Response Integration in Ensemble Neural Networks Using the Sugeno Integral and Fuzzy Inference System for Pattern Recognition

Miguel Lopez, Patricia Melin

Abstract:

Combining the outputs of multiple neural networks has been used in Ensemble architectures to improve the decision accuracy in many applications fields, including pattern recognition, in particular for the case of fingerprints. In this paper, we describe a set of experiments performed in order to find the optimal individual networks in terms of the architecture and training rule. In the second step, we used the fuzzy Sugeno Integral to integrate results of the ensemble neural networks. This method combines objective evidence in the form of the network's outputs, with subjective measures of their performance. In the third step, we used a Fuzzy Inference System for the decision process of finding the output of the ensemble neural networks, and finally a comparison of experimental results between Fuzzy Sugeno Integral and the Fuzzy Inference System are presented.

Keywords: *ensemble neural networks, fuzzy logic, pattern recognition, fingerprint recognition.*

1. Introduction

Personal identification using biometric measures, such as person's fingerprint, face, iris, retina, hand shape, has received a great deal of attention during the past few years. Biometric identification is now being studied as a way to confirm the identities of individuals [8]. The fingerprint is known to be the most representative biometric measure for authentication of individual persons. The main reason of its popularity is, it is unique and remains invariant with age during a lifetime. In most of the present fingerprint authentication systems, personal confirmation is performed by two step verification (one to one match) and identification (one to many matches). In the verification procedure, a quick response can be expected because the matching is executed only once. Conventional automatic fingerprint identification methods consist of two steps: feature extraction and feature matching. A critical step in automatic fingerprint identification is to match features automatically and reliably from input fingerprint images. The classical approaches are tends to be extremely tedious and time consuming. However, the performance of a features matching algorithm relies heavily on the quality of input fingerprint images. Since the inherent features of fingerprint data are its great complexity and high spatial-frequency details. Moreover, the difference among diverse classes of patterns is small, wich requires high discrimination capability. Identification problems, a particular case of point pattern matching, necessitate a large database search of individuals to determine whether a person is already in the database [7].

In this paper, we propose combining Ensemble Neural Networks with the Fuzzy Sugeno Integral for the decision process of the ensemble is output that achieves Fingerprints Personal authentication. Neural networks can be classified into recurrent and feed-forward categories. Feed-forward networks do not have feedback elements; the output is calculated directly from the input through feed-forward connections. In recurrent networks, the output depends not only on the current input to the network, but also on the current or previous outputs or states of the network. For this reason, recurrent networks are more powerful than feed-forward networks and are extensively used in control, optimization, and signal processing applications.

The ensemble neural network has three modules, with the same fingerprint input; the final decision of fingerprint recognition is done by an integration module, which has to take into account the results of each of the modules.

The integration module uses the fuzzy Sugeno integral to combine the outputs of the three modules. The fuzzy Sugeno integral allows the integration of responses from the three modules of the fingerprint.

There exists a lot of neural network architectures in the literature that work well when the number of inputs is relatively small, but when the complexity of the problem grows or the number of inputs increases, their performance decreases very quickly. For this reason, there has also been research work in compensating in some way the problems in learning of a single neural network over high dimensional spaces.

In some research work has been shown that the use of multiple neural systems have better performance or even solve problems that monolithic neural networks are not able to solve, in the case of multiple networks we can have the ensemble and modular type.

The term “ensemble” is used when a redundant set of neural networks is utilized.

In this case, each of the neural networks is redundant because it is providing a solution for the same task, as it is shown in Figure 1 [5].

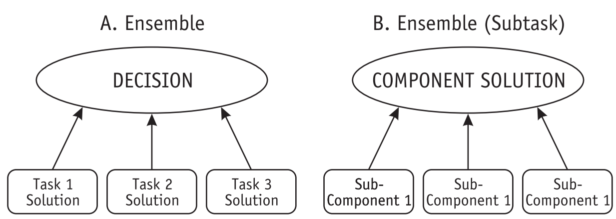

Fig. 1. Ensembles for one task and subtask.

In this approach we can find networks that use strongly separated architectures.

Each neural network works independently in its own domain, and is build and trained for a specific task. The final decision is based on the results of the individual networks, called agents or experts.

The Multiple Neural Networks are used when one obtains information of an object of different sources of information.

Mixture of Experts (ME): The ME can be viewed as a modular version of the multi-layer networks with supervised training or the associative version of competitive learning. In this design, the local experts are trained with the data sets to mitigate weight interference from one expert to the other.

Gate of Experts: In this case, an optimization algorithm is used for the gating network, to combine the outputs from the experts.

Hierarchical Mixture of Experts: In this architecture, the individual outputs from the experts are combined with several gating networks in a hierarchical way.

When considering modular networks to solve a problem, one has to take into account the following points:

1) Decompose the main problem into subtasks.
2) Organizing the modular architecture, taking into account the nature of each subtask.
3) Communication between modules is important, not only in the input of the system but also in the response integration.

The importance of this part of the architecture for pattern recognition is due to the high dimensionality of this type of problems. As a consequence in pattern recognition is good alternative to consider a modular approach.

This has the advantage of reducing the time required of learning and it also increases accuracy. In our case for fingerprint recognition, we consider applying an ensemble neural network structure for achieving pattern recognition.

How to integrate the different outputs given by the different modules of the system to generate the final output of the complete system.

2. Problem statement

Fuzzy integrals can be viewed as non-linear functions defined with respect to fuzzy measures. In particular, the "gλ-fuzzy measure" introduced by Sugeno can be used to define fuzzy integrals [1].

The ability of fuzzy integrals to combine the results of multiple information sources.

Definition 1. A function of sets g: $2x$-(0.1) is called a fuzzy measure if:

1) $g(0)=0$ $g(\mathrm{x})=1$
2) $g(A) \leq g(B)$ if $A \subset B$
3) if $\{Ai\}i\alpha=1$ is a sequence of increments of the measurable set then
$$\lim_{i \to \infty} g(Ai) = g\,(\lim_{i \to \infty} Ai)$$

From the general definition of the fuzzy measure, Sugeno introduced what is called "gλ-fuzzy measure", which satisfies the following additive property:

For every $A, B \subset X$ and $A \cap B = \theta$,

$g(A \cup B) = g(A) + g(B) + \lambda g(A)g(B)$

For some value of λ>-1.

This property says that the measure of the union of two disjoint sets can be obtained directly from the individual measures.

Using the concept of fuzzy measures, Sugeno developed the concept of fuzzy integrals, which are non-linear functions defined with respect to fuzzy measures like the gλ-fuzzy measure. One can interpret fuzzy integrals as finding the maximum degree of similarity between the objective and expected value.

In the experiments performed in this research work, we used the database of the Fingerprint Verification Competition FCV2000 [10]; the image size is 300 pixels wide and 300 pixels high with a resolution of 500 ppi, and representation of a gray scale. The fingerprints were acquired by using a low-cost optical sensor; up to four fingers were collected for each volunteer (forefinger and middle finger of both the hands). The database is 10 fingers wide (w) and 8 impressions per finger deep (d) (80 fingerprints in all); the acquired fingerprints were manually analyzed to assure that the maximum rotation is approximately in the range [-15°, 15°] and that each pair of impressions of the same finger have a non-null overlapping area.

Sample images from DATABASE [11] are shown in figures 2 and 3; each row shows different impressions of the same finger:

Fig. 2. Sample images from Database; each row shows different impressions of the same finger.

Fig. 3. Images from Database; all the samples are from different fingers and are ordered by quality (top-left: high quality, bottom-right: low quality).

2.1. Proposed Architecture

The architecture proposed in this work consists of three main modules, in which each of them in turn consists of a set of neural networks trained with the same data (fingerprints), which provides the modular architecture, we shown in the Figure 4.

For the creation of the ensemble neural networks, we used three monolithic neural network of 2 hidden layers with 36 and 18 neurons each layer, sigma of .00005, learning rate of .001, training function Scaled conjugate gradient back propagation.

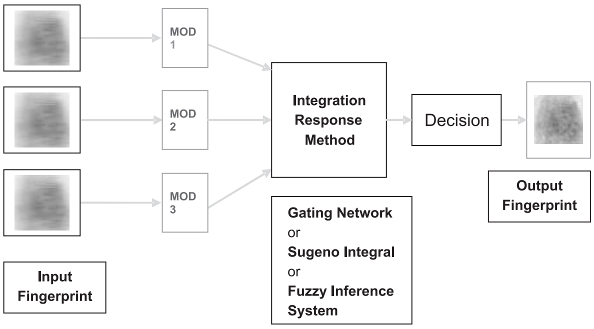

Fig. 4. Proposed Architecture Ensemble Neural Network for Fingerprint Recognition.

The input to the ensemble neural network is the complete fingerprint; and the ensemble neural network gives an answer for the modules of the input fingerprint.

2.1.1. Description of the Integration Module

The integration modules perform its task in two phases. In the first phase, it obtains two matrices. The first matrix, called h, of dimension 3x3, stores the larger index values resulting from the competition for each of the members of the modules [5].

The second matrix, called I, also of dimension 3x3, stores the fingerprint number corresponding to the particular index. Once the first phase is finished, the second phase is initiated, in which the decision is obtained.

Before making a decision, if there is consensus in the three modules, we can proceed to give the final decision, if there isn't consensus then we have search in matrix g to find the larger index values and then calculate the Sugeno fuzzy measures for each of the modules, using the following formula, $g(Mi) = h(A) + h(B) + \lambda h(A)h(B)$. Where λ is equal to 1. Once we have these measures, we select the largest one to show the corresponding fingerprint.

2.1.2. Experimental results using Sugeno Integral

The procedure to carry out the tests was first to train the modules of the ensemble neural networks with the database of the fingerprints, in total using 8 fingerprints of 10 people, that is 80 fingerprints in total, until being able to find which architecture of the ensemble neural network responds better to arrive to the desired error.

Once trained, the Sugeno integral integrates the answers of the modules, we used same people's 80 images with which they had applied noise blur motion, the Sugeno integral gives an answer for the stage of the final decision it shows the result if the fingerprint input was recognized. We show in Figure 5, 6,7,8,9, and 10, the experimental results using Sugeno integral.

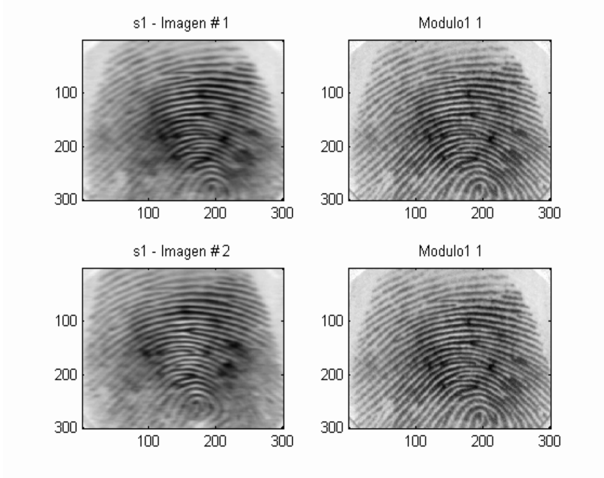

Fig. 5. Experimental results of the fingerprints using Sugeno integral.

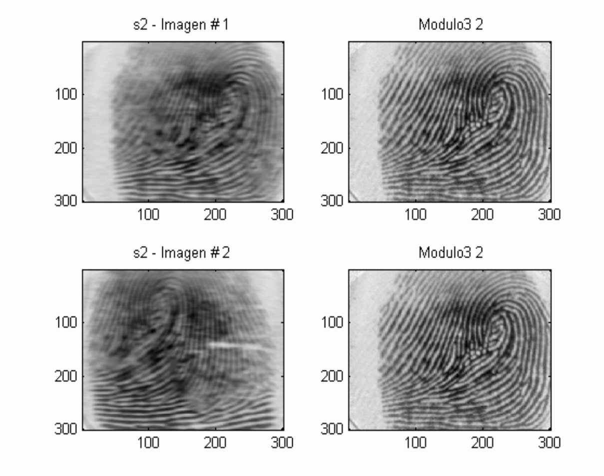

Fig. 6. Experimental results of the fingerprints using Sugeno integral.

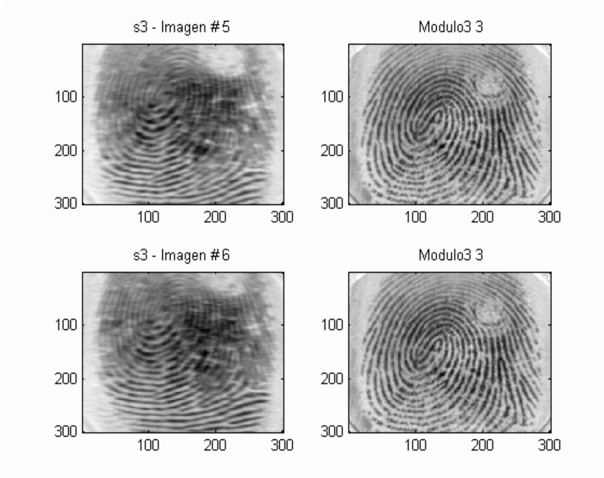

Fig. 7. Experimental results of the fingerprints using Sugeno integral.

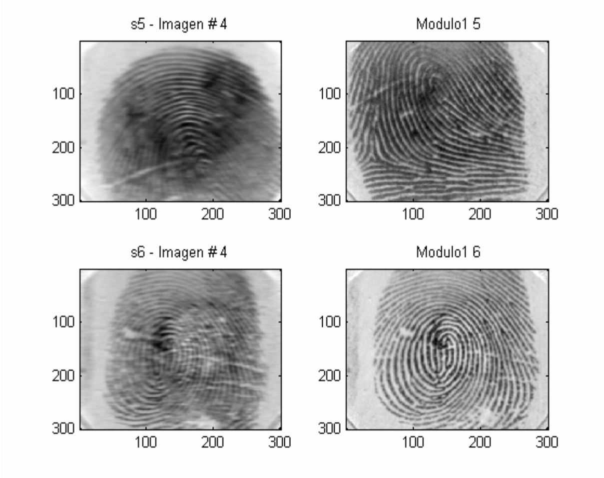

Fig. 8. Experimental results of the fingerprints using Sugeno integral.

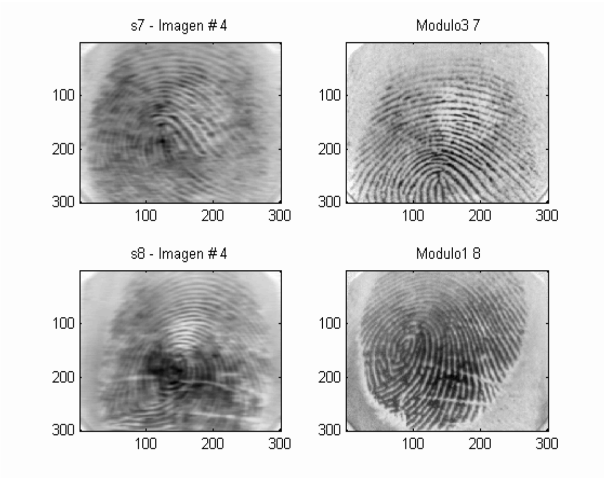

Fig. 9. Experimental results of the fingerprints using Sugeno integral.

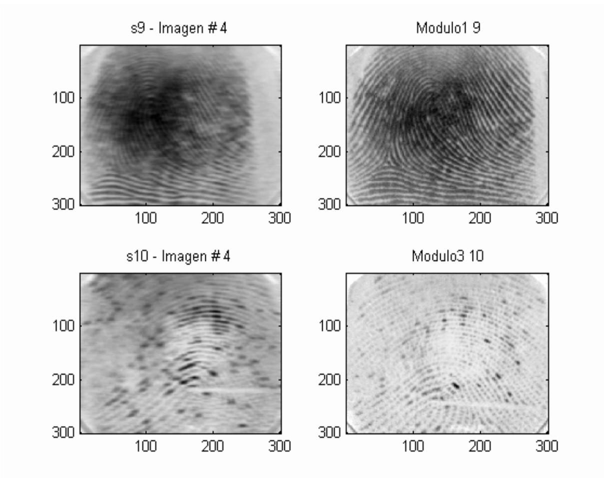

Fig. 10. Experimental results of the fingerprints using Sugeno integral.

The previous figures represent on the left side the fingerprint input with noise (blur motion) that enter to ensemble neural network, the person selected based on the fingerprint is indicated, and the right side shows the obtained the output using the Sugeno integral. It is also indicated the corresponding module, and the output and to that person corresponds, one can observe that in both cases the fingerprints were recognized.

We performed 30 trials of the fingerprint recognition always giving 100% recognition, and we show the results in table 1.

Table 1. Experimental Results using Sugeno Integral.

Training Method	Layers by module	Neurons by layers	Performance Function	Goal Error	Obtained Error by module 1,2,3	Epochs	Noise Distance 10 Pixels	Recognition Rate	Identification Rate
Trainscg	2	36,18	MSE	.001	0.00099935, 0.00097369, 0.00098878	1000	Blur Motion	80/80	77/80
Trainscg	2	36,18	MSE	.001	0.0009635, 0.00099609, 0.00095778	1000	Blur Motion	60/60	57/60
Trainscg	2	36,18	MSE	.001	0.0009535, 0.00099609, 0.00097778	1000	Blur Motion	40/40	37/40
Trainscg	2	36,18	MSE	.001	0.0009935, 0.00095609, 0.00096778	1000	Blur Motion	20/20	17/20

2.2. Response Integration using fuzzy inference system

We also used a Fuzzy Inference System as method of Response integration of results of the ensemble neural network output, considering as input three linguistic variables, Module 1, Module 2, and Module 3, and one output linguistic variable, Winning Activation of the three modules.

We show below some of the rules for the fuzzy inference system.

If (Module1 is ActMod1Low) and (Module2 is ActMod2Low) and (Module3 is ActMod3Medium) then (Winner Module is Module3)

If (Module1 is ActMod1Low) and (Module2 is ActMod2Low) and (Module3 is ActMod3High) then (Winner Module is Module3)

If (Module11 is ActMod1Low) and (Module2 is ActMod2Medium) and (Module3 is ActMod3Low) then (Winner Module is Module2)

If (Module1 is ActMod1Low) and (Module2 is ActMod2Medium) and (Module3 is ActMod3Medium) then (Winner Module is Module2)

Three membership functions were used for each linguistic variable of input and output of the triangular type, to be managed in a range from 0 to 1.

We show in figures 11, 12, 13, 14 and 15, the membership functions designed using the editor of fuzzy logic toolbox of MATLAB [19].

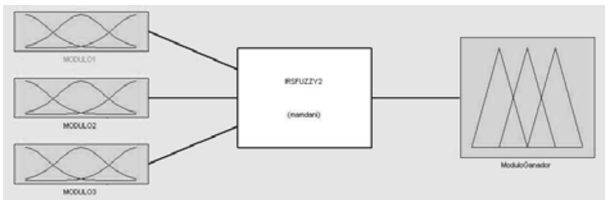

Fig. 11. Membership Functions of the Response Integrated Fuzzy System.

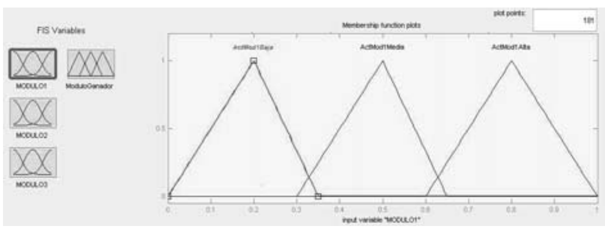

Fig. 12. Membership Functions of Input Module 1.

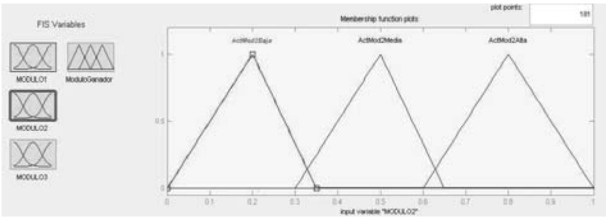

Fig. 13. Membership Functions of Input Module 2.

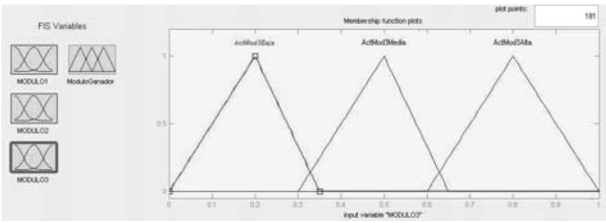

Fig. 14. Membership Functions of Input Module 3.

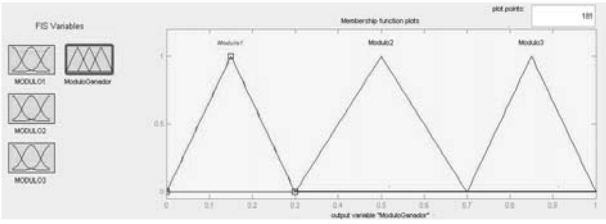

Fig. 15. Membership Functions of Fuzzy System Output.

We show in the figure 16 a graph of the performance of the Fuzzy Inference System.

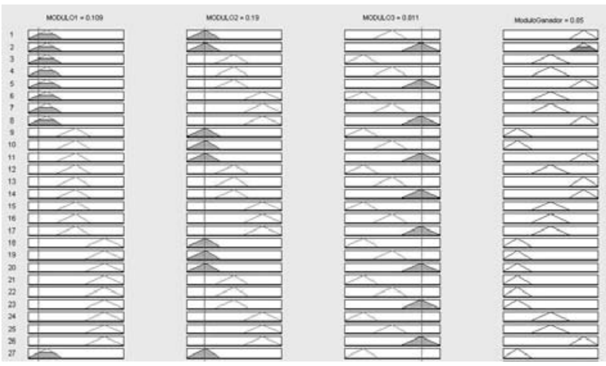

Fig. 16. Performance of the Response Integration Fuzzy System.

In the previous figure it is observed that module1 is winner, because the activation falls inside its range.

After that the fuzzy inference system selects the output winner module, it is required to know to which person belongs the fingerprint and to show the result, we shown following the algorithm of final decision.

```
if ((fuzzy system result>=0)&&(fuzzy system result
<=0.333))
        fprintf('Image Number: >>>%d\n',Answer1);
    fprintf('Index: >>>>>>>%f\n',W1);
    disp(Answer1)
 end
```

```
if ((fuzzy system result>=0.334)&&(fuzzy system result
<=0.666))
        fprintf('Image Number: >>>%d\n',Answer2);
    fprintf('Index: >>>>>>>%f\n',W2);
    disp(Answer2)
 end
```

```
if ((fuzzy system result>=0.667)&&(fuzzy system result
<=1))
        fprintf('Image Number: >>>%d\n',Answer3);
    fprintf('Index: >>>>>>>%f\n',W3);
    disp(Answer3)
 end
```

2.2.1. Experimental results using fuzzy inference system

Once the Ensemble Neural Network is trained, the fuzzy inference system integrates the answers of the modules. We used the same people's 80 images to which we had applied noise with blur motion, and the fuzzy inference system gives an answer for the stage of the final decision, and it shows the result if the fingerprint input was recognized. We show in Figures 17, 18, 19, 20 and 21, the experimental results using the fuzzy inference system.

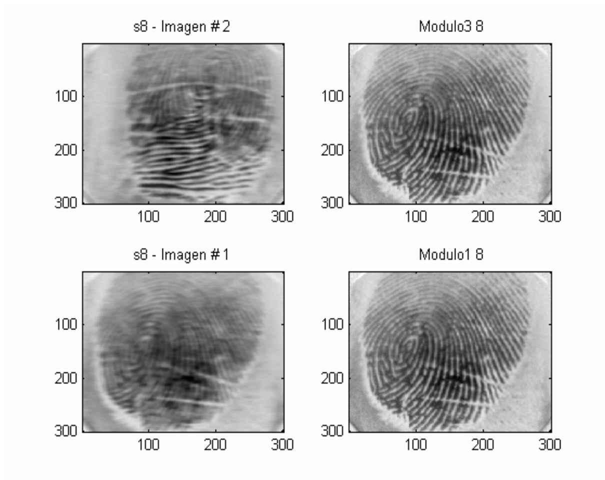

Fig. 17. Experimental results of the fingerprints using the Fuzzy Inference System.

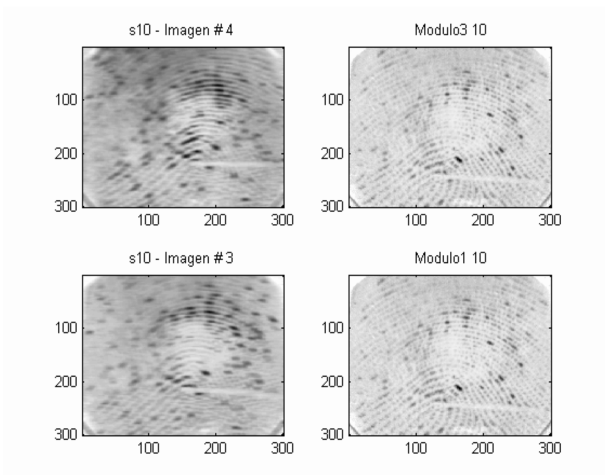

Fig. 18. Experimental results of the fingerprints using the Fuzzy Inference System.

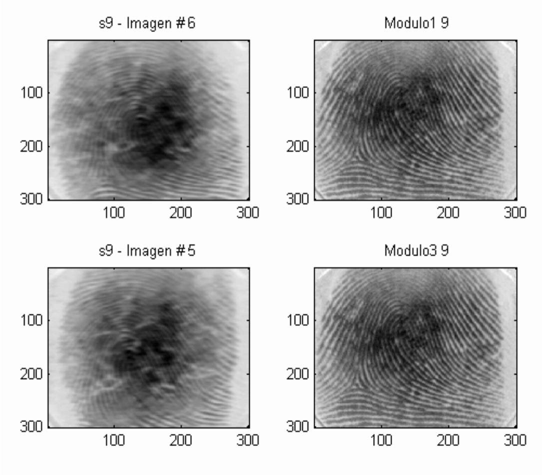

Fig. 19. Experimental results of the fingerprints using the Fuzzy Inference System.

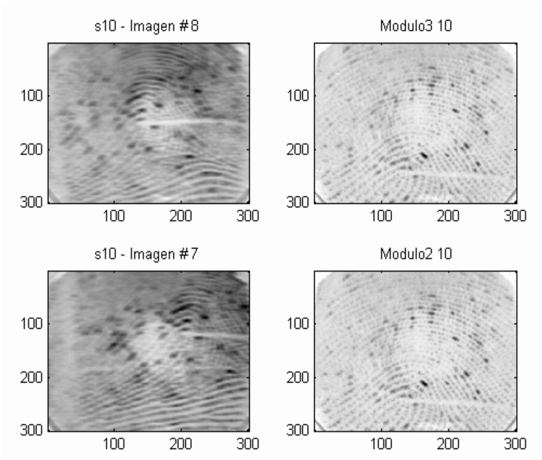

Fig. 20. Experimental results of the fingerprints using the Fuzzy Inference System.

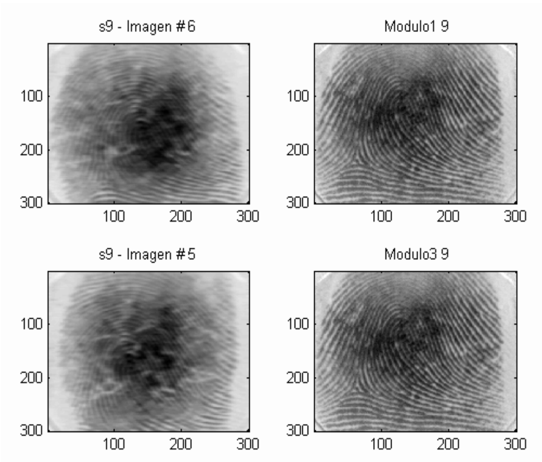

Fig. 21. Experimental results of the fingerprints using the Fuzzy Inference System.

The previous figures represent on the left side the fingerprint input with noise blur motion that enter to ensemble neural network. The person selected based on the fingerprint is indicated, and on the right side the obtained output using the fuzzy inference system integral, it is indicated that module, and provide the output and to which person corresponds, one can observe that in both cases the fingerprints were recognized.

We performed 30 trials of the fingerprint recognition average giving 100%, we show following results in the table 2.

Table 2. Experimental Results using Fuzzy Inference System.

Training Method	Layers by module	Neurons by layers	Performance Function	Goal Error	Obtained Error by module 1,2,3	Epochs	Noise Distance 10 Pixels	Recognition Rate	Identification Rate
Trainscg	2	36,18	MSE	.001	0.00099935, 0.00097369, 0.00098878	1000	Blur Motion	80/80	79/80
Trainscg	2	36,18	MSE	.001	0.0009635, 0.00099609, 0.00095778	1000	Blur Motion	60/60	59/60
Trainscg	2	36,18	MSE	.001	0.0009535, 0.00099609, 0.00097778	1000	Blur Motion	40/40	39/40
Trainscg	2	36,18	MSE	.001	0.0009935, 0.00095609, 0.00096778	1000	Blur Motion	20/20	19/20

2.2.2. Comparison between Sugeno Integral and Fuzzy Inference System

We show following in table 3 a comparative of experimental results between Sugeno integral and the fuzzy inference system.

The tests were carried out using blur motion with a displacement of 10 pixels. First, the training was made and later we used the recognition function of the Sugeno Integral and later using the recognition function of the Fuzzy Inference System, we performed 30 trials of the fingerprint recognition, and the results are shown next in table 3.

Table 3. Comparison of experimental results of Sugeno integral and the fuzzy inference system.

Training Method	Layers by module	Neurons by layers	Performance Function	Goal Error	Obtained Error by module 1,2,3	Epochs	Noise	Identification Rate Fuzzy Inference System	Identification Rate Sugeno Integral
Trainscg	2	36,18	MSE	.001	0.00099935, 0.00097369, 0.00098878	1000	Blur Motion	79/80	77/80
Trainscg	2	36,18	MSE	.001	0.0009635, 0.00099609, 0.00095778	1000	Blur Motion	69/70	67/70
Trainscg	2	36,18	MSE	.001	0.0009535, 0.00099609, 0.00097778	1000	Blur Motion	49/50	47/50
Trainscg	2	36,18	MSE	.001	0.0009935, 0.00095609, 0.00096778	1000	Blur Motion	29/30	27/30

3. Conclusions

Based on the experimental results, we can conclude that using the Sugeno integral as response integration of the output ensemble neural networks for the fingerprints is a good choice. It is necessary to make more tests, for example increasing the blurring, and adding other types of noise, to validate the proposed architecture of ensemble neural networks for fingerprints.

For the case of a fuzzy inference system as response integration for the ensemble neural network, we can conclude that the behavior can be improved and can make a difference respect with the Sugeno integral when the noise begins to grow or tests are made with another type of noise. We think that there is an advantage in using a fuzzy inference system to manage the uncertainty of the knowledge base in pattern recognition.

Future works will include, testing with other types of noise, using type-2 fuzzy logic as method of response integration, using feature extraction, and image compression, with the goal of improving the identification rate.

AUTHORS
Miguel Lopez* - PhD Student of Computer Science in the Universidad Autonoma de Baja California, Tijuana, B. C., México, and Computer Science in the Graduate Division Tijuana, Institute of Technology Tijuana, B. C., Mexico. E-mail: danym23@aol.com.
Patricia Melin - Computer Science in the Graduate Division Tijuana, Institute of Technology Tijuana, B. C., Mexico, E-mail: pmelin@tectijuana.mx.
* Corresponding author

References

[1] O. Mendoza, P. Melín, *The Fuzzy Sugeno Integral as a Decision Operator in the Recognition of Images with Modular Neural Networks*, Tijuana Institute of Technology, México.
[2] J. Urias, D. Solano, M. Soto, M. Lopez, P. Melin, *Type-2 Fuzzy Logic as a Method of Response Integration in Modular Neural Networks*, IC-AI 2006, pp. 584-590.
[3] P. Melín, F. González, G. Martínez: *Pattern Recognition Using Modular Neural Networks and Genetic Algorithms*. IC-AI 2004: 77-83.
[4] P. Melín, J. Urias, D. Solano, M. Soto, M. Lopez, O. Castillo, "Voice Recognition with Neural Networks, Type-2 Fuzzy Logic and Genetic Algorithms", *Engineering Letters*, vol. 13, no. 2, 2006, pp. 108-116
[5] P. Melín, A. Mancilla, M. Lopez, D. Solano, M. Soto, O. Castillo, *Pattern Recognition for Industrial Security using the Fuzzy Sugeno Integral and Modular Neural Networks*, Springer, 2007.
[6] P. Melin and O. Castillo, *Hybrid Intelligent Systems for Pattern Recognition*, Springer, 2005.
[7] Mohamed Mostafa Abd Allah, "Artificial Neural Networks Fingerprints Authentication with Clusters Algorithm", *Informatica*, vol. 29, 2005, pp. 303-307.
[8] Hassiba Nemmour, Youcef Chibani, "Neural Network Combination by Fuzzy Integral for Robust Change Detection in Remotely Sensed Imagery", *EURASIP Journal on Applied Signal Processing*, vol. 14, 200, pp. 2187-2195
[9] A. Sharkey, "On combining artificial neural nets", *Connection Science*, vol. 8, 1996, pp. 299-313.
[10] D. Maio, D. Maltoni, R. Cappelli, J. L. Wayman and A. K. Jain, "FVC2004: Third Fingerprint Verification Competition", *Proc. International Conference on Biometric Authentication (ICBA)*, Hong Kong, July 2004, pp. 1-7.
[11] D. Maltoni, D. Maio, A.K. Jain, S. Prabhakar, "The full FVC2000 and FVC2002 databases are available in the DVD", In: iidem, *Handbook of Fingerprint Recognition*, Springer: New York, 2003.
[12] M. Grabisch, T. Murofushi, M. Sugeno (Eds.), *Fuzzy Measures and Integrals: Theory and Applications*, Springer-Verlag, 2000, pp. 415-34.
[13] M. Grabisch, T. Murofushi, M. Sugeno (Eds.), *Fuzzy Measures and Integrals: Theory and Applications*, 2000, Springer-Verlag, pp. 348-73.
[14] J. Keller, P. Gader, and A. Hocaoglu, "Fuzzy integrals in image processing and recognition". In: M. Grabisch, T. Murofushi, M. Sugeno (Eds.), *Fuzzy Measures and Integrals: Theory and Applications*, Springer-Verlag, 2000, pp. 435-66.
[15] T. Murofushi, M. Sugeno, "An interpretation of fuzzy measure and the Choquet integral as an integral with respect to a fuzzy measure", *Fuzzy Sets and Systems*, vol. 29, issue 2, 1989, pp. 202-27.
[16] T. Murofushi, M. Sugeno, "The Choquet integral in multiattribute decision making". In: M. Grabisch *et al*. (Eds.), *Fuzzy Measures and Integrals: Theory and Applications*, Springer-Verlag, 2000, pp. 333-47.
[17] T. Murofushi, S. Soneda, "Techniques for reading fuzzy measures (III): interaction index". In: *Proceedings of the 9th Fuzzy System Symposium*, Saporo, Japan, 1993, pp. 693-696.
[18] M. Grabisch, "A new algorithm for identifying fuzzy measures and its application to pattern recognition". In: *Proceeding of the 4th IEEE International Conference on Fuzzy Systems*, Yokohama, Japan, 1995, pp.145-50.
[19] MATLAB Trade Marks, ©1994-2007 by The MathWorks, Inc.