# 6 Method for Response Integration in Modular Neural Networks with Type-2 Fuzzy Logic

We describe in this chapter a new method for response integration in modular neural networks using type-2 fuzzy logic. The modular neural networks were used in human person recognition. Biometric authentication is used to achieve person recognition. Three biometric characteristics of the person are used: face, fingerprint, and voice. A modular neural network of three modules is used. Each module is a local expert on person recognition based on each of the biometric measures. The response integration method of the modular neural network has the goal of combining the responses of the modules to improve the recognition rate of the individual modules. We show in this chapter the results of a type-2 fuzzy approach for response integration that improves performance over type-1 fuzzy logic approaches.

## 6.1 Introduction

Today, a variety of methods and techniques are available to determine unique identity, the most common being fingerprint, voice, face, and iris recognition (Melin and Castillo, 2005). Of these, fingerprint and iris offer a very high level of certainty as to a person's identity, while the others are less exact. A large number of other techniques are currently being examined for suitability as identity determinants. These include (but are not limited to) retina, gait (walking style), typing style, body odour, signature, hand geometry, and DNA. Some wildly esoteric methods are also under development, such as ear structure, thermal imaging of the face and other parts of the body, subcutaneous vein patterns, blood chemistry, anti-body signatures, and heart rhythm, to name a few (Urias et al., 2006).

The four primary methods of biometric authentication in widespread use today are face, voice, fingerprint, and iris recognition. All of these are supported in our approach, some more abundantly than others. Generally, face and voice are considered to be a lower level of security than fingerprint and iris, but on the other hand, they have a lower cost of entry. We describe briefly in this section some of these biometric methods.

O. Castillo and P. Melin: Type-2 Fuzzy Log.: Theory and Appl., STUDFUZZ 223, pp. 77–86, 2008.
springerlink.com

**Face Recognition.** Facial recognition has advanced considerably in the last 10 to 15 years. Early systems, based entirely on simple geometry of key facial reference points, have given way to more advanced mathematically-based analyses such as Local Feature Analysis and Eigenface evaluation. These have been extended though the addition of "learning" systems, particularly neural networks.

Face recognition systems are particularly susceptible to changes in lighting systems. For example, strong illumination from the side will present a vastly different image to a camera than neutral, evenly-positioned fluorescent lighting. Beyond this, however, these systems are relatively immune to changes such as weight gain, spectacles, beards and moustaches, and so on. Most manufacturers of face recognition systems claim false accept and false reject rates of 1% or better.

**Voice Recognition.** Software systems are rapidly becoming adept at recognising and converting free-flowing speech to its written form. The underlying difficulty in doing this is to flatten out any differences between speakers and understand everyone universally. Alternatively, when the goal is to specifically identify one person in a large group by their voice alone, these very same differences need to be identified and enhanced.

As a means of authentication, voice recognition usually takes the form of speaking a previously-enrolled phrase into a computer microphone and allowing the computer to analyse and compare the two sound samples. Methods of performing this analysis vary widely between vendors. None is willing to offer more than cursory descriptions of their algorithms--principally because, apart from LAN authentication, the largest market for speaker authentication is in verification of persons over the telephone.

**Fingerprint Recognition.** The process of authenticating people based on their fingerprints can be divided into three distinct tasks. First, you must collect an image of a fingerprint; second, you must determine the key elements of the fingerprint for confirmation of identity; and third, the set of identified features must be compared with a previously-enrolled set for authentication. The system should never expect to see a complete 1:1 match between these two sets of data. In general, you could expect to couple any collection device with any algorithm, although in practice most vendors offer proprietary, linked solutions.

A number of fingerprint image collection techniques have been developed. The earliest method developed was optical: using a camera-like device to collect a high-resolution image of a fingerprint. Later developments turned to silicon-based sensors to collect an impression by a number of methods, including surface capacitance, thermal imaging, pseudo-optical on silicon, and electronic field imaging.

As discussed, a variety of fingerprint detection and analysis methods exist, each with their own strengths and weaknesses. Consequently, researchers vary widely on their claimed (and achieved) false accept and false reject rates. The poorest systems offer a false accept rate of around 1:1,000, while the best are approaching 1:1,000,000. False reject rates for the same vendors are around 1:100 to 1:1000.

## 6.2 Proposed Approach for Recognition

Our proposed approach for human recognition consists in integrating the information of the three main biometric parts of the person: the voice, the face, and the fingerprint (Urias et al., 2006). Basically, we have an independent system for recognizing a person from each of its biometric information (voice, face, and fingerprint), and at the end we have an integration unit to make a final decision based on the results from each of the modules. In Figure 6.1 we show the general architecture of our approach in which it is clearly seen that we have one module for voice, one module for face recognition, and one module for fingerprint recognition. At the top, we have the decision unit integrating the results from the three modules. In this paper the decision unit is implemented with a type-2 fuzzy system.

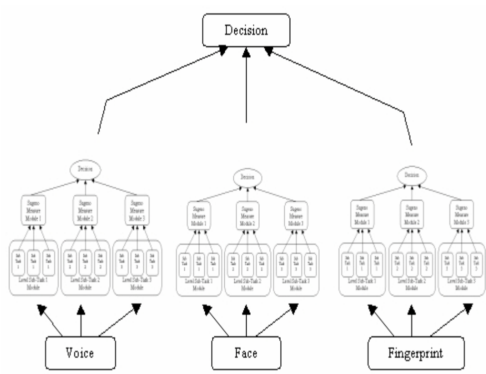


**Fig. 6.1.** Architecture of the proposed modular approach

## 6.3 Modular Neural Networks

This section describes a particular class of "modular neural networks", which have a hierarchical organization comprising multiple neural networks; the architecture basically consists of two principal components: local experts and an integration unit, as illustrated in Figure 6.2. In general, the basic concept resides in the idea that combined (or averaged) estimators may be able to exceed the limitation of a single estimator (Fogelman-Soulie, 1993). The idea also shares conceptual links with the "divide and conquer" methodology. Divide and conquer algorithms attack a complex problem by dividing it into simpler problems whose solutions can be combined to yield a solution to the complex problem (Monrocq, 1993). When using a modular network, a given task is split up among several local experts NNs (Happel and Murre, 1994). The average load on each NN is reduced in comparison with a single NN that must learn the entire original task, and thus the combined model may be able to surpass the limitation of a single NN. The outputs of a certain number of local experts ($O_i$) are mediated

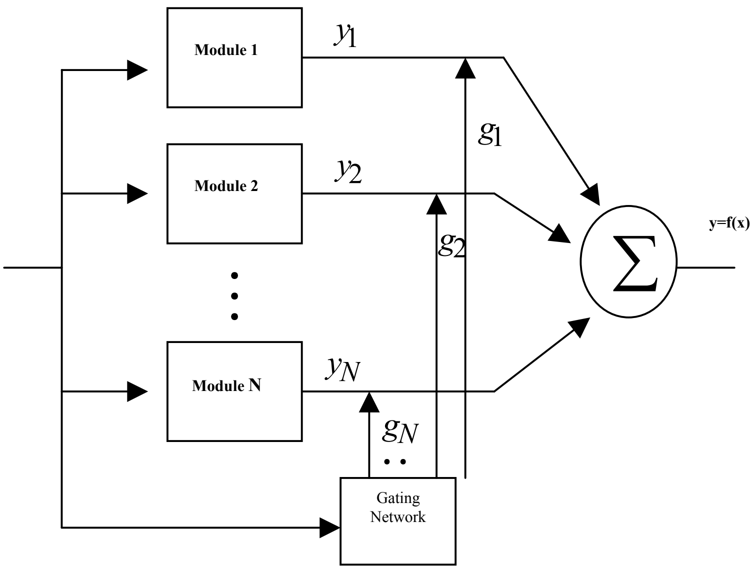


**Fig. 6.2.** Architecture of a modular neural network

by an integration unit. The integrating unit puts the outputs together using estimated combination weights ($g_i$). The overall output Y is given by equation (6.1).

$$Y_i = \Sigma g_i \, O_I \tag{6.1}$$

Nowlan, Jacobs, Hinton, and Jordan (Nowlan et al., 1991) described modular networks from a competitive mixture perspective. That is, in the gating network, they used the "softmax" function, which was introduced by (McCullagh and Nelder, 1994). More precisely, the gating network uses a softmax activation $g_i$ of ith output unit given by

$$G_i = \exp(ku_i) / \Sigma_j \exp(ku_j) \tag{6.2}$$

Where $u_i$ is the weighted sum of the inputs flowing to the ith output neuron of the gating network. Use of the softmax activation function in modular networks provides a sort of "competitive" mixing perspective because the ith local expert's output $O_i$ with a minor activation $u_i$ does not have a great impact on the overall output $Y_i$.

## 6.4 Integration of Results for Person Recognition Using Fuzzy Logic

On the past decade, fuzzy systems have displaced conventional technology in different scientific and system engineering applications, especially in pattern recognition and control systems. The same fuzzy technology, in approximation reasoning form, is resurging also in the information technology, where it is now giving support to decision making and expert systems with powerful reasoning capacity and a limited quantity of rules (Zadeh, 1998). For the case of modular neural networks, a fuzzy system can be used as an integrator or results (Melin and Castillo, 2005).

The fuzzy sets were presented by L. A. Zadeh in 1965 to process / manipulate data and information affected by unprobabilistic uncertainty / imprecision (Zadeh, 1975). These were designed to mathematically represent the vagueness and uncertainty of linguistic problems; thereby obtaining formal tools to work with intrinsic imprecision in different type of problems; it is considered a generalization of the classic set theory.

Type-2 fuzzy sets are used for modeling uncertainty and imprecision in a better way. These type-2 fuzzy sets were originally presented by Zadeh in 1975 and are essentially "fuzzy fuzzy" sets where the fuzzy degree of membership is a type-1 fuzzy set (Zadeh, 1996). The new concepts were introduced by (Mendel, 2001) allowing the characterization of a type-2 fuzzy set with a superior membership function and an inferior membership function; these two functions can be represented each one by a type-1 fuzzy set membership function. The interval between these two functions represent the footprint of uncertainty (FOU), which is used to characterize a type-2 fuzzy set. The uncertainty is the imperfection of knowledge about the natural process or natural state. The statistical uncertainty is the randomness or error that comes from different sources as we use it in a statistical methodology (Castillo et al., 2005).

## 6.5 Modular Neural Networks with Type-2 Fuzzy Logic as a Method for Response Integration

As was mentioned previously, type-2 fuzzy logic was used to integrate the responses of the three modules of the modular network. Each module was trained with the corresponding data, i.e. face, fingerprint and voice. Also, a set of modular neural networks was built to test the type-2 fuzzy logic approach of response integration. The architecture of the modular neural network is shown in Figure 6.3. From this figure we can appreciate that each module is also divided in three parts with the idea of also dividing each of the recognition problems in three parts.

Experiments were performed with sets of 20 and 30 persons. The trainings were done with different architectures, i.e. different number of modules, layers and nodes.

As can be appreciated from Figure 6.3, the first module was used for training with voice data. In this case, three different words were used for each person. The words used were: access, presentation, and hello.

The second module was used for training with person face data. In this case, two different photos were taken from each person, one in a normal position and the other with noise. The idea is that training with noise will make the recognition more robust to changes in the real world. We show in Figure 6.4 the photos of two persons in a normal situation and in a noisy situation.

The third module was used with fingerprint data of the group of persons. The fingerprint information was taken with a scanner. Noise was added for training the neural networks.

In all cases, each module is subdivided in three submodules, in this way making easier the respective recognition problem.

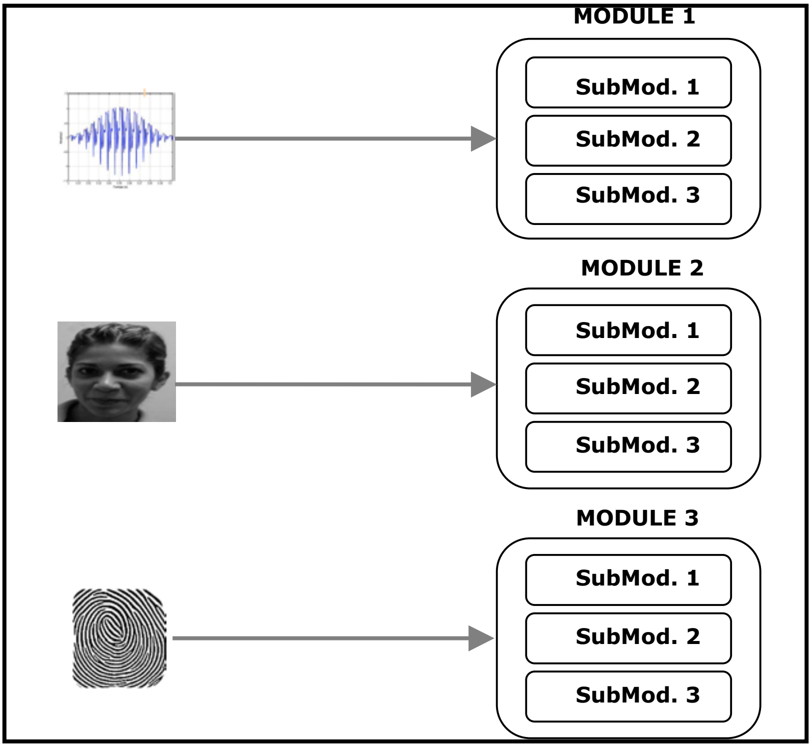


**Fig. 6.3.** Architecture of the Modular Network used for the recognition problem

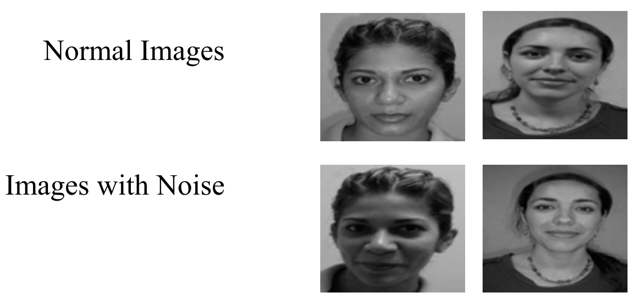


**Fig. 6.4.** Sample Photos of Faces in a Normal and Noisy Situation

## 6.6 Simulation Results

A set of different trainings for the modular neural networks was performed to test the proposed type-2 fuzzy logic approach for response integration in modular neural networks. We show in Table 1 some of these trainings with different numbers of modules, layers and nodes. The training times are also shown in this table to illustrate the performance with different training algorithms and conditions.

**Table 6.1.** Sample Trainings of the Modular Neural Network

| Red | Funcion de Entrenamiento | Num. de Capas | Neuronas | F. R. | % de Reconocimiento | Error Meta | Error Alcanzado | Epocas | Time |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Trainscg | V: Mod1: 2 | 48,49 | sse | 100% (20/20) | 0.001 | 0.000998658 | 3000 | 35 Min. |
| | | Mod2: 2 | 50,60 | sse | 100% (20/20) | 0.001 | 0.000998254 | 3000 | |
| | | Mod3: 2 | 60,70 | sse | 100% (20/20) | 0.001 | 0.00099876 | 3000 | |
| | | R: Mod4: 1 | 350 | mse | 100% (20/20) | 0.01 | 0.0099726 | 4000 | |
| | | Mod5: 1 | 400 | mse | 100%(20/20) | 0.01 | 0.0099546 | 4000 | |
| | | Mod6: 1 | 420 | mse | 100% (20/20) | 0.01 | 0.0098316 | 4000 | |
| | | H: Mod7: 1 | 350 | mse | 100% (20/20) | 0.01 | 0.0080223 | 4000 | |
| | | Mod8: 1 | 250 | mse | 100% (20/20) | 0.01 | 0.0086453 | 4000 | |
| | | Mod9: 1 | 300 | mse | 100% (20/20) | 0.01 | 0.0067892 | 4000 | |

| Red | Funcion de Entrenamiento | Num. de Capas | # de Neuronas | F.R. | % de Reconocimiento | Error Meta | Error Alcanzado | Epocas | Time |
|---|---|---|---|---|---|---|---|---|---|
| 10 | Trainscg | V: Mod1: 2 | 80,90 | sse | 100% (20/20) | 0.001 | 0.000999948 | 3000 | 1 Hra. 34 Min. |
| | | Mod2: 2 | 90,90 | sse | 100% (20/20) | 0.001 | 0.000992595 | 3000 | |
| | | Mod3: 2 | 80,90 | sse | 100% (20/20) | 0.001 | 0.000997131 | 3000 | |
| | Trainscg | R: Mod4: 1 | 20 | mse | 100% (20/20) | 0.01 | 0.124015 | 4000 | |
| | | Mod5: 1 | 15 | mse | 100% (20/20) | 0.01 | 0.0269689 | 4000 | |
| | | Mod6: 1 | 25 | mse | 100% (20/20) | 0.01 | 0.01698 | 4000 | |
| | Traingdx | H: Mod7: 1 | 350 | mse | 25% (5/20) | 0.01 | 0.037501 | 4000 | |
| | | Mod8: 1 | 230 | mse | 5% (1/20) | 0.01 | 0.0450007 | 4000 | |
| | | Mod9: 1 | 290 | mse | 5% (1/20) | 0.01 | 0.0425011 | 4000 | |

| Red | Funcion de Entrenamiento | Num. de Capas | # de Neuronas | F.R. | % de Reconocimiento | Error Meta | Error Alcanzado | Epocas | Time |
|---|---|---|---|---|---|---|---|---|---|
| 14 | Trainscg | V: Mod1: 2 | 85,95 | mse | 100% (30/30) | 0.001 | 0.000990206 | 3000 | 1 Hra. 23 Min. |
| | | Mod2: 2 | 95,90 | mse | 100% (30/30) | 0.001 | 0.000970259 | 3000 | |
| | | Mod3: 2 | 99,96 | mse | 93% (28/30) | 0.001 | 0.000995249 | 3000 | |
| | Trainscg | R: Mod4: 1 | 25 | mse | 0.3% (1/30) | 0.01 | 0.0880936 | 4000 | |
| | | Mod5: 1 | 20 | mse | 0.3% (1/30) | 0.01 | 0.0172602 | 4000 | |
| | | Mod6: 1 | 30 | mse | 0.3% (1/30) | 0.01 | 0.0127059 | 4000 | |
| | Traincsg | H: Mod7: 1 | 15 | mse | 96% (29/30) | 0.01 | 0.148242 | 4000 | |
| | | Mod8: 1 | 10 | mse | 90% (27/30) | 0.01 | 0.142394 | 4000 | |
| | | Mod9: 1 | 23 | mse | 96% (29/30) | 0.01 | 0.127423 | 4000 | |

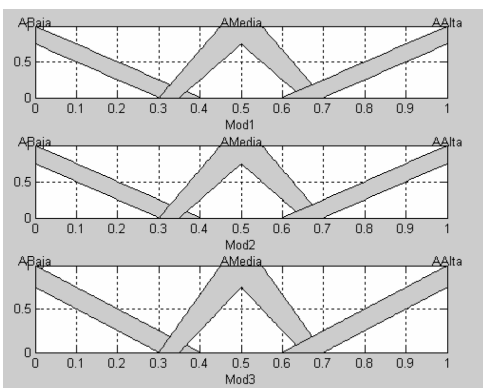


**Fig. 6.5.** Input variables of the type-2 fuzzy system

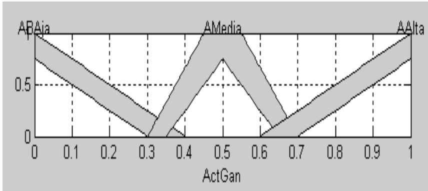


**Fig. 6.6.** Output variables of the type-2 fuzzy system

**Table 6.2.** Results of the Type-2 Fuzzy System with Triangular Membership Functions

| Funciones de Membresia Triangulares(7) | |
|---|---|
| **Entrenamiento** | **% de Reconocimiento** |
| 1 | 100% (20/20) |
| 2 | 100% (20/20) |
| 3 | 100% (20/20) |
| 4 | 100% (20/20) |
| 5 | 100% (20/20) |
| 6 | 5% (1/20) |
| 7 | 100% (20/20) |
| 8 | 65% (13/20) |
| 9 | 100% (20/20) |
| 10 | 100% (20/20) |
| 11 | 93% (28/30) |
| 12 | 96% (29/30) |
| 13 | 93% (28/30) |
| 14 | 93% (28/30) |
| 15 | 83% (25/30) |
| Resultados para cada uno de los entrenamientos , utilizando un Sistema Difuso con Funciones de MembresiaTriangulares | |

Once the necessary trainings were done, a set of tests were performed with different type-2 fuzzy systems. The fuzzy systems were used as response integrators for the three modules of the modular network. In the type-2 fuzzy systems, different types of membership functions were considered with goal of comparing the results and deice on the best choice for the recognition problem.

The best type-2 fuzzy system, in the sense that it produced the best recognition results, was the one with triangular membership functions. This fuzzy system has 3 input variables and one output variable, with three membership functions per variable. We show in Figures 6.5 and 6.6 the membership functions of the type-2 fuzzy system.

The recognition results of this type-2 fuzzy system for each training of the modular neural network are shown in Table 2.

In Table 6.2 we show the results for 15 trainings of the modular neural network. In each row of this table we can appreciate the recognition rate with the type-2 fuzzy system. We can appreciate that in 8 out of 15 cases, a 100% recognition rate was achieved.

The fuzzy systems with worst results for the modular neural network were the ones with Gaussian and Trapezoidal membership functions. We use 3 input variables and one output variable, as in the previous fuzzy system. We show in Figures 6.7 and 6.8 the Gaussian membership functions of this system.

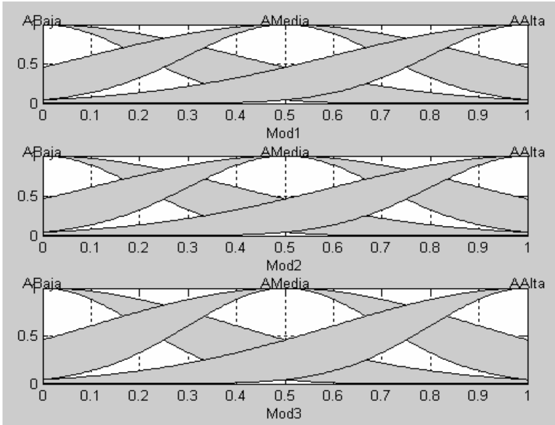


**Fig. 6.7.** Input variables for type-2 fuzzy system with Gaussian membership functions

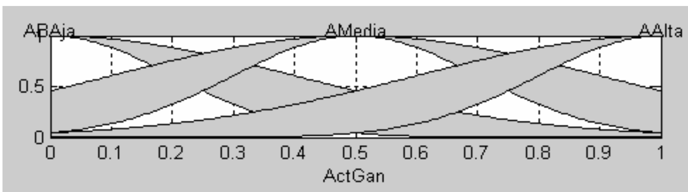


**Fig. 6.8.** Output variable for type-2 fuzzy system with Gaussian membership functions

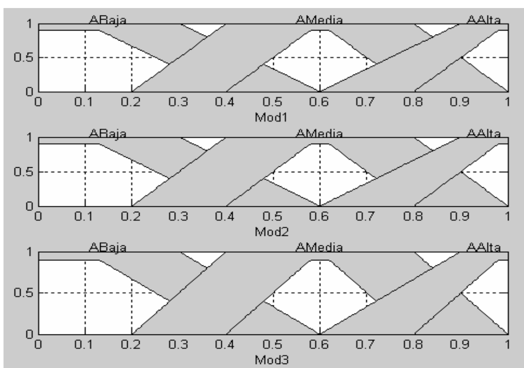


**Fig. 6.9.** Input variables for the Type-2 Fuzzy System with Trapezoidal Functions

We show in Figures 6.9 and 6.10 the Trapezoidal membership functions of another type-2 fuzzy system.

The results that were obtained with Gaussian and Trapezoidal membership functions are similar. We show in Table 3 the recognition results obtained with the type-2 fuzzy system with Trapezoidal membership functions. We can appreciate from Table 6.3

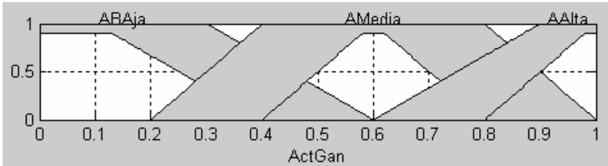


**Fig. 6.10.** Output variable for type-2 fuzzy system with Trapezoidal functions

**Table 6.3.** Recognition rates with the Type-2 System and Trapezoidal Functions

| Funciones de Membresia Trapezoidales (11) | |
|---|---|
| Entrenamiento | % de Reconocimiento |
| 1 | 100% (20/20) |
| 2 | 100% (20/20) |
| 3 | 55% (11/20) |
| 4 | 100% (20/20) |
| 5 | 100% (20/20) |
| 6 | 95% (19/20) |
| 7 | 100% (20/20) |
| 8 | 60% (12/20) |
| 9 | 55% (11/20) |
| 10 | 45% (9/20) |
| 11 | 96% (29/30) |
| 12 | 96% (29/30) |
| 13 | 100% (30/30) |
| 14 | 6% (2/30) |
| 15 | 3% (1/30) |
| Resultados para cada uno de los entrenamientos, utilizando un Sistema Difuso con Funciones de Membresia Trapezoidal | |

that only in 6 out of the 15 cases a 100% recognition rate is obtained. Also, there are 4 cases with low recognition rates.

We have to mention that results with a type-1 fuzzy integration of responses were performed in previous paper, in which the recognition rates were consistently lower by an average of 5%. We can state in conclusion that the type-2 fuzzy system for response integration is improving the recognition rate in the case of persons based on face, fingerprint and voice.

## 6.7 Summary

We described in this chapter a new method for response integration in modular neural networks that uses type-2 fuzzy logic to model uncertainty in the decision process. We showed different trainings of the modular neural networks, and tested different type-2 fuzzy systems for response integration. Based on the obtained recognition rates, the best results were achieved with a type-2 fuzzy system with triangular membership functions. The results obtained with this type-2 fuzzy system are better than the previously obtained by a similar type-1 approach.