

Genetic optimization of type-1, interval and intuitionistic fuzzy recognition systems

Patricia Melin

Tijuana Institute of Technology, Tijuana Mexico
e-mail: pmelin@tectijuana.mx

Received: 4 April 2018

Accepted: 20 April 2018

Abstract: In this paper a new method for fuzzy system optimization is presented. The proposed method performs the intuitionistic or type-2 fuzzy inference system design using a hierarchical genetic algorithm as an optimization method. This method is an improvement of a fuzzy system optimization approach presented in previous works where only the optimization of type-1 and interval type-2 fuzzy inference systems was performed considering a human recognition application. Human recognition is performed using three biometric measures namely iris, ear, and voice, where the main idea is to perform the combination of responses in modular neural networks using an optimized fuzzy inference system to improve the final results without and with noisy conditions. The results obtained show the effectiveness of the proposed method for designing optimal structures of fuzzy systems. The design of optimal structures of fuzzy systems include among other parameters; type of fuzzy logic (Type-1, interval type-2 and intuitionistic fuzzy logic), type of model (Mamdani model or Sugeno model), and consequents of the fuzzy if-then rules.

Keywords: Modular neural networks, Type-1 fuzzy logic, Interval type-2 fuzzy logic, Intuitionistic fuzzy logic, Human recognition, Hierarchical genetic algorithm.

2010 Mathematics Subject Classification: 03E72.

1 Introduction

Human recognition using biometric measures has demonstrated to be a good approach for authentication systems [11, 12, 13, 28], because these systems have as main advantage that a biometric measure cannot be stolen [10, 26, 27, 32] some of these biometric measures are ear, iris, fingerprint, voice and, hand geometry, among others. A widely known model to accomplish this task is the modular neural network (MNN). This kind of neural network model

has a significant learning improvement comparatively to a single neural network [12, 13, 21]. In modular neural networks, a problem is divided into smaller sub problems and their partial solutions or responses are combined to produce a final solution [10, 30, 34].

Soft computing consists of different techniques, among them fuzzy logic (FL), and this area can be highlighted as an approach that allows to reason with uncertainty. Fuzzy inference systems (FIS) are based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. In a type-1 fuzzy inference system (T1 FS), fuzzy sets allow the membership degree to be any value between 0 and 1, i.e. a crisp number. In the real world, this can help when in a situation it is difficult to decide if something belongs or not to a specific class [37–39]. In an interval type-2 fuzzy inference system (IT2 FS), the membership degree for each element of this set is a fuzzy set in $[0, 1]$ interval [3, 5, 19]. In a general type-2 fuzzy inference system (GT2 FS), three-dimensional membership functions (3D MF) are used and can be represented in four different ways: points, wavy slices, horizontal slices and vertical slices. In intuitionistic fuzzy systems uncertainty is modeled using membership and non-membership functions. Therefore, intuitionistic and type-2 fuzzy inference system are described using more parameters than a type-1 and an interval type-2 fuzzy inference system [20, 22]. It is worth mentioning that these fuzzy inference systems have been successfully applied in different areas, such as data classification, control problems, time series prediction, robotics, and human recognition [3].

It is important to mention that, a FIS needs to have an optimal structure to obtain better results, and this can be achieved using the knowledge of an expert or some optimization technique [4, 16], examples of the structural information are parameters of the membership functions and fuzzy if-then rules. Among some of these techniques applied to fuzzy inference system optimization, we can find; genetic algorithms (GAs) [14], particle swarm optimization (PSO) [36], cuckoo optimization algorithm (COA) [24], the bat algorithm (BA) [8] and chemical reaction optimization (CRO) [1].

In this work, fuzzy inference systems are used as integration units to combine MNN responses and hierarchical genetic algorithms (HGAs) are used to perform fuzzy inference system optimization. This optimization technique is a special kind of genetic algorithm. The difference is found in its structure because, a HGA is more flexible than a conventional GA [2, 15]. The main difference is found in the use of control genes that determinate the behavior of the other genes. These chromosomes may provide a good way to solve the problem and have demonstrated to achieve better results in complex problems than the conventional GA [9, 31, 35]. This technique was also chosen because it is one of the most used techniques in a wide range of applications because the same nature and familiarity of the algorithm allow its easy application. The application and adjustment of parameters of other algorithms previously mentioned force to have more specialized knowledge about the area in which it is inspired. This paper combines MNNs, FL and HGA, because their combination have demonstrated the effectiveness of a hybrid intelligence approach, where the individual limitations of the particular methods have been satisfied [18, 23, 25, 33].

The optimization is mainly performed because if we do not know the correct fuzzy inference system parameters and its structure, then it is almost impossible to achieve the best performance in any application, or at least if we have an expertise in the area where we will make the application perhaps good results could be obtained. For this reason, in this paper a HGA is proposed to perform the optimization of the structure and parameters of the FIS.

Experimental results of the proposed method show that the optimal architecture of fuzzy inference systems can be obtained and as a consequence the recognition rates can be improved with respect to previous works.

This paper is organized as follows. The description of the proposed method is presented in Section 2. In Section 3, the description of the databases and application are presented. The obtained results are explained in Section 4. The statistical comparisons of results are presented in Section 5. Finally, conclusions are offered in Section 6.

2 Intuitionistic fuzzy logic systems

According to Atanassov [1], an IFS on the universum $X \neq \emptyset$ is an expression A given by:

$$A = \{\langle x, \mu_A(x), \nu_A(x) \rangle \mid x \in X\}, \quad (1)$$

where the functions

$$\mu_A, \nu_A : X \rightarrow [0, 1] \quad (2)$$

satisfy the condition

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1 \quad (3)$$

and describe, respectively, the degree of the membership $\mu_A(x)$ and the non-membership $\nu_A(x)$ of an element x to A . Let

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x), \quad (4)$$

therefore, function π_A determines the degree of uncertainty.

According to [1] the geometrical forms of the intuitionistic fuzzy numbers can be generalized as follows: For the first case functions μ_A and ν_A satisfied the conditions [1]:

$$\sup_{y \in E} \mu_A(y) = \mu_A(x) = a, \quad \inf_{y \in E} \nu_A(y) = \nu_A(x) = b,$$

for each $x \in [x_1, x_2]$, and for the second case [1]:

$$\sup_{y \in E} \mu_A(y) = \mu_A(x_0) = a, \quad \inf_{y \in E} \nu_A(y) = \nu_A(x_0) = b.$$

For the first case we have:

μ_A is increasing function from $-\infty$ to x_1 ;
 μ_A is decreasing function from x_2 to $+\infty$;
 ν_A is decreasing function from $-\infty$ to x_1 ;
 ν_A is increasing function from x_2 to $+\infty$.

For the second case we have:

μ_A is increasing function from $-\infty$ to x_0 ;
 μ_A is decreasing function from x_0 to $+\infty$;
 ν_A is decreasing function from $-\infty$ to x_0 ;
 ν_A is increasing function from x_0 to $+\infty$.

Obviously, in both cases the functions μ_A and ν_A can be represented in the form

$$\mu_A = \mu_A^{\text{left}} \cup \mu_A^{\text{right}}, \quad \nu_A = \nu_A^{\text{left}} \cup \nu_A^{\text{right}},$$

where μ_A^{left} and ν_A^{left} are the left, while μ_A^{right} and ν_A^{right} are the right sides of these functions.

Therefore, the above conditions can be re-written in the (joint) form [1]:

$$\sup_{y \in E} \mu_A(y) = \mu_A(x) = a, \quad \inf_{y \in E} \nu_A(y) = \nu_A(x) = b,$$

for each $x \in [x_1, x_2]$ and in the particular case, when $x_1 = x_0 = x_2$, μ_A^{left} is increasing function; μ_A^{right} is decreasing function; ν_A^{left} is decreasing function and ν_A^{right} is increasing function. Following [1], we will consider, ordered by generality, the definitions:

1. In the graphical representation in both cases above $a = 1$, $b = 0$.
2. $\sup_{y \in E} \mu_A(y) = \mu_A(x_0) > 0.5 > \nu_A(x_0) = \inf_{y \in E} \nu_A(y)$.
3. $\sup_{y \in E} \mu_A(y) = \mu_A(x_0) \geq 0.5 \geq \nu_A(x_0) = \inf_{y \in E} \nu_A(y)$.
4. $\sup_{y \in E} \mu_A(y) = \mu_A(x_0) > \nu_A(x_0) = \inf_{y \in E} \nu_A(y)$.
5. $\sup_{y \in E} \mu_A(y) = \mu_A(x_0) \geq \nu_A(x_0) = \inf_{y \in E} \nu_A(y)$.
6. $\sup_{y \in E} \mu_A(y) = \mu_A(x_0) > 0$.
7. $\inf_{y \in E} \nu_A(y) < 1$.

This is just a brief description of the extensive work on this area of Prof. Atanassov.

3 Proposed method

The proposed method combines the responses of MNNs using FL as response integrator, where each MNN deals with a biometric measure and provides an input to the fuzzy integrator. The proposed method allows the use of "N" number of inputs, this parameter is established depending on the responses to be combined, i.e., the number of modular neural networks and, a final output is obtained, in this case represented with an output in the fuzzy integrator. In this work, three modular neural networks are used to compare with previous works, where each MNN performs the identification using a different biometric measure, and the fuzzy inference system is shown in Figure 1.

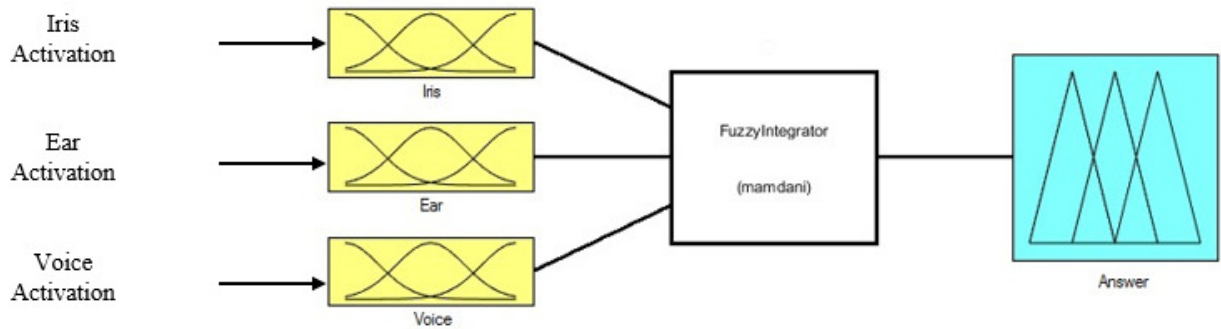


Figure 1. Fuzzy inference system for human recognition using iris, ear and voice

3.1 Optimization of fuzzy inference systems

The proposed HGA performs mainly the optimization of type-2 and intuitionistic fuzzy systems, but for reasons of comparison with previous works the type-1 and the interval type-2 fuzzy inference system optimization is also performed because some improvements are obtained with respect to those previous optimizations, such as: number of membership functions (one previous work [21] only uses 2 or 3 membership functions in each variable), the fuzzy rules (the previous work [21] randomly selected them), and in [29] optimizations do not have a reinitialization process. Having said that, the proposed method allows the optimization of the type of fuzzy logic (type-1, interval type-2 fuzzy logic or general type-2 fuzzy logic), type of system (Mamdani Model or Sugeno Model), type of membership functions (Trapezoidal or GBell), number of membership functions in each inputs and output variables, their parameters, the consequents of the fuzzy rules and the fuzzy if-then rules. The chromosome of the proposed hierarchical genetic algorithm for the fuzzy inference systems is shown in Figure 2, where control genes allow determining the type of fuzzy logic, type of system and number of MFs for each variable (inputs and outputs) and depending of their values, the rest of the genes are activated.

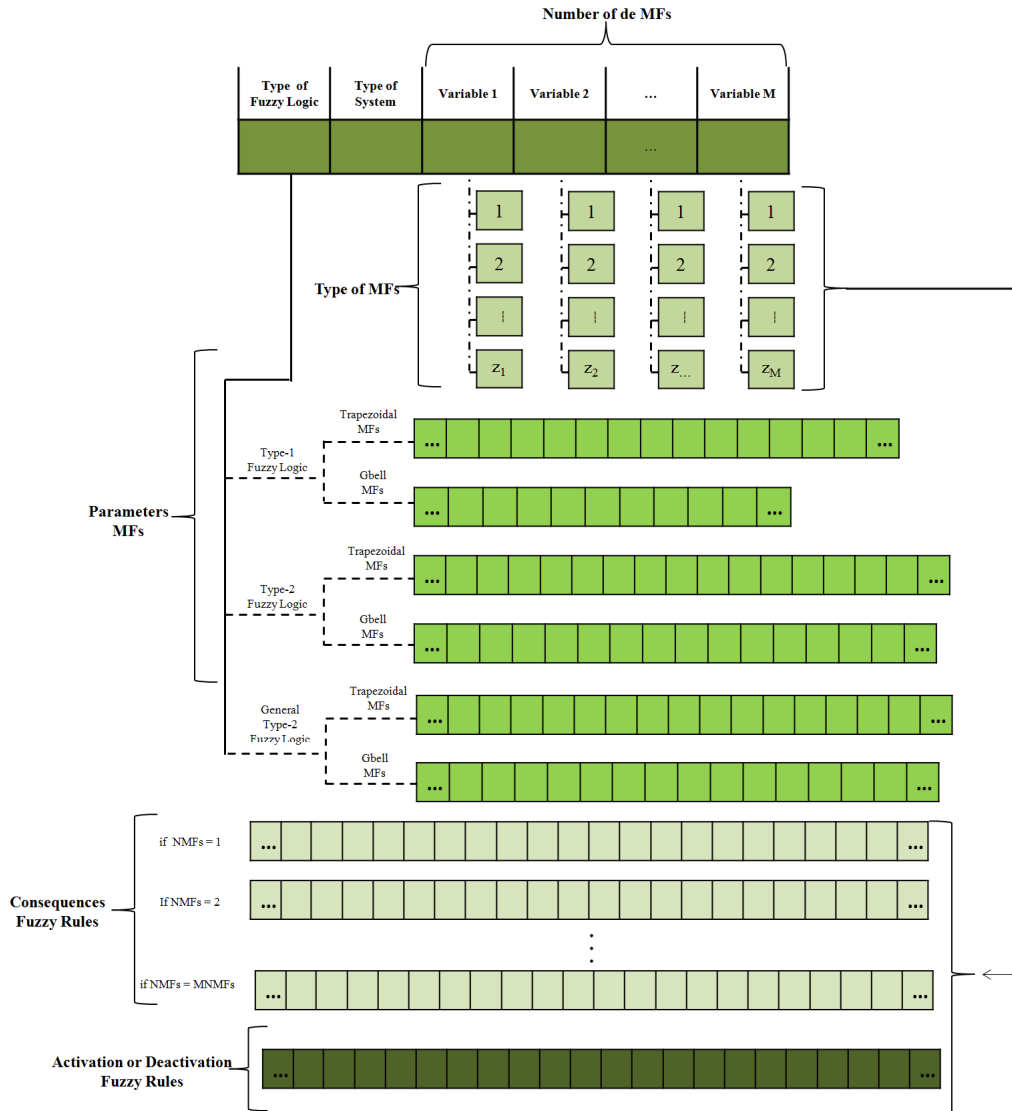


Figure 2. Chromosome of the proposed HGA for the fuzzy inference systems

3.2 Optimization of membership functions

The number of membership functions in each variable (inputs and output), the type of these membership functions (MFs) and their parameters are all considered in the optimization process. A contribution of the proposed method is in this point, because usually when the optimization of fuzzy inference systems is performed, the number of MFs is always fixed, i.e. only the membership function parameters are optimized, and when the optimization of the type of membership functions is performed all the membership functions of all the variables are of the same type. In the proposed optimization, each MF of each variable (inputs and output) is optimized, i.e., the combination of MFs in the same variable and different number of membership functions in each variable can be possible depending on the type of fuzzy logic.

In this paper, only 2 types of MFs are used (Trapezoidal and GBell). The question would be, why are we using only these kinds of membership functions in this work?. The answer is easy, because the hierarchical genetic algorithm has a wide range of search, allowing for example when trapezoidal membership functions are used, their points can be very close to each other and looking to be like a triangular membership function. The same case occurs with the GBell membership function when their points are modified; it can look to be like a Gaussian membership function.

3.3 Optimization of fuzzy rules

The proposed optimization performs the fuzzy if-then rules design in two parts; the consequents and the number of fuzzy rules (using the activation genes). To perform the consequents optimization, depending of the maximum number of membership functions (MNMFs) used in each variable (this number is freely established before the evolution) all the possible rules are generated. To illustrate an example, we will assume that the fuzzy inference system has 3 inputs and 1 output, and the MNMFs are 3, i.e., each input can have up to 3 membership functions in each variable. The total number of possible fuzzy if-then rules is given by the equation:

$$\text{TNFR} = \text{MNMFs}^N, \quad (5)$$

where N corresponds to the number of inputs in the fuzzy inference system and MNMFs corresponds to the maximum number of membership functions. In this work, N is 3, MNMFs is 5 and TNFR is 125. These fuzzy rules are shown in Figure 3, where 125 fuzzy rules are represented, and the genes for the consequents and activations of these fuzzy rules are used to complete the fuzzy rules used for the optimized fuzzy inference system. In the case of the consequents, the chromosome will have 125 genes for each possible number of membership functions, i.e. in the example described above, there are 125 genes, where the values can be from 1 to 2 (for when the output of the fuzzy inference system has only 2 membership functions), 125 genes where the value can be from 1 to 3 (for when the output of the fuzzy inference system has 3 membership functions) and so on. For the activations, there are 125 genes (one for each fuzzy rule).

When an individual of the HGA is going to be evaluated, depending of the number of membership functions indicated by the genes for the inputs. We are going to assume that based on the chromosome value of an individual, this one form the FIS shown in Figure 4, this FIS is

used to perform human recognition and its parameters were obtained by the proposed method, where the number of membership functions for each input is respectively 2, 5 and 3. The possible fuzzy rules for this combination are considered with the consequents and activations values. These fuzzy if-then rules can be observed in Figure 5.

The consequents are taken depending on the number of membership functions indicated by the gene for the output. As in Figure 4 can be observed, the fuzzy inference system has 3 membership functions in the output, for this reason the consequents are considered from the genes with values from 1 to 3 as Figure 6 shows.

Number of Membership Functions				Consequents				Activation
Rule	Input							
	1	2	3					
1	1	1	1	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
2	1	1	2	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
3	1	1	3	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
4	1	1	4	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
5	1	1	5	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
6	1	2	1	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
7	1	2	2	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
8	1	2	3	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
9	1	2	4	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
10	1	2	5	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
11	1	3	1	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
12	1	3	2	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
13	1	3	3	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
14	1	3	4	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
15	1	3	5	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
16	1	4	1	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
17	1	4	2	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
18	1	4	3	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
19	1	4	4	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
20	1	4	5	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
21	1	5	1	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
22	1	5	2	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
23	1	5	3	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
24	1	5	4	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
25	1	5	5	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
26	2	1	1	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
27	2	1	2	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
.			
.			
.			
123	5	5	1	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
122	5	5	2	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
123	5	5	3	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
124	5	5	4	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
125	5	5	5	1 to 2	1 to 3	1 to 4	1 to 5	0 or 1

Figure 3. Total number of possible fuzzy rules

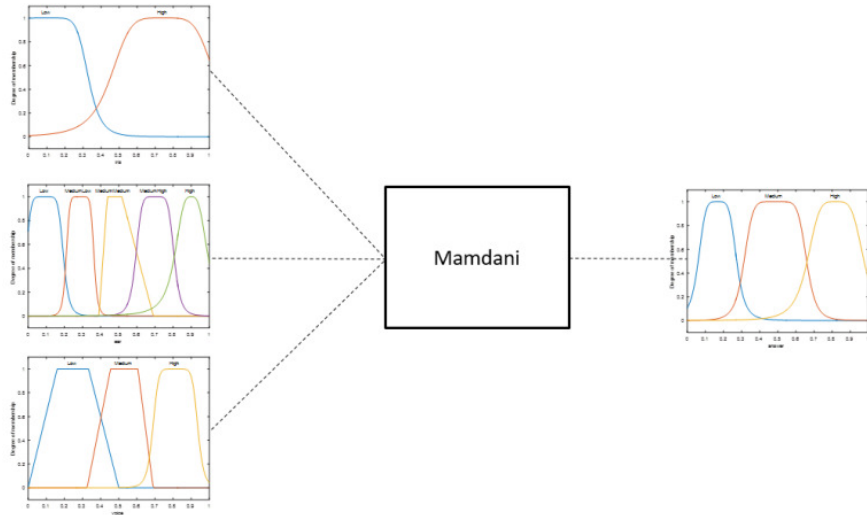


Figure 4. Fuzzy inference system optimization, Mamdani type

Number of Membership Functions					Consequents				Activation
Rule	Input								
	1	2	3						
1	1	1	1		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
2	1	1	2		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
3	1	1	3		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
6	1	2	1		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
7	1	2	2		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
8	1	2	3		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
11	1	3	1		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
12	1	3	2		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
13	1	3	3		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
16	1	4	1		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
17	1	4	2		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
18	1	4	3		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
21	1	5	1		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
22	1	5	2		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
23	1	5	3		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
26	2	1	1		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
27	2	1	2		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
28	2	1	3		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
31	2	2	1		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
32	2	2	2		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
33	2	2	3		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
36	2	3	1		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
37	2	3	2		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
38	2	3	3		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
41	2	4	1		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
42	2	4	2		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
43	2	4	3		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
46	2	5	1		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
47	2	5	2		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1
48	2	5	3		1 to 2	1 to 3	1 to 4	1 to 5	0 or 1

Figure 5. Possible fuzzy if-then rules

Number of Membership Functions					Consequents		Activation
Rule	Input						
	1	2	3				
1	1	1	1		1 to 3		0 or 1
2	1	1	2		1 to 3		0 or 1
3	1	1	3		1 to 3		0 or 1
6	1	2	1		1 to 3		0 or 1
7	1	2	2		1 to 3		0 or 1
8	1	2	3		1 to 3		0 or 1
11	1	3	1		1 to 3		0 or 1
12	1	3	2		1 to 3		0 or 1
13	1	3	3		1 to 3		0 or 1
16	1	4	1		1 to 3		0 or 1
17	1	4	2		1 to 3		0 or 1
18	1	4	3		1 to 3		0 or 1
21	1	5	1		1 to 3		0 or 1
22	1	5	2		1 to 3		0 or 1
23	1	5	3		1 to 3		0 or 1
26	2	1	1		1 to 3		0 or 1
27	2	1	2		1 to 3		0 or 1
28	2	1	3		1 to 3		0 or 1
31	2	2	1		1 to 3		0 or 1
32	2	2	2		1 to 3		0 or 1
33	2	2	3		1 to 3		0 or 1
36	2	3	1		1 to 3		0 or 1
37	2	3	2		1 to 3		0 or 1
38	2	3	3		1 to 3		0 or 1
41	2	4	1		1 to 3		0 or 1
42	2	4	2		1 to 3		0 or 1
43	2	4	3		1 to 3		0 or 1
46	2	5	1		1 to 3		0 or 1
47	2	5	2		1 to 3		0 or 1
48	2	5	3		1 to 3		0 or 1

Figure 6. Fuzzy if-then rules selection

The number of fuzzy if-then rules is found by the genes that indicate the activation or deactivation of the fuzzy rules (as it was mentioned, each fuzzy rule has a particular gen). If the value of the gene is 0 the fuzzy rule is not used, and if the value is 1 it is used, this is for all the possible fuzzy rules depending on the combination indicated by the genes for the inputs. In Figure 7, the process when only the fuzzy rules with an activation gene with value 1 are chosen can be observed.

Number of Membership Functions					Number of Membership Functions					
Rule	Input			Consequents	Activation	Rule	Input			Consequents
	1	2	3				1	2	3	
1	1	1	1	1 to 3	1	1	1	1	1	1
2	1	1	2	1 to 3	1	2	1	1	2	1
3	1	1	3	1 to 3	1	3	1	1	3	3
6	1	2	1	1 to 3	1	6	1	2	1	2
7	1	2	2	1 to 3	1	7	1	2	2	2
11	1	3	1	1 to 3	1	11	1	3	1	2
12	1	3	2	1 to 3	1	12	1	3	2	2
13	1	3	3	1 to 3	1	13	1	3	3	2
18	1	4	3	1 to 3	1	18	1	4	3	3
23	1	5	3	1 to 3	1	23	1	5	3	2
27	2	1	2	1 to 3	1	27	2	1	2	1
33	2	2	3	1 to 3	1	33	2	2	3	3
36	2	3	1	1 to 3	1	36	2	3	1	1
37	2	3	2	1 to 3	1	37	2	3	2	2
38	2	3	3	1 to 3	1	38	2	3	3	3
47	2	5	2	1 to 3	1	47	2	5	2	2

Figure 7. Activated fuzzy rules

Finally, the resulting fuzzy if-then rules are formed and added to the fuzzy integrator and the fuzzy inference system can be used and evaluated. In Fig. 8, the resulting fuzzy if-then rules are shown. It is important to remember that the antecedents of the fuzzy rules are automatically generated by the proposed method. The consequents and the use of each fuzzy rule (activation) are determined and optimized by the genes in the hierarchical genetic algorithm.

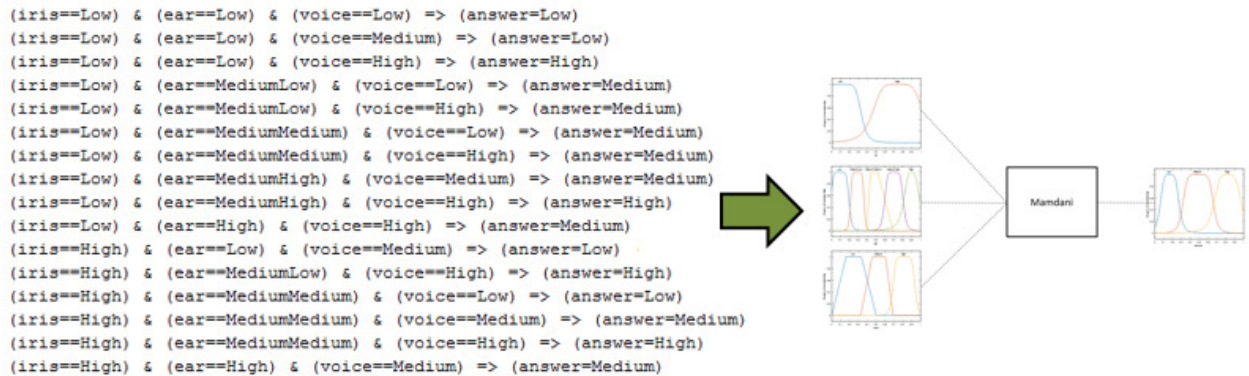


Figure 8. Final process for fuzzy rules optimization

We can summarize this process in Figure 9 and with 4 main steps:

1. The MNMFs is 5, i.e. all possible fuzzy rules are 125.
2. The fuzzy inference system has 2, 5 and 3 MFs respectively in the inputs, and the possible rules for these combinations are 30.
3. As the output has 3 MFs, the consequents with values among 1 to 3 are used,
4. Only the fuzzy rules with activated genes are added to the fuzzy integrator (Figure 9).

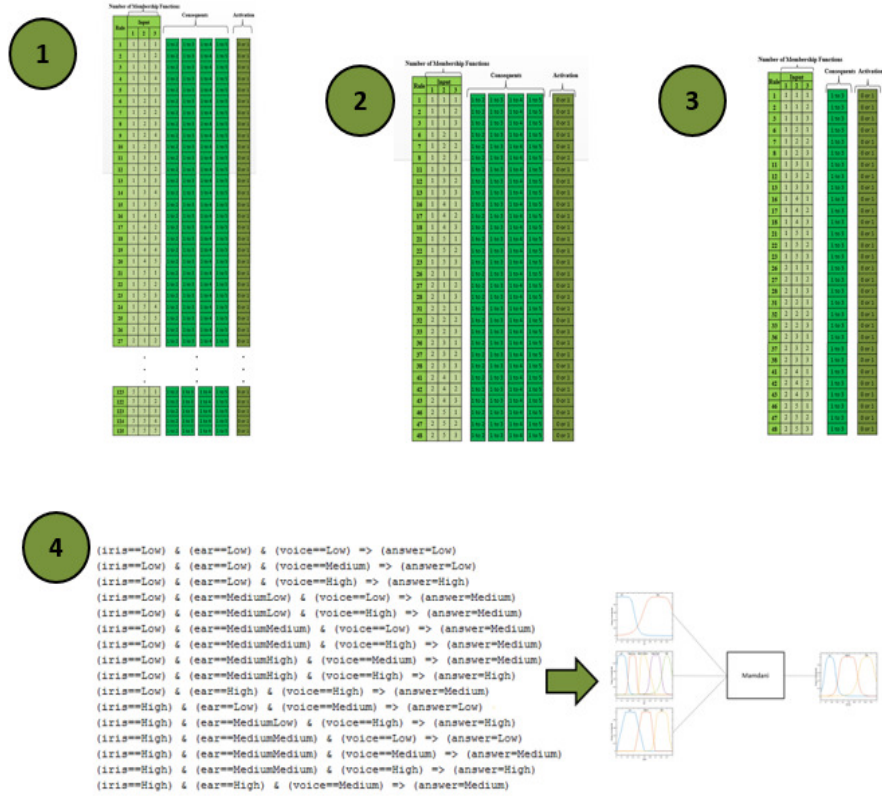


Figure 9. Summary of the process for fuzzy rules optimization

In the proposed method, the values for the minimum and maximum number of membership functions are from 2 to 5, but this range can be increased or decreased, the name of each membership functions (linguistic labels) depending of the number of membership functions used in the fuzzy inference system are shown in Table 1, and these names can be also easily modified. For the proposed method, the number of alpha planes in the optimization a range from 50 to 200 is established, because in [20] good results were found in this range.

NMFs	Labels (Linguistic labels)				
2	'Low'				'High'
3	'Low'		'Medium'		'High'
4	'Low'	'MediumLow'		'MediumHigh'	'High'
5	'Low'	'MediumLow'	'MediumMedium'	'MediumHigh'	'High'

Table 1. Labels of the MFs

The genetic parameters [15] used to test the proposed hierarchical genetic algorithm are shown in Table 2, and these parameters are the same used in [21] and [29].

Genetic Operator / Parameters	Value
Population size	10
Maximum number of generations	100
Selection	Roulette wheel
Selection Rate	0.85
Crossover	Single Point
Crossover Rate	0.9
Mutation	bga
Mutation Rate	0.01

Table 2. Table of parameters for the HGA for the FIS optimization

3.4 Elitism and reinitialization process

The elitism used for the fuzzy inference optimization is the conventional method, where the individual with the best performance is saved to avoid being modified with the genetic operators. The reinitialization process is activated when in the evolution, the objective error does not change during 10 generations, and then a new population is generated. In this population, the best individual of the last generation is inserted and the rest of the population is randomly generated and the evolution continues.

3.5 Comparison with previous works

In [21], the maximum number of membership functions was from 2 to 3, only 2 types of fuzzy logic were optimized: type-1 and interval type-2 fuzzy logic, and the fuzzy rules were randomly created based on a percentage provided by a gene. In [29], the maximum number of membership functions was from 2 to 5, also only 2 types of fuzzy logic were optimized: type-1 and interval type-2 fuzzy logic, and the consequents of the fuzzy rules were optimized. This optimization does not perform intuitionistic fuzzy systems optimization and do not have a reinitialization process. To understand the difference between the previous works and the proposed method, Table 3 presents a summary of the most important aspects of the optimizations.

Case	HGA [21]	HGA [29]	Proposed Method
Type of MFs	Trapezoidal GBell	Trapezoidal GBell	Trapezoidal GBell
Combination of MFs	Yes	Yes	Yes
Number of MFs	2 to 3	2 to 5	2 to 5
Fuzzy Rules	Yes (Number of rules)	Yes (Consequents)	Yes (Antecedents and consequents)
Type of Fuzzy Logic	Type-1 Interval Type-2	Type-1 Interval Type-2	Type-1 Interval Type-2 Intuitionistic
Elitism	Yes	Yes	Yes
Reinitialization process	No	No	Yes

Table 3. Comparison with previous works and proposed optimization

4 Human recognition application

In this section, the application and databases used to test the proposed method are described in more detail.

4.1 Modular neural networks

A modular neural network is a kind of an artificial neural network (ANN), where the computation performed by a MNN is decomposed into two or more modules. In this work, 3 modules are used in each MNN, where each module learns information of a certain amount of persons. In this work, the human recognition of 77 persons is performed and the division of persons per module is illustrated in Figure 10.

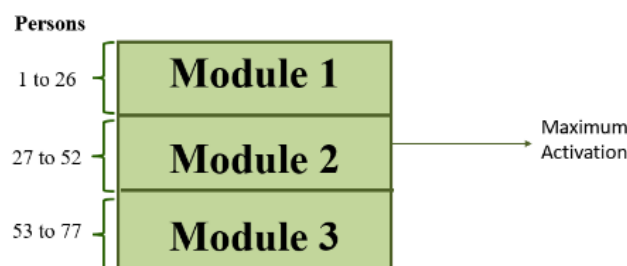


Figure 10. Division of each MNN

Each module is a multi-layer feed-forward (MLF) neural network trained with the back-propagation learning algorithm, and the variations used were: gradient descent with scaled conjugate gradient (SCG), gradient descent with adaptive learning and momentum (GDX) and gradient descent with adaptive learning (GDA). The neurons of the hidden layers use a hyperbolic tangent sigmoid transfer function, and in the output layer the neurons use a sigmoid transfer function, and this transfer function limits the output of each neuron between a value of 0 and 1. To obtain a final output (maximum activation) of each MNN, the winner takes all method is used. The number of neurons for the inputs layers depend of the information (image size or voice sample) and the number of neurons for the outputs layers depend of the number of persons learned by each module, as in this work 3 modules are used, the neurons used are respectively 26, 26 and 25 (for each MNN).

As it was already mentioned, the final output of each MNN is its maximum activation, as 3 MNNs are used, 3 activations with values between 0 and 1 will be the inputs of the FIS, and using the fuzzy if-then rules a final output can be obtained.

4.2 Human recognition

The general architecture of the proposed method presented in [21] is shown in Figure 11, each modular neural network (MNN) is design with 3 modules. In [21], the optimization of the modular neural networks and fuzzy inference systems are performed. In that work 3 biometric measures are used: iris; ear and voice, one modular neural network (MNN) for each biometric measure where, the responses of each modular neural network are combined using an optimized fuzzy inference system.

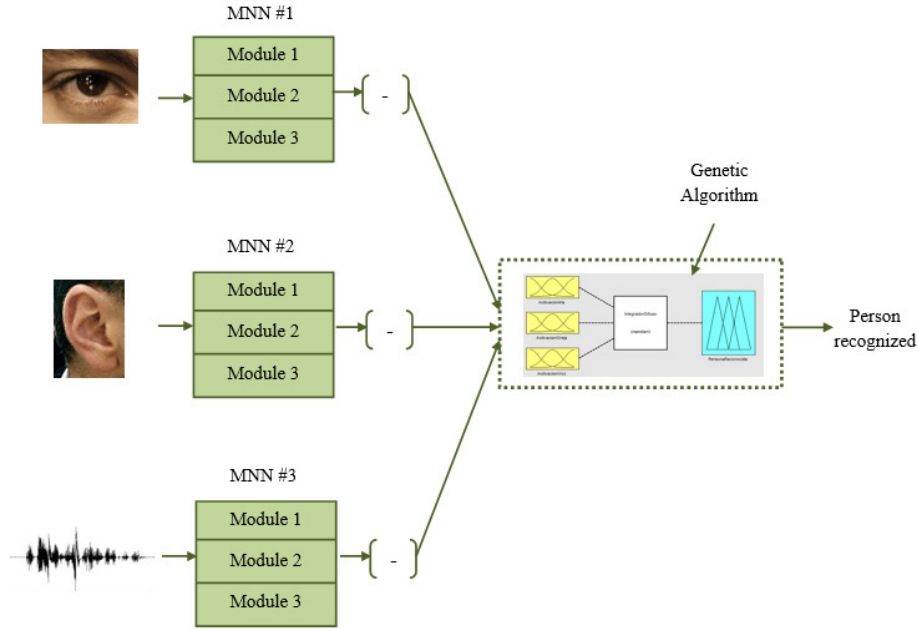


Figure 11. Architecture of the MNN for person recognition based on iris, ear and voice biometrics [21]

The hierarchical genetic algorithm aims at minimizing the fitness function (error of recognition). The fitness function is given by:

$$F = \frac{\sum_{i=1}^T X_i}{T}, \quad (6)$$

where X_i is 0 if the person is correctly identified and 1 if not, and T is total number of data points (combinations) used for testing. For comparison with the previous work, the recognition rate is shown and given by:

$$R = \frac{T - \sum_{i=1}^T X_i}{T} \times 100. \quad (7)$$

4.3 Databases

In this section, the databases used in [21] and [29] are presented. The human recognition is performed for 77 persons, and for this reason only the first 77 persons of each database are used. These databases were chosen, because they were also used by other authors [10][12][13].

4.3.1 Iris Database

The database of human iris from the Institute of Automation of the Chinese Academy of Sciences (CASIA) was used [7]. Each person has 14 images (7 for each eye). The image dimensions are 320×280 , JPEG format. In Figure 12 some examples of the human iris images are shown. As image preprocessing, the method developed by [17] is used to find the coordinates and radius of the iris and pupil, iris is cut and a new image with a dimension of 21×21 is produced, finally the images are converted from vector to matrix form.

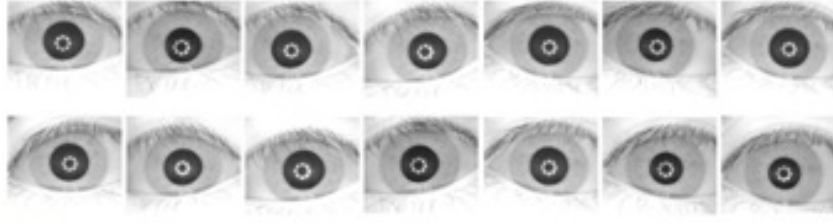


Figure 12. Examples of the human iris images from CASIA database

4.3.2 Ear Database

The database of the University of Science and Technology of Beijing is used [6]. The image dimensions are 300×400 pixels, BMP format, and each person has 4 images. Figure 13 shows examples of the human ear images. For this database, a cut of the ear manually, a new image is created and resized to 132×91 and finally, the images are converted from vector to matrix form.

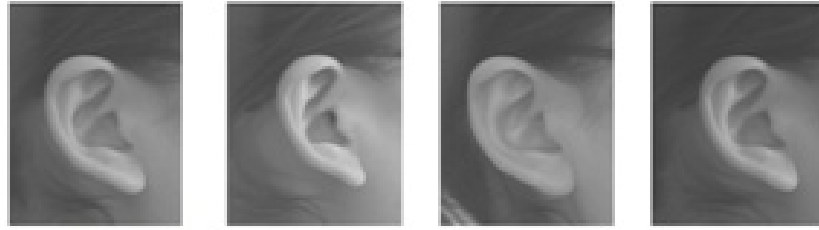


Figure 13. Examples of Ear Recognition Laboratory from the University of Science & Technology Beijing (USTB).

4.3.3 Voice Database

This database was collected from students of Tijuana Institute of Technology. Each person has 10 voice samples. Each sample is in the Microsoft's audio file format WAV. The word that they said in Spanish was "ACCESAR". Mel Frequency Cepstral Coefficients were used to preprocess the voice.

5 Experimental results

In this section, a comparison of the results achieved using a previous method [21] and the proposed method is shown, and a summary results and comparisons of results achieved comparing with [29] are shown in section 4.3. This work is focus on the fuzzy inference systems, where the combinations of activations of the biometric measures are performed using an improved fuzzy inference system, i.e. the results shown in this section are obtained of the combination of 462 sets ($T = 462$).

5.1 Previous results

In [21], 7 cases were established for combining different trainings of iris, ear and voice, using non-optimized and optimized trainings (in that work also a modular neural network optimization was proposed). These 7 cases were used without noise and with noise (Gaussian) in the images for the testing phase. In Tables 4 and 5, the training results and their combinations are presented.

Case	Iris	Ear	Voice
1	EI3 96.32%	EO3 66.23%	EV1 92.64%
2	EI3 96.32%	EO1 97.40%	EV3 93.94%
3	EI5 96.97%	EO2 85.71%	EV5 93.07%
4	EI2 97.19%	EO4 100.00%	EV4 94.81%
5	Iris (Optimized) V1 98.48%	EO4 100.00%	Voice (Optimized) V1 96.54%
6	EI4 97.19%	EO5 74.02 %	EV4 94.81%
7	Iris (Optimized) V1 98.48%	Ear(Optimized) V2 83.11%	Voice (Optimized) V1 96.54%

Table 4. Trainings used for forming the seven cases (without noise) [21]

Case	Iris	Ear	Voice
1	EI3 88.96%	EO3 66.23%	EV1 46.32%
2	EI3 50.65%	EO1 44.16%	EV3 93.94%
3	EI5 72.29%	EO2 66.23%	EV5 59.31%
4	EI2 53.25%	EO4 85.71%	EV4 87.01%
5	Iris (Optimized) V1 63.42%	EO4 77.92%	Voice (Optimized) V1 81.82%
6	EI4 68.40%	EO5 51.95 %	EV4 94.81%
7	Iris (Optimized) V1 70.78%	Ear (Optimized) V2 53.24%	Voice (Optimized) V1 81.82%

Table 5. Trainings used for forming the seven cases (with noise) [21]

The results achieved in [21] using its HGA are shown in Tables 6, where cases without noise and noise are shown, for noise cases Gaussian noise (statistical noise having a probability density function) was added to the images and voice samples, where the best, average and worst results are presented (of 20 evolutions). The proposed method in this paper has now the challenge of improving these results.

Case	Cases without Noise			Cases with Noise		
	Best	Average	Worst	Best	Average	Worst
1	99.78	99.19	96.32	91.55	90.71	89.39
2	100	100	100	99.56	98.80	96.32
3	99.56	99.21	98.48	83.54	82.16	80.52
4	100	100	100	96.10	93.80	87.88
5	100	100	100	90.47	88.02	85.71
6	100	99.47	97.62	96.53	95.13	92.64
7	99.78	99.53	99.13	86.79	84.40	77.27

Table 6. Comparison of optimized results [21]

5.2 Results of the proposed method

The results achieved, using the proposed method, are shown below. In this case, 20 evolutions for each case without noise and noise are performed. Each evolution allows to generate a new best FIS with different: type of fuzzy logic, number of MFs in each variable, parameters of these MFs and fuzzy if-then rules.

5.2.1 Results of cases without noise

The best, average and worst results of the previous work [21] and the proposed method are shown in Table 7. In those cases where a 100% of recognition rate had not been obtained in [21], the recognition rate is now improved using the proposed method.

Case	HGA [21]			Proposed Method		
	Best	Average	Worst	Best	Average	Worst
1	99.78	99.19	96.32	99.78	99.66	99.57
2	100	100	100	100	100	100
3	99.56	99.21	98.48	100	99.64	99.35
4	100	100	100	100	100	100
5	100	100	100	100	100	100
6	100	99.47	97.62	100	99.87	99.57
7	99.78	99.53	99.13	100	99.83	99.78

Table 7. Comparison of optimized results (cases without noise)

In Figure 14, the averages of each method are shown, where the results obtained using the proposed method are better in almost all the cases (except in those cases where a 100 of recognition rate had been already obtained in [21]).

The best evolution of case # 3 is the evolution #11, and the convergence can be observed in Figure 15. In this case, a 100% of recognition rate is obtained in only 33 generations.

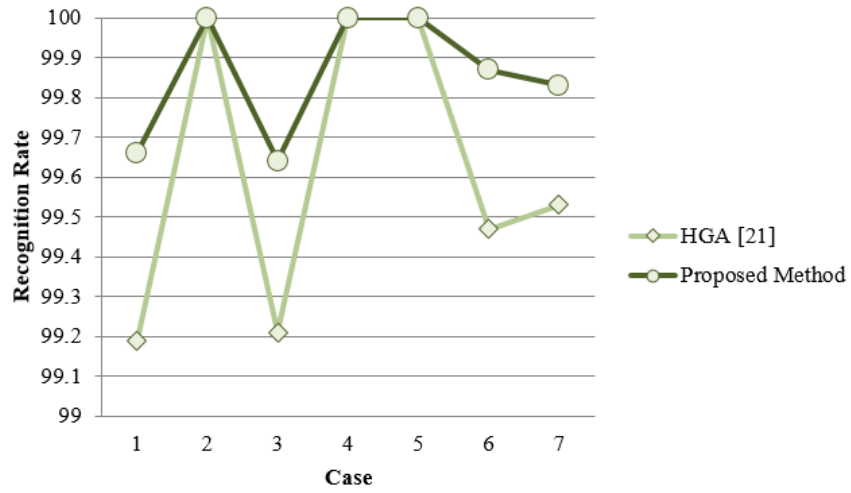


Figure 14. Averages for cases without noise

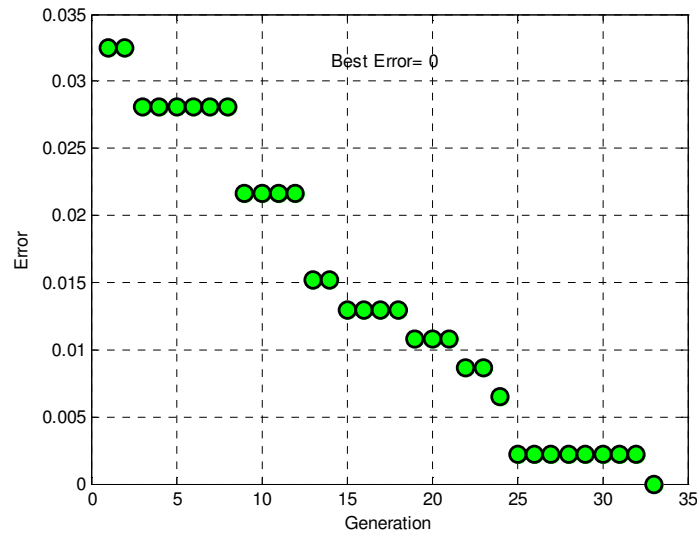


Figure 15. Convergence of case #3 (evolution #11)

The best fuzzy inference system for this case is using type-1 fuzzy logic, Sugeno type, using 12 fuzzy rules out of 20 possible fuzzy rules. The inputs of the fuzzy integrator are shown in Figure 16, and the fuzzy rules generated by the proposed hierarchical genetic algorithm are shown in Figure 17.

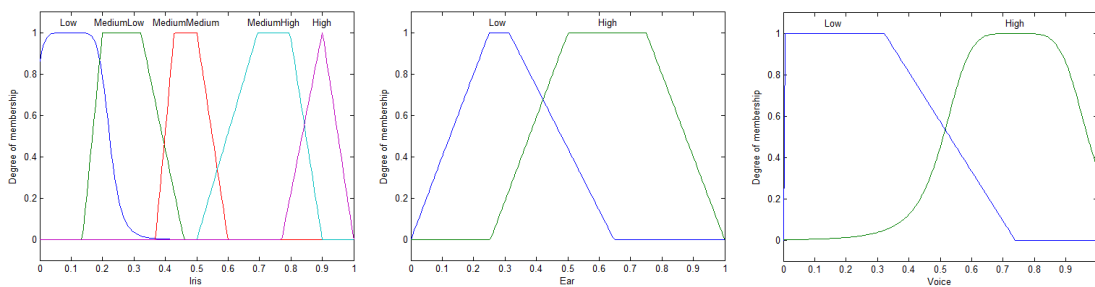


Figure 16. Best fuzzy inference system (case #3)

1. If (Iris is Low) and (Ear is High) and (Voice is Low) then (Output is High)
2. If (Iris is Low) and (Ear is High) and (Voice is High) then (Output is High)
3. If (Iris is MediumLow) and (Ear is Low) and (Voice is Low) then (Output is Low)
4. If (Iris is MediumLow) and (Ear is Low) and (Voice is High) then (Output is Low)
5. If (Iris is MediumLow) and (Ear is High) and (Voice is Low) then (Output is Low)
6. If (Iris is MediumLow) and (Ear is High) and (Voice is High) then (Output is High)
7. If (Iris is MediumHigh) and (Ear is Low) and (Voice is Low) then (Output is Low)
8. If (Iris is MediumHigh) and (Ear is High) and (Voice is Low) then (Output is Low)
9. If (Iris is MediumHigh) and (Ear is High) and (Voice is High) then (Output is High)
10. If (Iris is High) and (Ear is Low) and (Voice is Low) then (Output is Low)
11. If (Iris is High) and (Ear is High) and (Voice is Low) then (Output is Low)
12. If (Iris is High) and (Ear is High) and (Voice is High) then (Output is Low)

Figure 17. Best fuzzy rules (case #3)

The best evolution of case #6 is evolution #4, and the convergence behavior can be observed in Figure 18. In this case, a 100% of recognition rate is obtained in only 95 generations.

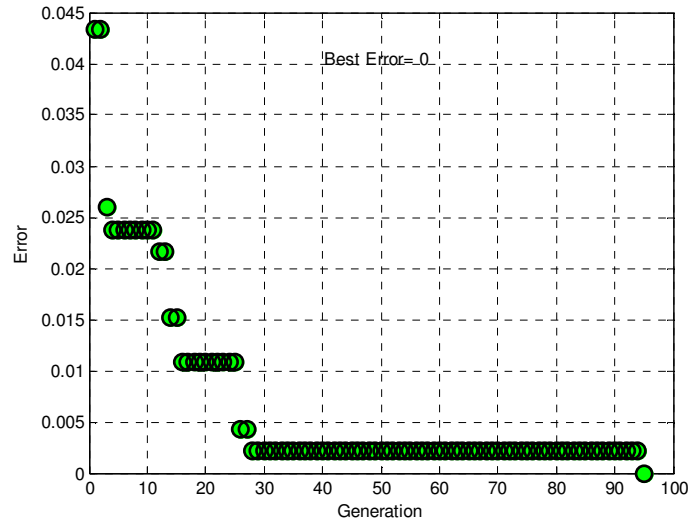


Figure 18. Convergence of case #6 (evolution #4)

The best fuzzy inference system for this case is using interval type-2 fuzzy logic, of Sugeno type, using only 12 fuzzy rules out of 30 possible fuzzy rules. The inputs of the fuzzy integrator are shown in Figure 19, and the fuzzy rules generated by the proposed hierarchical genetic algorithm are shown in Figure 20.

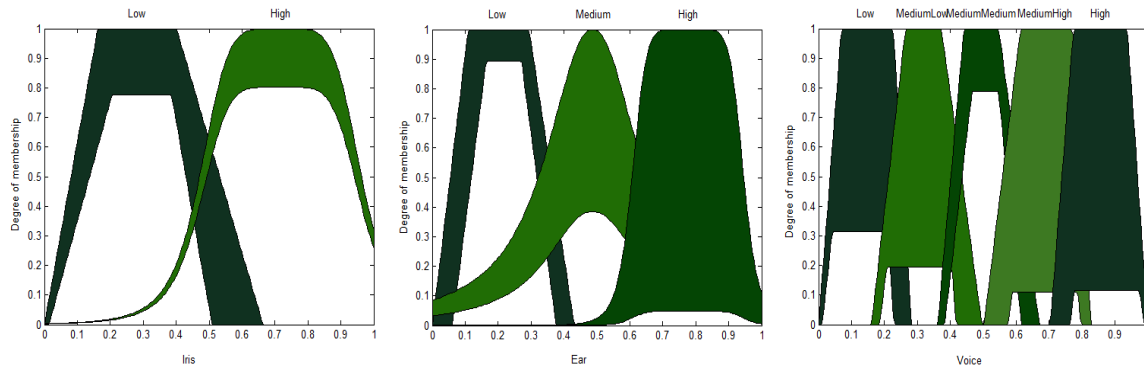


Figure 19. Best fuzzy inference system (case #6)

1. If (Iris is Low) and (Ear is Low) and (Voice is Low) then (Output is MediumHigh)
2. If (Iris is Low) and (Ear is Low) and (Voice is MediumLow) then (Output is MediumLow)
3. If (Iris is Low) and (Ear is Medium) and (Voice is Low) then (Output is High)
4. If (Iris is Low) and (Ear is Medium) and (Voice is High) then (Output is High)
5. If (Iris is Low) and (Ear is High) and (Voice is MediumLow) then (Output is MediumHigh)
6. If (Iris is Low) and (Ear is High) and (Voice is MediumMedium) then (Output is MediumHigh)
7. If (Iris is Low) and (Ear is High) and (Voice is MediumHigh) then (Output is MediumLow)
8. If (Iris is High) and (Ear is Low) and (Voice is MediumLow) then (Output is Low)
9. If (Iris is High) and (Ear is Medium) and (Voice is Low) then (Output is Low)
10. If (Iris is High) and (Ear is Medium) and (Voice is MediumLow) then (Output is Low)
11. If (Iris is High) and (Ear is Medium) and (Voice is MediumMedium) then (Output is High)
12. If (Iris is High) and (Ear is High) and (Voice is High) then (Output is High)

Figure 20. Best fuzzy rules (case #6)

5.2.2 Results of cases with noise

The best, average and worst results of the previous work [21] and the proposed method are shown in Table 8. In all cases, the proposed method in this paper allows to improve the previously obtained results, especially if we observe the worst values, they are also improved with the proposed method.

Case	HGA [21]			Proposed method		
	Best	Average	Worst	Best	Average	Worst
1	91.55	90.71	89.39	92.86	92.37	92.21
2	99.56	98.80	96.32	99.78	99.49	99.35
3	83.54	82.16	80.52	84.63	83.78	83.33
4	96.10	93.80	87.88	98.05	96.95	96.32
5	90.47	88.02	85.71	92.42	90.54	89.18
6	96.53	95.13	92.64	96.97	96.05	95.45
7	86.79	84.40	77.27	87.45	86.65	86.15

Table 8. Comparison of optimized results (cases with noise)

In Figure 21, the averages of each method are shown, where the results obtained, using the proposed method, are better in all the cases.

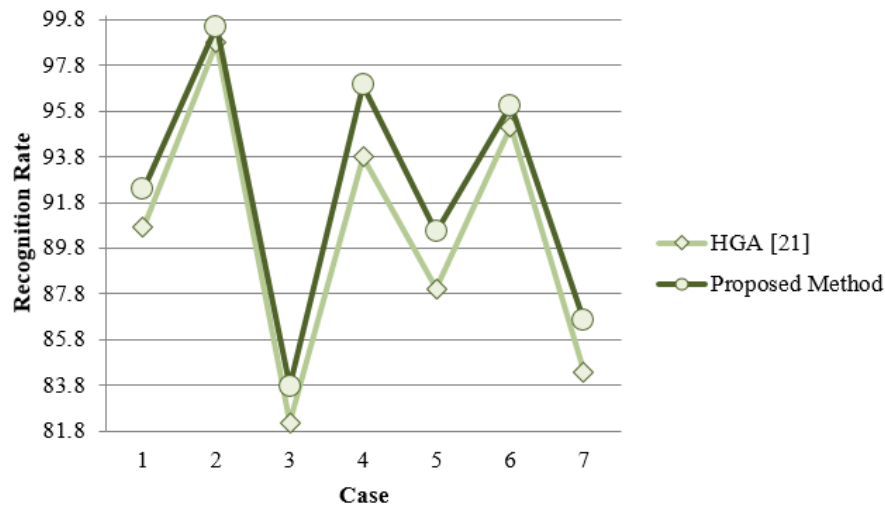


Figure 21. Averages for cases with noise

The best evolution of case # 1 is evolution #14, and the convergence behavior can be observed in Figure 22. In this case, a recognition rate of 92.86% is obtained.

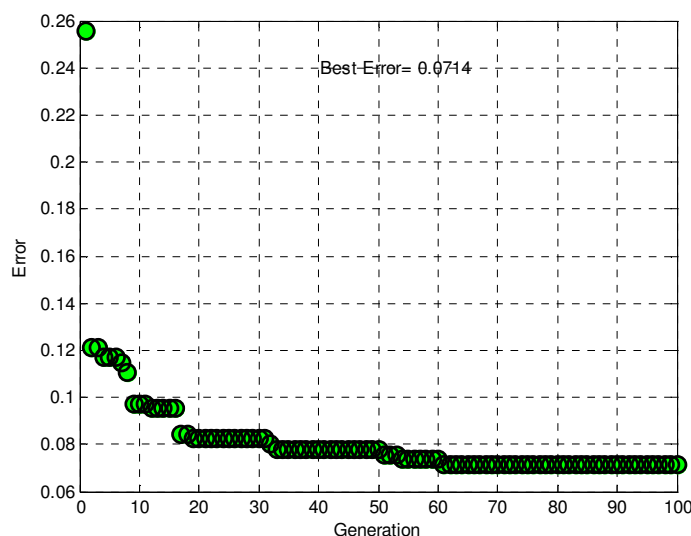


Figure 22. Convergence of case #1 (evolution #14)

6 Conclusion

In this paper, a method that combines modular neural networks (MNNs) responses using fuzzy logic as response integrators was proposed. A hierarchical genetic algorithm is proposed to optimize fuzzy inference systems, where the main contribution of the proposed method is to allow the optimization of the type of fuzzy logic (Type-1, Interval Type-2 and Intuitionistic fuzzy logic) and allow combination of different type of membership functions in the same variable and mainly the number of membership functions in each variable (inputs and output) with a range from 2 to 5 (but this range can be increased or decreased) and the optimization of fuzzy rules (number of rules and consequents), and a reinitialization process which had not been proposed in other previous works. The optimization of the type of system (Mamdani Model or Sugeno Model) is also proposed. Using a statistical comparison, we can prove that the results are significantly improved when the proposed method is used, i.e. that the increase of the range of the number of membership functions, optimization of fuzzy rules (number and consequents) and the use of intuitionistic and type-2 fuzzy logic allow improving the results.

References

- [1] Atanassov, K. (1986). Intuitionistic fuzzy sets, *Fuzzy Set and Systems*, 20(1), 87–96.
- [2] Bhatia, S., Bawa, A., & Kaur Attri, V. (2015). A review on genetic algorithm to deal with optimization of parameters of constructive cost model. *International Journal of Advanced Research in Computer and Communication Engineering*, 4(4), 405–408.

- [3] Castillo, O., & Melin P. (2008) *Type-2 Fuzzy Logic Theory and Applications*, Springer Verlag, Berlin, 20–43.
- [4] Castillo, O., Neyoy, H., Soria, J., Melin, P., & Valdez, F. (2015). A new approach for dynamic fuzzy logic parameter tuning in ant colony optimization and its application in fuzzy control of a mobile robot. *Applied soft computing*, 28, 150–159.
- [5] Castro, J. R., Castillo, O., Melin, P., & Rodríguez-Díaz, A. (2008). Building Fuzzy Inference Systems with a New Interval Type-2 Fuzzy Logic Toolbox", *Transactions on Computational Science*, 1, 104–114.
- [6] Database Ear Recognition Laboratory from the University of Science & Technology Beijing (USTB). Found on the Web page: <http://www.ustb.edu.cn/resb/en/index.htm> asp (Accessed 21 September 2009).
- [7] Database of Human Iris. Institute of Automation of Chinese Academy of Sciences (CASIA). Found on the Web page: <http://www.cbsr.ia.ac.cn/english/IrisDatabase.asp> (Accessed 21 September 2009).
- [8] Fister, I., Rauter, S., Yang, X. S., & Ljubič, K. (2015). Planning the sports training sessions with the bat algorithm. *Neurocomputing*, 149, 993–1002.
- [9] Garcia-Capulin, C. H., Cuevas, F. J., Trejo-Caballero, G., & Rostro-Gonzalez, H. (2015). A hierarchical genetic algorithm approach for curve fitting with B-splines. *Genetic Programming and Evolvable Machines*, 16(2), 151–166.
- [10] Gaxiola, F., Melin, P., Valdez, F., & Castillo, O (2012) Neural Network with Type-2 Fuzzy Weights Adjustment for Pattern Recognition of the Human Iris Biometrics, *MICAI*, 2, 259–270.
- [11] González, B., Valdez, F., Melin, P., & Prado-Arechiga, G. (2015). Fuzzy logic in the gravitational search algorithm for the optimization of modular neural networks in pattern recognition. *Expert Systems with Applications*, 42(14), 5839–5847.
- [12] Gutierrez, L., Melin P. & Lopez, M. (2010) Modular Neural Network for Human Recognition from Ear Images Using Wavelets, *Soft Computing for Recognition Based on Biometrics*, 121–135.
- [13] Gutierrez, L., Melin P. & Lopez, M. (2010) Modular neural network integrator for human recognition from ear images, *IJCNN*, 1–5.
- [14] Hidalgo, D., Melin, P., & Castillo, O. (2012). An optimization method for designing type-2 fuzzy inference systems based on the footprint of uncertainty using genetic algorithms. *Expert Systems with Applications*, 39(4), 4590–4598.
- [15] Man, K. F., Tang, K. S., & Kwong, S. (1999). *Genetic Algorithms: Concepts and Designs*, Springer.
- [16] Martínez-Soto, R., Castillo, O., & Aguilar, L. T. (2014). Type-1 and Type-2 fuzzy logic controller design using a Hybrid PSO–GA optimization method. *Information Sciences*, 285, 35–49.

- [17] Masek, L.& Kovesi, P. (2003) MATLAB Source Code for a Biometric Identification System Based on Iris Patterns. The School of Computer Science and Software Engineering, The University of Western Australia.
- [18] Melin P.(2015) Pattern Recognition with Modular Neural Networks and Type-2 Fuzzy Logic, *Handbook of Computational Intelligence*, 1509–1515.
- [19] Melin, P., & Castillo, O. (2014). A review on type-2 fuzzy logic applications in clustering, classification and pattern recognition. *Applied soft computing*, 21, 568–577.
- [20] Melin, P., Gonzalez, C. I., Castro, J. R., Mendoza, O., & Castillo, O. (2014). Edge-detection method for image processing based on generalized type-2 fuzzy logic. *IEEE Transactions on Fuzzy Systems*, 22(6), 1515–1525.
- [21] Melin, P., Sánchez, D., & Castillo, O. (2012). Genetic optimization of modular neural networks with fuzzy response integration for human recognition. *Information Sciences*, 197, 1–19.
- [22] Mendel, J. M. (2014). General type-2 fuzzy logic systems made simple: a tutorial. *IEEE Transactions on Fuzzy Systems*, 22(5), 1162–1182.
- [23] Murmu, S., & Biswas, S. (2015). Application of fuzzy logic and neural network in crop classification: A review. *Aquatic Procedia*, 4, 1203–1210.
- [24] Nandy, S., Yang, X. S., Sarkar, P. P., & Das, A. (2015). Color image segmentation by cuckoo search. *Intelligent Automation & Soft Computing*, 21(4), 673–685.
- [25] Porwal, A., Carranza, E. J. M., & Hale, M. (2004). A hybrid neuro-fuzzy model for mineral potential mapping. *Mathematical Geology*, 36(7), 803–826.
- [26] ProQuest Information and Learning Company., History of Voice Recognition Technology, The, Information Management Journal. 07 Oct, 2009.
- [27] Saleh, M. (2006) Using Ears as a Biometric for Human Recognition, Arab Academy for Science and Technology and Maritime Transport, Cairo, Egypt, September 2006.
- [28] Sánchez, D., & Melin, P. (2014). Optimization of modular granular neural networks using hierarchical genetic algorithms for human recognition using the ear biometric measure. *Engineering Applications of Artificial Intelligence*, 27, 41–56.
- [29] Sánchez D., & Melin P. (2016) *Hierarchical Modular Granular Neural Networks with Fuzzy Aggregation*, Springer.
- [30] Santos, J. M., Alexandre, L. A., & De Sa, J. M. (2006). Modular neural network task decomposition via entropic clustering, in: ISDA, 1, 62–67.
- [31] Seitzer, J. (2014) Zooming In, Zooming Out: A Framework for Hierarchical Genetic Algorithms, *Systemics, Cybernetics And Informatics*, 12(4), 1–5.
- [32] Singh, Y. N. (2015). Human recognition using Fisher' s discriminant analysis of heartbeat interval features and ECG morphology. *Neurocomputing*, 167, 322–335.
- [33] Tahmasebi, P., & Hezarkhani, A. (2012). A hybrid neural networks-fuzzy logic-genetic algorithm for grade estimation. *Computers & geosciences*, 42, 18–27.

- [34] Tahmasebi, P., & Hezarkhani, A. (2011). Application of a modular feedforward neural network for grade estimation. *Natural resources research*, 20(1), 25–32.
- [35] Tang, K.S., Man, K.F., Kwong, S., Liu, Z.F.(1998) Minimal fuzzy memberships and rule using hierarchical genetic algorithms, *IEEE Trans. Ind. Electron.* 45 (1), 162–169.
- [36] Vázquez J.C., Valdez F. & Melin P. (2015) Comparative Study of Particle Swarm Optimization Variants in Complex Mathematics Functions, *Fuzzy Logic Augmentation of Nature-Inspired Optimization Metaheuristics*, 163–178.
- [37] Zadeh L. A. (1965) Fuzzy Sets, *Journal of Information and Control*, 8, 338–353.
- [38] Zadeh L. A. (2008) Is there a need for fuzzy logic?, *Information Sciences*, 178, 2751–2779.
- [39] Zadeh, L. A. (2005). Toward a generalized theory of uncertainty (GTU)—an outline. *Information sciences*, 172(1-2), 1–40.