Chapter 3

Iris Segmentation using Adaptive Histogram Equalization and Median Filtering

Iris Segmentation is one of the vital steps of iris recognition system where iris region is isolated from rest of the image. Besides the detection of iris outer and inner boundaries, detection of artifacts such as eyelid, eyelashes, specular reflections etc. make the segmentation more difficult as well as increase the computational time of the system. This chapter presents an iris segmentation approach based on Adaptive Histogram Equalization (AHE) and median filtering. Segmented iris patterns are classified using ANN. A comparison of the proposed segmentation approach with some of the existing approaches is carried out in this chapter. The chapter concludes with the experimental results.

3.1 Introduction

Iris recognition system is one of the most reliable biometric systems for personal identification due to unique properties of iris and high degree of randomness (Sahmoud *et al.*, 2013; Lefevre *et al.*, 2013). Typically, iris recognition systems consist of five modules *viz*. Image Acquisition, Iris Segmentation, Normalization, Feature extraction and Matching (Sun *et al.*, 2013). In order to achieve the high performance iris recognition system, proper segmentation of an iris is required. For real time application, the computational time of the system is also considered. The segmentation step is a vital step for overall performance of the system. The segmentation refers to the isolation of an iris region from an eye image by properly detecting the iris inner and outer boundaries.

The artifacts such as eyelid, eyelashes, specular reflections etc. make the segmentation more difficult which in turn decrease the system performance. In order to reduce the implementation time and increase the segmentation accuracy, a segmentation approach based on Adaptive Histogram Equalization and median filtering techniques is proposed in this chapter. In the following sections, a brief introduction to AHE, median filtering and related works is provided followed by proposed segmentation approach and experimental results.

Iris segmentation is one of the vital steps of iris recognition system. This step consists of demarcating iris inner and outer boundaries, detection and removal of artifacts such as eyelashes, eyelids and reflections. Daugman (1993) introduced the Integro-Differential Operator (IDO) for detecting iris boundaries. Wildes (1997) performed iris segmentation with the help of edge detection and CHT. Matveev *et al.* (2014) proposed a segmentation approach based on Hough Transform (HT). Libor *et al.*, (2003) applied modified canny edge detection method and CHT to detect inner and outer boundary of an iris. In order to improve the speed of the iris segmentation Ma *et al.* (2004)], Zubi *et al.* (2007) roughly determine the iris region in advance before applying Hough Transform. Shah *et al.* (2009) extracted the iris region from an eye image by using Geodesic Active contours (GACs). Al-Daoud *et al.* (2012) proposed a method based on competitive chords to detect pupil-iris and iris-sclera boundaries. Roy *et al.* (2012) applied parallel game-theoretic decision making procedure to elicit iris boundaries. Shin *et al.* (2012) applied circular edge detector algorithm to detect the iris boundaries. Abdullah *et al.* (2014) applied active contour method for complete segmentation of an iris. Daugman's approach works on local scale and fails to detect circle boundaries where there is noise such as reflections in the image (Al-Daoud *et al.*, 2012). Segmentation method based on HT is computationally expensive to detect the coordinates of the iris (He *et al.*, 2007).

There are several challenges regarding accurate iris segmentation. A segmentation approach based on adaptive histogram equalization and median filtering for iris segmentation is proposed and presented in this chapter. The proposed segmentation approach is a fast iris segmentation approach and also helps to improve iris classification performance.

3.2 Proposed Segmentation Approach

The proposed Iris segmentation approach based on AHE and median filtering is presented in this chapter. AHE is an image enhancement technique used to increase the contrast of an image. The proposed approach consists of following important steps:

i. Pupil Localization
ii. Iris Localization
iii. Isolation of eyelids, eyelashes and reflections
iv. Iris normalization

These steps are explained in the subsequent sections. The overview of the proposed approach is shown in Figure.3.1.

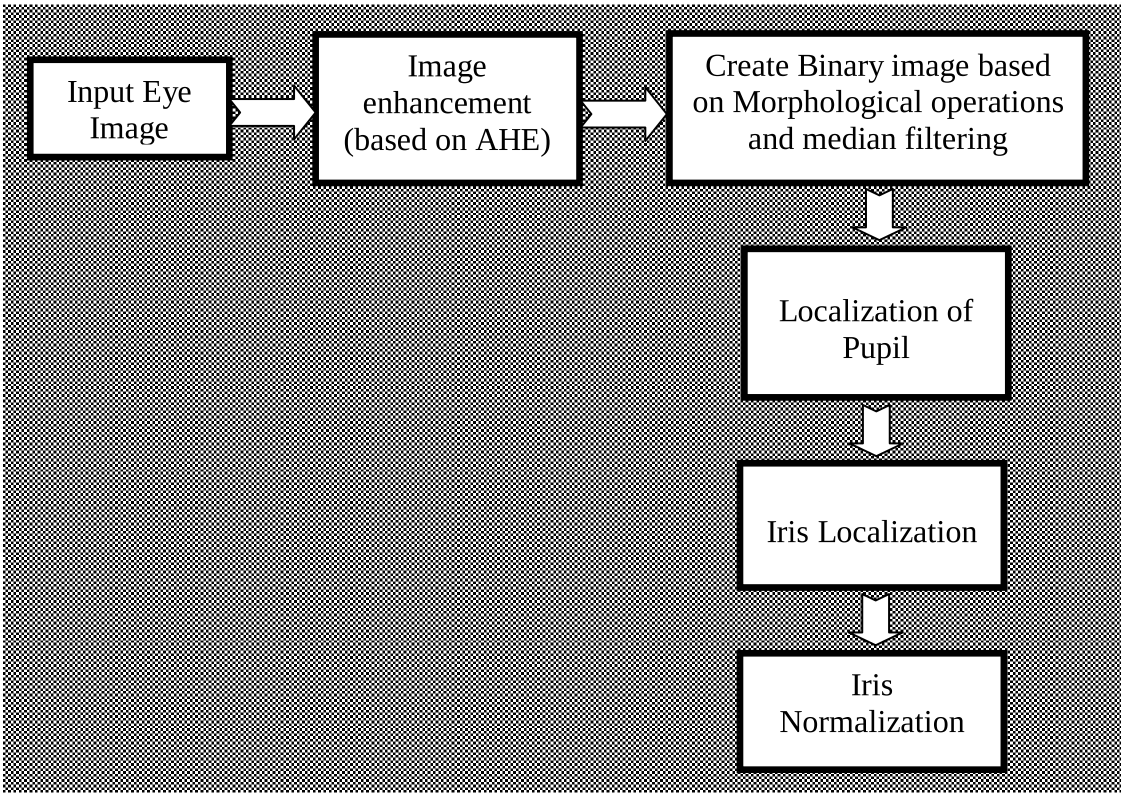

Figure 3.1 Proposed segmentation approach

3.2.1 Pupil Localization

The radius, r_p, and centre coordinates (C_x, C_y) of a pupil is calculated according to the algorithm 3.1 by considering the fact that the pupil is generally darkest region in the image.

AHE is applied in step (i) to increase contrast of an image which help to isolate the eyelashes near or over the pupil. The median filter in step (v) is used to eliminate the white spots. The output of this process is illustrated in Figure 3.2.

Algorithm 3.1: Calculation of a radius, r_p, and centre co-ordinates, (C_x, C_y), of pupil

Input: Eye image, I

Output: Radius, r_p, and centre co-ordinates, (C_x, C_y) of pupil.

i. Apply AHE to the input image.
ii. Remove the eyelashes (if present) over or on the iris image through linear thresholding.
iii. Create a binary image with threshold value $t < 90$.
iv. Apply morphological operation 'dilate' and 'erode' in the resulted image followed by flood fill.
v. Filter the image with two dimensional [15,15] median filter.
vi. Remove the smaller region (outliers).
vii. Determine the centroid of detected pupil region (C_x, C_y).
viii. The horizontal radius, r_x, equal to number of ones from the point (C_x, C_y) to the left side of the pupil. The vertical radius, r_y, equal to number of ones from the point (C_x, C_y) to the top of the pupil. r_p is equal to the average of r_x and r_y.

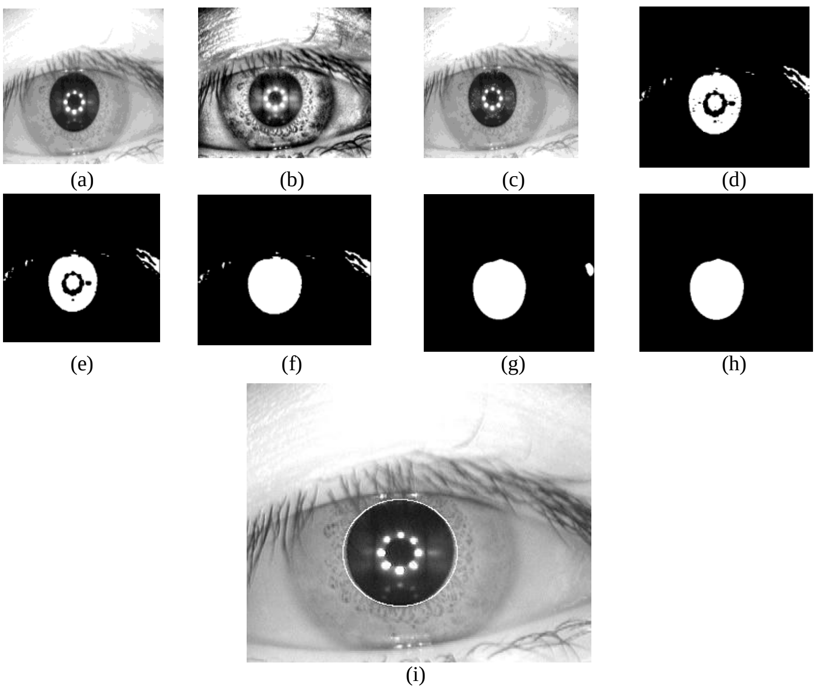

Figure 3.2 (a) Original Image (b) Image after application of AHE (c) Image with eyelash removed from the boundary of pupil (d) Binary image (e) Image after morphological operations (f) Image after flood fill (g) Image after median filtering (h) Detected pupil region (i) Localized pupil

AHE is an image processing technique used to improve the local contrast in the image. This is achieved by computing histogram of a local image region centered at given pixel to determine the mapped value for that pixel (Pizer *et al.*, 1987). Median filtering is a nonlinear operation that is often used in image processing to reduce "salt and pepper noise". It is an effective technique when goal is to simultaneously reduce noise and preserve the edge (Al-Zubi *et al.*, 2007).

3.2.2 Iris Localization

In iris localization, only region closer to pupil is considered because:

i. Sometimes iris outer boundary may not be detected properly.
ii. More discriminating information is provided by the region closer to the pupil.
iii. Eyelashes and eyelids rarely occlude this region.

The center coordinates of an iris is same as the coordinates of the pupil i.e. (c_x, c_y). The radius, r_i, of iris outer boundary is obtained by incrementing radius of pupil, r_p, by 40. The radius, r_i , is defined by equation (3.1).

$$r_i = r_p + 40 \tag{3.1}$$

3.2.3 Isolation of Eyelids, Eyelashes and Reflections

To isolate the eyelashes and reflection simple linear thresholding technique is used. The region with pixel value less than 100 is considered as eyelash and the pixel value greater than 240 is considered as reflection. The top and bottom eyelid is isolated by canny edge detection method and Radon Transform (Aydi *et al.*, 2013).

3.2.4 Iris Normalization

In order to form the rectangular iris image of fixed size to overcome the iris inconsistencies due to pupil dilation, scale variance, rotation variance etc., Daugman's Rubber Sheet Model has been applied on the segmented iris image. The Rubber Sheet Model is a linear model that transformed each point within the segmented iris to the polar co-ordinates (r, θ). where, r is on the interval [0, 1] and θ is an angle in [0, 2π] using Equation (3.2) .

$$\begin{aligned} x &= x_c + r \times cos\theta \\ y &= y_c + r \times sin\theta \end{aligned} \tag{3.2}$$

where, (x_c, y_c) denotes coordinates of centre of the iris, (x, y) denotes coordinates of the points between pupil and iris boundaries in the direction θ. This process is illustrated in Figure 3.3. In the present work, segmented iris images are transformed into images of size 24×240.

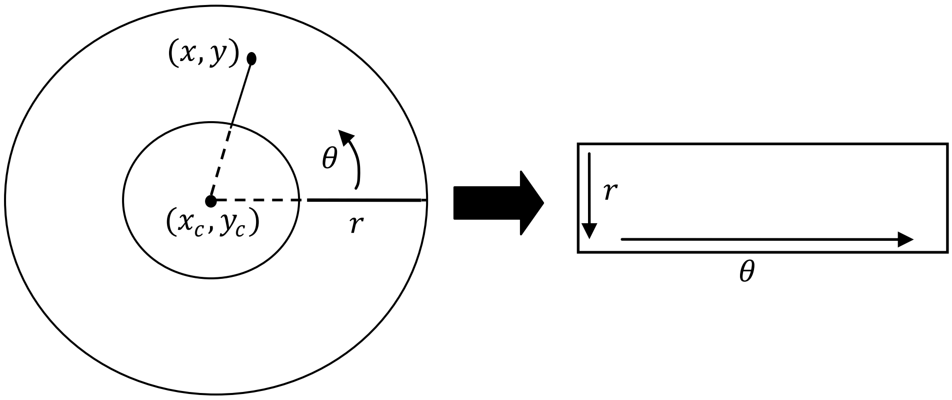

Figure 3.3 Iris Normalization using Rubber Sheet Model

Figure 3.4 shows the sample five eye images of CASIA Iris Interval v3 database and outputs at key stages of the proposed segmentation approach.

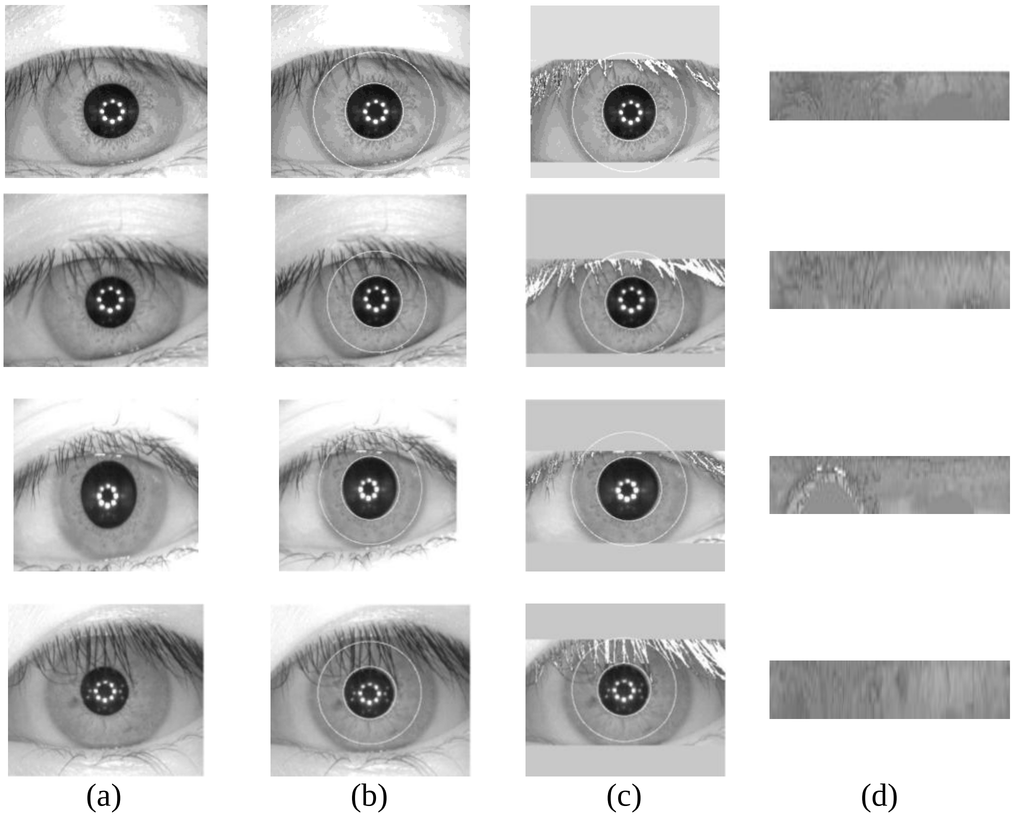

Figure 3.4 (a) Original eye image (b) Segmented iris (c) Image after removal of eyelids and eyelashes (d) Normalized Iris

3.3 Iris Segmentation

This section presents the experimental setup and experimental results of proposed iris segmentation approach over CASIA iris Interval v3 database.

3.3.1 Experimental Setup

CASIA Iris Interval v3 database (Biometrics Ideal, 2014) obtained from public domain digital repository is employed here to evaluate the performance of the proposed iris segmentation approach. This database consists of 2655 images from 249 persons. Each image is an 8 bit gray level value of resolution 320*280. Total 200 images of left eye of 40 persons are taken for the experimentation. The experiments were implemented in MATLAB 7.12.0 and executed on Intel Core i3 2.4 GHz with 3 GB RAM. Discrete Cosine Transform (DCT) (Sarhan *et al.*, 2009) is employed to extract features from the normalized iris and the extracted features are classified by using feed forward neural network in order to evaluate the performance of proposed segmentation approach on iris classification accuracy. The segmentation time, accuracy and Receiver Operating Characteristic (ROC) are used for performance assessment of the proposed segmentation approach. In order to verify the acceptance of the proposed approach, existing iris segmentation algorithms *viz.* Daugman's (1993), Masek's (2003) and Abdullah *et al.*, (2014) have been implemented and the results are compared with the proposed iris segmentation approach.

3.3.2 Experimental Results

The running time of iris segmentation of 200 iris images from CASIA v3 interval iris dataset is measured and is shown in Figure 3.5. To validate the results obtained by the proposed segmentation approach over CASIA Iris v3 interval iris dataset, Daugman's (1993) segmentation approach, Masek's (2003) segmentation approach and Abdullah's segmentation approach (Abdullah *et al.*, 2014) are implemented, and results are compared with the proposed approach as shown in Table 3.1.

From Table 3.1 it is observed that the proposed segmentation approach is efficient compare to other three approaches *viz.* Daugman (1993), Masek (2003) and Abdullah *et al.* (2014) with respect to the running time for iris segmentation.

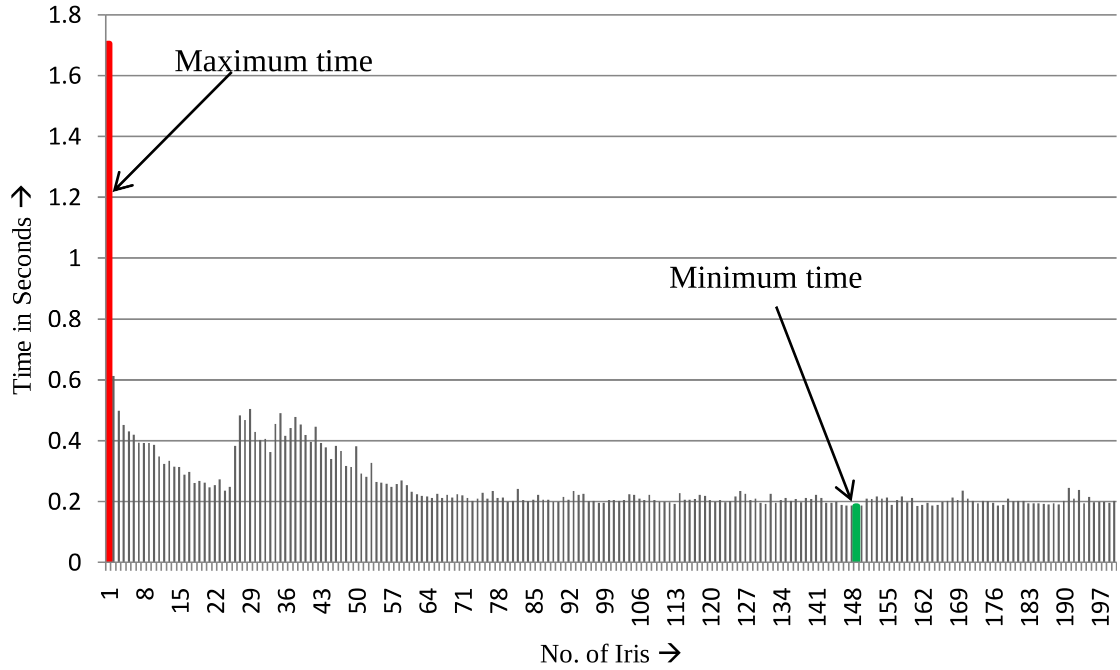

Figure 3.5 Running time for iris segmentation by the proposed approach

Table 3.1 Iris Segmentation results over CASIA v3 Interval dataset

Method	**Technique**	**Running time of iris segmentation**		
		Min. time (Sec.)	**Max time (Sec.)**	**Avg. time (Sec.)**
Daugman, 1993	IDO is used to detect iris inner and outer boundary.	10.45	61.10	27.70
Masek, 2003	Modified Canny edge detection method and CHT is used to detect inner and outer boundary. Isolation of top and bottom eyelids using HT. Linear thresholding techniques to isolate reflection end eyelashes.	7.28	37.94	19.47
Abdullah *et al.*, 2014	Combination of morphological operations and Chan-Vese active contour model is used for iris segmentation.	12.41	13.04	12.40
Proposed iris segmentation approach	Pupil localization by simple morphological operations with the use of AHE and median filtering technique. Eyelashes and reflections are removed by linear thresholding. Top and bottom eyelid is isolated using canny and radon transform	**0.18**	**1.70**	**0.26**

In order to evaluate the performance of the proposed segmentation approach on iris classification accuracy over existing approaches, the extracted DCT features from segmented iris are classified by using feed forward neural network. The network architecture and optimal network design parameters are shown in Figure 3.6 and Table 3.2 respectively.

In Figure 3.6, $x_i, i = 1,2, \ldots m$ represents network input, $k_i, i = 1,2, \ldots z$ denotes hidden neuron, $y_i, i = 1,2, \ldots n$, represents i^{th} class of the network. Based on the confusion matrix, the image classification accuracy of the segmented iris images obtained by the neural network with varying hidden layer neuron is shown in Table 3.3. The accuracy is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where, *TP* stands for True Positive, *TN* stands for True Negative, *FP* stands for False Positive and *FN* stands for False Negative respectively.

To compare the performance, ROC curves of the proposed approach, Daugman's approach, Masek's approach and Abdullah *et al.* approach over the CASIA Iris v3 interval iris dataset are plotted as shown in Figure 3.7. From the experimental results, it is observed that the image classification accuracy for the input iris images by the proposed approach is maximum (98.5 %) compared to other three existing approaches for the considered dataset.

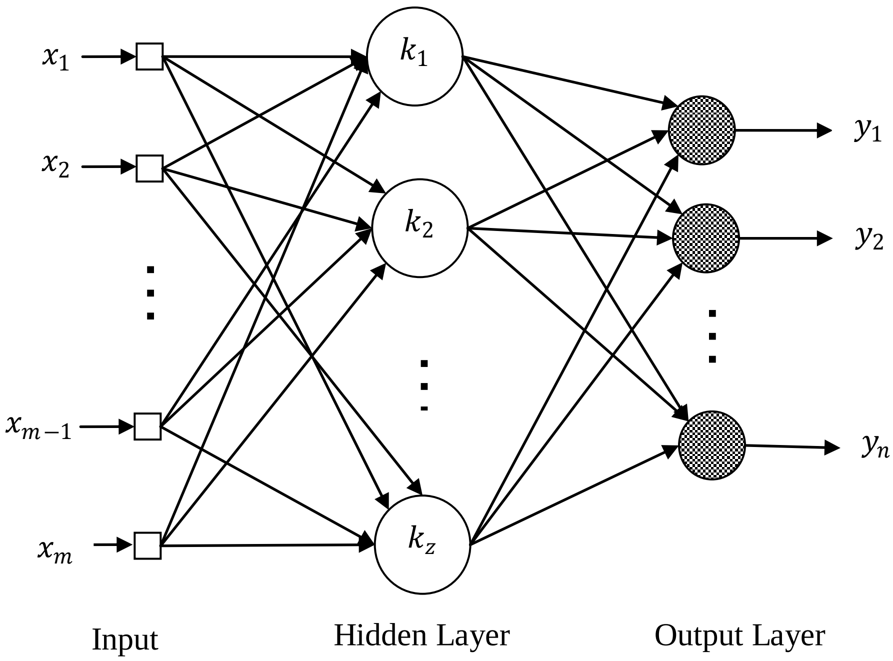

Figure 3.6 Network architecture

Table 3.2 Optimal network design parameters

Training function	:	'*traingda*'
Transfer function	:	'*tansig*' for hidden layer '*purelin*' for output layer
Initial learning rate	:	0.3
Epochs	:	5000
Error goal	:	0.0001
Minimum gradient	:	0.0001

Table 3.3 Neural network iris classification accuracy

Segmentation Method	**No. of Neurons**	**Accuracy in %**
Daugman, 1993	10	48.50
	15	83.00
	20	90.30
	25	90.33
	30	95.75
	35	95.50
	40	94.53
Masek, 2003	10	46.60
	15	67.33
	20	84.66
	25	85.50
	30	94.57
	35	94.50
	40	93.00
Abdullah *et al*, 2014	10	48.76
	15	76.54
	20	92.59
	25	95.57
	30	96.91
	35	96.00
	40	93.53
Proposed Approach	10	45.85
	15	66.67
	20	83.23
	25	94.83
	30	**98.50**
	35	98.50
	40	93.57

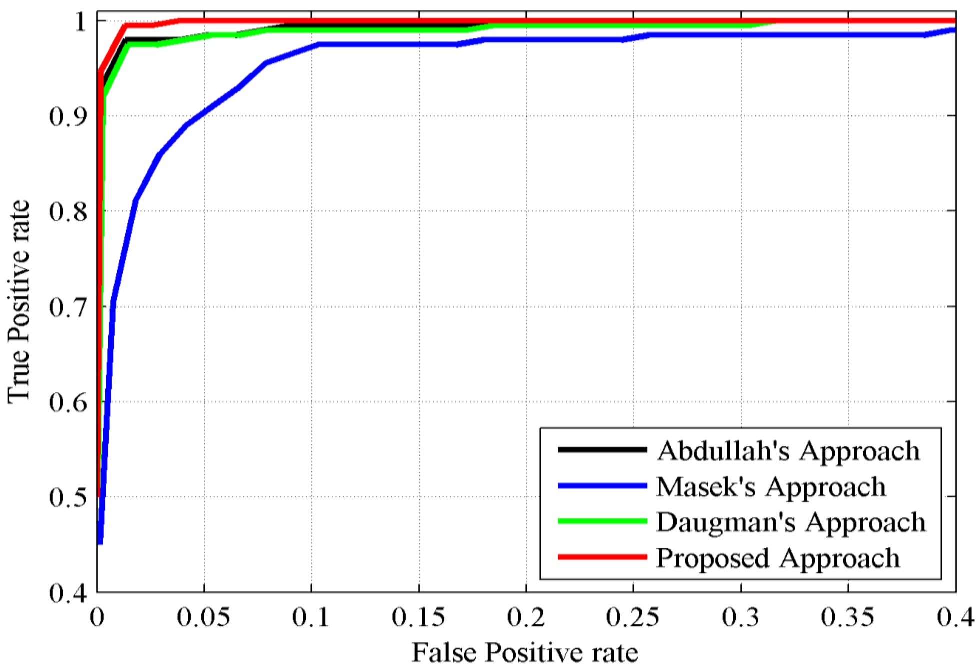

Figure 3.7 ROC curve of the proposed approach, Daugman's approach, Masek's approach and Abdullah *et al.* approach over the CASIA Iris v3 interval iris dataset

From the image classification output of the ANN in Table 3.3 and the ROC plot in Figure 3.7 it is observed that the proposed approach outperforms Daugman's approach, Masek's approach and Abdullah's approach in terms of image classification accuracy. This is achieved due to efficient iris segmentation of the input iris image. Therefore, it can be concluded that the proposed approach for iris segmentation is more efficient compared to existing approaches over the considered datasets.

With regard to the time complexity, the Daugman's IDO approach has the time $(X.Y.R)$. At every pixel level x ($x \in [0;X]$) and y ($y \in [0;Y]$), the operator requires R scan to compute circle parameters (Daugman, 2003). Masek (2003) has adopted Circular Hough Transform (CHT) for the detection of iris boundaries. The CHT is performed on three-dimensional space of circle parameters (a,b,r) describing circles in two-dimensional space, where, (a,b) represents centre coordinates and r represents radius of the circle, respectively. Therefore, its time complexity is equals to $\mathrm{O}(n^3)$ (Sahmoud *et al.*, 2013). The time complexity of Chan-Vese active contour model adopted by Abdullah *et al.* (2014) for iris segmentation is $\mathrm{O}(M.N)$ for each iteration, where $M \times N$ is the size of the image. The time complexity of proposed segmentation approach is $\mathrm{O}(n)$, where n is number of pixel with value 1 in horizontal and vertical direction from centroid $\mathrm{O}(C_x, C_y)$. Although there is some loss of iris information, the proposed approach is a fast segmentation approach which outperforms some of the existing approaches.

3.4 Chapter Summary

An iris segmentation approach based on Adaptive histogram equalization and median filtering technique is presented in this chapter. The Adaptive histogram equalization is used to enhance the iris image. Simple morphological operations and two dimensional median filtering techniques are used to detect the iris. The Radon transform with canny edge detection method is applied to isolate upper and lower eyelids. The noises such as eyelashes and reflections are removed through the linear thresholding. Segmented iris patterns are then classified using ANN. From the experimental results, it is observed that the image classification accuracy for segmented iris images obtained by the proposed approach based on Adaptive Histogram Equalization and median filtering is maximum compared to some of the existing approaches *viz.* Daugman (1993), Masek (2003) and Abdullah *et al.* (2014) over the considered dataset. It is also observed that proposed approach takes reasonable amount of time to perform iris segmentation.

The computation of algorithmic parameters such as threshold values for image binarization in the iris recognition system is usually based on fixed values. In order to improve the performance of the iris recognition system, Quantum-behaved Particle Swarm Optimization (QPSO) based approach for accurate iris segmentation has been developed and presented in the next chapter. A hybrid recognition algorithm for iris recognition is also presented in the next chapter.