SIGNATURE RECOGNITION WITH A HYBRID APPROACH COMBINING MODULAR NEURAL NETWORKS AND FUZZY LOGIC FOR RESPONSE INTEGRATION

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Abstract:

This paper describes a modular neural network (MNN) with fuzzy integration for the problem of signature recognition. Currently, biometric identification has gained a great deal of research interest within the pattern recognition community. For instance, many attempts have been made in order to automate the process of identifying a person's handwritten signature; however this problem has proven to be a very difficult task. In this work, we propose a MNN that has three separate modules, each using different image features as input, these are: edges, wavelet coefficients, and the Hough transform matrix. Then, the outputs from each of these modules are combined using a Sugeno fuzzy integral and a fuzzy inference system. The experimental results obtained using a database of 30 individual's shows that the modular architecture can achieve a very high 99.33% recognition accuracy with a test set of 150 images. Therefore, we conclude that the proposed architecture provides a suitable platform to build a signature recognition system. Furthermore we consider the verification of signatures as false acceptance, false rejection and error recognition of the MNN.

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

1. Introduction

Recently, there has been an increased interest in developing biometric recognition systems for security and identity verification purposes [2]. Such systems usually are intended to recognize different types of human traits, which include a person's face, their voice, fingerprints, and specific hand-writing traits [2].

Particularly, the handwritten signature that each person posses is widely used for personal identification and has a rich social tradition. In fact, currently it is almost always necessary in all types of transactions that involve legal or financial documents.

However, it is not a trivial task for a computational system to automatically recognize a person's signature for the following reasons. First, there can be a great deal of variability when a person signs a document. This can be caused by different factors, such as a person's mood, free time to write the signature, and the level of concentration during the actual act of signing a document. Second, because signatures can be so diverse it is not evident which type of features should be used in order to describe and effectively differentiate among them. For instance, some signatures are mostly written using straight-line segments, and still others have a much smoother form with curved and circular lines. Finally, many signatures share common traits that make them appear quite similar depending on the types of features that are analyzed.

In this work, we present a handwritten signature recognition system using Modular Neural Networks (MNNs) with the Sugeno fuzzy integral. We have chosen a MNN because they have proven to be a powerful, robust, and flexible tool, useful in many pattern recognition problems [13], [14]. In fact, we only extract simple and easily computed image features during our preprocessing stage, these features are: image edges, wavelet transform coefficients, and the Hough transform matrix. The MNN we propose uses these features to perform a very accurate discrimination of the input data used in our experimental tests. Therefore, we have confirmed that a MNN system can solve a difficult biometric recognition problem using a simple set of image features.

2. Problem statement and outline of our proposal

The problem we address in this paper is concerned with the automatic recognition of a person's signature that is captured on a Tablet PC. We suppose that we have

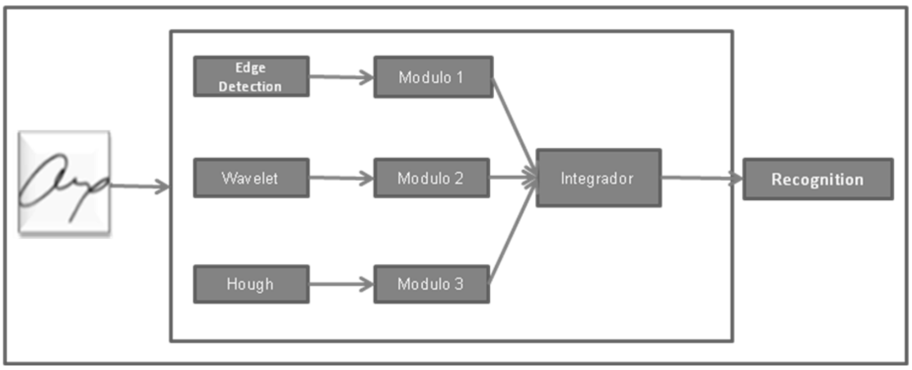

Fig. 1. General architecture of the proposed Modular Neural Network for signature recognition.

a set of N different people, and each has a unique personal signature. The system is trained using several samples from each person, and during testing it must determine the correct label for a previously unknown sample.

The system we are proposing consists on a MNN with three separate modules. Each module is given as input the features extracted with different feature extraction methods: edge detection, wavelets transform, and Hough transform. The responses from each of the modules are combined using a Sugeno fuzzy integral, which determines the person to whom the input signature corresponds. A general schematic of this architecture is shown in Figure 1, where all of the modules and stages are clearly shown.

In the following section we present a brief review of some of the main concepts needed to understand our work.

3. Background Theory

In this section we provide a general review of artificial neural networks and modular architectures, we discuss how the output from the modular system can be integrated using Sugeno fuzzy integrals, and we describe the feature extraction methods that provide the input for each of the modules in our MNN.

3.1. Modular Neural Networks

Artificial Neural Networks (ANNs) are information processing systems that employ a conceptual model that is based on the basic functional properties of biological neural networks. In the past twenty or thirty years, ANN research has grow very rapidly, in the development of new theories of how these systems work, in the design of more complex and intricate models, and in their application to a diverse set problem domains. Regarding the latter, application domains for ANN include pattern recognition, data mining, time series prediction, robot control, and in the development of hybrid methods with fuzzy logic and genetic algorithms, to mention but a few examples [7], [13], [14].

In canonical implementations, most systems employ a monolithic network in order to solve the given task. However, when a system needs to process large amounts of data or when the problem is highly complex, then it is not trivial, and sometimes unfeasible, to establish a good architecture and topology for a single network that can solve the problem. For instance, in such problems a researcher might attempt to use a very large and complex ANN. Nevertheless, large networks are often difficult to train, and for this reason they rarely achieve the desired performance [13].

In order to overcome some of the aforementioned shortcomings of mo-nolithic ANNs, many researchers have proposed modular approaches [11]. MNNs are based on the general principle of divide-and-conquer, where one attempts to divide a large problem into smaller subproblems that are easier to solve independently. Then, these partial solutions are combined in order to obtain the complete solution for the original problem.

MNNs employ a parallel combination of several ANNs, and normally contain two main components: (1) local experts; and (2) an integrating unit. The basic architecture is shown in Figure 1 [16].

Each module consists of a single ANN, and each is considered to be an expert in a specific task. After the input is given to each module it is necessary to combine all of the outputs in some way, this task is carried out by a special module called an integrator. The simplest form of integration is given by a gating network that basically switches between the outputs of the different modules based on simple criteria, such as the maximum level of activation. However, a better combination of the responses from each module can be obtained using more elaborate methods of integration, such as the Sugeno fuzzy integral [16].

3.2. Sugeno Fuzzy Integral

The Sugeno fuzzy integral is a nonlinear aggregation operator that can combine different sources of information [4], [8], [9]. The intuitive idea behind this operator is based on how humans integrate information

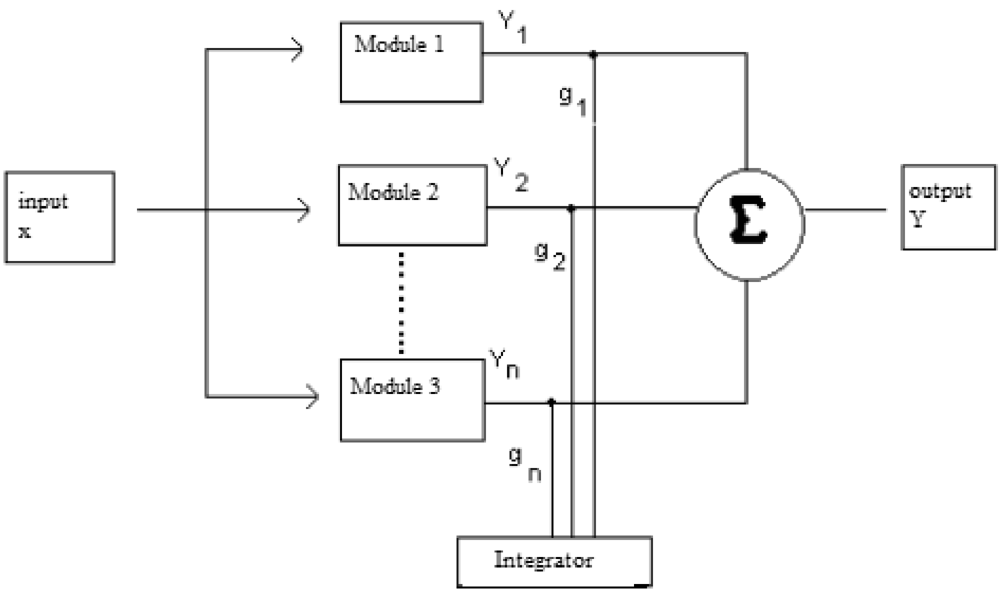

Fig. 2. Architecture of a Modular Network.

during a decision making process. In such scenarios it is necessary to evaluate different attributes, and to assign priorities based on partially subjective criteria. In order to replicate this process on an automatic system, a good model can be obtained by using a fuzzy representation [5], [8], [12]. Finally, several works have shown that the use of a Sugeno fuzzy integral as a MNN integrator can produce a very high level of performance [6], [8], [11], and for these reasons we have chosen it for the system we describe here.

3.3. Fuzzy Systems

Fuzzy theory was initiated by Lotfi A. Zadeh in 1965 with his seminal paper "Fuzzy sets". Before working on fuzzy theory, Zadeh was a well-respected scholar in control theory. A big event in the 70's was the birth of fuzzy controllers for real systems. In 1975, Mamdani and Assilian established the basic framework of fuzzy controller and applied the fuzzy controller to control a steam engine. Their results were published in another seminal paper in fuzzy theory "An experiment in linguistic synthesis with a fuzzy logic controller". They found that the fuzzy controller was very easy to construct and worked remarkably well [3], [15].

The fuzzy inference system is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. It has found successful applications in a wide variety of field, such as automatic control, data classification, decision analysis, experts systems, times series prediction, robotics, and patter recognition [3], [15]. The basic structure of a fuzzy inference system consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion [3].

3.4. Feature Extraction

In this work, we employ three individual modules, and each receives different image features extracted from the original image of a person's signature. Each of these feature extraction methods are briefly described next.

3.4.1. Edge detection

For images of handwritten signatures, edges can capture much of the over-all structure present within, because people normally write using a single color on a white background. Hence, we have chosen to apply the Canny edge detector to each image that generates a binary image of edge pixels, see Fig 3.

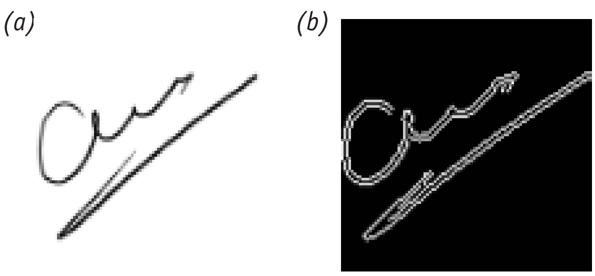

Fig. 3. (a) Original image of a signature. (b) Image edges.

3.4.2. Wavelet Transform

The wavelet transform decomposes a signal using a family of orthogonal functions, it accounts for both the frequency and the spatial location at each point. The most comon application is the Discrete Wavelet Transform (DWT) using a Haar wavelet [17]. The DWT produces a matrix of wavelet coefficients that allows us to compress, and if needed reconstruct, the original image. In Figure 4 we can observe the two compression levels used in our work.

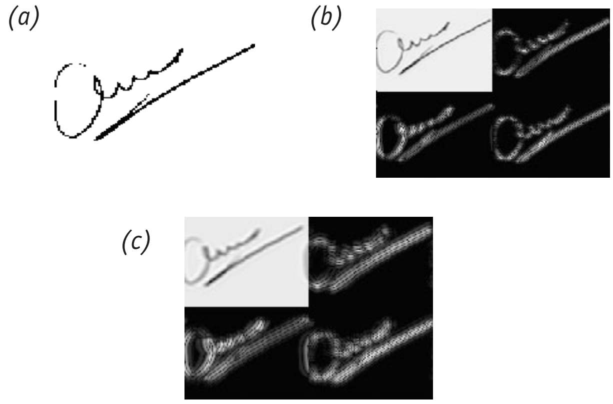

Fig. 4. (a) Original image of a signature. (b) First level of decomposition. (c) Second level of decomposition.

3.4.3. Hough Transform

In the third and final module we employ the Hough transform matrix as our image features [1]. The Hough transform can extract line segments from the image. In Figure 5 we show a sample image of a signature and its corresponding Hough transform matrix. Finally, in order to reduce the size of the matrix, and the size of the corresponding ANN, we compress the information of the Hough matrix by 25%.

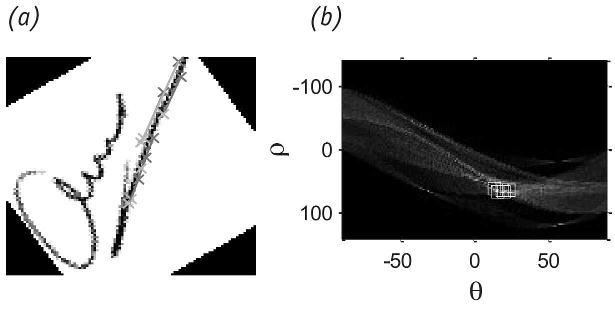

Fig. 5 (a) Sample of a signature image with some of the lines found by the Hough transform (b) The Hough transform matrix.

3.4.4. Verification of signatures

Currently, security practice always involves PIN number, password, and access card. However, these signs are not very reliable, since it can be forgotten or lost [2].

Automatic signature verification is one of the most practical ways to verify human's identify. Signature verification can be used in many applications such as security, access control, or financial and contractual matters.

The process of signature verification often consists of a learning stage and a testing stage, as shown in figure 6. In the learning stage, the verification system uses the feature extracted from one or several training samples to build a reference signature database. In the testing stage the user inputs the signature into input device. Then the system uses this information to extract the reference in the database, and compares the features extracted from the input signature with the reference. Finally the verification process out whether the test signature is genuine or not.

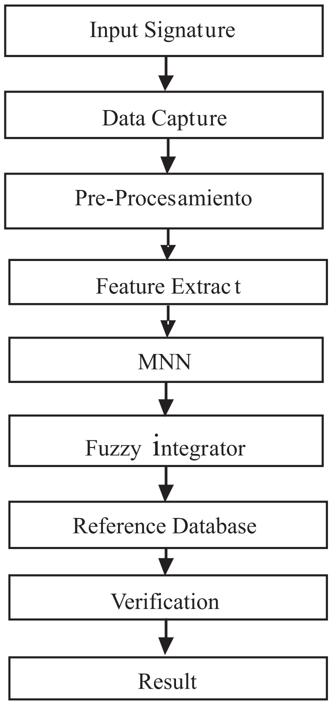

Fig. 6. Signature verification process.

In the research area of signature verification, a type I error rate and type II error rate are usually called false reject rate (FRR) and false acceptance rate (FAR) respectively. To minimize the type II errors, which represent the acceptance of the counterfeited signatures will normally increase the type I errors, which are the rejections of genuine signature. In most case, type II error rate is considered to be more important, but it is not a must. This will depend on the purpose, design, characteristics and application of the verification systems. If the system requests a high security, false accept rate should reduced to its lowest; if the security is not so strict, the system can be adjust to its lowest average false rate.[2]

The fuzzy system will answer the greater activation of the 3 modules signing, taking the form of higher activation winner; this means the 27 rules in the system are considered fuzzy.

Once the winner module did a signature verification process to know whether the signature that shows fuzzy integrator corresponds to the person. For this we also conducted 30 trainings with 150 different samples of genuine signatures, to make activation and get an average of this activation. The average of the activations is used as to whether a signature is forged or genuine.

Typically when the signature is authentic we obtain a high activation and when the signature is false the activation is low, although not necessarily, as may happen if there is a high activation but the signature is false activation or a low but firm is true, so we take into account four different cases:

1. False acceptance (FRA).
2. False rejection (FRR).
3. Error.
4. Signature Authentic.

After taking as reference the average of activations, 85 samples were collected from forged signatures of 17 persons and 65 authentic samples of 13 persons, giving a total of 150 samples between false and authentic signatures of 30 persons. In total 210 images of signatures of each module for the training signatures are authentic.

Table 1 shows the case that can be given upon verification of signatures, taken as a basis the average activations.

Table 1. Signature verification procedure.

Recognizes	Overcome threshold	Original signature	Result
Yes	Yes	No	False Acceptance
Yes	No	Yes	False Rejection
No	Yes	Yes	Error
No	No	Yes	Error
No	No	No	Correct
No	Yes	No	Correct

4. Experiments

In this section we present our database of signature images, describe our experimental set-up, and detail the experimental results we have obtained using monolithic and modular networks.

4.1. Image Database

For this work we build a database of images with the signatures of 30 different people, students and professors from the computer science department at the Tijuana Institute of Technology, BC, México. We collected 12 samples of the signature from each person; this gives a total of 360 images in total. Sample images from the database are shown in Figure 7.

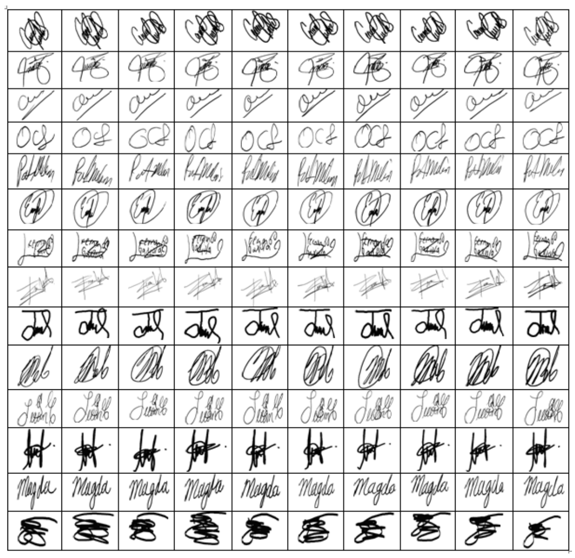

Fig. 7. Images from our database of signatures. Each row shows different samples from the signature of the same person.

4.2. Experimental setup

In this work, we are interested in verifying the performance of our proposed MNN for the problem of signature recognition. Therefore, in order to obtain comparative measures we divide our experiments into four separate tests.

1. First, we use each module as a monolithic ANN for signature recognition. Therefore, we obtain three sets of results, one for each module, where in each case a different feature extraction method is used.
2. Second, we train our MNN using all three modules concurrently and the Sugeno fuzzy integral as our integration method.
3. Third, we train our MNN using all three modules concurrently and the Fuzzy System as our integration method.
4. Fourth, Signature verification: false acceptance, false rejection.

In all tests 210 images were chosen randomly and used for training, and the remaining 150 were used as a testing set. Additionally, after some preliminary runs it was determined that the best performance was achieved when the ANNs were trained with the Scaled Conjugate Gradient (Trainscg) algorithm, with a goal error of 0.001. Moreover, all networks had the same basic ANN architecture, with two hidden layers. In what follows, we present a detailed account of each of these experimental tests.

4.2.1. Monolithic ANNs

The results for the first monolithic ANN are summarized in Table 2. The table shows a corresponding ID number for each training case, the total epochs required to achieve the goal error, the neurons in each hidden layer, and the total time required for training. Recognition performance is shown with the number of correct recognitions obtained with the 150 testing images, and the corresponding accuracy score. In this case, the best performance was achieved in the third training run where the algorithm required 78 epochs, and the ANN correctly classified 131 of the testing images.

Table 2. Performance for a monolithic ANN using edge features; bold indicates best performance.

No	Epochs	Neurons	Time	Correct	Accuracy (%)
01	80	100-100	00:01:11	123/150	82
02	59	100-100	00:01:18	120/150	80
03	**78**	**100-100**	**00:01:07**	**131/150**	**87**
04	90	100-100	00:01:26	117/150	78
05	80	100-100	00:01:08	119/150	79
06	78	100-100	00:01:34	123/150	82
07	53	100-100	00:00:46	123/150	82
08	79	80-90	00:01:08	123/150	82
09	55	80-90	00:00:56	128/150	85
10	58	80-90	00:00:58	122/150	81

The second monolithic ANN uses the wavelet features as input, and the obtained results are summarized in Table 3. In this case the best performance was obtained in the third training run, with a total of 5 epochs, and 144 correctly classified images. It is obvious that wavelet features provide a very good discriminative description of the signature images we are testing.

Table 3. Performance for a monolithic ANN using wavelet features.

Train	Epochs	Neurons	Time	Correct	Accuracy (%)
01	12	100-100	00:00:18	135/150	90
02	30	100-100	00:00:25	138/150	92
03	**05**	**100-100**	**00:00:08**	**144/150**	**96**
04	09	100-100	00:00:11	140/150	93
05	06	80-90	00:00:08	142/150	95
06	05	80-90	00:00:05	140/150	93
07	10	80-90	00:00:14	141/150	94
08	07	80-90	00:00:09	138/150	92
09	10	80-90	00:00:15	140/150	93
10	05	80-90	00:00:06	137/150	91

Finally, the third monolithic ANN uses the Hough transform matrix, and the corresponding results are shown in Table 4. The best performance is achieved in the fourth training run, with a total of 6 epochs and 141 correctly classified images.

Table 4. Performance for a monolithic ANN using the Hough transform.

Train	Epochs	Neurons	Time	Correct	Accuracy (%)
01	63	100-100	00:00:19	135/150	90
02	65	100-100	00:00:51	140/150	93
03	68	100-100	00:00:19	141/150	94
04	**06**	**80-90**	**00:00:08**	**141/150**	**94**
05	04	80-90	00:00:05	140/150	93
06	45	80-90	00:00:11	138/150	92
07	08	80-90	00:00:09	138/150	92
08	05	80-90	00:00:08	137/150	91
09	05	80-90	00:00:06	137/150	91
10	33	50-50	00:00:20	138/150	92

It is important to note that in all three cases, the monolithic methods did achieve good results. The best performance was obtained using wavelet features, and the Hough transform matrix also produced very similar results. On the other hand, the simple edge features produced a less accurate recognition than the other two methods.

4.2.2. Modular Neural Network with Sugeno Fuzzy Integral

The final experimental results correspond to the complete MNN described in Figure 1, and Table 5 summarizes the results of ten independent training runs. For the modular architecture, performance was consistently very high across all runs, and the best recognition accuracy of 98% was achieved in half of the runs. In fact, even the worst performance of 95% is better or equal than all but one of the monolithic ANNs (see Table 3).

Table 5. Results for the Modular Neural Network with fuzzy Sugeno Integral.

Train	Epochs	Time	Correct	Accuracy (%)
01	**55**	**00:00:49**	**147/150**	**98**
02	150	00:01:34	146/150	97
03	180	00:01:53	144/150	96
04	300	00:02:20	147/150	98
05	150	00:01:30	147/150	98
06	155	00:01:45	146/150	97
07	320	00:02:49	147/150	98
08	310	00:02:38	148/150	98
09	285	00:01:58	145/150	96
10	03	00:00:02	143/150	95

4.2.3. Modular Neural Network with a Fuzzy System

We use a fuzzy systems integrator for the three modules of the network. The fuzzy systems are of Mamdani type, contain three inputs (module 1, module 2, module 3) output (winner module), and 27 rules. Several tests were performed with the fuzzy systems that have the same input, and out-put rules, but with different functions of membership: Triangular, trapezoidal and Gaussian.

In figures 8, 9, 10 we show the fuzzy systems with trapezoidal Membership functions, Triangular and Gaussian.

The results obtained with the fuzzy system as an integrator of MNN with different membership functions (see table 6), were good, in this case the best result was obtained in the training with 9 Gaussian membership function, with a total of 223 epochs, and 149 images are classified cor-rectly. The method of training is scaled conjugate gradient (Transcg). Overcoming the best result with fuzzy Sugeno integral (see Table 5).

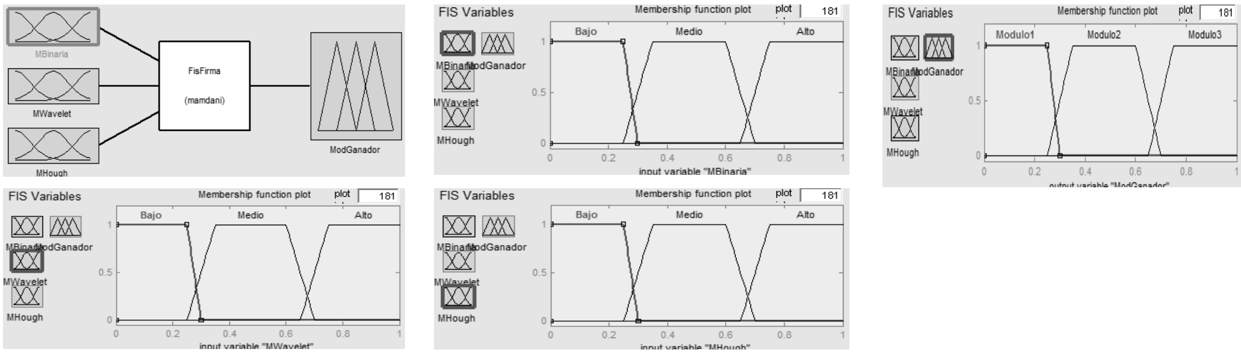

Fig. 8. Representation of fuzzy systems with trapezoidal membership functions.

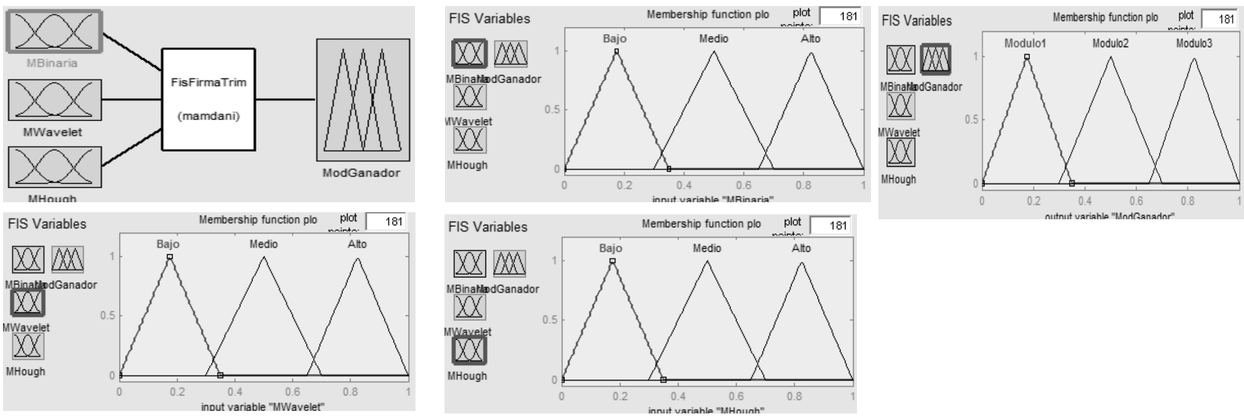

Fig. 9. Representation of fuzzy systems with Triangular membership functions.

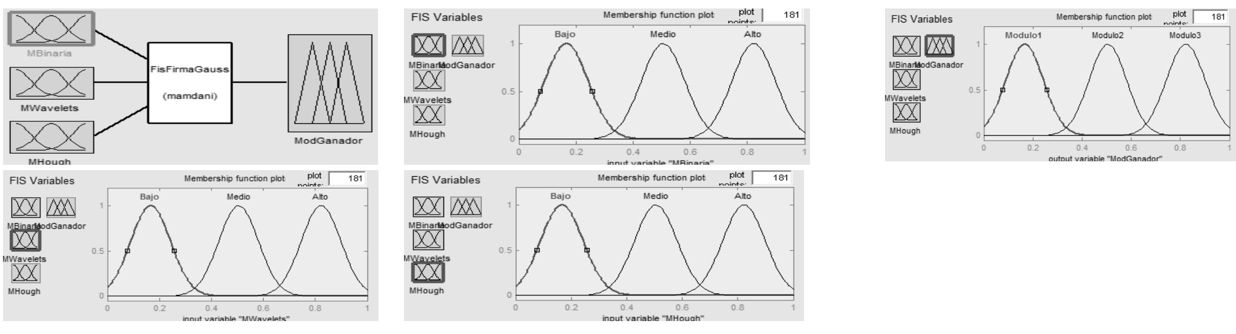

Fig. 10. Representation of fuzzy systems with Gaussian membership functions.

Table 6. Results for the Modular Neural Network with fuzzy system.

Train	Membership Funtion	Error goal	Epochs	Time	Correct	Accuracy (%)
01	**Triangular**	**0.001**	**232**	**00:03:42**	**148/150**	**98.66**
02	Triangular	0.001	560	00:09:15	146/150	97.33
03	Triangular	0.001	710	00:11:05	148/150	98.66
04	**Trapezoidal**	**0.001**	**96**	**00:01:37**	**147/150**	**98.00**
05	Trapezoidal	0.001	302	00:08:01	147/150	98.00
06	Trapezoidal	0.001	304	00:08:03	146/150	97.33
07	Gaussian	0.001	150	00:02:50	146/150	97.33
08	Gaussian	0.001	257	00:06:02	149/150	99.33
09	**Gaussian**	**0.001**	**223**	**00:03:17**	**149/150**	**99.33**

4.2.4. Modular Neural Network with a Fuzzy System adding uniform random noise

After multiple tests done with the fuzzy system, and taking into account that the best result was obtained with Gaussian membership functions, we applied noise to the images of signatures, using "uniform random noise". The noise level of 0.5 was applied. Table 7 shows the top 10 results. The best training is the one in the second row, with a total of 146 correctly classified images.

Table 7. Result with uniform random noise.

Train	Method	Time	Correct	Accuracy (%)
01	Trainscg	00:02:56	141/150	92.66
02	**Trainscg**	**00:02:57**	**146/150**	**97.33**
03	Trainscg	00:04:50	144/150	96.00
04	Trainscg	00:03:25	143/150	95.33
05	Trainscg	00:04:20	144/150	96.00
06	Trainscg	00:03:09	141/150	94.00
07	Trainscg	00:06:50	139/150	92.66
08	Trainscg	00:02:54	141/150	94.00
09	Trainscg	00:03:33	146/150	97.33
10	Trainscg	00:05:56	144/150	96.00

4.2.5. Results of verification of signatures

Table 8 shows the results as a percentage for each case: false acceptance, false rejection, error recognition and the percentage of correct signatures.

5. Summary, conclusions and future work

In this paper we have addressed the problem of signature recognition, a common behavioral biometric measure. We proposed a modular system using ANNs and three types of image features: edges, wavelet coefficients, and the Hough transform matrix. In our system, the responses from each module were combined using a Sugeno fuzzy integral and a fuzzy inference system. In order to test our system, we built a database of image signatures from 30 different individuals. In our experiments, the proposed architecture achieves a very high recognition rate, results that confirm the usefulness of the proposal.

In our tests, we have confirmed that the modular approach always out-performs, with varying degrees, the monolithic ANNs tested here. However, in some cases the difference in performance was not very high, only 3 or 2 percent. Nevertheless, we believe that if the recognition problem is made more difficult then the modular approach will more clearly show a better overall performance. Furthermore, our results also show that even with the simple image features used in this work, each of the ANN modules is indeed capable of learning very good discriminating functions that can correctly differentiate between our set of image signatures.

Moreover, the fuzzy system as a unit exceeds the percentage achieved with recognition of Sugeno fuzzy integral. For this reason the last experiments were conducted with the fuzzy system integrator.

Table 8. Results from the verification of signatures.

Train	Time	False Acceptance (%)	False Rejection (%)	Error Recognition (%)	Correct Sgnatures (%)
01	00:06:32	9.33	8.00	1.33	81.33
02	00:06:03	7.33	18.00	0.66	74.00
03	00:07:32	10.00	5.33	2.00	82.66
04	00:08:03	14.66	2.00	1.33	82.00
05	00:08:02	7.33	18.00	0.66	74.00
06	00:09:00	16.00	4.00	1.33	78.66
07	00:06:06	6.66	14.00	1.33	78.00
08	00:06:42	11.33	10.66	1.33	76.66
09	00:06:52	15.33	4.66	2.00	78.00
10	00:06:13	12.00	6.00	2.66	79.33

Finally, the results we have obtained suggest several possible extensions for our work, which include the following:

1. Test the system with a more challenging image database, using more signatures and a smaller set of training samples, in order to verify the robustness of our approach.
2. Optimizing the MNN architecture with a genetic algorithm.

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