Chapter 6

Iris Recognition using Modular Neural Network and Fuzzy Inference based Score Level Fusion

In chapter 5, Modular Neural Network match score fusion strategy has been presented for iris image recognition. In this chapter a hybrid approach based on Modular Neural Network and Fuzzy Inference System is presented to further improve the recognition performance by reducing False Acceptance Rate (FAR) and False Rejection Rate (FRR). Modular Neural Networks have been used as a recognizer whose outputs are fused together with the fuzzy inference system to determine the actual class (identity) of a query iris image. Experimental results demonstrate the effectiveness of the proposed approach.

6.1 Introduction

To deal with the secure and precise recognition of a person in today's technological world, the recognition system based on physiological and behavioral characteristics are used in different application domains such as healthcare, citizen registration, passport, border control, access control etc. (Farmanullah *et al.*, 2016). Banking sector is also initiating to install the iris recognition system in the ATMs to replace the traditional PIN based verification during transaction (Lee, 2017).

As stated in chapter 2, typical iris recognition system consists of four steps *viz*. Image Acquisition, Segmentation, Feature Extraction and Recognition. Each of these steps plays a pivotal role in the recognition system. The system has two modules *viz.* enrolment and recognition module. During enrolment, iris image features are extracted and stored in the database as a reference. During recognition, features from query iris image is extracted and compared with features stored in the database (Daugman, 2004; Boles *et al.*, 1998).

The task of iris recognition system is to recognize an iris image precisely and accurately with less False Acceptance Rate (FAR) and False Rejection Rate (FRR). The iris, annular part between sclera and pupil, is segmented from rest of the eye image which may contain noises such as eyelashes, eyelids, reflections etc. These noises damage the texture information which in turn increases the FAR and FRR of the system. To deal with this, the idea of fusion strategy has been adopted by different authors. Rahulkar *et al.* (2012) proposed score level fusion strategy using *k*-out-of-*n*: A, a post classifier, to reduce the FRR of the recognition system. Park *et al.* (2007) used Hamming Distance and support vector machine to perform score level fusion. The authors Shin *et al.* (2012), Santos *et al.* (2012) presented an iris recognition system based on score level fusion strategy in an unconstraint environment. Marsico *et al.* (2012) presented iris matching approach based on combination of LBP and discriminable textons (BLOBs), local features of an iris. The fusion strategy is also adopted by Eskandari *et al.*(2013), Islam(2014), Ganorkar *et al.* (2013) , Thul *et al.* (2016) and Madane *et al.* (2016), Mozumder *et al.* (2016) for accurate recognition of an iris image.

In the present work a combination of Modular Neural Network and Fuzzy Inference based Score Level Fusion is proposed to reduce the FAR and FRR of the iris recognition system. A modular neural network has been used as a recognizer whose outputs are fused together with the fuzzy inference system to determine the actual class (identity) of an iris image. The system consists of six modules of neural networks and the fuzzy inference system. During enrolment, iris image is divided into six segments and each Module is trained with their corresponding segment. During recognition, six segments of query iris image are fed into their corresponding trained module where each module responds with the class of the segments. These outputs go through the fuzzy inference process for final recognition. The proposed iris recognition approach using modular neural network and fuzzy inference based score level fusion is presented in the following sections.

6.2 Iris Recognition Approach with Modular Neural Network and Fuzzy Inference based Score Level Fusion

In the present work, fuzzy inference system is incorporated into the output of modular neural network for recognition of an iris image. This section begins with a brief introduction to fuzzy inference system followed by a description of segmentation and feature extraction stages of iris recognition system adopted in the present work.

6.2.1 Fuzzy Inference System

A fuzzy inference system is a system that uses fuzzy set theory to map inputs (features) to outputs (classes). It has been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision. Because of its multidisciplinary nature, fuzzy inference systems are associated with a number of names, such as fuzzy-rule-based systems, fuzzy expert systems, fuzzy modeling, fuzzy associative memory, fuzzy logic controllers and simple fuzzy systems.

Fuzzy inference systems have been used in a number of systems to introduce intelligence behavior. In fuzzy inference system process, there are four major steps, which include fuzzification of the input variables, rule evaluation, aggregation of the rule outputs, and finally defuzzification (Fuzzy Toolbox, 1999).

6.2.2 Segmentation and Feature Extraction

Segmentation means the isolation of an iris part from the rest of the eye image. It is one of the vital steps for iris recognition system which may affect the overall performance of the system. The more accurate the segmentation better will be the recognition performance. Due to inconsistencies of size of the iris image, normalization is done to make the iris image size uniform for better recognition accuracy. This section mainly focuses on the recognition step of the system. The iris segmentation is based on

Quantum-behaved Particle Swarm Optimization (QPSO) as explained in section 4.2 of chapter 4. The normalization is performed by using Daugman's rubber sheet model as described in section 3.2 of chapter 3. The sample of segmented and normalized iris images from IIT Delhi iris dataset (IITD Iris Database, 2008) is shown in Figure 6.1.

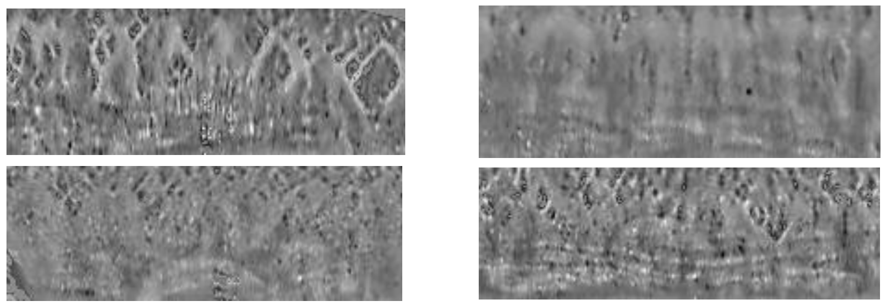


Figure 6.1 Sample segmented and normalized iris image from IIT Delhi database

For a set of *N* classes with *n* iris images per class, DCT features are extracted from each of the iris images according to the algorithm 5.1 as described in section 5.4 of chapter 5.

Let

$$F_i = [f_{i1}, \dots, f_{ij}, \dots, f_{in}] \tag{6.1}$$

be an $N \times n$ DCT feature matrix of i^{th} class where, f_{ij} denotes the features of j^{th} iris image of i^{th} class. The reference vector, F, of all training iris images are defined as the concatenation of $F_i, i = 1, 2, \dots, n$ by equation (6.2):

$$\begin{aligned} F &= [F_1, F_2, \dots, F_N] \\ &= [f_{11}, \dots, f_{ij}, \dots, f_{in} | f_{21}, \dots, f_{2j}, \dots, f_{2n} | \dots | f_{N1}, \dots, f_{Nj}, \dots, f_{Nn}] \end{aligned} \tag{6.2}$$

This reference vector, F, is used to train the modular neural networks.

6.2.3 Proposed Iris Recognition Approach with Modular Neural Network and Fuzzy Inference based Score Level Fusion

The proposed hybrid recognition approach based on Modular Neural Network and fuzzy inference system is shown in Figure 6.2. Each iris image is divided into six segments. The DCT features are extracted from each segment and reference vector, F, is constructed as described in section 6.2.2. The system consists of six modules and the fuzzy inference system. Each ANN module is trained with their corresponding segment features. More details about training can be found in section 5.4 of chapter 5.

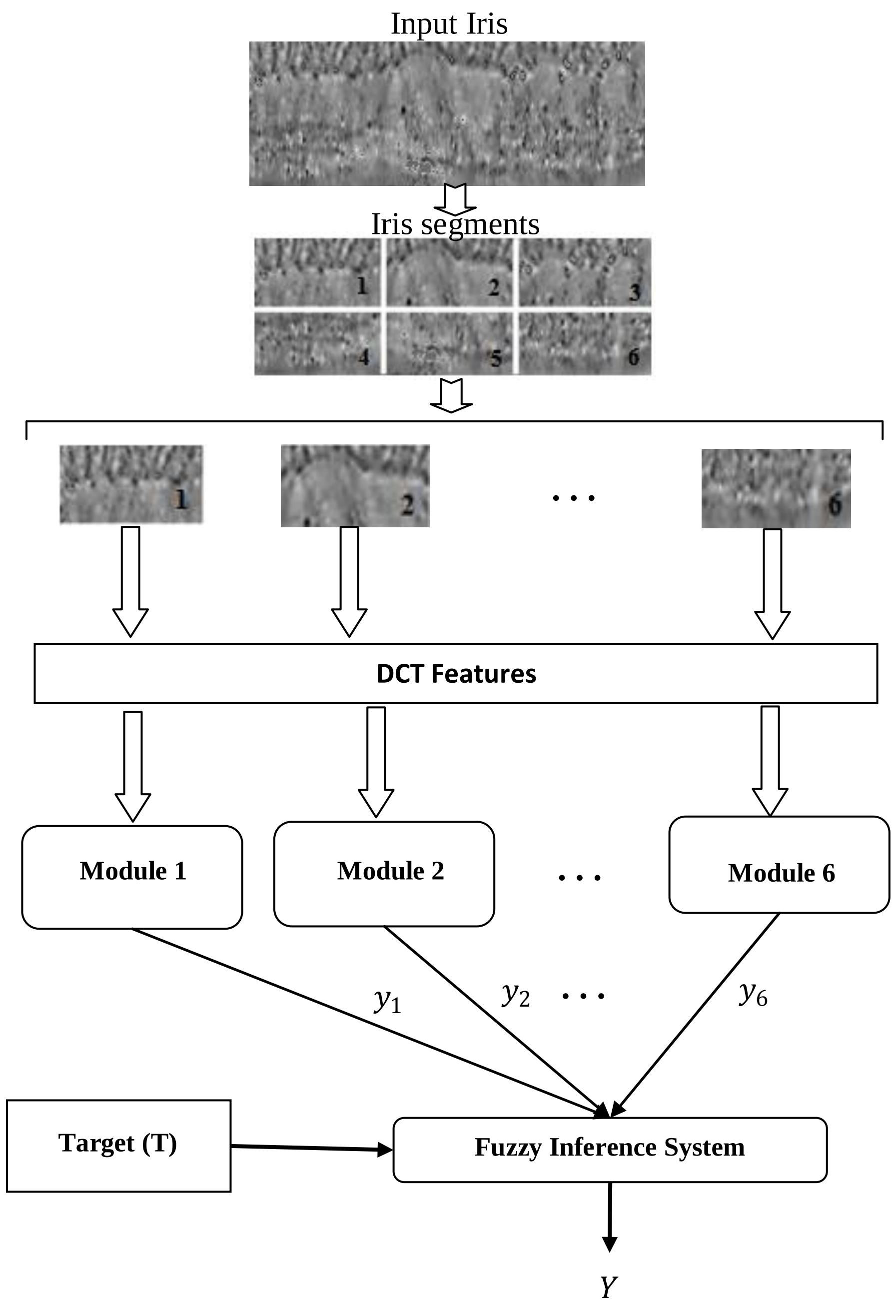


Figure 6.2 Proposed recognition approach

During iris recognition, DCT features of each segment of a query iris image are presented into the corresponding trained modules for recognition. Each module responds with the class, y_i, of the segment. These outputs are fed into the fuzzy inference system along with the target vectors.

Firstly, Fuzzy inference system, defines a fuzzy set, Y, in T on the output of each module y by equation (6.3) (Zimmermann, 1996):

$$Y = \{(y, \mu_Y(y)) | y \in T\} \tag{6.3}$$

where, T is the universal set of vectors representing the classes of iris image stored as a reference and $\mu_Y(y)$ is the membership value of Y defined by equation (6.4):

$$\mu_Y(y) = \begin{cases} 0, & 0 \le s \le a \\ 2 \times \left(\frac{s-a}{1-a}\right)^2, & a \le s \le \frac{a+1}{2} \\ 1 - 2 \times \left(\frac{s-1}{1-a}\right)^2, & \frac{a+1}{2} < s \le 1 \end{cases} \tag{6.4}$$

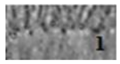
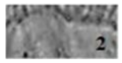
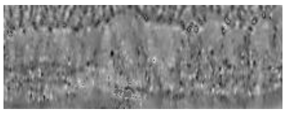
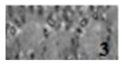
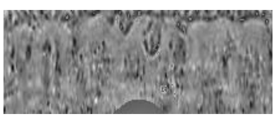
where, a denotes threshold value and s denotes the similarity rate calculated by equation (6.5):

$$s = 1 - \sqrt{(y-t)^2} \tag{6.5}$$

where, t represents the target. Next, the inference system chooses the output of modules having membership value, μ_Y, greater than zero and discards the rest. Finally, voting operation is performed among the selected output for final recognition of an iris image. The example of iris image recognition procedure over IIT Delhi iris dataset is shown in Table 6.1.

With incorporation of fuzzy inference system, any noisy or misclassified segment can be discarded, before the score fusion, using membership value μ_Y as because these segments most probably will have the membership value zero. As a result of which recognition performance of the system improves considerably. This approach is also capable of rejecting the imposters more accurately as it reveals in the experimental result.

Table 6.1 Example of iris image recognition procedure over IIT Delhi dataset

Query Image	Segments	Output (y)	Membership value, μ_y	Selected Output	Recognized class
		1	0.25	√	
		1	0.71	√	
		1	0.41	√	**1**
(class 1)		1	0	×	
		1	0.13	√	
		1	0.54	√	
		36	0	×	
		14	0	×	
		17	0	×	Rejected
(Imposter)		1	0	×	
		25	0	×	
		22	0	×	

6.3 Experimental Results

The experiments were performed on Windows 7 environment with Intel i3 processor (2.4 GHz) and 3 GB RAM by using MATLAB 7.0 software. The proposed recognition approach was evaluated on IIT Delhi iris dataset and MMU2 iris dataset. The left eye of each person is selected for experimentation and the images considered for experiments from the IIT Delhi database and MMU2 iris database (2010) for a different purpose during experiments are tabulated in Table 6.2.

Table 6.2 Division of IIT Delhi iris dataset and MMU2 iris dataset

Dataset	Purpose	No. of Sample	No. of image/sample	Total
IIT Delhi Iris Dataset	Training	90	4	360
	Testing	90	1	90
	Imposter	50	3	150
MMU2 Iris Dataset	Training	70	4	280
	Testing	70	1	70
	Imposter	30	3	90

The architecture of the module used for iris image recognition consists of five small Multi-Layer Perceptron (MLP) neural networks. Each MLP consists of input, hidden and output layer with 50, 24 and 1 neurons, respectively. The optimal parameters of MLP are tabulated in Table 6.3. The average training and validation performance of the MLPs are presented in Table 6.4 and Figure 6.3.

Table 6.3 Optimal parameters of MLP

Training Function	*'trainrp'*
Transfer function	'*tansig'* for first layer *'purelin'* for second layer
Learning rate	0.30
Epochs	2000
Error Goal	0.0001
Minimum gradient	0.0001

Table 6.4 Network training performance

No. of Hidden neuron	MAE	RMSE	Accuracy
21	0.0535	0.0085	88.68
22	0.0635	0.0087	89.73
23	0.0455	0.0086	98.68
24	**0.0580**	**0.0055**	**100**
25	0.1205	0.03267	100
26	0.0657	0.0122	94.73
27	0.0552	0.0108	98.68
28	0.0756	0.0139	88.15
29	0.0364	0.0055	95.73
30	0.0643	0.01396	97.36

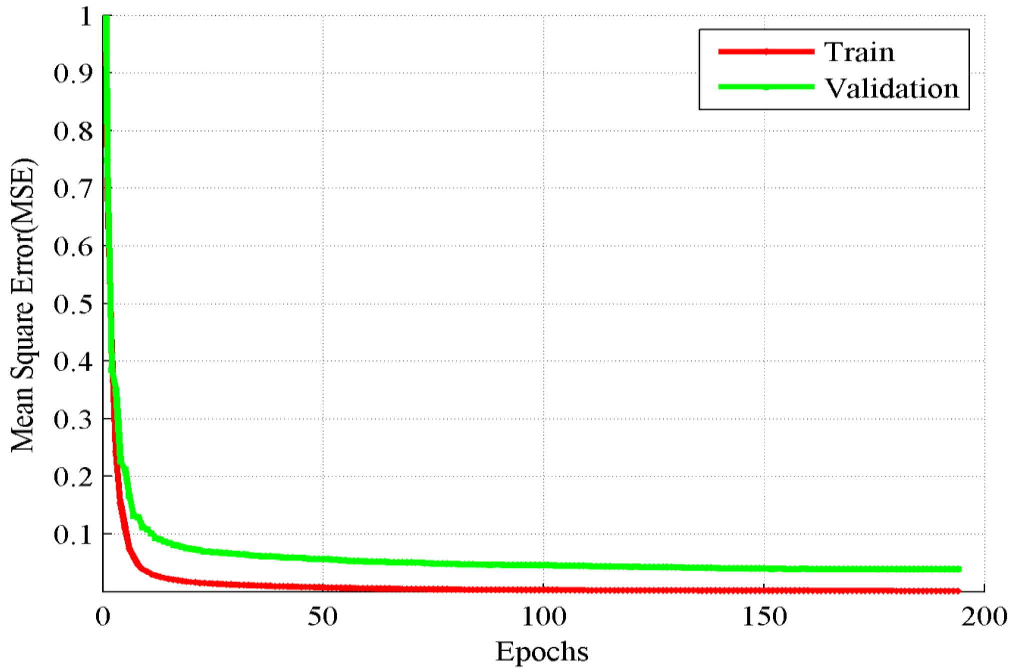


Figure 6.3 Network training and validation performance

The recognition of an iris image is done with the help of trained modules and fuzzy inference system as explained in section 6.2.3. The FAR, FRR, Recognition Accuracy and running time are used as performance measures of the proposed hybrid iris image recognition approach based on Modular Neural Network and fuzzy inference system. The threshold value, *a*, for class separation is determined from FAR and FRR of the system. To evaluate the proposed recognition approach, its performance is compared with the different recognition approaches *viz.* Masek (2003), Rai *et al.* (2014), and Pirale *et al.* (2016). The recognition performances is evaluated in both verification and identification mode. The False Acceptance Rate (FAR), False Rejection Rate (FRR) and accuracy are calculated by equation (6.6), (6.7) and (6.8), respectively (Bodade *et al.*, 2014).

$$FAR = \frac{No.\,of\ times\ imposter\ accepted}{Total\ no.\,of\ comparison} \tag{6.6}$$

$$FRR = \frac{No.of\ times\ pretender\ rejected}{Total\ no.of\ comparison} \tag{6.7}$$

$$Accuracy = \left(1 - \frac{FAR + FRR}{2}\right) \times 100 \tag{6.8}$$

The FAR and FRR at different threshold values over is shown in Figure 6.4 and can be concluded that threshold value, a, equal to 0.84 is suitable to be chosen as a threshold between intra-class and inter-class.

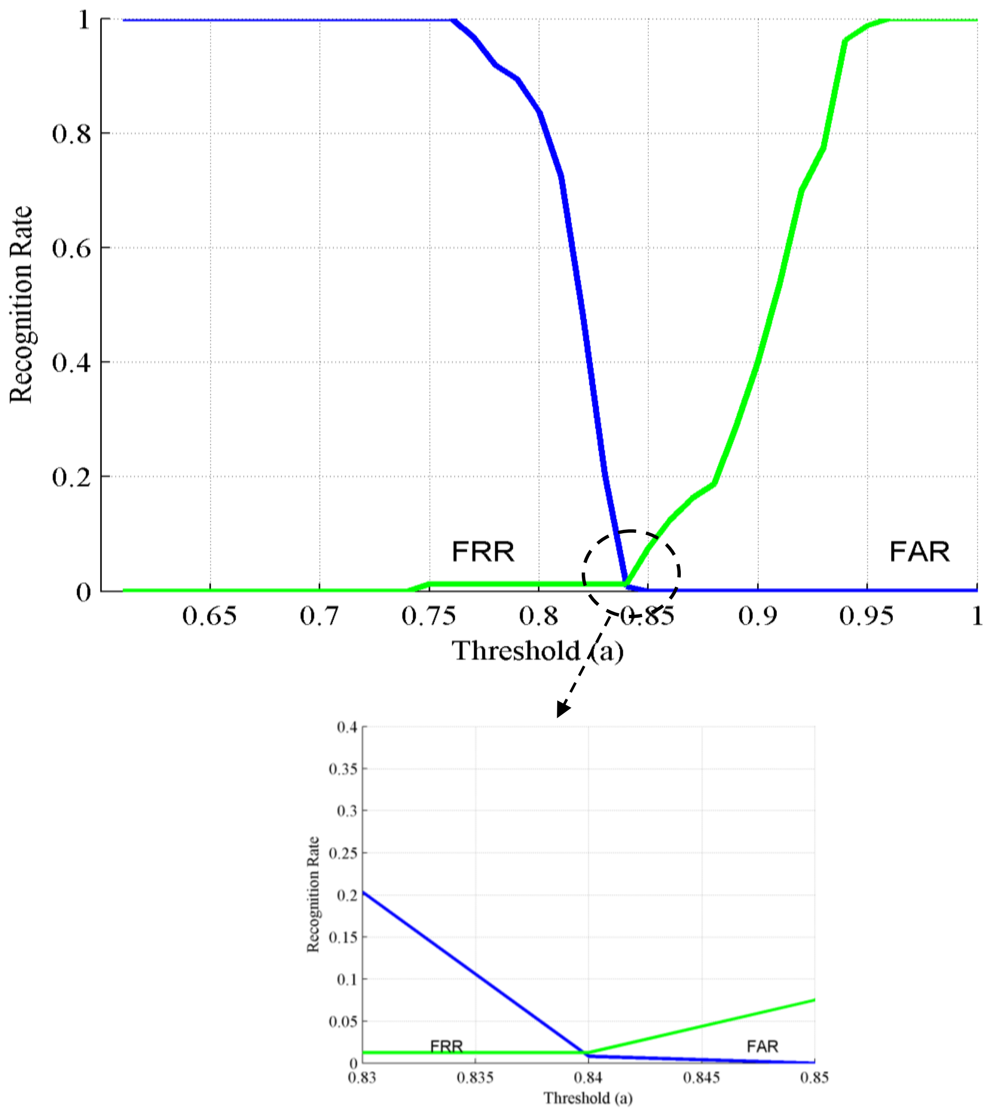


Figure 6.4 FAR and FRR at different threshold value, a

6.3.1 Verification Performance

During verification, system tries to match query iris image with specific iris template from the database (one-to-one comparison). The proposed hybrid iris recognition approach based on Modular Neural Network and fuzzy inference system achieves 99.07% and 98.73% of verification accuracy with FAR equals to 0.0081and 0.0111 on the considered IIT Delhi iris dataset and MMU2 dataset, respectively. The recognition performance on verification mode with different value of $'a'$ is presented in Table 6.5 and Table 6.6 over IIT Delhi iris dataset and MMU2 iris dataset respectively.

Table 6.5 Recognition performance on verification mode over IIT Delhi dataset

Threshold (a)	FAR	FRR	Accuracy (%)
0.81	0.1463	0.0105	92.1566
0.82	0.0894	0.0105	95.0021
0.83	0.0243	0.0105	98.2541
0.84	**0.0081**	**0.0105**	**99.0671**
0.85	0.0000	0.0526	97.3684
0.86	0.0000	0.1052	94.7368
0.87	0.0000	0.1368	93.1578
0.88	0.0000	0.1578	92.1052
0.89	0.0000	0.2315	88.4210
0.9	0.0000	0.3263	83.6842

Table 6.6 Recognition performance on verification mode over MMU2 dataset

Threshold (a)	FAR	FRR	Accuracy (%)
0.55	0.1222	0.0142	93.18
0.56	0.1111	0.0142	93.73
0.57	0.0555	0.0142	96.51
0.58	**0.0111**	**0.0142**	**98.73**
0.59	0.0111	0.0285	98.02
0.60	0.0111	0.0285	98.02
0.61	0	0.0571	97.14
0.62	0	0.0714	96.43
0.63	0	0.0857	95.71
0.64	0	0.1000	95.00

6.3.2 Identification Performance

During Identification, the system tries to find query iris image from entire iris templates stored in the database as references (one-to-many comparison). The proposed hybrid iris recognition approach based on Modular Neural Network and fuzzy inference system achieves the identification accuracy of 98.96% and 98.18% with FAR equals to 0.0081 and 0.0111 on the considered IIT Delhi iris dataset and MMU2 iris dataset, respectively. The recognition performance on identification mode of the proposed approach with different values of $'a'$ over considered IIT Delhi iris dataset and MMU2 iris dataset are presented in Table 6.7 and Table 6.8, respectively.

Table 6.7 Recognition performance on identification mode over IIT Delhi iris dataset

Threshold (a)	FAR	FRR	Accuracy (%)
0.81	0.7235	0.0125	63.19
0.82	0.4796	0.0125	75.39
0.83	0.2032	0.0125	89.21
0.84	**0.0081**	**0.0125**	**98.96**
0.85	0.0000	0.0750	96.25
0.86	0.0000	0.1250	93.75
0.87	0.0000	0.1625	91.87
0.88	0.0000	0.1875	90.62
0.89	0.0000	0.2875	85.62
0.9	0.0000	0.4000	80.00

Table 6.8 Recognition performance on identification mode over MMU2 iris dataset

Threshold (a)	FAR	FRR	Accuracy (%)
0.55	0.2111	0.0142	88.73
0.56	0.1222	0.0142	93.18
0.57	0.0666	0.0142	95.96
0.58	**0.0222**	**0.0142**	**98.18**
0.59	0.0111	0.0571	96.59
0.60	0.0111	0.0571	96.59
0.61	0	0.0571	97.14
0.62	0	0.1142	94.29
0.63	0	0.1142	94.29
0.64	0	0.1285	93.57

6.3.3 A Comparative Study

In order to evaluate the proposed hybrid iris image recognition approach based on Modular Neural Network and Fuzzy Inference System, the performance of the proposed approach is compared with the performances of the different approaches *viz.*

Masek (2003), Rai *et al.* (2014) and Pirale *et al.* (2016). The comparison result with respect to recognition accuracy during verification and identification and the running time of the proposed hybrid approach, Masek (2003), Rai *et al.* (2014) and Pirale *et al.* (2016) approaches over the IIT Delhi iris dataset and the MMU2 iris dataset are presented in Table 6.9 and in Table 6.10, respectively.

Table 6.9 Comparison of result of the proposed hybrid approach, Masek (2003), Rai *et al.* (2014) and Pirale *et al.* (2016) approaches over the IIT Delhi iris dataset

Method	**Recognition Accuracy**		**Running time (approx.)**	
	Verification (%)	**Identification (%)**	**Verification (Sec.)**	**Identification (Sec.)**
Masek (2003)	98.67	98.10	0.11	13.80
Rai *et al.*(2014)	95.85	92.68	0.13	11.20
Pirale *et al.* (2016)	93.57	91.57	2.45	2.89
Proposed Recognition Approach	**99.06**	**98.96**	**0.69**	**2.46**

Table 6.10 Comparison of result of the proposed hybrid approach, Masek (2003), Rai *et al.* (2014) and Pirale *et al.* (2016) approaches over the MMU2 iris dataset

Method	**Recognition Accuracy**		**Running time (approx.)**	
	Verification (%)	**Identification (%)**	**Verification (Sec.)**	**Identification (Sec.)**
Masek (2003)	97.34	97.10	0.11	11.81
Rai *et al.*(2014)	94.85	91.67	0.13	8.20
Pirale *et al.* (2016)	92.57	89.87	1.45	1.89
Proposed Recognition Approach	**98.73**	**98.18**	**0.65**	**1.79**

In Table 6.9 the verification and identification accuracies obtained by the proposed recognition approach over IID Delhi iris dataset are 99.06% and 98.96%. Similarly, in Table 6.10 the verification and identification accuracies over MMU2 iris dataset are 98.73% and 98.18%, which are higher than some of the existing approaches *viz.* Masek (2003), Rai *et al.* (2014) and Pirale *et al.* (2016). With respect to the running time during verification and identification, as seen from the Table 6.9 and Table 6.10, the proposed recognition approach outperforms Masek (2003), Rai *et al.* (2014) and Pirale *et al.* (2016) approaches over the considered IIT Delhi iris dataset and MMU2 iris dataset.

The time complexity of modular neural network during testing is $\mathrm{O}(k.m.w)$, where k represents number of modules, m represents size of input pattern and w represents size of weight vector. The complexity of fuzzy inference system is $\mathrm{O}(m)$. Therefore, total time complexity is equal to $\mathrm{O}(k.m.w)$. Time complexity of Masek *et al.* (2003) approach of iris recognition is $\mathrm{O}(mn)$ where $m \times n$ represents the size of iris templates. Rai *et al.* (2014) performed recognition using SVM and hamming distance. The time complexity of SVM is $\mathrm{O}(n^3)$. The time complexity of the proposed approach $\mathrm{O}(k.m.w)$ is similar to that of Pirale *et al.* (2016), but, due to modular approach of neural network recognition with small network size, proposed approach outperforms with respect to computational (running) time.

6.4 Chapter Summary

In this chapter, fuzzy inference system is used as a fusion strategy during iris image recognition. A set of modular neural networks are used as a classifier whose outputs are processed by fuzzy inference system for accurate recognition of an iris image. The standard IIT Delhi iris dataset and MMU2 Iris dataset has been used to evaluate the proposed recognition approach. The proposed approach achieved 99.06% and 98.86% accuracy during iris image verification and identification respectively over the IIT Delhi iris dataset and 98.96% and 98.18% accuracy during iris image verification and identification respectively over the MMU2 iris dataset. The proposed iris recognition approach outperforms some of the existing approaches *viz.* Masek (2003), Rai *et al.* (2014) and Pirale *et al.* (2016) in terms of recognition accuracy and the running time. The experimental results demonstrate the efficiency of the proposed hybrid iris recognition approach based on Modular Neural Network and Fuzzy Inference System over the considered datasets.

In the next chapter, the overall summary of the investigation with future scope of work is presented.