

# TYPE-1 AND TYPE-2 FUZZY INFERENCE SYSTEMS AS INTEGRATION METHODS IN MODULAR NEURAL NETWORKS FOR MULTIMODAL BIOMETRY AND ITS OPTIMIZATION WITH GENETIC ALGORITHMS

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## Abstract:

We describe in this paper a comparative study between Fuzzy Inference Systems as methods of integration in modular neural networks for multimodal biometry. These methods of integration are based on techniques of type-1 fuzzy logic and type-2 fuzzy logic. Also, the fuzzy systems are optimized with simple genetic algorithms. First, we considered the use of type-1 fuzzy logic and later the approach with type-2 fuzzy logic. The fuzzy systems were developed using genetic algorithms to handle fuzzy inference systems with different membership functions, like the triangular, trapezoidal and Gaussian; since these algorithms generate the fuzzy systems automatically. Then the response integration of the modular neural network was tested with the optimized fuzzy integration systems. The comparative study of type-1 and type-2 fuzzy inference systems was made to observe the behavior of the two different integration methods for modular neural networks for multimodal biometry.

**Keywords:** modular neural networks, type-2 fuzzy logic, pattern recognition, genetic algorithms.

## 1. Introduction

**Biometry**, is a discipline that studies the recognition of the people through its physiological characteristics (fingerprint, face, retina...) or of behavior (voice, signature,...). The interest of the society to use biometric patterns to identify or verify the authenticity of the people has had a drastic increase, that it is reflected in the appearance of diverse practical applications like identity Passports that include biometrics characteristics. Biometry provides a true identification of people, since this technology is based on the recognition of unique corporal characteristics, reason why recognizes the people based on who they are. Only biometric identification can provide a really efficient and precise control of the people, since it is possible to know with a high degree of certainty that the person that went through this form of recognition is the recognized person. As it is habitual in many scientific disciplines, before making a search of the solutions to the problem, it is reasonable and preferable to stop a moment and to make an analysis of the problem. The result of this analysis will be a vision of the different parts that form the whole, having transformed the initial task, probably complex, in a set of more elementary subtasks, susceptible to be approached in a simpler and efficient way. Once this is done, the problem is transformed into the opposite: to integrate the obtained partial results of each of the subtasks and of generating the solution to the complete problem [1].

The primary goal of this research was to implement type-1 fuzzy logic and type-2 fuzzy logic as methods to integrate the obtained partial results of each of the modules by which the modular neural network was formed and to optimize the type-1 and type-2 fuzzy systems with genetic algorithms; this with the purpose of obtaining the optimal results in the recognition, and making a comparison between the different fuzzy logic methods.

## 2. Modular neural networks

As it is common in many scientific disciplines, before making the search of the solutions to the problem, it is reasonable and preferable to stop a moment and make an analysis of the problem. The result of this analysis will be a vision of the different parts that form the whole, having transformed the initial task, probably complex, in a set of more elementary subtask, able to be approached in a simpler and efficient way. Once this is done, the problem is transformed into the opposite: *to integrate* the obtained partial results of each one of the subtasks and of generating the solution to the complete problem. The first step is to divide the task (problem) in to subtasks, and later to create and to organize in a suitably way the constructed subsystems to allow the communication among them and thus to integrate them as a whole, which provides the desired solution. The idea of modularity, as it was proposed in the origins of the connectionist computation, has been inspired in the biological models. A review of the physiological structures of the nervous system in vertebrate animals reveals the existence of a representation and hierarchical modular processing of the information [11].

Considering as a basis the biological indications, one of the first modular approaches to complex systems was proposed by Jacobs and Jordan that can use two types of different methods of learning:

- *Supervised Learning*: during which an external teacher provides for each input the correct output. However, this teacher does not specify which module is the one that must learn the corresponding pair (input, desired output).
- *Unsupervised Learning*: that basically consists of a competitive learning, in that different modules do competitive learning whit the presented example [11].

In general, a computational system can be considered a modular structure if it is possible to divide it in two or more modules, in which each individual module can evaluate different or the same inputs without communicating with the others. The outputs of the modules are

aggregated by an integrating unit, which decides:

- How the modules are combined to form the final output of the system.
- How each module must learn the patterns.

It is important to mention that the use of the RNM to solve a problem in particular, requires ample knowledge of the problem to be able to make the subdivision of the problem, and to build the suitable modular architecture to solve it, in such a way that it is possible to train each of the modules independently, and later to integrate the knowledge learned by each module, in the global architecture [2].

### 2.1. Methods of integration

According to the form in which the division of the tasks takes place, the integration method allows to integrate or to combine the results given by each of the constructed modules. Some of the commonly used methods of integration are: Average, Gating Network, fuzzy Inference Systems, Mechanism of voting using softmax function, the winner takes everything to it, among others [2].

In this paper we will describe methods of integration based Fuzzy Inference Systems, since it is one that is of interest to us in this research work.

We show next the block diagram of the modular neural network (see Figure 1).

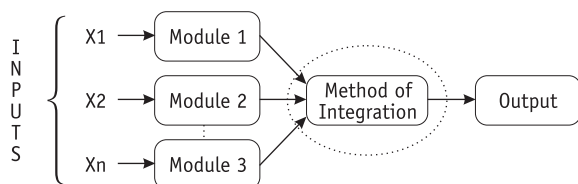


Fig. 1. Blocks diagram of a modular neural network.

## 3. Type-1 Fuzzy logic

Fuzzy Logic was born in 1965 with the publication of "Fuzzy Sets" [14] written by Lotfi A. Zadeh in the University of California in Berkeley for the Information and Control magazine, which was based on the work of J. Lukasiewicz [15] on multiple-valued logic. Once the foundations of fuzzy logic became firm, their applications have grown in number and diversity, and its influence within basic sciences, has become more visible and more substantial [16]. Fuzzy Logic creates mathematical approaches in the solution of certain kinds of problems. Fuzzy Logic produces exact results from vague data, thus it is particularly useful in electronic or computational applications.

### 3.1. Type-1 Fuzzy Inference System

The basic structure of fuzzy inference system consists of three conceptual components: a set of rules, which contains a selection of fuzzy rules; a data base (or dictionary), that defines the used membership functions in the rules; and a reasoning mechanism, that makes the inference procedure (usually fuzzy reasoning). The basic fuzzy inference system can take fuzzy or traditional inputs, but the outputs that are produced are always fuzzy sets. Some times it is necessary to have a traditional output, especially when a fuzzy inference system is used as a controller. Then, a "defuzzification" method is needed to extract the numerical value of output (see Figure 2).

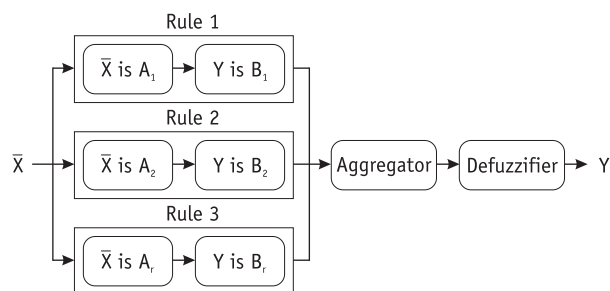


Fig. 2. Fuzzy Inference System.

A Fuzzy Inference System is a non linear mapping of its input space to its output space. This mapping is obtained by means of a set of fuzzy if-then rules, each of which describes the local behavior of the mapping.

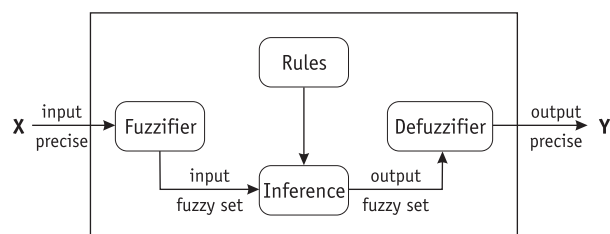


Fig. 3. Basic structure of Type-1 Fuzzy Inference System.

In this paper we study the integration method of modular neural networks. We use type-1 and type-2 fuzzy inference systems as integration methods and genetic algorithms are used to optimize the structure of the fuzzy system.

## 4. Type-2 fuzzy logic

The original Fuzzy logic (FL), was proposed by Lotfi Zadeh, more than 40 years ago, and this cannot fully handle all the uncertainty present in real-world problems. "To handle," it is understood as "to model and to reduce to the minimum the effect of". That type-1 fuzzy logic cannot completely do this, sounds paradoxical because this has the uncertainty connotation. Type-2 Fuzzy Logic can handle uncertainty because it can model it and reduce to the minimum their effects. Also, if all the uncertainties disappear, type-2 fuzzy logic reduces to type-1 fuzzy logic, in the same way that, if the randomness disappears, the probability is reduced to the determinism [18]. Fuzzy sets and fuzzy logic are the foundation of fuzzy systems, and have been developed looking to model the form as the brain manipulates inexact information. Type-2 fuzzy sets are used to model uncertainty and imprecision; originally they were proposed by Zadeh in 1975 and they are essentially "fuzzy-fuzzy" sets in which the membership degrees are type-1 fuzzy sets.

### 4.1. Type-2 Fuzzy Inference System

A fuzzy Inference System is a system based on rules that uses fuzzy logic, instead of Boolean logic, to analyze data [5,10]. Its basic structure includes four main components:

- *Fuzzifier*. It translates inputs (real values) to fuzzy values.
- *Inference System*. Type-1 or type-2 applies a mechanism of fuzzy reasoning to obtain a fuzzy output.
- *Defuzzifier/Type Reducer*. The defuzzifier it translates an output to precise values; the type reducer transforms a fuzzy set of type-2 to type-1; and
- *Knowledge Base*. It contains a set of fuzzy rules, known as base rules, and a set of membership functions known as the data base.

In Figure 4 we can appreciate the basic structure of a type-2 Fuzzy Inference System.

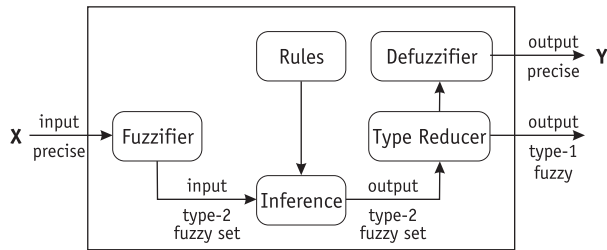


Fig. 4. Basic structure of Type-2 Fuzzy Inference System.

Uncertainty is "the imperfection in the knowledge on the state or the processes of the nature". The statistical uncertainty is "the randomness or the originating error of several sources like described when using statistical methodology" [3].

### 5. Genetic algorithms

The Genetic Algorithm (GA), is a search technique based on Darwin's theory of evolution, and has received tremendous popularity anywhere in the world during the past few years. They are adaptive methods that can be used to solve search and optimization problems. They are based on the genetic process of the living organisms. Throughout the generations, the populations evolve in the same form as in nature, with the principles of natural selection and the survival of fittest, postulated by Darwin.

Simulating evolution, GA's are able to create solutions to problems of the real world. The evolution of these solutions towards optimal values of the problem depends largely on a suitable codification of the solutions [5]. The use of new representations and the construction of new operators to manipulate information have caused that the present conception of a GA is quite different and more general than the original idea. The basic structure of a GA is shown in Figure 5 [6].

```

Procedure Genetic Algorithm
Begin
  t=0
  to initialize P(t)
  to evaluate P(t)
  While (the condition of shutdown is not fulfilled) do
    begin
      t=t+1
      to select P(t) from P(t-1)
      to apply crossover and mutation on P(t)
      to evaluate P(t)
    end
  end
end
    
```

Fig. 5. Structure of a generational GA.

### 6. General idea of the modular architecture

In this paper we are making a comparison between the integration methods of a modular neural network; this comparison is done with the integration method as fuzzy systems, which used techniques of type-1 Fuzzy logic and type-2 Fuzzy Logic. These methods of integration were implemented in modular neural networks for biometry. In others words, the MNN's were trained to make the recognition of persons using their face, fingerprint and voice. These features of a persons are the 3 more important biometric measures in the field of pattern recognition, at the moment. Next, we show the general architecture of the modular system in Figure 6.

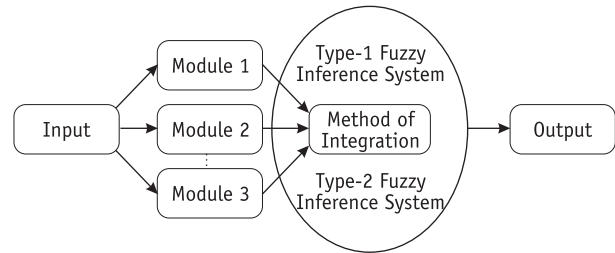


Fig. 6. General Scheme of the pattern recognition system.

Now we describe in more detail the pattern recognition system (Figure 7).

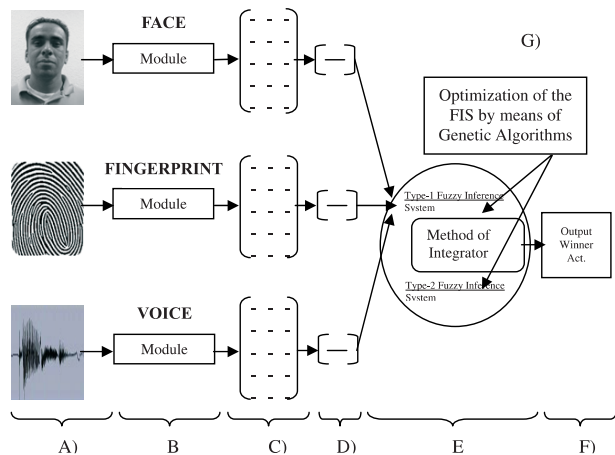


Fig. 7. Structure of a generational GA.

We describe in more detail the modular of the pattern recognition system in the following section.

#### 6.1. Description of the problem and the solution

In this section we describe in detail the different parts of the recognition system.

##### A) Input data

We describe at this point the input data used in the modular architecture for pattern recognition:

*Face*: Images of the faces of 30 different people were used to make the training of the MNN without noise, we also use 30 images of the face of these same people but with different gestures, to use them in the training with noise. The used images were preprocessed with a wavelet function to obtain better results in the training, as given in [25]. These images were obtained from a group of

students of Tijuana Institute of Technology, combined with some others of the ORL data base. The size of these images is of 268 x 338 pixels with extension .bmp. These are shown in Figure 8.



Fig. 8. Data base used for the training of faces.

**Fingerprint:** Images of the fingerprints of 30 different people were used to make the training without noise. Then it was added random noise to the fingerprint use them in the training with noise. The used images were preprocessed with a wavelet function to obtain better results in the training, as given in [25]. These images were obtained from a group of students of Tijuana Institute of Technology, combined with some others of the ORL data base. The size of these images is of 268 x 338 pixels with extension .bmp. These are shown in Figure 9.

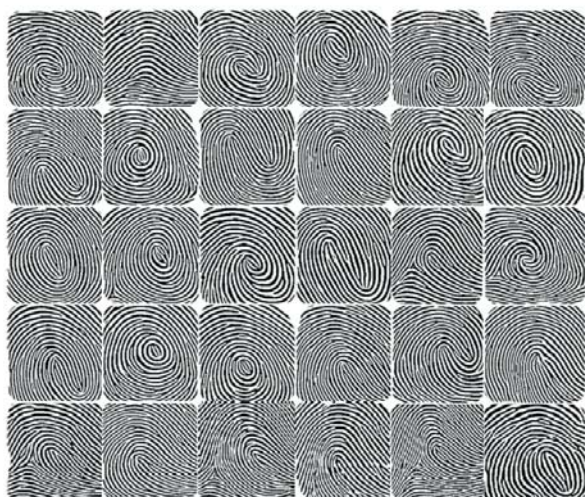


Fig. 9. Data base used for the training of.

**Voice:** For the training of module of voice was used word spoken by different persons. With samples of 30 persons as with the face and fingerprint. We applied the Mel cepstrals coefficients [24], as preprocessing for the training in the MNN.

The used three Spanish words as follows:

- Accesar
- Hello
- Presentation

Where some people will say the words in Spanish "Accesar", others "Hello", and some other "Presentation".

We also have to mention that random noise was added to the voice signals to train the MNN with noisy signals.

*B) Modules of the mnn for the training*

The modular neural network that is considered in this paper has three modules, one for the face, another one for the fingerprint and finally another for the voice, each of the three modules has three submodules. In others words, the architecture of the modules could be visualized as in Figure 10:

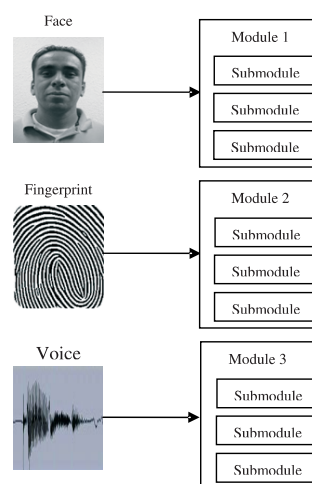


Fig. 10. Architecture of the modular neural network for the training.

It is possible to mention that for each trained module and each submodule, different architectures were used, that is to say, different number of neurons, layers, etc., and different training methods.

*C) Output of the Modular Neural Network (MNN)*

The output of the MNN is a vector that is formed by 30 activations (in this case because the network has been trained with 30 different people).

*D) Competition between activations*

In this step the competition between the 30 winning activations is carried out, thus the final result from the MNN is obtained; where it is an activation by module, these activations were used to input the fuzzy system, this data represented then the higher activation from a each module, in others words, three results were obtained; one for the module of the face, another one for module of the fingerprint and another one for the module of the voice.

*E) Integration of the MNN (Type-1 and Type-2 Fuzzy Inference System)*

In this part, once the winning activations are obtained for each module, they are input to the fuzzy inference

system, in which these activations are evaluated and depending on the characteristics of the fuzzy system, a result of final output is obtained, which will give us, the winning module.

*F) Final output (Winning Activation)*

The result of the fuzzy system will give us to which module belongs, once this data is obtained we will be able to know that a person has been recognized.

*G) Optimization of the fuzzy systems by means of genetic algorithms*

The optimization of the fuzzy systems consists of, as

the name indicates it, optimizing the membership functions of the fuzzy systems, for the type-1 and type-2 fuzzy logic, with genetic algorithms.

**7. Results**

The simulation results were obtained after several steps were carried out. First, a set of trainings with the MNN were done. Second, several fuzzy systems (type-1 and type-2) were developed by using a genetic algorithm. The data used for training was obtained from previous research work and was also used to test the fuzzy integration modules.

Table 1. Training of the modular neural network.

MNN	Training Method	Layers by submodules	Neurons by layers	Performance function	Goal error	Error	Epochs	Recognized persons	% of recognition	Time of training
1	Trainscg	R: SubMod1: 2	198,160	MSE	0.01	0.00992082	4000	30	100	3 hrs 2 min
		SubMod2: 2	287,136	MSE	0.01	0.00990072	4000	30	100	
		SubMod3: 2	285,95	MSE	0.01	0.00996058	4000	30	100	
		H: SubMod4: 2	63,42	MSE	0.01	0.0200279	4000	19	63	
		SubMod5: 2	70,50	MSE	0.01	0.00993908	4000	30	100	
		SubMod6: 2	60,42	MSE	0.01	0.0328742	4000	23	77	
		V: SubMod7: 2	35,45	MSE	0.001	0.000985456	3000	29	97	
		SubMod8: 2	31,35	MSE	0.001	0.000968815	3000	29	97	
		SubMod9: 2	22,38	MSE	0.001	0.000984716	3000	23	77	
2	Trainscg	R: SubMod1: 2	400,150	MSE	0.01	0.00999066	4000	30	100	3 hrs 50 min
		SubMod2: 2	420,100	MSE	0.01	0.00996782	4000	30	100	
		SubMod3: 2	410,125	MSE	0.01	0.00997436	4000	30	100	
		H: SubMod4: 2	350,130	MSE	0.01	0.00999281	4000	29	97	
		SubMod5: 2	250,140	MSE	0.01	0.00999318	4000	29	97	
		SubMod6: 2	300,135	MSE	0.01	0.00999893	4000	30	100	
		V: SubMod7: 2	85,95	MSE	0.001	0.00476453	3000	7	23	
		SubMod8: 2	85,90	MSE	0.001	0.000978912	3000	28	93	
		SubMod9: 2	90,90	MSE	0.001	0.000987834	3000	28	93	
3	Trainscg	R: SubMod1: 2	200,160	MSE	0.01	0.00989252	4000	30	100	2 hrs 57 min
		SubMod2: 2	300,150	MSE	0.01	0.00969909	4000	30	100	
		SubMod3: 2	320,85	MSE	0.01	0.00996425	4000	30	100	
		H: SubMod4: 2	77,53	MSE	0.01	0.0295881	4000	20	67	
		SubMod5: 2	72,61	MSE	0.01	0.0199445	4000	20	67	
		SubMod6: 2	74,53	MSE	0.01	0.00999007	4000	27	90	
		V: SubMod7: 2	40,55	MSE	0.001	0.000984098	3000	29	97	
		SubMod8: 2	38,58	MSE	0.001	0.00099729	3000	25	83	
		SubMod9: 2	42,56	MSE	0.001	0.000987742	3000	28	93	
4	Trainscg	R: SubMod1: 2	250,150	MSE	0.01	0.0099579	4000	30	100	1 hr 59 min
		SubMod2: 2	310,100	MSE	0.01	0.00996268	4000	30	100	
		SubMod3: 2	315,90	MSE	0.01	0.00984851	4000	30	100	
		H: SubMod4: 2	15,25	MSE	0.01	0.170638	4000	1	3	
		SubMod5: 2	15,20	MSE	0.01	0.175748	4000	1	3	
		SubMod6: 2	15,30	MSE	0.01	0.0873482	4000	1	3	
		V: SubMod7: 2	45,50	MSE	0.001	0.000979182	3000	27	90	
		SubMod8: 2	47,55	MSE	0.001	0.000972833	3000	27	90	
		SubMod9: 2	25,30	MSE	0.001	0.00167415	3000	17	57	
5	Trainscg	R: SubMod1: 2	40,30	MSE	0.01	0.000999915	4000	26	87	3 hrs 50 min
		SubMod2: 2	30,20	MSE	0.01	0.00116395	4000	3	10	
		SubMod3: 2	25,35	MSE	0.01	0.0318143	4000	1	3	
		H: SubMod4: 2	23,38	MSE	0.01	0.0650265	4000	1	3	
		SubMod5: 2	10,42	MSE	0.01	0.473676	4000	1	3	
		SubMod6: 2	15,33	MSE	0.01	0.653342	4000	6	20	
		V: SubMod7: 2	25,82	MSE	0.001	0.128213	3000	21	70	
		SubMod8: 2	5,200	MSE	0.001	0.0648562	3000	15	50	
		SubMod9: 2	10,8	MSE	0.001	0.0281692	3000	0	0	

Once we collected the data, the training phase of MNN with different architectures, was initiated, this with the purpose of being able to make comparisons between the different tests. We choose 5 of them (see Figure 7.1) to test of integration module with the type-1 and type-2 fuzzy systems optimized with GA's and to obtain a comparison of the results.

After we obtained the necessary trainings of the MNN's, the genetic algorithm was used to obtain the type-1 fuzzy inference system with triangular membership functions and to use it then as integration method, therefore it was optimized with the genetic algorithm that allowed to obtain the type-1 fuzzy inference system with trapezoidal membership functions, and then with the genetic algorithm to obtain the type-1 fuzzy inference system with Gaussian membership functions and to test the different methods to integrate the results given by the MNN's.

We show in Table 1 (see page before) the training of the modular neural networks for response integration.

### 7.1. Type-1 fuzzy inference system

As was mentioned previously several type-1 fuzzy inference systems were build, using Triangular, Trapezoidal and Gaussian membership functions; next we show the obtained fuzzy systems optimized by the GA. It is worth mentioning that not all the systems that were obtained are shown here because they were too many; therefore we show only one of each membership function.

#### 7.1.1. Type-1 fuzzy system

The type-1 fuzzy inference system shown in Figure 11 is a fuzzy system that has three inputs (activation of the face, activation of the fingerprint and activation of the voice), which are composed by three membership functions each; and an output that defines the winning activation after going through the Mamdani motor of inference.

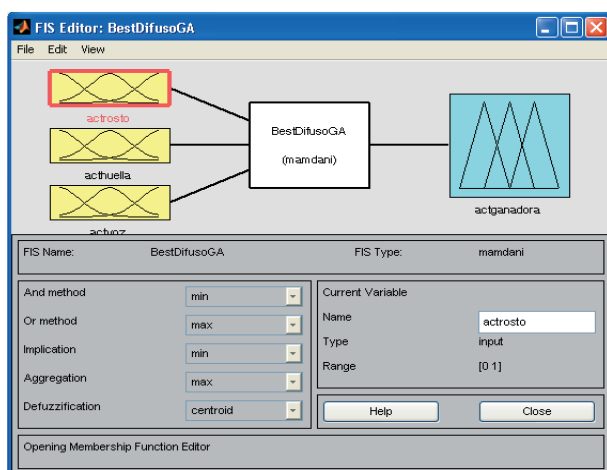


Fig. 11. Graphical representation of the Type-1 Fuzzy Inference System with its inputs and outputs.

As it was already mentioned different types of membership functions were used, therefore it is possible to observe next the different optimized systems created by the GA. It can be noticed that different values of the membership functions are obtained for each type; and

this is true well as for the inputs as for the outputs of each fuzzy system.

#### 7.1.1.1. Triangular type-1 fuzzy system

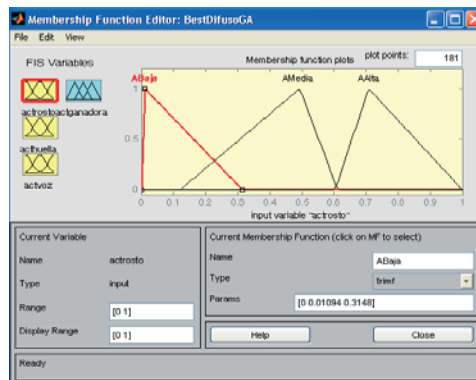


Fig. 12. First input variable (higher activation of the face).

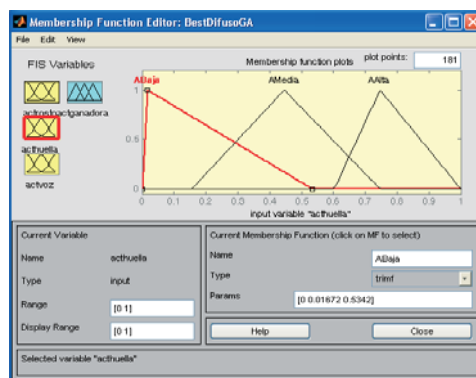


Fig. 13. Second input variable (higher activation of the fingerprint).

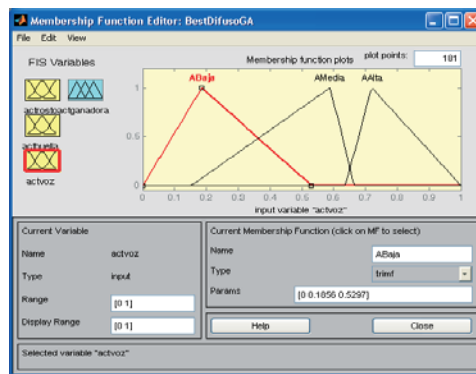


Fig. 14. Third input variable (higher activation of the voice).

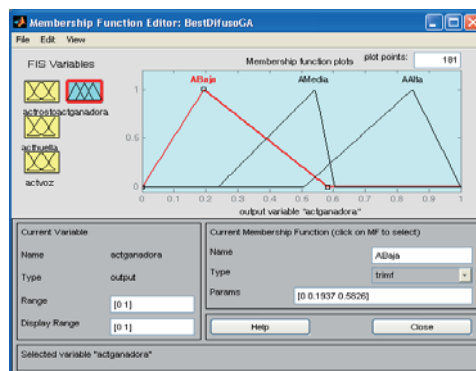


Fig. 15. Variable of output (winner activation).

In the previous figures (12, 13, 14 and 15), it is possible to appreciate the values that the parameters from each triangular membership function for each variable, as well as inputs as the output, for the type-1 fuzzy system. In this case the GA was used with a population of 55 individuals, a maximum of generations of 100, mutation of 0.001, crossover of 0.6 of simple point type; which lasted of 2 minutes and it was stopped at generation 12, the obtained error was 0.000017082.

7.1.1.2. Trapezoidal type-1 fuzzy system

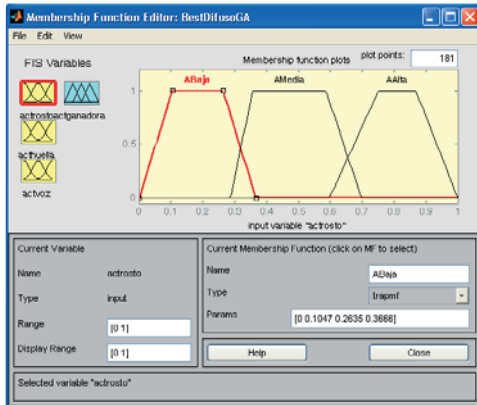


Fig. 16. First input variable (higher activation of the face).

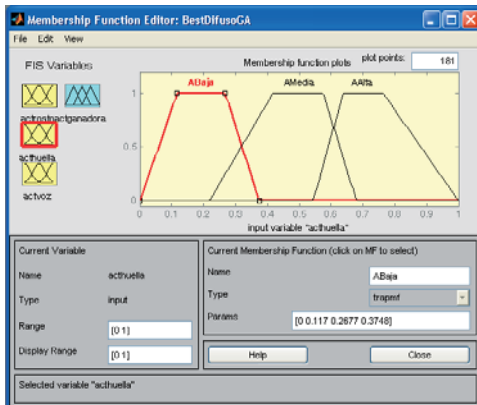


Fig. 17. Second input variable (higher activation of the fingerprint).

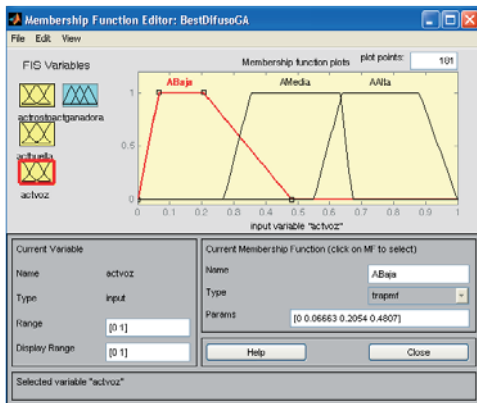


Fig. 18. Third input variable (higher activation of the voice).

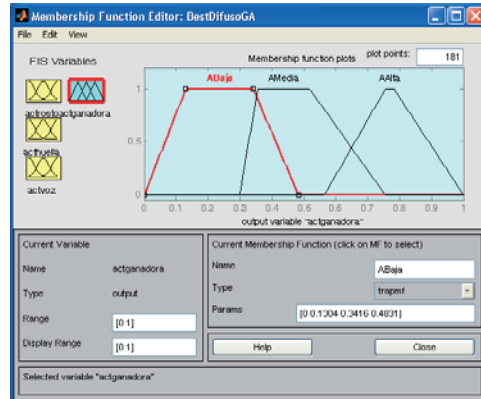


Fig. 19. Variable of output (winner activation).

In the previous figures (16, 17, 18 and 19), it is possible to appreciate the values that the parameters from each trapezoidal membership function for each variable, as well as of inputs as the output, for the type-1 fuzzy system. In this case the GA was used with a population of 85 individuals, a maximum of generations of 100, mutation of 0.0001, crossover of 0.25 of simple point type; which lasted of 12 minutes and it was stopped at generation 36, the obtained error was 0.000046453.

7.1.1.3. Gaussian Type-1 fuzzy system

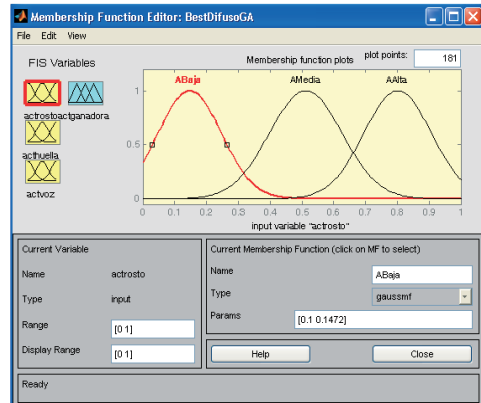


Fig. 20. First input variable (higher activation of the face).

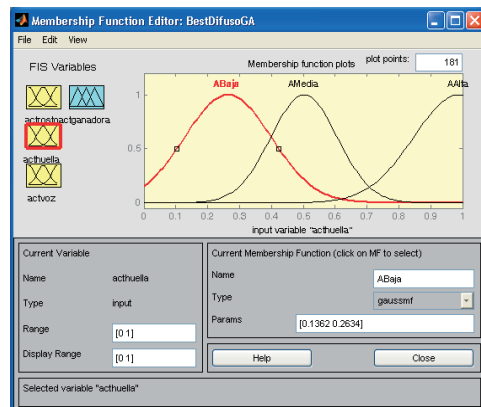


Fig. 21. Second input variable (higher activation of the fingerprint).

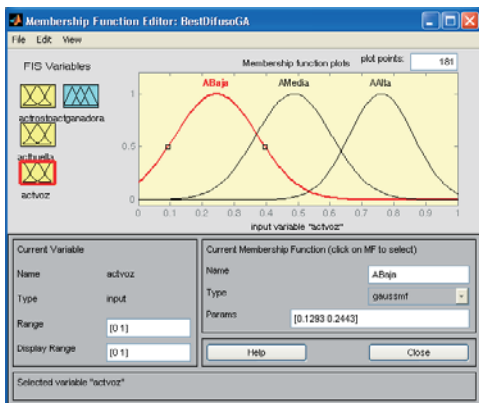


Fig. 22. Third input variable (higher activation of the voice).

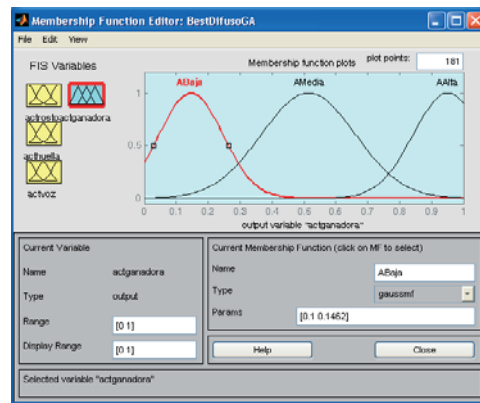


Fig. 23. Variable of output (winner activation).

In the previous figures (20, 21, 22 and 23), it is possible to appreciate the values that the parameters from each Gaussian membership function for each variable, as well as inputs as the output, for the type-1 fuzzy system. In this case the GA was used with a population of 50 individuals, a maximum of generations of 100, mutation of

0.001, crossover of 0.65 of multipoint type; which lasted of 4 minutes and it was stopped at generation 21, the obtained error was 0.00011068. We have to mention that the previously shown fuzzy systems are the ones with the smallest errors. In the following tables (2, 3 and 4) we show all the obtained results.

Table 2. Results of the GA applied Type-1 Fuzzy Inference Systems with Triangular memberships functions.

No.	Tipo MF's	Ind	Max Gen	Mutation	TypeMut	Crossover	TypeCross.	GGAP	Stopped Gen	Lasted of GA	Best Error
1	Triangular	100	150	0.0001	mutbga	0.1	xovmp	0.85	29	14 min	0.000673922
2	Triangular	90	100	0.0001	mutbga	0.2	xovmp	0.85	100	35 min	6.617518707
3	Triangular	80	100	0.0001	mutbga	0.3	xovmp	0.85	15	5 min	0.000038401
4	Triangular	70	100	0.0001	mutbga	0.5	xovmp	0.85	31	28 min	1.130730602
5	Triangular	60	100	0.0001	mutbga	0.45	xovmp	0.85	43	10 min	0.0004582
6	Triangular	50	100	0.001	mutbga	0.65	xovmp	0.85	100	20 min	0.00020151
7	Triangular	40	100	0.001	mutbga	0.7	xovsp	0.85	7	2 min	0.000075054
8	Triangular	30	100	0.01	mutbga	0.6	xovmp	0.85	100	10 min	0.0000014054
9	Triangular	20	100	0.01	mutbga	0.8	xovsp	0.85	10	1 min	0.00050029
10	Triangular	10	100	0.1	mutbga	0.9	xovsp	0.85	4	10 seg	0.00522077
11	Triangular	5	100	0.1	mutbga	1	xovsp	0.85	11	15 seg	0.00263167
12	Triangular	15	100	0.1	mutbga	0.95	xovsp	0.85	8	27 seg	0.00123392
13	Triangular	25	100	0.01	mutbga	0.85	xovsp	0.85	26	20 seg	0.000073374
14	Triangular	35	100	0.01	mutbga	0.65	xovmp	0.85	96	12 min	0.00040778
15	Triangular	45	100	0.001	mutbga	0.75	xovsp	0.85	19	3 min	0.00104095
16	Triangular	55	100	0.001	mutbga	0.6	xovsp	0.85	12	2 min	0.000017082
17	Triangular	65	100	0.001	mutbga	0.4	xovsp	0.85	16	4 min	0.0000412577
18	Triangular	75	100	0.0001	mutbga	0.35	xovsp	0.85	99	27 min	0.000085732
19	Triangular	85	100	0.0001	mutbga	0.25	xovsp	0.85	18	6 min	0.00119261
20	Triangular	95	100	0.0001	mutbga	0.15	xovsp	0.85	100	37 min	0.02178055

Table 3. Results of the GA applied Type-1 Fuzzy Inference System with Trapezoidal memberships functions.

No.	Tipo MF's	Ind	Max Gen	Mutation	TypeMut	Crossover	TypeCross.	GGAP	Stopped Gen	Lasted of GA	Best Error
1	Trapezoidal	100	150	0.0001	mutbga	0.1	xovsp	0.85	42	16 min	0.00099803
2	Trapezoidal	90	100	0.0001	mutbga	0.2	xovmp	0.85	100	33 min	0.000164958
3	Trapezoidal	80	100	0.0001	mutbga	0.3	xovmp	0.85	100	31 min	0.00203463
4	Trapezoidal	70	100	0.0001	mutbga	0.5	xovmp	0.85	100	28 min	0.01164289
5	Trapezoidal	60	100	0.0001	mutbga	0.45	xovmp	0.85	100	23 min	0.00162315
6	Trapezoidal	50	100	0.001	mutbga	0.65	xovmp	0.85	15	3 min	0.00019062



7	Trapezoidal	40	100	0.001	mutbga	0.7	xovsp	0.85	13	2 min	0.00075258
8	Trapezoidal	30	100	0.01	mutbga	0.6	xovmp	0.85	13	1 min	0.00113649
9	Trapezoidal	20	100	0.01	mutbga	0.8	xovsp	0.85	100	8 min	0.00158774
10	Trapezoidal	10	100	0.1	mutbga	0.9	xovsp	0.85	10	1 min	0.0002004
11	Trapezoidal	5	100	0.1	mutbga	1	xovsp	0.85	100	2 min	4.66257156
12	Trapezoidal	15	100	0.1	mutbga	0.95	xovsp	0.85	100	6 min	0.00331437
13	Trapezoidal	25	100	0.01	mutbga	0.85	xovsp	0.85	100	10 min	0.01206595
14	Trapezoidal	35	100	0.01	mutbga	0.65	xovmp	0.85	100	13 min	0.00456134
15	Trapezoidal	45	100	0.001	mutbga	0.75	xovsp	0.85	100	6 min	0.00254746
16	Trapezoidal	55	100	0.001	mutbga	0.6	xovsp	0.85	100	21 min	0.00536313
17	Trapezoidal	65	100	0.001	mutbga	0.4	xovsp	0.85	100	25 min	1.243885488
18	Trapezoidal	75	100	0.0001	mutbga	0.35	xovsp	0.85	35	10 min	0.001008539
19	Trapezoidal	85	100	0.0001	mutbga	0.25	xovsp	0.85	36	12 min	0.000046453
20	Trapezoidal	95	100	0.0001	mutbga	0.15	xovsp	0.85	100	17 min	0.01042749

Table 4. Results of the GA applied Type-1 Fuzzy Inference System with Gaussian memberships functions.

No.	Tipo MF's	Ind	Max Gen	Mutation	TypeMut	Crossover	TypeCross.	GGAP	Stopped Gen	Lasted of GA	Best Error
1	Gaussian	100	150	0.0001	mutbga	0.1	xovmp	0.85	3	1 min	0.000164788
2	Gaussian	90	100	0.0001	mutbga	0.2	xovmp	0.85	41	15 min	0.183854323
3	Gaussian	80	100	0.0001	mutbga	0.3	xovmp	0.85	5	2 min	0.00181081
4	Gaussian	70	100	0.0001	mutbga	0.5	xovmp	0.85	100	26 min	0.000615959
5	Gaussian	60	100	0.0001	mutbga	0.45	xovmp	0.85	10	4 min	0.02483356
6	Gaussian	50	100	0.001	mutbga	0.65	xovmp	0.85	21	4 min	0.00011068
7	Gaussian	40	100	0.001	mutbga	0.7	xovsp	0.85	53	9 min	0.06011866
8	Gaussian	30	100	0.01	mutbga	0.6	xovmp	0.85	5	34 seg	0.03585971
9	Gaussian	20	100	0.01	mutbga	0.8	xovsp	0.85	17	1 min	0.006970346
10	Gaussian	10	100	0.1	mutbga	0.9	xovsp	0.85	5	12 seg	0.04190672
11	Gaussian	5	100	0.1	mutbga	1	xovsp	0.85	3	5 seg	0.0045917
12	Gaussian	15	100	0.1	mutbga	0.95	xovsp	0.85	25	1 min	0.26194236
13	Gaussian	25	100	0.01	mutbga	0.85	xovsp	0.85	16	1 min	0.10640646
14	Gaussian	35	100	0.01	mutbga	0.65	xovmp	0.85	5	46 seg	0.00346566
15	Gaussian	45	100	0.001	mutbga	0.75	xovsp	0.85	3	30 seg	0.00036119
16	Gaussian	55	100	0.001	mutbga	0.6	xovsp	0.85	100	21 min	0.0474117
17	Gaussian	65	100	0.001	mutbga	0.4	xovsp	0.85	100	24 min	0.01250863
18	Gaussian	75	100	0.0001	mutbga	0.35	xovsp	0.85	2	36 seg	0.000164788
19	Gaussian	85	100	0.0001	mutbga	0.25	xovsp	0.85	11	4 min	0.00444927
20	Gaussian	95	100	0.0001	mutbga	0.15	xovsp	0.85	100	37 min	0.03247838

7.2.1. Type-2 fuzzy system

The type-2 fuzzy inference system shown in Figure 24 is a fuzzy system that has three inputs (activation of the face, activation of the fingerprint and activation of the voice), which are composed by three membership functions each; and an output that defines the winning activation after going through the Mamdani motor of inference.

As it was already mentioned different types of membership functions were used, therefore it is possible to observe next the different optimized systems created by the GA. It can be noticed that different values of the membership functions are obtained for each type; and this is true well as for the inputs as for the outputs of each fuzzy system.

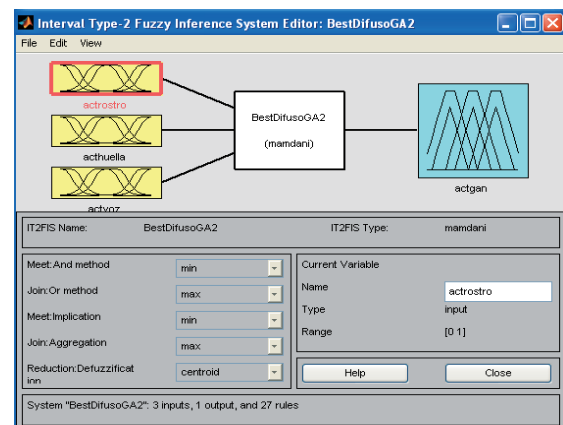


Fig. 24. Graphical representation of the Type-2 Fuzzy Inference System with its inputs and outputs.

7.2.1.1. *Triangular type-2 fuzzy system*

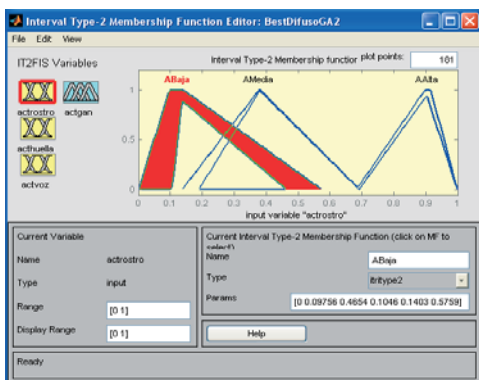


Fig. 25. First input variable (higher activation of the face).

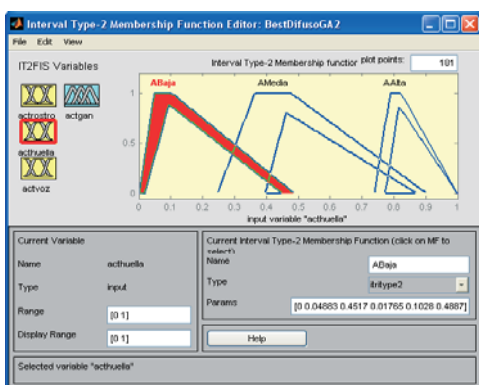


Fig. 26. Second input variable (higher activation of the fingerprint).

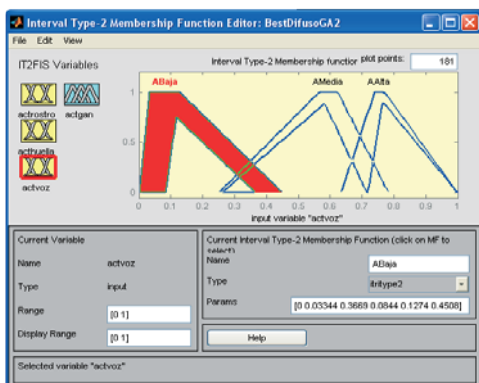


Fig. 27. Third input variable (higher activation of the voice).

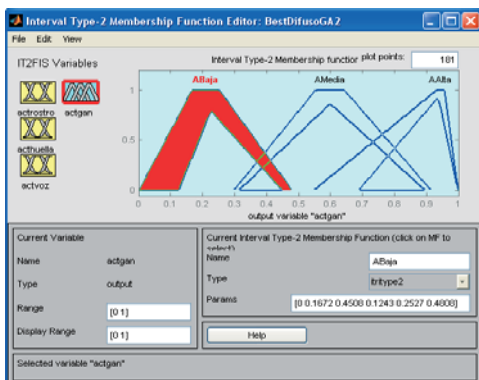


Fig. 28. Variable of output (winner activation).

In the previous figures (25, 26, 27 and 28), it is possible to appreciate the values that the parameters from each triangular membership function for each variable, as well as inputs as the output. For the type-2 fuzzy system. In this case the GA was used with a population of 40 individuals, a maximum of generations of 100, mutation of 0.001, crossover of 0.7 of simple point type; which lasted of 19 minutes and it was stopped at generation 51, the obtained error was 0.000011385.

7.2.1.2. *Trapezoidal type-2 fuzzy system*

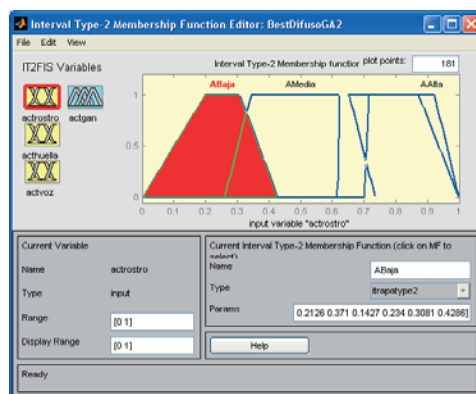


Fig. 29. First input variable (higher activation of the face).

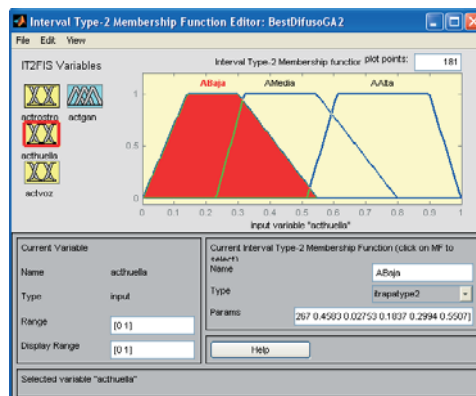
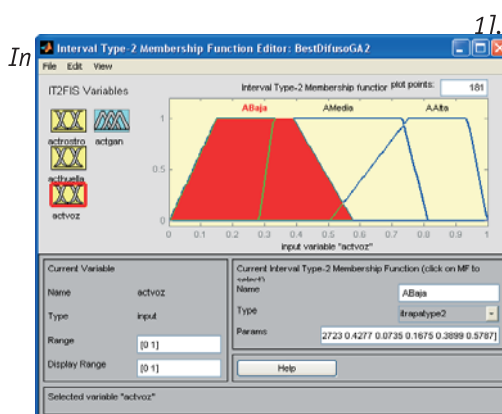


Fig. 30. Second input variable (higher activation of



In

11.

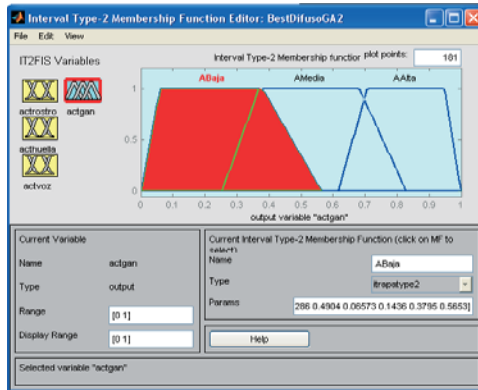


Fig. 32. Variable of output (winner activation).

In the previous figures (29, 30, 31 and 32), it is possible to appreciate the values that the parameters from each trapezoidal membership function for each variable, as well as of inputs as the output, for the type-2 fuzzy system. In this case the GA was used with a population of 80 individuals, a maximum of generations of 100, mutation of 0.0001, crossover of 0.3 of multipoint type; which lasted of 13 minutes and it was stopped at generation 10, the obtained error was 0.0247836.

7.2.1.3. Gaussian Type-2 fuzzy system

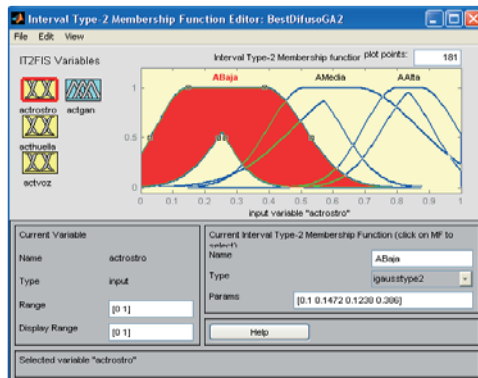


Fig. 33. First input variable (higher activation of the face).

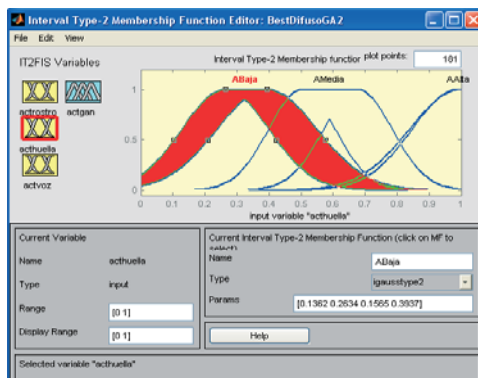


Fig. 34. Second input variable (higher activation of the fingerprint).

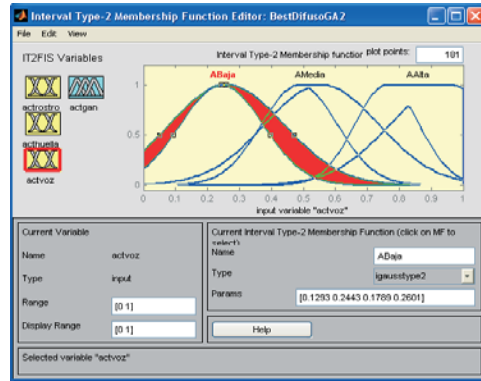


Fig. 35. Third input variable (higher activation of the voice).

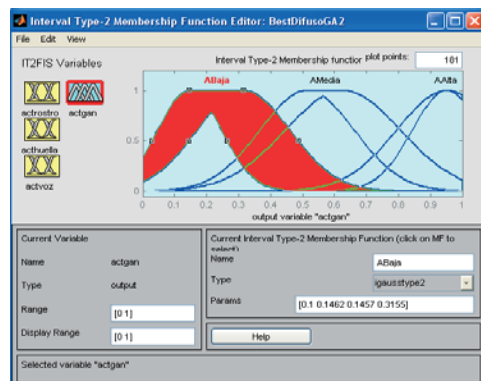


Fig. 36. Variable of output (winner activation).

In the previous figures (33, 34, 35 and 36), it is possible to appreciate the values that the parameters from each Gaussian membership function for each variable, as well as inputs as the output, for the type-2 fuzzy system. In this case the GA was used with a population of 55 individuals, a maximum of generations of 100, mutation of 0.001, crossover of 0.6 of simple point type; which lasted of 50 seconds and it was stopped at generation 4, the obtained error was 0.0000103302. We have to mention that the previously shown fuzzy systems are the ones with the smallest errors. In the following tables (5, 6 and 7) we show all the obtained results.

Table 5. Results of the GA applied Type-2 Fuzzy Inference Systems with Triangular memberships functions.

No.	Tipo MF's	Ind	Max Gen	Mutation	TypeMut	Crossover	TypeCross.	GGAP	Stopped Gen	Lasted of GA	Best Error
1	Triangular	100	150	0.0001	mutbga	0.1	xovmp	0.85	150	1 hr	0.243493825
2	Triangular	90	100	0.0001	mutbga	0.2	xovmp	0.85	14	4 min	0.001130642
3	Triangular	80	100	0.0001	mutbga	0.3	xovmp	0.85	100	30 min	0.42196264
4	Triangular	70	100	0.0001	mutbga	0.5	xovmp	0.85	100	29 min	0.441835768
5	Triangular	60	100	0.0001	mutbga	0.45	xovmp	0.85	100	22 min	0.22838559
6	Triangular	50	100	0.001	mutbga	0.65	xovmp	0.85	100	20 min	0.41049033
<b>7</b>	<b>Triangular</b>	<b>40</b>	<b>100</b>	<b>0.001</b>	<b>mutbga</b>	<b>0.7</b>	<b>xovsp</b>	<b>0.85</b>	<b>51</b>	<b>19 min</b>	<b>0.000011385</b>
8	Triangular	30	100	0.01	mutbga	0.6	xovmp	0.85	100	8 min	0.53426876
9	Triangular	20	100	0.01	mutbga	0.8	xovsp	0.85	100	5 min	0.240057
10	Triangular	10	100	0.1	mutbga	0.9	xovsp	0.85	100	4 min	0.60376824
11	Triangular	5	100	0.1	mutbga	1	xovsp	0.85	44	1 min	0.2344504
12	Triangular	15	100	0.1	mutbga	0.95	xovsp	0.85	100	6 min	0.37926694
13	Triangular	25	100	0.01	mutbga	0.85	xovsp	0.85	100	10 min	0.04789974
14	Triangular	35	100	0.01	mutbga	0.65	xovmp	0.85	8	1 min	0.00900691
15	Triangular	45	100	0.001	mutbga	0.75	xovsp	0.85	100	17 min	0.42580788
16	Triangular	55	100	0.001	mutbga	0.6	xovsp	0.85	100	21 min	0.01624613
17	Triangular	65	100	0.001	mutbga	0.4	xovsp	0.85	88	25 min	0.00232443
18	Triangular	75	100	0.0001	mutbga	0.35	xovsp	0.85	100	28 min	0.559013461
19	Triangular	85	100	0.0001	mutbga	0.25	xovsp	0.85	100	31 min	0.21063925
20	Triangular	95	100	0.0001	mutbga	0.15	xovsp	0.85	100	39 min	0.38952551

Table 6. Results of the GA applied Type-2 Fuzzy Inference System with Trapezoidal memberships functions.

No.	Tipo MF's	Ind	Max Gen	Mutation	TypeMut	Crossover	TypeCross.	GGAP	Stopped Gen	Lasted of GA	Best Error
1	Trapezoidal	100	150	0.0001	mutbga	0.1	xovmp	0.85	150	5 hrs 58 min	0.542291089
2	Trapezoidal	90	100	0.0001	mutbga	0.2	xovmp	0.85	100	3 hrs 49 min	2.325
<b>3</b>	<b>Trapezoidal</b>	<b>80</b>	<b>100</b>	<b>0.0001</b>	<b>mutbga</b>	<b>0.3</b>	<b>xovmp</b>	<b>0.85</b>	<b>10</b>	<b>13 min</b>	<b>0.0247836</b>
4	Trapezoidal	70	100	0.0001	mutbga	0.5	xovmp	0.85	100	29 min	0.682264153
5	Trapezoidal	60	100	0.0001	mutbga	0.45	xovmp	0.85	100	24 min	0.4822949
6	Trapezoidal	50	100	0.001	mutbga	0.65	xovmp	0.85	100	17 min	0.73576041
7	Trapezoidal	40	100	0.001	mutbga	0.7	xovsp	0.85	36	34 min	0.035355
8	Trapezoidal	30	100	0.01	mutbga	0.6	xovmp	0.85	100	12 min	0.73576041
9	Trapezoidal	20	100	0.01	mutbga	0.8	xovsp	0.85	100	5 min	0.76300909
10	Trapezoidal	10	100	0.1	mutbga	0.9	xovsp	0.85	100	3 min	0.65602506
11	Trapezoidal	5	100	0.1	mutbga	1	xovsp	0.85	100	2 min	0.70884404
12	Trapezoidal	15	100	0.1	mutbga	0.95	xovsp	0.85	100	4 min	0.60458736
13	Trapezoidal	25	100	0.01	mutbga	0.85	xovsp	0.85	100	7 min	0.32737116
14	Trapezoidal	35	100	0.01	mutbga	0.65	xovmp	0.85	100	9 min	0.90410197
15	Trapezoidal	45	100	0.001	mutbga	0.75	xovsp	0.85	100	13 min	0.60458736
16	Trapezoidal	55	100	0.001	mutbga	0.6	xovsp	0.85	100	15 min	0.60458736
17	Trapezoidal	65	100	0.001	mutbga	0.4	xovsp	0.85	100	16 min	0.76300909
18	Trapezoidal	75	100	0.0001	mutbga	0.35	xovsp	0.85	100	29 min	0.875249036
19	Trapezoidal	85	100	0.0001	mutbga	0.25	xovsp	0.85	100	33 min	0.81848755
20	Trapezoidal	95	100	0.0001	mutbga	0.15	xovsp	0.85	100	38 min	0.57939829

Table 7. Results of the GA applied Type-2 Fuzzy Inference System with Gaussian memberships functions.

No.	Tipo MF's	Ind	Max Gen	Mutation	TypeMut	Crossover	TypeCross.	GGAP	Stopped Gen	Lasted of GA	Best Error
1	Gaussian	100	150	0.0001	mutbga	0.1	xovmp	0.85	3	1 min	0.003115353
2	Gaussian	90	100	0.0001	mutbga	0.2	xovmp	0.85	6	2 min	0.001610318
3	Gaussian	80	100	0.0001	mutbga	0.3	xovmp	0.85	9	3 min	0.00294546
4	Gaussian	70	100	0.0001	mutbga	0.5	xovmp	0.85	100	25 min	0.0000787919
5	Gaussian	60	100	0.0001	mutbga	0.45	xovmp	0.85	100	21 min	0.00115187
6	Gaussian	50	100	0.001	mutbga	0.65	xovmp	0.85	100	18 min	0.0001781
7	Gaussian	40	100	0.001	mutbga	0.7	xovsp	0.85	4	37 sec	0.0000218
8	Gaussian	30	100	0.01	mutbga	0.6	xovmp	0.85	11	2 min	0.00298097
9	Gaussian	20	100	0.01	mutbga	0.8	xovsp	0.85	78	6 min	0.00239668
10	Gaussian	10	100	0.1	mutbga	0.9	xovsp	0.85	3	8 sec	0.00681549
11	Gaussian	5	100	0.1	mutbga	1	xovsp	0.85	2	3 sec	0.00031891
12	Gaussian	15	100	0.1	mutbga	0.95	xovsp	0.85	100	5 min	0.01700403
13	Gaussian	25	100	0.01	mutbga	0.85	xovsp	0.85	36	4 min	0.00047306
14	Gaussian	35	100	0.01	mutbga	0.65	xovmp	0.85	15	2 min	0.0000915214
15	Gaussian	45	100	0.001	mutbga	0.75	xovsp	0.85	100	16 min	0.00089849
16	Gaussian	55	100	0.001	mutbga	0.6	xovsp	0.85	4	50 sec	0.0000103302
17	Gaussian	65	100	0.001	mutbga	0.4	xovsp	0.85	20	5 min	0.00135865
18	Gaussian	75	100	0.0001	mutbga	0.35	xovsp	0.85	25	7 min	0.001623653
19	Gaussian	85	100	0.0001	mutbga	0.25	xovsp	0.85	8	3 min	0.00373201
20	Gaussian	95	100	0.0001	mutbga	0.15	xovsp	0.85	14	5 min	0.00031598

7.3. Results of the type-1 integration

Table 8. Results of the response integration of the MNN's with Type-1 FIS for the best training.

Best Training the MNN's			
Fuzzy System	% of Recognition for the FIS with Triangular MF's	% of Recognition for the FIS with Trapezoidal MF's	% of Recognition for the FIS with Trapezoidal MF's
1	100% (30/30)	100% (30/30)	100% (30/30)
2	100% (30/30)	100% (30/30)	100% (30/30)
3	100% (30/30)	100% (30/30)	100% (30/30)
4	100% (30/30)	100% (30/30)	100% (30/30)
5	100% (30/30)	100% (30/30)	100% (30/30)

Table 9. Results of the response integration of the MNN's with Type-1 FIS for the worse training.

Worse Training the MNN's			
Fuzzy System	% of Recognition for the FIS with Triangular MF's	% of Recognition for the FIS with Trapezoidal MF's	% of Recognition for the FIS with Trapezoidal MF's
1	0% (0/30)	0% (0/30)	0% (0/30)
2	0% (0/30)	0% (0/30)	0% (0/30)
3	0% (0/30)	0% (0/30)	0% (0/30)
4	0% (0/30)	0% (0/30)	0% (0/30)
5	0% (0/30)	0% (0/30)	0% (0/30)

7.4. Results of the type-2 integration

Table 10. Results of the response integration of the MNN's with Type-2 FIS for the best training.

Best Training the MNN's			
Fuzzy System	% of Recognition for the FIS with Triangular MF's	% of Recognition for the FIS with Trapezoidal MF's	% of Recognition for the FIS with Trapezoidal MF's
1	100% (30/30)	100% (30/30)	100% (30/30)
2	100% (30/30)	100% (30/30)	100% (30/30)
3	100% (30/30)	100% (30/30)	100% (30/30)
4	100% (30/30)	100% (30/30)	100% (30/30)
5	100% (30/30)	100% (30/30)	100% (30/30)

Table 11. Results of the response integration of the MNN's with Type-2 FIS for the worse training.

Worse Training the MNN's			
Fuzzy System	% of Recognition for the FIS with Triangular MF's	% of Recognition for the FIS with Trapezoidal MF's	% of Recognition for the FIS with Trapezoidal MF's
1	7% (2/30)	7% (2/30)	7% (2/30)
2	7% (2/30)	7% (2/30)	7% (2/30)
3	7% (2/30)	7% (2/30)	7% (2/30)
4	7% (2/30)	7% (2/30)	7% (2/30)
5	7% (2/30)	7% (2/30)	7% (2/30)

### 7.5. Comparison errors between type-1 and type-2 fuzzy inference systems

Table 12. Average Errors for the Fuzzy Inference Systems with Triangular membership functions.

Type-1	Type-2
Average Error	Average Error
0.389196189	0.269979242

Table 13. Average Errors for the Fuzzy Inference Systems with Trapezoidal membership functions.

Type-1	Type-2
Average Error	Average Error
0.298306163	0.688638346

Table 14. Average Errors for the Fuzzy Inference Systems with Gaussian membership functions.

Type-1	Type-2
Average Error	Average Error
0.041501285	0.002356073

## 8. Conclusions

In this paper a study of fuzzy integration methods for MNN's is presented. Type-1 and type-2 fuzzy system are considered as integration methods for a MNN's in biometry applications. The fuzzy systems were optimized using GA to be able to make an accurate comparison of type-1 and type-2 fuzzy logic as methods of integration. A comparison with simulation results for pattern recognition was made.

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