the creation of feature \( f_i \). Thus, for completely “noisy” (poorest quality) and “noise free” (optimal quality) features, the weight assignment will be respectively equal to 0 and 1.

**Similarity Measure:** The similarity measure is calculated by Manhattan distance (MD) metric. Feature vector under test and each of the five values of features corresponding to five angles of rotation are taken. We consider the minimum value among these five MD value as a similarity value. User authenticity is determined according to the measured similarity obtained.

**6.6.4 Experimental results and discussions:**

Proposed method has been tested with images of UBIRIS and CASIA V3 iris image databases. We compare our approach with some best known algorithms as Daugman [3], Wildes [8], and Ma et.al. [11]. In order to compare the performance with existing methods, we have implemented existing methods and tested with same set of databases. Extensive experiments on different iris image databases are performed to evaluate the accuracy of the proposed method. The experiments are completed in two modes: identification (one-to-one) and verification (one-to-many). Figure 6.12(a) and 6.12(b) show the FAR and FRR curve for different threshold values (C) for CASIA-V3 and UBIRIS iris database respectively. ERR values for different iris databases from FAR and FRR curve are calculated.

![Fig. (6.12a): FAR and FRR for different threshold values (CASIA-V3 +Quality measure)](image-url)

**Fig. (6.12a):** FAR and FRR for different threshold values (CASIA-V3 +Quality measure)
Comparative study of iris recognition system using WPNN and Gabor Wavelet

Fig. (6.12 b) : FAR and FRR for different threshold values (UBIRIS+Quality measure)

Table 6.5 Comparison of the iris recognition Performance of various methods

<table>
<thead>
<tr>
<th>Methodology</th>
<th>Correct recognition rate (CRR) (%)</th>
<th>Equal error rate (ERR) (%)</th>
<th>Required bit to represent feature vector</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UBIRIS</td>
<td>CASIA-V3</td>
<td>UBIRIS</td>
</tr>
<tr>
<td>2D Gabor filter</td>
<td>89.24</td>
<td>99.88</td>
<td>10.76</td>
</tr>
<tr>
<td>Wildes</td>
<td>-</td>
<td>97.81</td>
<td>-</td>
</tr>
<tr>
<td>Ma et. al.</td>
<td>-</td>
<td>96.22</td>
<td>-</td>
</tr>
<tr>
<td>Proposed Approach</td>
<td>92.86</td>
<td>97.6</td>
<td>7.14</td>
</tr>
<tr>
<td>(Without Quality factor)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed approach</td>
<td>96.20</td>
<td>98.34</td>
<td>3.8</td>
</tr>
<tr>
<td>(With Quality factor)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The CRR, ERR and number of bits required to store a feature vector for different method are listed in Table 6.5. From Table 6.5, we see that our approach provides a
higher CRR and lower ERR and at the same time with a lesser number of bits required to store the feature vectors.

6.7 Concluding remarks

A novel and efficient method is proposed to extract iris features and matching technique to compare iris features. Proposed method uses Haar wavelet transform with three appropriate packets from one sub image and two appropriate packets from four sub image. The Haar wavelet transform is easy to compute and fast compared to the other methods on texture analysis. Further, Haar wavelet transform allows keeping the count of feature vectors into a significantly lesser numbers. This is indeed without affecting the accuracy of the results. This way we are able to represent feature vectors with less bits. In addition to the savings in the number of feature vectors, another contribution in our approach is to assign a weight to each feature vector and hence to increase more accuracy in the similarity measure.

Obtained results show a performance improvement of iris recognition system by incorporating proposed quality measures in the typical system. Our approach is comparable to all existing approaches with respect to the number of bits to represent feature vectors and processing time. So far the recognition accuracy rate is concerned our approach is also leads the existing approaches. In fact, accuracy rate in our approach and Daugman approach is not remarkably differing. However, Daugman’s accuracy rate is at the expense of a higher number of computations and may be impractical for several online authentication systems.