Chapter 5
Interval Type-2 Fuzzy Integral Match Score Fusion

In the previous chapter, information fusion at match score level has been discussed. In this chapter, an interval type-2 fuzzy integral (IT2-FI) approach is proposed as a generalization of fuzzy integral to fuse match scores in multibiometrics. The performance of the proposed IT2-FI based match scores fusion method is compared with four existing fusion methods *viz*. sum, product, max and fuzzy integral (type-1 FI). The evaluation processes are carried out on two multibiometric types *viz.* Multi-classifier biometric system and Multimodal biometric system. Experimental results demonstrate the effectiveness of IT2-FI in match score fusion.

5.1 Introduction

Fuzzy logic has been employed in the designing of intelligent systems for decision making, identification and pattern recognition. In multibiometric systems, information from difference sources is combined to make decision and the match scores are the most enrich and efficient biometric sources. The match scores from different sources can be characterized by its fuzzyness and can be aggregated based on the fuzzy measure. Within aggregation operators, fuzzy integrals are known to be one of the most powerful and flexible functions as they permit the aggregation of information under different assumptions on the independence of the information sources (Kuncheva, 2004). A brief introduction to fuzzy integral based match score fusion is presented in the next section.

5.2 Fuzzy Integral Match Score Fusion

Fuzzy integral (FI) introduced by Sugeno (Cho and Kim, 1995) is a good competitor of classifier combiners. In fuzzy integral, the expected worth of subset of classifiers called

fuzzy measures (like weight) are measured and each measure expresses how much each subset of experts supports to an input evidence. In literature, there are many types of fuzzy integral. Sugeno fuzzy integral and the Choquet fuzzy integral are the most popular types among them (Kuncheva, 2004). Sugeno fuzzy integral is used in the present work.

5.2.1 Fuzzy Measure (Kuncheva, 2004)

Fuzzy measure (μ) is defined by the function μ: $P(X) \rightarrow [0, 1]$ satisfying the conditions in Equations (5.1) and (5.2).

$$\mu(\emptyset) = 0, \ \mu(X) = 1 \tag{5.1}$$

$$\mu(A) \leq \mu(B), \text{ if } A \subset B \text{ and } A, B \in P(X) \tag{5.2}$$

where, X is a finite set. $\mu(A)$ represents the importance or the power of coalition A for the fusion problem. Following this definition, λ-fuzzy measure is calculated using Equation (5.3).

$$\lambda + 1 = \prod_{i=1}^{L} (1 + \lambda \mu_i), \lambda > -1 \ \& \ \lambda \neq 0 \tag{5.3}$$

where, μ_i is the individual importance of classifier D_i , $i = 1, 2, \ldots , L$.

5.2.2 Fuzzy Integral (Kuncheva, 2004)

Fuzzy integral (Sugeno) $S(g_i)$ of a function g: $P(X) \rightarrow [0, 1]$ with respect to μ is defined by Equation (5.4).

$$S(g_i) = \max_{i=1}^{N} (\min(g(x_i), \mu(A_i)) \tag{5.4}$$

where, $g(x_i)$ is the indices to be permuted so the $0 \leq g(x_1) \leq \ldots \leq g(x_n) \leq 1$ and $A_i = \{ x_i, x_{i+1}, \ldots, x_N \}$, $A_1 = \emptyset$.

The Sugeno measure $\mu(A_i)$ can be calculated recursively from the fuzzy densities as given in Equation (5.5)

$$\mu(A_1) = \mu(x_1)$$

$$\mu(A_i) = \mu(x_i) + \mu(A_{i-1}) + \lambda \mu(x_i) \mu(A_{i-1}) \tag{5.5}$$

5.3 Proposed Interval Type-2 Fuzzy Integral Match Score Fusion Approach

The concept of type-2 fuzzy sets was introduced by Zadeh (Liang and Mendel, 2000) as an extension of the concept of an ordinary (i.e. type-1) fuzzy set. In type-2 fuzzy set, grades of membership are fuzzy (subsets of [0, 1]) and are known as the primary memberships. Corresponding to each primary membership, there is a secondary membership which defines the possibilities for the primary membership.

Definition 1: A type-2 fuzzy set $\tilde{A}$ in X is a fuzzy set whose membership grades are fuzzy. This implies that $\mu_{\tilde{A}}(x)$ is a fuzzy set in U for all x, i.e. $\mu_{\tilde{A}}: X \rightarrow \tilde{P}(U)$ where, $\tilde{P}(U)$ be the set of fuzzy sets in U (Greenfield and Chiclana, 2013). Then, $\tilde{A}$ is represented in Equation (5.6)

$$\mu(A_i) = \mu(x_i) + \mu(A_{i-1}) + \lambda\, \mu(x_i)\mu(A_{i-1}) \tag{5.6}$$

It follows that $\forall x \in X \;\; \exists J_x \subseteq U$ such that $\mu_{\tilde{A}}(x)$: $J_x \rightarrow U$ is given by Equation (5.7).

$$\mu_{\tilde{A}}(x) = \{(x, \mu_{\tilde{A}}(x)(u)) | \mu_{\tilde{A}}(x)(u) \in U \;\; \forall u \in J_x \in U \tag{5.7}$$

X is the primary domain and J_x the primary membership of x while U is known as the secondary domain and $\mu_{\tilde{A}}(x)$ the secondary membership of x.

Then, Equation (5.7) is rewritten as Equation (5.8)

$$\tilde{A} = \{(x, (u, \mu_{\tilde{A}}(x)(u))) | \mu_{\tilde{A}}(x)(u) \in U, \;\; \forall x \in X \Lambda \forall u \in J_x \subseteq U\} \tag{5.8}$$

An interval type-2 fuzzy set is a type-2 fuzzy set whose secondary membership grades (i.e. $\mu_{\tilde{A}}(x)$(u)) are all 1. In the interval case, Equation (5.8) is reduced to Equation (5.9).

$$\tilde{A} = \{(x, (u, 1)), \;\; \forall x \in X \Lambda \forall u \in J_x \subseteq U\} \tag{5.9}$$

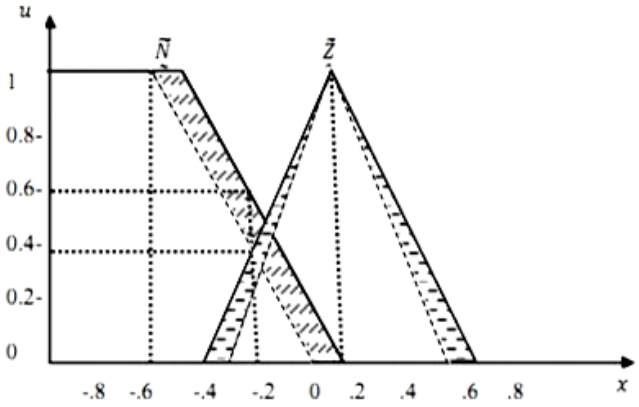
Definition 2: Footprint Of Uncertainty (FOU) is the projection of the type-2 fuzzy set onto the *x*-*u* plane that satisfies Equation (5.10).

$$FOU(\tilde{A}) = \bigcup_{x \in X} J_x \tag{5.10}$$

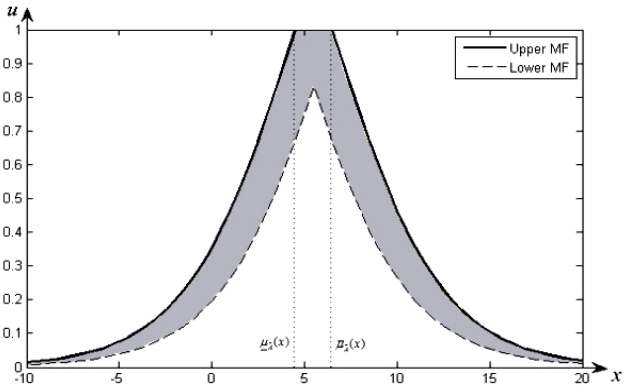
Definition 3: The Lower Membership Function (LMF) of a type-2 fuzzy set is the type-1 membership function associated with the lower bound of the FOU and is denoted by $\underline{\mu}_{\tilde{A}}(x)$.

Definition 4: The Upper Membership Function (UMF) of a type-2 fuzzy set is the type-1 membership function associated with the upper bound of the FOU and is denoted by $\bar{\mu}_{\tilde{A}}(x)$.

The shaded region in Figure 5.1 is the FOU. The solid line denotes upper MFs and the dashed line denotes lower MFs. The FOU is bounded by a lower membership $\underline{\mu}_{\tilde{A}}(x)$ and an upper membership $\bar{\mu}_{\tilde{A}}(x)$, both of which are T1 FSs, consequently, the membership grade of each element of an IT2 FS is an interval $[\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)]$.



(a)



(b)

Figure 5.1 (a) Two IT2 fuzzy sets (b) FOU (shaded area) of Logsig MFs with Uncertain Mean (the centres of Logsig MFs varies from 4.5 to 6.5)

In the present work, the evidences (i.e. scores) of classifiers are fuzzified into interval type-2 fuzzy and the uncertainty of the evidences as well as the fuzzy integral is handled correspondingly. In order to extend fuzzy integral to IT2-FI, the uncertainty is modeled by using interval type-2 fuzzy sets. The steps are shown in Figure 5.2 and the different steps are described in Algorithm 5.1.

Algorithm 5.1: IT2-FI

Input: Scores of *n* classifiers.

Output: Class representing maximum probability.

Step 1: The scores of i^{th} classifiers (i.e. evidences) are fuzzified into IT-2 Fuzzy by using the *logsig* function given by Equation (5.11).

$$f(x_i) = 2/(1+\exp(-(x_i-\bar{x})/\sigma)) \tag{5.11}$$

where, $\bar{x}$ is mean and σ is standard deviation.

Considering the case of *logsig* primary MF having a fixed standard deviation σ and an uncertain mean that takes on values in $[\bar{x}_l, \bar{x}_u]$, the upper MF $\bar{\mu}_{\tilde{A}}(x)$ is given by Equation (5.12).

$$\bar{\mu}_{\tilde{A}}(x) = \begin{cases} 2/(1+\exp(-(x_i-\bar{x}_l)/\sigma)), & x_i < \bar{x}_l \\ 1, & \bar{x}_l \le x_i \le \bar{x}_u \\ 2/(1+\exp(-(\bar{x}_u-x_i)/\sigma)), & \bar{x}_u < x_i \end{cases} \tag{5.12}$$

and the lower MF $\underline{\mu}_{\tilde{A}}(x)$ is given by Equation (5.13).

$$\underline{\mu}_{\tilde{A}}(x) = \begin{cases} 2/(1+\exp(-(x_i-\bar{x}_u)/\sigma)), & x_i \le (\bar{x}_l+\bar{x}_u)/2 \\ 2/(1+\exp(-(\bar{x}_l-x_i)/\sigma)), & x_i > (\bar{x}_l+\bar{x}_u)/2 \end{cases} \tag{5.13}$$

Step 2: The *max* and the *min* operator are replaced with the *interval join* and the *interval meet* operator respectively (Liang and Mendel, 2000). Consider a problem with each information source *i* in an interval $[\underline{g}(x_i), \bar{g}(x_i)]$ and corresponding fuzzy measures with an interval $[\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)]$, IT2-FI is computed by extending Equation (5.4) to Equation (5.14).

$$[S_L, S_U] = \underset{i=1}{\overset{N}{join}}(meet(\underline{g}(x_i), \bar{g}(x_i), [\underline{\mu}_{\tilde{A}}(x_i), \bar{\mu}_{\tilde{A}}(x_i)]) \tag{5.14}$$

In IT2-FI, the fuzzy lambda (λ) and fuzzy measures are to be computed for each extreme of the interval with the same manner of the fuzzy Integral by using Equation (5.5).

Step 3: The output of interval type-2 fuzzy integral is an interval of possible solutions. A final decision is made after type-reduction to type-1 Fuzzy Integral. For this purpose, the Nie-Tan type-reduction (Nie and Tan, 2008) method is employed in the present work. This method involves taking the mean of the lower and upper membership functions of the interval type-2 fuzzy set, so creating a type-1 fuzzy set as in Equation (5.15).

$$\mu_T(x_i) = \frac{1}{2}[\underline{\mu}_{\tilde{A}}(x_i) + \bar{\mu}_{\tilde{A}}(x_i)] \tag{5.15}$$

where, *T* is the resultant type-1 fuzzy set.

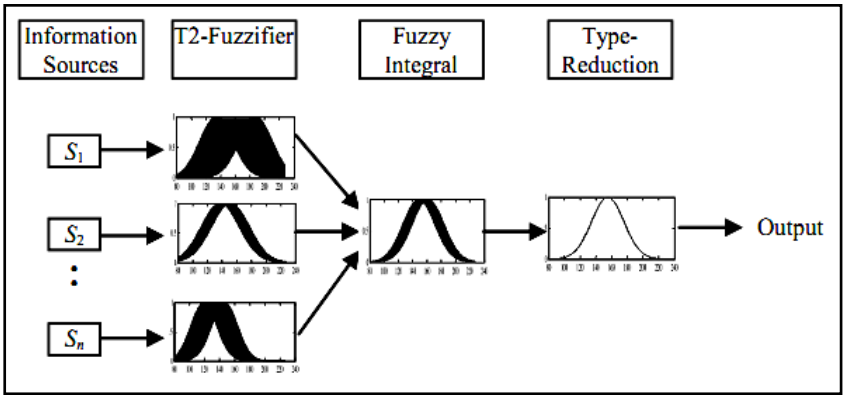


Figure 5.2 Interval Type-2 Fuzzy Integral

5.4 Experimental Results and Discussion

Experimental results of the performance evaluation of the proposed interval type-2 fuzzy integral (IT2-FI) based match score fusion method is presented in this section. The evaluation processes are carried out on two multibiometric types: (a) Multiple classifier system and (b) Multimodal biometric system. The details of each system are discussed in the next subsections.

5.4.1 Multiple Classifiers Framework

The proposed interval type-2 fuzzy integral (IT2-FI) based match score fusion approach is employed to fuse the scores obtained by three classifiers *viz.* fuzzy k-NN and two neural networks with *logsig* and *tansig* transfer functions in iris recognition system as it is one of the most accurate and reliable biometric systems. The systems are evaluated on the CASIA-IrisV1 and CASIA-IrisV3-Interval database. The stages of iris recognition for the present work are summarized in Figure 5.3 and the different stages are described in the subsequent subsections.

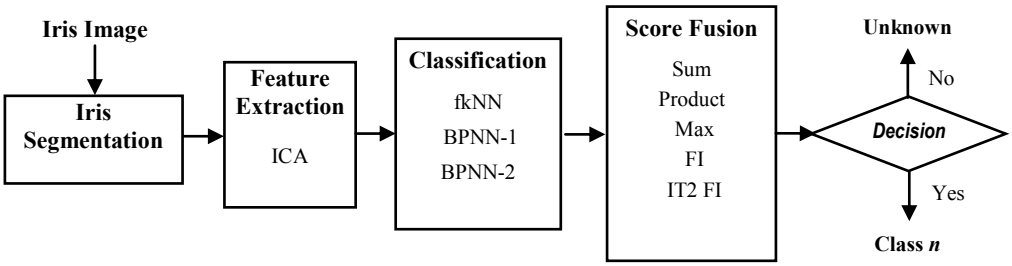


Figure 5.3 Iris Recognition System with Multiple Classifiers

5.4.1.1 Iris Segmentation

In iris recognition, the segmentation stage which consists of the localization of inner and outer boundary of iris and, normalize segmented iris, is crucial as the performance of whole system depends on segmentation accuracy. Therefore, many researches have been conducted in this field and most of the works are based essentially on two main methods: an integro-differential algorithm (Daugman, 1993) and an algorithm based on the circular Hough transform (Wildes, 1997). The two iris segmentation algorithms employed in the present work are as follows:

5.4.1.1.1 *Segmentation using Local Intensity*

The pupil is distinguishable in iris image because of its very low intensity (black or almost black). Pixels with intensity greater than 70 are converted to 1(black) and others are converted to 0 (white) by applying a linear threshold (of value 70). Thus, pupil region is identified in iris image. An imaginary horizontal line is drawn through the center of the pupil. Along this line, the signal composed by pixel intensity is analyzed outward on both side of the pupil, starting from its edges by using windowing technique and tries to detect the outer radii of iris as abrupt increase of intensity level greater than a threshold *d*. In this experience, window size is taken as 10 and threshold *d* as 18. Then, iris pattern (40×40 pixels) is extracted from iris areas at the left and right of the pupil with an average mask of 3×3 pixels. Details of the steps are discussed in Section 3.3.2.

5.4.1.1.2 *Segmentation using Hough Transform with Canny Edge Detection*

An edge map of the input eye image is generated by employing Canny edge detection (Liu *et al*., 2003). From the edge map, the iris inner (pupil) and outer (sclera) circles are detected by applying the circular Hough transform (Wildes, 1997). The eyelid occlusion is removed using a linear Hough transform. The presence of eyelashes is identified using a simple thresholding technique.

Subsequently, a normalization process is required in order to transform the segmentation iris into a fixed dimension. This is done with Daugman's rubber sheet model (Daugman, 2004), which maps the circular iris image into a rectangular.

5.4.1.2 Feature Extraction

During segmentation, iris pattern (40×40 pixels) is isolated from iris image (320×280 pixels) with a 98% reduction in size. Still a large amount of redundant information is

associated with iris pattern. In this stage, dimension of iris pattern is reduced using ICA to a vector of size 40 in order to reduce dimension of problem and also to minimize classification error. These feature extraction method is discussed in Section 3.3.2.

5.4.1.3 Classification

The obtained iris pattern is classified by using fuzzy k-NN and two neural networks with *logsig* and *tansig* transfer functions. Each classifier is described in the following subsection.

5.4.1.3.1 *Fuzzy k-NN Classifier* (fk-NN)

In k-NN classifier, the mean Euclidean distance between the centroid of the train image and the test image is computed and a cluster is formed by choosing the closest point. Fuzzy k-NN classifier is an extension of k-NN classifier (Keller *et al*., 1995). In fk-NN classification, the subsequent fuzzy information is derived from the training data and these information are used to set a defuzzification threshold dynamically. One advantage is that a decision is not made if confidence is low and classified as *unknown*.

Let $X = \{x_1, x_2, \ldots, x_n\}$ be a labeled set of n samples. A membership $\mu_i(x)$ to a test vector x to class i is assigned according to the relationship given in Equation (5.16).

$$\mu_i(x) = \sum_{j=1}^{k} \mu_{ij} (1/ \| x - x_j \|^{2/(m-1)}) \Big/ \sum_{j=1}^{k} (1/ \| x - x_j \|^{2/(m-1)}) \qquad (5.16)$$

where, μ_{ij} is the membership of the j^{th} neighbor to the i^{th} class and is determined from the training data. $\|x\text{-}x_j\|$ is the L-norm distance between the test vector x, and the k^{th} nearest neighbor vector x_j and m (> 1.0) is the "strength" of the fuzzy distance function.

5.4.1.3.2 *Neural Network*

Neural network is a powerful tool for solving pattern recognition problems. The problem in hand belongs to supervised learning and multilayer perception (MLP) NN well suited (Bishop, 2006). In the present work, the input layer contains a set of input nodes that represent the iris features, one hidden layer containing computation nodes, and an output layer containing node that represent iris classes. Backpropagation learning methods provides an efficient method for changing the weights in a feed-forward network and it minimizes the total squared error of the output computed. Each neuron in a hidden output layer is activated by Equation (5.17).

$$net_i = \sum w_{ij} o_j \quad \text{and} \quad y_i = f(net_i) \tag{5.17}$$

where, net_i is the activation of the i^{th} neuron, j is the set of neurons in the preceding layer, w_{ij} is the weight of the connection between neuron i and neuron j, o_j is the output of neuron j and y_i is the transfer function. The transfer functions of two backpropagation neural networks (*viz*. BPNN-1 and BPNN-2) are *tansig* and *logsig* respectively and are given by Equation (5.18).

$$f_{BPNN-1}(net_i) = \frac{2}{1+\exp^{-2*net_i}} - 1 \quad \text{and} \quad f_{BPNN-2}(net_i) = \frac{1}{1+\exp^{-net_i}} \tag{5.18}$$

5.4.1.4 Score Fusion

The scores produced by the three classifiers are combined in this module to make final decision. In the present work, the performance of proposed interval type-2 fuzzy integral (IT2-FI) match score fusion approach is compared with other four score fusion methods *viz*. the sum rule, max-rule, product-rule and fuzzy integral.

5.4.1.5 Experimental Results

5.4.1.5.1 *Iris Databases*

In the present work, iris images are taken from the CASIA-IrisV1 database (CASIA, 2006) collected by the Chinese Academy of Sciences' Institute of Automation. The database consists of 756 gray scale iris images (7 sample images for each 108 classes) of size 320×280 pixels. The images are taken in two sessions, three samples during the first session and four samples during the second by a digital optical sensor designed by NLPR (National Laboratory of Pattern Recognition – Chinese Academy of Sciences).

CASIA-IrisV3 database is a superset of CASIA-IrisV1 database and it consists of three subsets *viz*. CASIA-IrisV3-Interval, CASIA-IrisV3-Lamp and CASIA-IrisV3-Twins. The present work employs iris images from CASIA-IrisV3-Interval. It consists of 2655 gray scale iris images of size 320×280 pixels collected from 249 subjects.

5.4.1.5.2 *Experimentation based on Segmentation using Local Intensity*

Experiments are conducted in MATLAB 7.11 environment. In this experiment, the iris patterns of CASIA-IrisV1 iris images obtained with the ICA feature extraction method are employed. ICA feature extraction method was found to be the best feature method

for iris recognition over the considered dataset as reported in Section 3.3.3. The iris patterns are classified by using the three classifiers *viz*. fk-NN, BPNN-1 and BPNN-2. The 3-layer architecture of BPNNs employed in the present work is shown in Figure 3.10. The number of nodes in the hidden layer (*Hn*), initial learning rate (*Lr*) and learning rate increment (*Inc*) are determined based on the process of trial and error. Both BPNNs are run five times for each tuple (*Hn*, *Lr*, *Inc*) and the best Equal Error Rate (EER) is listed against the corresponding tuple in Table 5.1. The network design parameters of the two BPNNs are summarized in Table 5.2. For each class, five instances are used in the training and the remaining two for testing. Each classifier produces a matching score matrix of size (250×50) containing 250 genuine scores and 250×49 imposter scores during training and matching score matrix of size (100×50) containing 100 genuine scores and 100×49 imposter scores during testing. The matching scores produced by the three classifiers are combined by using the proposed IT2-FI.

Table 5.1 BPNN Network Results

Hn	Lr	Inc	EER (BPNN-1)	EER (BPNN-2)	Hn	Lr	Inc	EER (BPNN-1)	EER (BPNN-2)
30	1.05	1.01	0.3735	0.1964		1.10	1.01	0.4132	0.2524
		1.05	0.3449	0.1727			1.05	0.3524	0.1849
		1.10	0.4191	0.2665			1.10	0.3726	0.1948
		1.15	0.4895	0.3637			1.15	0.3839	0.1962
		1.20	0.3664	0.2244			1.20	0.4180	0.2164
		1.25	0.4447	0.3365			1.25	0.3664	0.1665
		1.30	0.3961	0.2836			1.30	0.4978	0.2612
	1.10	1.01	0.4200	0.2574		1.15	1.01	0.3855	0.2249
		1.05	0.3648	0.2038			1.05	0.4027	0.2327
		1.10	0.3831	0.2357			1.10	0.3759	0.1978
		1.15	0.3934	0.2595			1.15	0.4154	0.2235
		1.20	0.4244	0.3117			1.20	0.5033	0.2875
		1.25	0.3775	0.2601			1.25	0.4281	0.2158
		1.30	0.4969	0.4414			1.30	0.4122	0.1953
	1.15	1.01	0.3858	0.2294		1.20	1.01	0.4330	0.2720
		1.05	0.4008	0.2566			1.05	0.4250	0.2540
		1.10	0.3775	0.2393			1.10	0.3833	0.2045
		1.15	0.4118	0.2956			1.15	0.5693	0.3574
		1.20	0.4883	0.4140			1.20	0.4045	0.2051
		1.25	0.4229	0.3372			1.25	0.5388	0.3044
		1.30	0.4091	0.3301			1.30	0.5973	0.3377
	1.20	1.01	0.4172	0.2774		1.25	1.01	0.3565	0.1962
		1.05	0.4105	0.2800			1.05	0.3771	0.2083
		1.10	0.3758	0.2475			1.10	0.2663	0.1982
		1.15	0.5308	0.4726			1.15	0.3435	0.1610
		1.20	0.3934	0.2954			1.20	0.4708	0.2604
		1.25	0.5054	0.4756			1.25	0.4544	0.2368
		1.30	0.5542	0.5707			1.30	0.4906	0.2556
	1.25	1.01	0.3468	0.2002		1.30	1.01	0.4346	0.2735
		1.05	0.3633	0.2297			1.05	0.3250	0.1587
		1.10	0.2747	0.1188			1.10	0.3609	0.1842
		1.15	0.3364	0.2130			1.15	0.4833	0.2826
		1.20	0.4383	0.3750			1.20	0.4042	0.2050
		1.25	0.4251	0.3701			1.25	0.3558	0.1580
		1.30	0.4541	0.4320			1.30	0.4606	0.2326
	1.30	1.01	0.4008	0.2790	50	1.05	1.01	0.3782	0.3165
		1.05	0.3165	0.1750			1.05	0.4091	0.3250
		1.10	0.3441	0.2229			1.10	0.4097	0.3016
		1.15	0.4383	0.3738			1.15	0.4061	0.5235
		1.20	0.3775	0.2951			1.20	0.4038	0.3622
		1.25	0.3402	0.2468			1.25	0.4036	0.5414
		1.30	0.4209	0.3930			1.30	0.3719	0.6395
40	1.05	1.01	0.3527	0.1925		1.10	1.01	0.3752	0.2273
		1.05	0.3228	0.1566			1.05	0.3706	0.2599
		1.10	0.4006	0.2203			1.10	0.3726	0.1663
		1.15	0.4746	0.2750			1.15	0.3639	0.2591
		1.20	0.3453	0.1558			1.20	0.3676	0.4136
		1.25	0.4275	0.2154			1.25	0.3683	0.4163
		1.30	0.3765	0.1678			1.30	0.3669	0.4798

Table 5.1 BPNN Network Results (contd...)

Hn	Lr	Inc	EER (BPNN-1)	EER (BPNN-2)	Hn	Lr	Inc	EER (BPNN-1)	EER (BPNN-2)
	1.15	1.01	0.3682	0.2816		1.20	1.01	0.3707	0.1805
		1.05	0.3673	0.1967			1.05	0.3743	0.3387
		1.10	0.3660	0.2452			1.10	0.3817	0.1981
		1.15	0.3679	0.3833			1.15	0.3920	0.3265
		1.20	0.3684	0.3218			1.20	0.3931	0.3643
		1.25	0.3669	0.2867			1.25	0.3996	0.2417
		1.30	0.3619	0.4207			1.30	0.4020	0.3900
	1.20	1.01	0.3664	0.2183		1.25	1.01	0.3578	0.3330
		1.05	0.3628	0.2580			1.05	0.3654	0.1974
		1.10	0.3607	0.2755			1.10	0.3730	0.3364
		1.15	0.3609	0.2892			1.15	0.3797	0.2236
		1.20	0.3546	0.3038			1.20	0.3804	0.2293
		1.25	0.3528	0.3204			1.25	0.3873	0.4261
		1.30	0.3489	0.3029			1.30	0.3943	0.3972
	1.25	1.01	0.3497	0.2031		1.30	1.01	0.3375	0.3246
		1.05	0.3524	0.2113			1.05	0.3419	0.2213
		1.10	0.3529	0.2279			1.10	0.3488	0.2736
		1.15	0.3516	0.2348			1.15	0.3521	0.3156
		1.20	0.3531	0.2529			1.20	0.3552	0.3191
		1.25	0.3515	0.2683			1.25	0.3377	0.2679
		1.30	0.3541	0.2816			1.30	0.2898	0.4854
	1.30	1.01	0.3406	0.1861	70	1.05	1.01	0.3346	0.2739
		1.05	0.3716	0.1966			1.05	0.3197	0.2371
		1.10	0.3721	0.2097			1.10	0.4350	0.1735
		1.15	0.3760	0.2255			1.15	0.4779	0.3095
		1.20	0.3811	0.2400			1.20	0.2611	0.2386
		1.25	0.3878	0.2528			1.25	0.4779	0.1924
		1.30	0.3706	0.2619			1.30	0.3505	0.3048
60	1.05	1.01	0.4936	0.2767		1.10	1.01	0.2663	0.1985
		1.05	0.4837	0.2490			1.05	0.3381	0.4902
		1.10	0.4729	0.1908			1.10	0.2663	0.2152
		1.15	0.4790	0.3559			1.15	0.4609	0.2214
		1.20	0.4855	0.2864			1.20	0.5271	0.1650
		1.25	0.4991	0.2405			1.25	0.5210	0.1758
		1.30	0.4696	0.3963			1.30	0.3168	0.1833
	1.10	1.01	0.3937	0.2005		1.15	1.01	0.3830	0.2425
		1.05	0.3972	0.5147			1.05	0.3705	0.2569
		1.10	0.4097	0.2367			1.10	0.4763	0.2597
		1.15	0.4071	0.2546			1.15	0.2205	0.2744
		1.20	0.4181	0.1980			1.20	0.3653	0.3878
		1.25	0.4279	0.2197			1.25	0.5871	0.3286
		1.30	0.4371	0.2383			1.30	0.5680	0.1775
	1.15	1.01	0.3794	0.2449		1.20	1.01	0.2580	0.1787
		1.05	0.3877	0.2698			1.05	0.4851	0.3226
		1.10	0.3972	0.2856			1.10	0.5214	0.1801
		1.15	0.4025	0.3156			1.15	0.4692	0.2839
		1.20	0.4121	0.4653			1.20	0.3269	0.3036
		1.25	0.4214	0.4107			1.25	0.5956	0.1933
		1.30	0.4217	0.2307			1.30	0.4614	0.3000

Table 5.1 BPNN Network Results (contd...)

Hn	Lr	Inc	EER (BPNN-1)	EER (BPNN-2)	Hn	Lr	Inc	EER (BPNN-1)	EER (BPNN-2)
	1.25	1.01	0.3172	0.3297		1.30	1.01	0.4395	0.2472
		1.05	0.4632	0.1880			1.05	0.3567	0.1621
		1.10	0.3423	0.3059			1.10	0.2360	0.1913
		1.15	0.4957	0.1944			1.15	0.2113	0.2111
		1.20	0.6743	0.1911			1.20	0.3517	0.2045
		1.25	0.3978	0.3409			1.25	0.3274	0.1648
		1.30	0.4767	0.3056			1.30	0.2221	0.2872
	1.30	1.01	0.4937	0.3213	90	1.05	1.01	0.3707	0.2635
		1.05	0.6014	0.2107			1.05	0.3743	0.2371
		1.10	0.3368	0.2487			1.10	0.3817	0.1817
		1.15	0.4872	0.2744			1.15	0.3920	0.3389
		1.20	0.3047	0.2659			1.20	0.3931	0.2727
		1.25	0.4556	0.2143			1.25	0.3996	0.2290
		1.30	0.3188	0.3734			1.30	0.4020	0.3774
80	1.05	1.01	0.3139	0.2609		1.10	1.01	0.3578	0.1823
		1.05	0.2997	0.2258			1.05	0.3654	0.4679
		1.10	0.4504	0.1652			1.10	0.3730	0.2152
		1.15	0.4096	0.2947			1.15	0.3797	0.2315
		1.20	0.2439	0.2273			1.20	0.3804	0.1800
		1.25	0.4504	0.1832			1.25	0.3873	0.1998
		1.30	0.3291	0.2903			1.30	0.3943	0.2167
	1.10	1.01	0.2330	0.1805		1.15	1.01	0.3375	0.2130
		1.05	0.2982	0.4457			1.05	0.3419	0.2346
		1.10	0.4099	0.1957			1.10	0.3488	0.2484
		1.15	0.2330	0.2013			1.15	0.3521	0.2744
		1.20	0.4701	0.1500			1.20	0.3552	0.4047
		1.25	0.4645	0.1598			1.25	0.3377	0.3571
		1.30	0.2789	0.1667			1.30	0.2898	0.2007
	1.15	1.01	0.3200	0.2109		1.20	1.01	0.3346	0.1504
		1.05	**0.1787**	0.2234			1.05	0.3197	0.2823
		1.10	0.4011	0.2258			1.10	0.4350	0.1651
		1.15	0.3091	0.2386			1.15	0.4779	0.2720
		1.20	0.3046	0.3372			1.20	0.2611	0.3036
		1.25	0.4975	0.2857			1.25	0.4779	0.2014
		1.30	0.2113	0.1543			1.30	0.3505	0.3250
	1.20	1.01	0.4567	**0.1489**		1.25	1.01	0.2663	0.2664
		1.05	0.3876	0.2688			1.05	0.3381	0.1580
		1.10	0.4178	0.1501			1.10	0.2663	0.2691
		1.15	0.3743	0.2366			1.15	0.4609	0.1789
		1.20	0.2557	0.2530			1.20	0.5271	0.1834
		1.25	0.3678	0.1611			1.25	0.5210	0.3409
		1.30	0.4796	0.2500			1.30	0.3168	0.3178
	1.25	1.01	0.2337	0.2637		1.30	1.01	0.3830	0.2497
		1.05	0.3506	0.1504			1.05	0.3705	0.1702
		1.10	0.2538	0.2447			1.10	0.4763	0.2104
		1.15	0.3766	0.1556			1.15	0.2205	0.2428
		1.20	0.2982	0.1529			1.20	0.3653	0.2455
		1.25	0.5194	0.2727			1.25	0.5871	0.2060
		1.30	0.3613	0.2444			1.30	0.5680	0.3734

Table 5.2 BPNN Network Design Parameters for Multiple Classifier Biometric System with ICA Iris Patterns obtained using Local Intensity and Windowing Technique over CASIA-IrisVI dataset.

Parameters	**BPNN-1**	**BPNN-2**
Training function	*traingda*	*traingda*
Transfer function	*tansig*	logsig
No. of neuron in hidden layer	80	80
Initial learning rate	1.15	1.2
Learning rate increment	1.05	1.01
Epochs	50,000	50,000
Error goal	0.0000005	0.0000005

The performance of the proposed IT2-FI is compared with four existing fusion methods *viz*. sum, product, max and fuzzy integral (type-1 FI) in terms of Area under Curve (AUC), Equal Error Rate (EER) and Running time (RT) in sec. and is summarized in Table 5.3. The running time in Table 5.3 is the time taken by each of the methods for combining the matching scores. The ROC curves of fusion methods are shown in Figure 5.4. Experimental observations show that the proposed IT2-FI outperforms the others four fusion strategies, including the type-1 FI, in term of both AUC and EER. However, the running time of the proposed approach, IT2-FI based iris recognition, is comparatively higher than the other four approaches pertaining to the computational time needed for the computation of the lower and the upper membership functions of the interval type-2 fuzzy set.

Table 5.3 Performances of Different Fusion Methods in Multiple Classifier Biometric System with ICA Iris Patterns obtained using Local Intensity and Windowing Technique over CASIA-IrisVI dataset.

Fusion Methods	**AUC**	**ERR**	**RT (in sec)**
Sum	0.9443	0.1087	0.1552
Product	0.9810	0.0109	0.1838
Max	0.8126	0.1183	**0.1169**
FI	0.9676	0.0101	0.6410
Proposed IT2-FI	**0.9993**	**0.0001**	0.7669

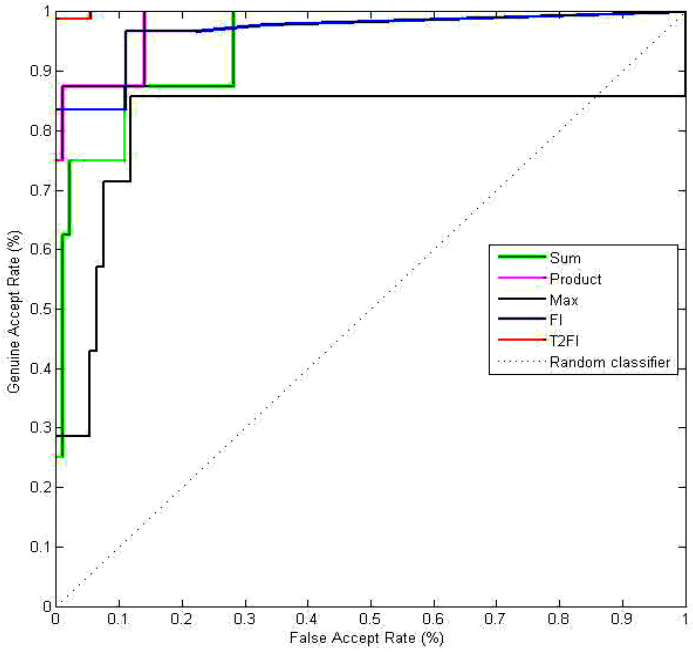


Figure 5.4 ROCs of Different Fusion Methods in Multiple Classifier Biometric System with ICA Iris Patterns obtained using Local Intensity and Windowing Technique over CASIA-IrisVI dataset.

5.4.1.5.3 *Experimentation based on Segmentation using Hough Transform with Canny Edge Detection*

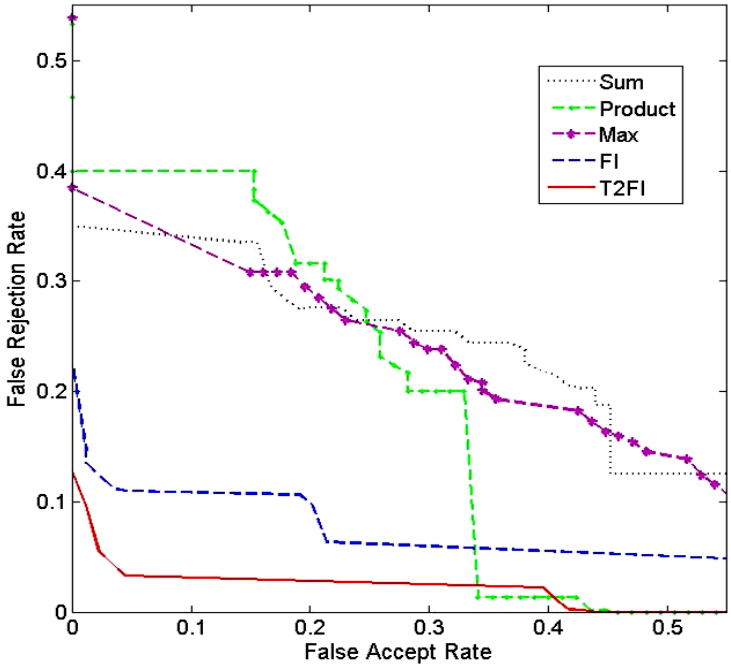
The experiment is conducted in MATLAB 7.11 environment. In the present work, CASIA-IrisV1 and CASIA-IrisV3-Interval databases are employed and 350 iris images (of 50 person/classes) from each database are used. For each class, out of the total seven images, five instances are used in the training and the remaining two for testing. In this experiment, the segmentation is carried out based on the algorithm proposed by Masek and Kovesi (2003). In this algorithm, iris segmentation is carried out using Hough transform with Canny edge detection and normalized using Daugman's rubber sheet model (see Section 5.4.1.1.2). The size of normalized iris templates is reduced to a vector of size 40 using ICA. ICA feature extraction method was found to be the best feature method for iris recognition over the considered dataset as reported in Section 3.3.3. In classification stage, the iris patterns are classified by using the three classifiers *viz*. fk-NN, BPNN-1 and BPNN-2. The network design parameters of the two BPNNs are summarized in Table 5.4. Each classifier produces a matching score matrix of size (250×50) containing 250 genuine scores and 250×49 imposter scores during training and matching score matrix of size (100×50) containing 100 genuine scores and 100×49

imposter scores during testing. The matching scores produced by the three classifiers are combined by using the proposed interval type-2 fuzzy integral (IT2-FI) based fusion method.

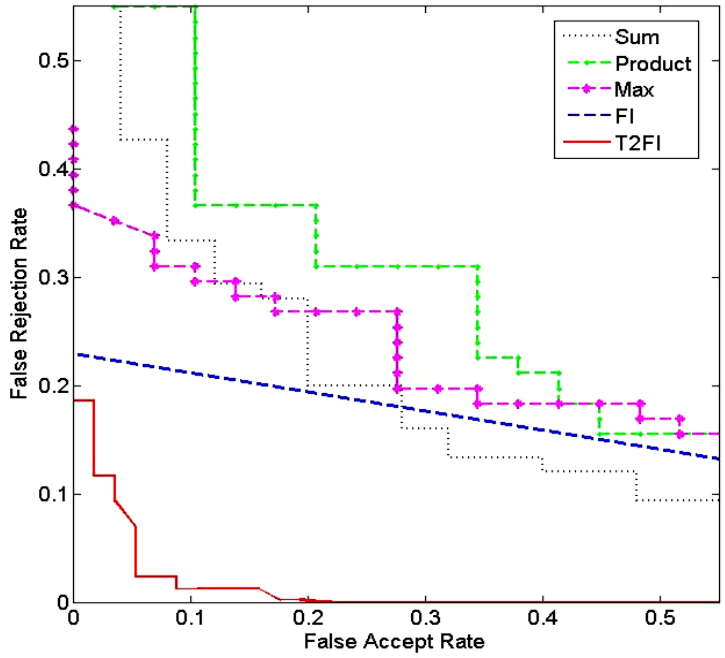
Table 5.4 BPNN Network Design Parameters for Multiple Classifier Biometric System with ICA based Iris Patterns obtained using Hough Transform with Canny Edge Detection Method

Parameters	**BPNN-1**	**BPNN-2**
Training function	*traingda*	*traingda*
Transfer function	*tansig*	logsig
No. of neuron in hidden layer	80	80
Initial learning rate	1.15	0.20
Learning rate increment	1.12	1.02
Epochs	50,000	50,000
Error goal	0.000001	0.000001

The performance of the proposed IT2-FI based approach is compared with four existing fusion methods *viz*. sum, product, max and fuzzy integral (type-1 FI) in terms of EER, FRR and running time (RT) in sec. and are tabulated in Table 4.5. The running time in Table 5.5 is the time taken (in sec) by each of the methods for combining the matching scores. The ROC curves of fusion methods are shown in Figure 5.5. It is observed that the proposed IT2-FI match score fusion method achieves the best performance of 0.05 ERR and 0.05 FRR at zero FAR over CASIA-V1 iris database. The experimental results over benchmark dataset demonstrate that the proposed IT2-FI outperforms others four fusion strategies, including the type-1 FI, in terms of EER and FRR. However, the running time of the proposed approach, IT2-FI based iris recognition, is comparatively higher than the other four approaches pertaining to the computational time needed for the computation of the lower and the upper membership functions of the interval type-2 fuzzy set.



(a)



(b)

Figure 5.5 ROCs of Different Fusion Methods in Multiple Classifier Biometric System with ICA based Iris Patterns obtained using Hough Transform with Canny Edge Detection Method over (a) CASIA-IrisV1 (b) CASIA-IrisV3-Interval.

Table 5.5 Performances of Different Fusion Methods in Multiple Classifier Biometric System with ICA based Iris Patterns obtained using Hough Transform with Canny Edge Detection Method

Fusion Methods	CASIA-V1.0			CASIA-V3		
	EER	FRR at FAR =0	RT (in sec.)	EER	FRR at FAR =0	RT (in sec.)
Sum	0.26	0.3500	0.0406	0.2	0.6133	0.0200
Product	0.24	0.4000	0.0489	0.31	0.7606	0.0129
Max	0.25	0.3846	0.0384	0.28	0.3662	**0.0112**
FI	0.13	0.2247	0.1159	0.21	0.2289	0.1189
Proposed IT2-FI	**0.05**	**0.1287**	0.1304	0.06	0.1680	0.1414

5.4.2 Multimodal Biometric System

In the multimodal biometric system, three biometric traits *viz*. fingerprint, signature and iris are employed and their matching scores are combined using the proposed IT2-FI based match score fusion method. Designing of the multimodal database is described in next subsection.

5.4.2.1 Multimodal Database Design

The Multimodal Database employed in the present experimentation consists of scores of three biometric traits *viz*. fingerprint, signature and iris. Fingerprint and signature matching scores are taken from the MCYT-score database (ATVS, 2007) and iris match scores are the match scores generated by the BPNN-1 classifier for ICA based iris patterns obtained in the multiple classifier biometric system experimentation.

MCYT is a bimodal biometric database in which fingerprint and signature have been the selected biometric modal and the maximization of the significance has been carried out in two different ways (Ortega-Garcia *et al*., 2003). The former strategy has led to MCYT baseline corpus and the later one has led to MCYT extended corpus. In MCYT baseline corpus, fingerprint and signature of 330 individuals have been acquired. The MCYT extended corpus had acquired 100 more individuals in a multi-session procedure, to incorporate intrinsic short-term signature variability, signature size variability, over-the-shoulder and time constrained signature forgeries and several sensor devices for fingerprint acquisition. In the MCYT-score database, there are three datasets of bimodal matching scores for two biometric traits *viz*. fingerprints and signatures from 75 subjects consisting 75×7 client and 75×10 impostor

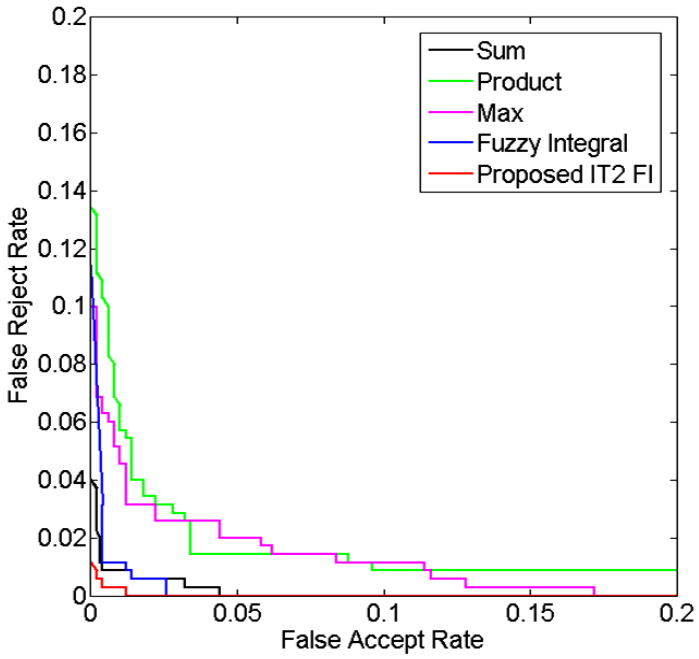
bimodal match scores. The MCYT-score database contains high quality fingerprint for 95% of the 75 subjects, and lowest quality fingerprint for the remaining 5% (Fierrez-Aguilar *et al*., 2005).

5.4.2.2 Experimental Results

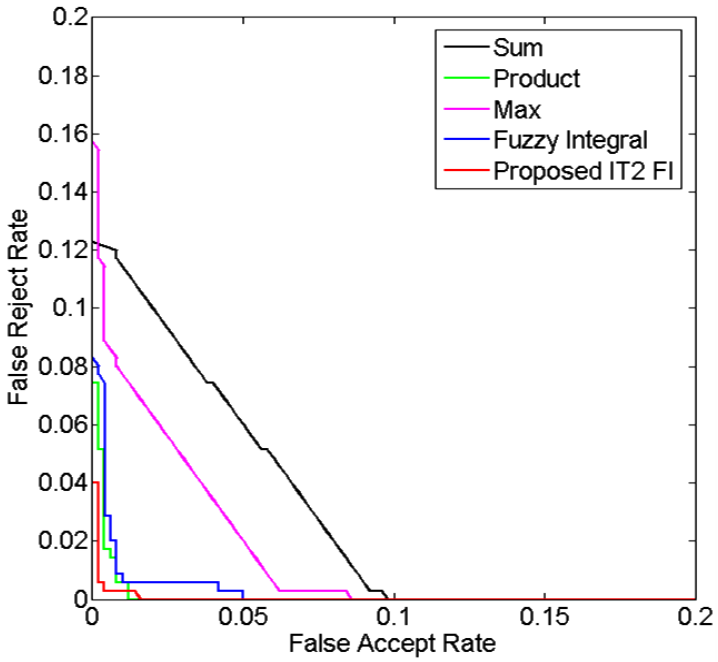
In the present experimentation, the dataset consists of (50×7) client and (50×10) impostor match scores for each modal i.e. fingerprint, signature and iris. The performance of the proposed IT2-FI based match score fusion method is compared with four existing fusion methods *viz*. sum, product, max and fuzzy integral (type-1 FI) in terms of EER, FRR at zero FAR and running time (RT) in sec. and is tabulated in Table 5.6. The running time in Table 5.6 is the time taken by each of the methods for combining the match scores. The ROC curves of fusion methods are shown in Figure 5.6. The proposed IT2-FI fusion method achieves its best performance of 0.0042 EER with iris match scores over CASIA-IrisV3-Interval and 0.0114 FRR at zero FAR with iris match scores over CASIA-IrisV1. Experimental observations show that the proposed IT2-FI outperforms over others four fusion methods.

Table 5.6 Performances of Different Fusion Methods in Multimodal Biometric System with ICA based Iris Patterns obtained using Hough Transform with Canny Edge Detection Method

Fusion Methods	**FP + Signature + Iris(ICA) over CASIA-IrisV1**			**FP + Signature + Iris(ICA) over CASIA-IrisV3-Interval**		
	EER	**FRR at FAR =0**	**RT (in sec.)**	**EER**	**FRR at FAR =0**	**RT (in sec.)**
Sum	0.0082	0.0400	0.0373	0.0541	0.1229	0.0146
Product	0.0282	0.0134	0.0390	0.0082	0.0742	0.0254
Max	0.0258	0.1000	0.0360	0.0371	0.1571	**0.0130**
FI	0.0107	0.1143	0.0624	0.0085	0.0828	0.0273
Proposed IT2-FI	0.0046	**0.0114**	0.0656	**0.0042**	0.0400	0.0617



(a)



(b)

Figure 5.6 ROCs of Different Fusion Methods in Multimodal Biometric System with ICA based Iris Patterns obtained using Hough Transform with Canny Edge Detection Method over FP + Signature + Iris (ICA) over (a) CASIA-IrisV1 (b) CASIA-IrisV3-Interval

5.7 Chapter Summary

In this chapter, a new approach to match score fusion for multibiometric systems namely interval type-2 fuzzy integral (IT2-IF) is proposed. Performance of the proposed IT2-FI is evaluated into two multibiometric types *viz*. (a) Multiple classifier system and (b) Multimodal biometric system.

In the multiple classifier system, the match scores of iris patterns generated by three classifiers *viz*. fuzzy k-NN and two neural networks are combined using the proposed interval type-2 fuzzy integral (IT2-FI) fusion method.

In the multimodal biometric system, three biometric traits namely, fingerprint, signature and iris are employed. Fingerprint and signature match scores are taken from the MCYT-score database and iris match scores are the match scores generated by the BPNN-1 classifier for ICA based iris patterns in the multiple classifier biometric system experimentations.

From the experimental results, it is observed that the proposed interval type-2 fuzzy integral (IT2-FI) based match score fusion approach outperforms the four other fusion methods including the type-1 FI in terms of EER and FRR in the multiple classifier biometric system as well as the multimodal biometric system over the considered datasets. The proposed IT2-FI based match score fusion approach is found to be promising for iris recognition. However, as future work, steps are needed to be taken to make the IT2-FI based match score fusion approach run faster with special attention to achieve trade-off between accuracy and the running time.

In the next chapter, to address the problem of template security in a multibiometric system, a cancelable multibiometric based on BioHashing is proposed.