Genetic Optimization of Neural Networks for Person Recognition Based on the Iris

Patricia Melin*, Victor Herrera, Danniela Romero, Fevrier Valdez, Oscar Castillo
Tijuana Institute of Technology
Calzada Tecnologico s/n, Tijuana, mexico
e-mail: pmelin@tectijuana.mx*

Abstrak

Tulisan ini menjabarkan penerapan arsitektur jaringan syaraf modular untuk kegunaan identifikasi orang menggunakan citra iris mata sebagai ukuran biometrik. Database iris mata manusia diperoleh dari Institut Automasi Akademi Ilmu Pengetahuan Cina (CASIA). Hasil simulasi ditunjukkan dengan menggunakan pendekatan jaringan syaraf modular, optimasinya menggunakan algorima genetik dan penggabungannya dengan metode lain seperti metode jaringan gerbang, integrasi fuzi tipe-1 dan penggabungan fuzi teroptimasi dengan algoritma genetik. Hasil simulasi menunjukkan tingkat indetifikasi yang bagus saat mengggunakan integrator fuzi dan struktur terbaik dimiliki oleh algoritma genetik.

Kata kunci: *algoritma genetik, biometrik iris, fuzi, jaringan syaraf tiruan, optimasi*

Abstract

This paper describes the application of modular neural network architectures for person recognition using the human iris image as a biometric measure. The iris database was obtained from the Institute of Automation of the Academy of Sciences China (CASIA). We show simulation results with the modular neural network approach, its optimization using genetic algorithms, and the integration with different methods, such as: the gating network method, type-1 fuzzy integration and optimized fuzzy integration using genetic algorithms. Simulation results show a good identification rate using fuzzy integrators and the best structure found by the genetic algorithm.

Keywords: *fuzzy, neural networks, iris biometry, optimization, genetic algorithms*

1. Introduction

The recognition of persons using biometrics is a problem that has been considered by many researchers [1-4]. Biometrics plays an important role in public safety and to accurately identify each individual to distinguish them from each other [5]. This problem has been studied more thoroughly in recent years thanks to advances in computational power that have allowed the implementation of more complex algorithms using different techniques [6], [7]. Biometric identification systems are those based on physical characteristics or morphology of human beings to perform some kind of recognition [8], [9].

Traditional systems used in accessing control are based on magnetic cards, card systems with bar code systems capture key or a combination. These systems involve the use of a card that must be carried always and which is not exempt from being lost, damaged, be stolen or forged, thus security is more vulnerable to failure. For this reason, systems that are more robust and with higher reliability are needed to avoid the problems mentioned above. Pattern recognition systems based on neural networks have been given recently considerable interest [10-15].

There are different techniques and methods that can be used for feature extraction, and today it is easier to recognize a person by the existing biometric methods. For example, a person can be recognized for its iris, fingerprints, and face, recognizable by his voice, signature, hand geometry, ear, vein structure, retina, facial thermography and others that exist [16-19]. At this moment, biometric methods have been implemented using different devices to create patterns and generate the code that identifies the persons [20-23].

Biometrics refers to an identification and authentication technology that is transforming a biological, morphological, or behavioral characteristic into a numerical value. Its aim is to

Received March 3, 2012; Revised April 18, 2012; Accepted April 26, 2012

attest to the uniqueness of a person from far irrepressible immutable part of the body [5]. Another definition mentions that biometrics is based on the premise that each individual is unique and has distinctive physical traits or behaviors, which can be used to identify or validate [24].

Within the large field of biometrics where one can highlight, fingerprint recognition, retinal and voice, among others, we can highlight the iris recognition as a biometric tool for person recognition in a unique and highly accurate fashion [1], [2].

This paper presents research work on integrating results of a modular neural network using the CASIA database, and obtaining the best identification when using type-1 fuzzy logic integrators developed by the genetic algorithms. Optimization of the neural networks was performed with genetic algorithms (GAs), which are essentially a method that creates a population of individuals to find the most appropriate one by simulating evolution [25-28]. This process is based on natural selection by using operators such as the crossover and mutation to create new individuals. The modular neural network architectures and the chromosomes produced by the genetic algorithms with the best parameters found for the network were tested for their performance and operation, and the results of the different integrators, such as the gating network and type-1 fuzzy logic integrators, were compared for this problem.

2. Research Method

Neural networks are composed of many elements (Artificial Neurons), grouped into layers that are highly interconnected (with the synapses), which are trained to react (or give values) in a way you want to input stimuli. These systems emulate in some way, the human brain. Neural networks are required to learn to behave (Learning) and someone should be responsible for the teaching or training (Training), based on prior knowledge of the environment problem [7], [5].

A neural network is a system of parallel processors connected together as a directed graph. Schematically, each processing element (neuron) of the network is represented as a node. These connections provide a hierarchical structure trying to emulate the physiology of the brain for processing new models to solve specific problems in the real world. What is important in developing neural networks is their useful behavior by learning to recognize and apply relationships between objects and patterns of objects specific to the real world. In this respect neural networks are tools that can be used to solve difficult problems [29], [8], [30]. Artificial neural networks are inspired by the architecture of the biological nervous system, which consists of a large number of relatively simple neurons that work in parallel to facilitate rapid decision-making [24].

Fuzzy logic was proposed for the first time in the mid-sixties at the University of California Berkeley by the brilliant engineer Lotfi A. Zadeh [31], [32]. Who proposed what it's called the principle of incompatibility: "As the complexity of system increases, our ability to give precise instructions and build on their behavior decreases to a threshold beyond which the accuracy and meaning are mutually exclusive characteristics." Then introduced the concept of a fuzzy set, under which lies the idea that the elements on which to build human thinking are not numbers but linguistic labels. Fuzzy logic can represent the common knowledge as a kind of language that is mostly qualitative and not necessarily a quantity in a mathematical language by means of fuzzy set theory and the characteristic functions associated with them [32].

Fuzzy logic has gained a great reputation for the variety of applications, ranging from control of complex industrial processes to the design of artificial devices for automatic deduction, through the construction of household electronic appliances and entertainment as well as diagnostic systems [33-38].

Fuzzy logic is an area of soft computing, which allows one computer system to the reason for the uncertainty [31]. This corresponds, in the real world, to many situations where it is difficult to decide unequivocally whether or not something belongs to a specific class [39-42]. Fuzzy logic is a useful tool for modeling complex systems [43-48]. However, it is often difficult for human experts to define the fuzzy sets and fuzzy rules used by these systems [36]. This is particularly true for type-2 fuzzy systems that use uncertain membership functions and that have recently been applied to many real-world problems [49-57].

Genetic algorithms were introduced by the first time by a professor of the University of Michigan named John Holland [31], [5]. A genetic algorithm, it is a mathematical highly parallel algorithm that transforms a set of mathematical individual objects with regard to the time using operations based on evolution. The Darwinian laws of reproduction and survival of the fittest can be used, and after having appeared of natural form a series of genetic operations between (among) individuals that stand out for the sexual recombination [25], [26]. For the passage from one generation to another a series of genetic operators are applied. The most commonly used operators are selection, crossover and mutation [15]. Each of the individuals is in the habit of being a chain of characters (letters or numbers) of fixed length that adjust to the model of the chains of chromosomes, and one associates to them with a certain mathematical function that reflects the fitness.

There exists a diversity of methods of integration or aggregation of information, like voting method, fuzzy integration, and gating networks [25]. However, we concentrate in this section (for illustrative purposes) on the gating network method.

Integration by Gating Network: in this case decomposition of a learning task into sub tasks learned through the modules of cooperation is performed. The benefits of working with Gating Network are: best overall performance, reuse of existing patterns heterogeneity expert classifiers, need not be the same type; different features can be used for different classifiers.

There are several implementations of the modular neural network, but the most important is by nature of using the gating network. In some cases, this corresponds to a single neuron to evaluate the performance of the other modules of experts. Other embodiment of the gating network is based on a neural network trained with a different data set for training the networks of experts [5]. In Figure 1 a scheme of the gating network integrator is presented.

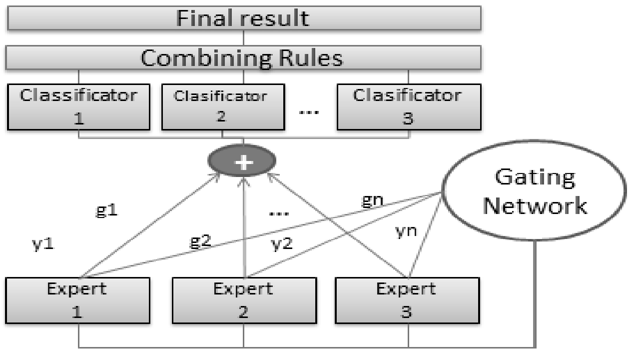

Figure 1. Representation of the gating network integration method

2.1. Iris Image Preprocessing

Due to the unique, stable and accessible characteristics of iris patterns, personal identification based on the iris pattern has become one of the most reliable techniques [1-4]. The idea of using iris patterns to identify people was first proposed in 1936 by the ophthalmologist Frank Burch. However, it was not until 1987, when Leonard Flom and Aran Safir, American ophthalmologists, patented the concept of Burch. His interest in developing the system, led to contact with John G. Daugman, then a professor at the University of Harvard so he developed the necessary algorithms for biometric recognition through the pattern of the iris [7]. These algorithms, patented by Daugman in 1994 and partly published in [14], are the basis of all iris recognition systems that exist today.

Various studies carried out for iris recognition, as the work of M. Ahmad Sarhan [7], which uses neural networks and the cosine transform for iris-based identification. The iris as an identifier is perhaps one of the most foreign to people, as among us do not recognize the appearance of the iris. This identifier is one of the most accurate among biometric systems [7].

The database of human iris is from the Automation Institute of the Academy Sciences of China [58]. This institution has several databases of iris, and we used in this work version 3 of the database, which consists of 14 images per person (7 of each eye), we used only the first 77 people the total database. The image dimensions are 320x280 pixels, the format is JPEG, and 8 images were used for training and 6 for testing.

In the pre-processing stage, different methods were applied for feature extraction and noise removal, in order to extract the region of interest (iris) of the captured image, apply some filters on it, this in order to help the modular neural network, to obtain a high recognition of the images (see Figure 2).

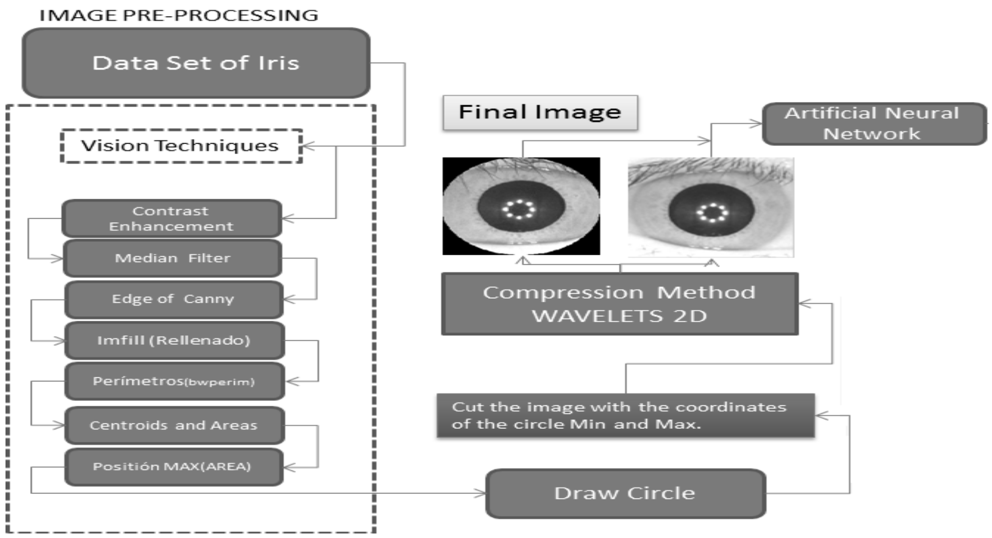

Figure 2. General diagram of pre-processing for the CASIA database

Figure 3 shows the resulting image, after making a cut to the image, according to the maximum and minimum. As shown in the image this can be done in 2 ways: one is filling the outer parts of the circle, leaving them in black and giving us a better appreciation of the center of the iris, and the other way is to let the image with their property and leaving more features in the image for the network.

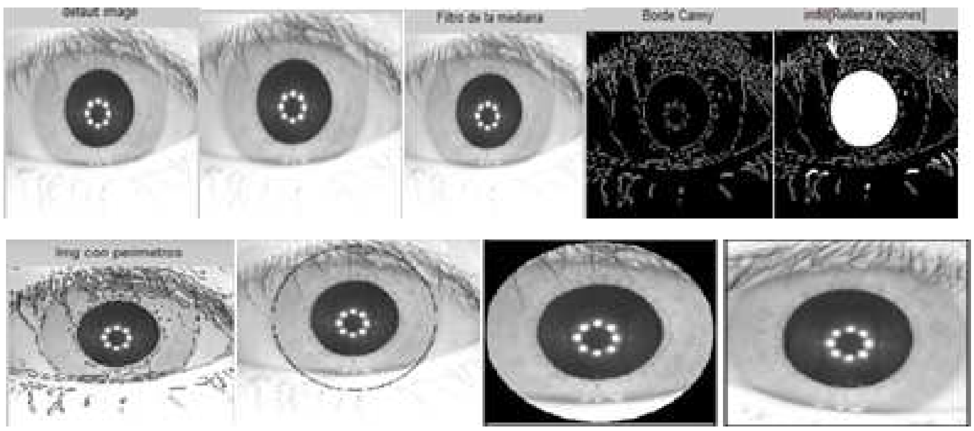

Figure 3. Result of applying different techniques of vision to the center of the iris

Once we have all the database with pre-processing and before putting each image into the modular neural network, we compressed the images to 320 x 280 (25x25) using a wavelet transform 2D rate with “symmlet” of order 8, with 2 levels of decomposition (see Figure 4).

We proceed to vectorize each image within a matrix containing the first 33 persons, another array of vectors with the following 33 (34-66), and the last 33 persons in the same way (67-99).

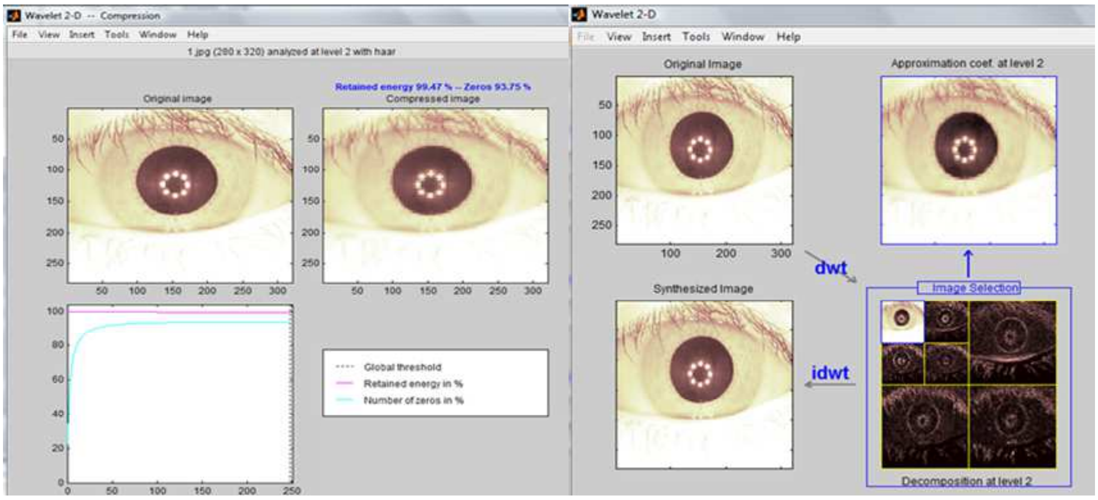

Figure 4. Application of the wavelet transform in 2D

In the first 33 persons we have 14 samples, which means that there are 7 pictures or samples of the right eye and 7 samples of the left eye, of which we took 8 sample images for training and 6 images to validate that the images will be recognized according to the 8 above, then you have two arrays of vectors, the first containing the training images and the other the validation matrix, with (8 * 33), 264 vectors in the matrix of training and (6 * 33), 198 images shown in the validation matrix. The same was done for persons (34-66) and (67-99), for each of the modules of the modular neural network.

2.2. Statement of the Problem and Proposed Method

We studied several methods of fuzzy integration that can be applied to modular neural networks for person recognition using biometric iris images as well to develop alternative methods for response integration of the modular neural network, such as the gating network and the winner takes all. Figure 5 shows the general architecture that was used in this work.

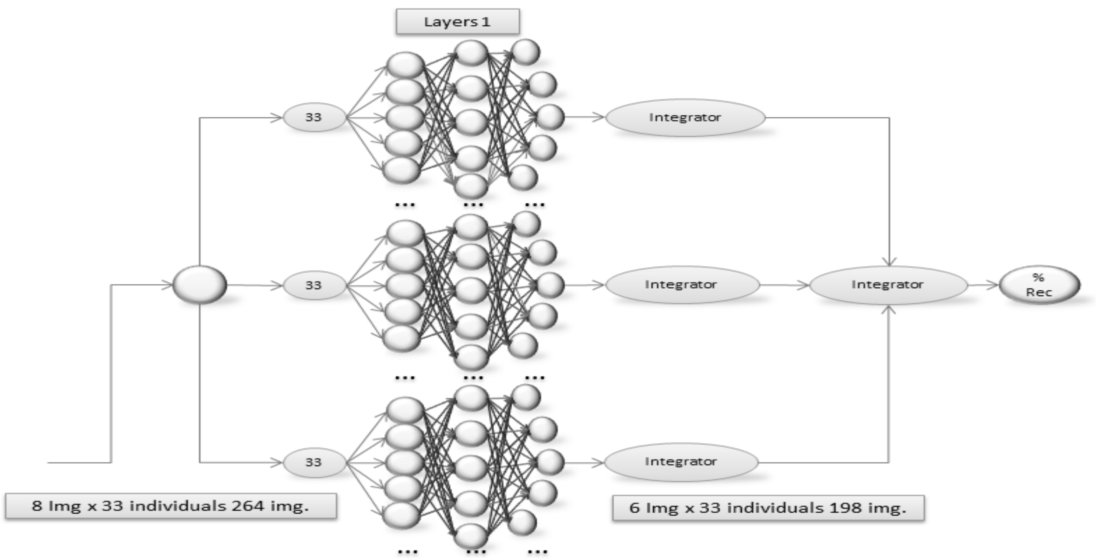

Figure 5. General architecture of the modular neural network

The modular neural network consists of 3 modules, each module consists of a multilayer perceptron, which is an artificial neural network (ANN) consisting of multiple layers, and this allows you to solve problems that are not linearly separable. The perceptron uses a matrix to represent neural networks and it is a tertiary discriminator that traces its input x (a binary vector) to a single output value f (x) (a single binary value) through the matrix.

The first module is specialized for the first 33 people who were vectorized, the following 33 for the second module and the last 33 for the third module, forming a modular neural network, and training is conducted according to the sequence of modules 1^{st}, 2^{nd} and 3^{rd}. The parameters of the (MNN) are shown on Table 1.

In this case each module is fed with the same information, to find a suitable architecture for each of the 3 modules, a study in an empirical way was done to know how many neurons are appropriate for the ANN to have a learning that is acceptable according to the type of training used. This will depend on the number of neurons used for such training, which may learn faster or slower and therefore have a good or bad learning, for this reason is that neurons adapt to the learning method along with the epochs. To know which structure is right for the first, second and third, module, unlike ensemble neural networks, modular neural networks (MNN) in each module are powered by vectors of different data, leading to architectures that are not uniform. The main advantage of this method is that each module produces a different result, which can be helpful because the training is not leaved to one expert module. This has an effect on the outcome of the integration, which takes into account that each module has different results. The network consists of three modules, the weight distribution is random for the first step of the network, and once this is completed the network will adjust the weights in each of the connections of the layers of the neural network. The results of each module of the modular network with the gating network integrator and arbitrary parameters, without pre-processing, (the result of the integration of the 3 modules), are shown in Table 2.

Table 1. Parameters of the modular neural network

M. Training	Error	Epochs	#Neurons	Learning Rate
Trainscg: Scaled conjugate Traingda: Gradient descent with momentum and adaptive learing Traingdx: Gradient descent with adaptive learning factor	0.0001	5000 y 8000	Undefined	0.01

Table 2. Results of the modular neural network without preprocessing in the image

Module	Error	Time	Epochs	Total ID	Error Image	N# neurons C1 Y C2	% ID
Traingda*3	0.00001	00:03:30	8000	530/594	64	170,141	90.18%
Traingdx*3	0.00001	00:02:46	5000	539/594	55	200,200	90.74%
Trainscg*3	0.00001	00:02:44	8000	530/594	64	170,141	90.40 %
Traingdx*3	0.00001	00:03:15	5000	540/594	54	200,250	90.91%
Traingdx*3	0.00001	00:05:14	5000	534/594	60	300,300	89.90%
Traingda*3	0.00001	00:03:58	5000	530/594	64	200,200	89.23%
Traingda*3	0.00001	00:07:46	5000	534/594	60	300,300	89.90%
Gda, Scg, Gdx	0.00001	00:02:32	5000	527/594	67	200,200	88.72%
Scg, Gda, Gdx	0.00001	00:03:26	8000	529/594	65	170,141	90.40%
Gda, Gda, Gdx	0.00001	00:03:44	8000	528/594	66	170,141	88.89%
Gdx, Gda, Scg	0.00001	00:03:27	5000	535 /594	59	200,200	90.07%

Table 2 shows results obtained from various trainings performed in each of the modules, the best methods that obtained a high recognition percentage were *traingda*, *traingdx*, *trainscg*, which achieved a recognition above 90%, with 90.18, 90.91 and 90.40 % respectively with a time of 3minutes and 30 seconds, 3 minutes 15 seconds and 3 minutes 26 seconds, with 8000, 5000, and 8000 epochs respectively, and a target error of 0.00001 for the ANN. These trainings were performed without pre-processing and with an uncompressed image. These results were not satisfactory, because there are parameters that have very large values, such as the neurons. For this reason it was chosen to use a genetic algorithm to find an appropriate rate of recognition, and thus obtain the appropriate type of training, the number of neurons and hidden layers, and once we get these parameters take the mean and standard deviation of how many times the genetic algorithm can find a high percentage of recognition. The results of each module of the modular neural network with gating network integration and with pre-processing (the result of the integration of the 3 modules) are shown in Table 3.

Table 3. Results of the Modular Neural Network in the image with preprocessing

Module	Error	Time	Epochs	Total ID	Error Image	N# neurons C1 Y C2	% ID
Traingda*3	0.00001	00:04:50	8000	570/594	24	170,141	95.89%
Traingdx*3	0.00001	00:03:36	5000	565/594	29	200,200	94.97%
Trainscg*3	0.00001	00:04:07	8000	555/594	39	170,141	93.40 %
Traingdx*3	0.00001	00:03:56	8000	560/594	34	250,200	94.18%
Trainscg*3	0.00001	00:04:22	5000	555/594	39	150,100	93.33%
Traingda*3	0.00001	00:04:12	5000	548/594	46	200,200	92.23%
Traingda*3	0.00001	00:04:36	5000	547/594	47	150,100	91.92%
Gda/ Scg/ Gdx	0.00001	00:02:24	5000	551/594	43	200,200	92.60%
Scg/ Gda/ Gdx	0.00001	00:02:53	8000	544/594	50	170,141	91.43%
Gda/ Gda/ Gdx	0.00001	00:03:28	8000	530/594	64	170,141	89.10%
Gdx/ Gda/ Scg	0.00001	00:02:55	5000	549 /594	45	200,200	92.80%

Table 3 shows the results of the trainings conducted, pre-image processing and compression, which can be seen that the rates increased by almost 4% of recognition with the same parameters of the training carried out previously, the methods with high percentage were *traingda*, *traingdx*, *trainscg* with 95.89, 94.97 and 93.33% respectively with a time of 4minutes 50 seconds, 3 minutes 36 seconds and 4 minutes 22 seconds, with 8000, 5000 and 5000 epochs respectively, and a goal error of the ANN of 0.00001.

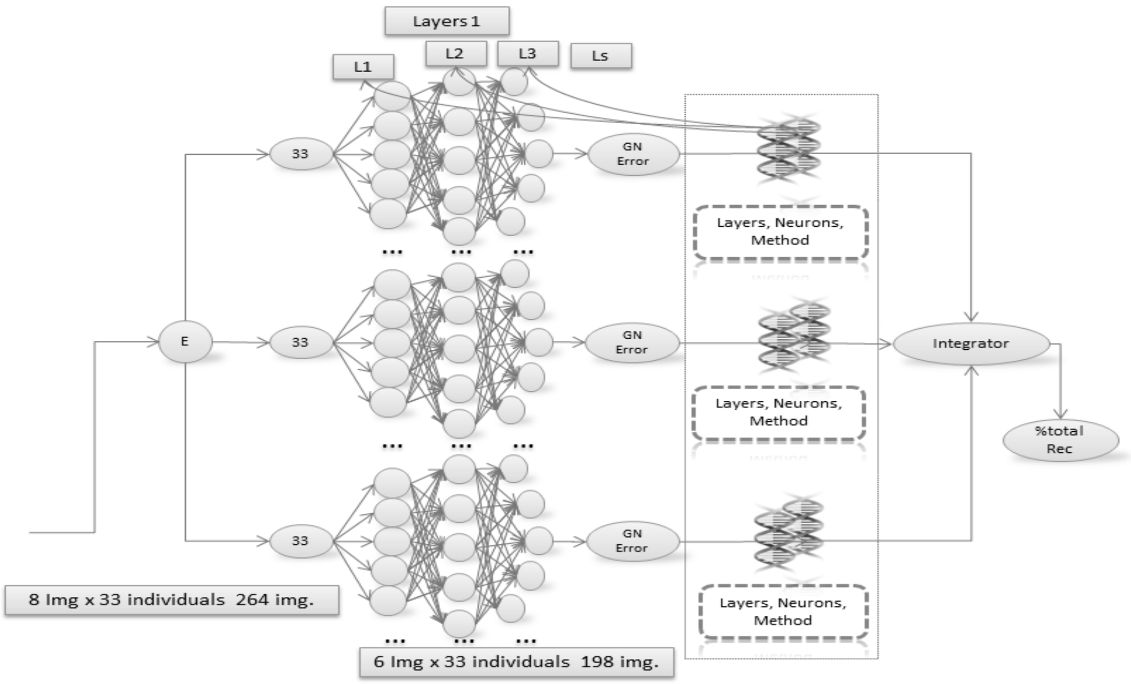

Figure 6. General architecture of optimized modular neural network

2.3. Optimization of the Architecture

To optimize the modular neural network a genetic algorithm was used to find the optimal architecture and an appropriate recognition rate. The general scheme of the MNN indicating the three modules and the integrator is shown in Figure 6.

Once it was verified that the GA found a good optimization result, it was decided to run the GA 10 times to find the standard deviation and average of the results for the neurons, methods, and the number of layers. The summary of the training behavior for the GA was obtained with the results of the 10 experiments and this forms the basis of possible comparisons with other optimization approaches. The parameters of the chromosome that were used in the GA are shown in Table 4.

The real chromosome is composed of 3 layers {1, 2, 3}, and each layer is composed of 250 neurons, which varied over a range from 0 to 250 values and 4 training methods. The training methods are shown on Table 5.

Table 4. Parameters of the chromosome for the GA

Modul	Layer 1 (neurons)	…….	Layer 3 (neurons)	Method
M1	0….250	…….	0….250	1:4
M2	0….250	…….	0….250	1:4
M3	0….250	…….	0….250	1:4

Table 5. Training for the GA

Selected Methods	
Trainscg	Scaled conjugate
Traingdm	Gradient descent with momentum
Traingdx	Gradient descent with momentum and adaptive learning factor
Traingda	Gradient descent with adaptive learning factor

3. Results and Analysis

The results of executing 10 times the genetic algorithm (GA) for each of the modules are shown in the following Tables: Module 1 in Table 6, Module 2 in Table 7 and Module 3 in Table 8. The results for the optimization of Module 1 for 10 runs of the genetic algorithm are shown in Table 6.

Table 6. Results of the genetic algorithm run by generations for module 1

GENERATIONS													
		...9	10	11	12	13	14	15	16	17	18	19	20
RUN	Ind	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152
1	10	0.0606	0.0606	0.0606	0.0606	0.0606	0.0606	0.0606	0.0606	0.0202	0.0202	0.0202	0.0202
2	10	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101	0.0101
3	10	0.0202	0.0202	0.0202	0.0202	0.0202	0.0202	0.0202	0.0202	0.0202	0.0202	0.0202	0.0101
...	...	...	...	...	...	...	...	...	...	...	...	...	...
10	10	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152
GENERATION RUN AVERAGE													
		0.0247	0.0237	0.0237	0.0237	0.0207	0.0202	0.0202	0.0202	0.0162	0.0162	0.0162	0.0152
GENERATION IS AVERAGE STANDARD DEVIATION													
		0.0159	0.0165	0.0165	0.0165	0.0148	0.0149	0.0149	0.0149	0.0046	0.0046	0.0046	0.0048
		B/E/GA		B/E/P-G/C		%		STD-B/P-G/C		BEST METHOD		TIME	
		0.0101		0.0152		98.48		0.004761		traingda		09:33:06	

The results for the optimization of Module 2 for 10 runs of the genetic algorithm are shown in Table 7. The results for the optimization of Module 3 for 10 runs of the genetic algorithm are shown in Table 8. In Tables 6, 7 and 8 we show the results of the trainings performed with the genetic algorithm, with 20 generations, 10 individuals and 10 runs, showing the average in each generation run and the standard deviation of each generation and run, better error (B /E /GA) found by the genetic algorithm (GA), better training method and execution time of the 10 runs. Once the 10 runs of the GA were achieved, we obtained the best architectures of the different training (150 per run).

Table 7. Results of the genetic algorithm run by generations for module 2

GENERATIONS													
		... 9	10	11	12	13	14	15	16	17	18	19	20
RUN	Ind												
1	10	0.0303	0.0303	0.0303	0.0303	0.0303	0.0303	0.0303	0.0303	0.0303	0.0303	0.0303	0.0303
2	10	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152	0.0152
3	10	0.0051	0.0051	0.0051	0.0051	0.0051	0.0051	0.0051	0.0051	0.0051	0.0051	0.0051	0.0051
...	...	...	...	...	...	...	...	...	...	...	...	...	...
9	9	0.0455	0.0152	0.0152	0.0051	0.0051	0.0051	0.0051	0	0	0	0	0
10	10	0.0556	0.0556	0.0202	0.0202	0.0202	0.0202	0.0202	0.0202	0.0202	0.0202	0.0202	0.0202
GENERATION RUN AVERAGE													
		0.0596	0.0566	0.052	0.0439	0.0439	0.0439	0.0394	0.0389	0.0359	0.0328	0.0328	0.0328
GENERATION IS AVERAGE STANDARD DEVIATION													
		0.0458	0.0478	0.0501	0.0456	0.0456	0.0456	0.0419	0.0424	0.0357	0.036	0.036	0.036
		B/E/GA		B/P-G/C		% REC		STD-B/P-G/C		BEST METHOD		TIME	
		0.0000		0.0202		97.9798		0.0328		trainscg		09:56:32	

Table 8. Results of genetic algorithm run by generations for module 3

GENERATIONS													
		... 9	10	11	12	13	14	15	16	17	18	19	20
RUN	Ind												
1	10	0.01010101	0.01010101	0.01010101	0.01010101	0.00505051	0.00505051	0.00505051	0.00505051	0.00505051	0.00505051	0.00505051	0.00505051
2	10	0.02525253	0.02525253	0.02525253	0.02525253	0.01515152	0.01515152	0.01515152	0.01515152	0.01515152	0.01515152	0.01515152	0.01515152
3	10	0.02525253	0	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
9	9	0.01010101	0.01010101	0.01010101	0.01010101	0.01010101	0.01010101	0.01010101	0.01010101	0.01010101	0.01010101	0.01010101	0.01010101
10	10	0.01010101	0.01010101	0	0	0	0	0	0	0	0	0	0
GENERATION RUNAVERAGE													
		0.03888889	0.03787879	0.03383838	0.02525253	0.01818182	0.01414141	0.01414141	0.01414141	0.01414141	0.01414141	0.01414141	0.01414141
GENERATION IS AVERAGE STANDARD DEVIATION													
		0.053611	0.05430435	0.04473492	0.03383797	0.0305081	0.02913966	0.02913966	0.02913966	0.02913966	0.02913966	0.02913966	0.02913966
		B/E/GA		B/P-G/C		% REC		BEST METHOD		Mejor método		Time:	
		0.0000		0.0141		98.59		0.0291		traingda		10:49:31	

As comparison of results, we can mention that in [47] a 93.33% recognition rate was achieved, while in this work we were able to obtain recognition rates of 99.76%. This fact shows that the proposed approach can outperform similar neural approaches in the literature for iris recognition.

4. Conclusion

The best result for person recognition using the iris biometric measurement was obtained through a set of modular neural network architectures with 3 layers in each module, with 116 and 117 neurons in the first hidden layer, 116 and 113 in the 2nd hidden layer, and 112 to 114 neurons in the third hidden layer. The average percentage in each generation of the genetic algorithm run is as follows: for the first module, a recognition rate of 98.48%, with an average error of 0.0152, for the 2nd module of 97.98%, with an average error of 0.0202, and for the third module of 98.59% with an average error of 0.0141. For validation of the gating network integration architecture the average was 98.48%, for the fuzzy integrator with Triangular type membership functions, the validation of this integrator was on average 99.37%, and for the fuzzy integrator with Gaussian membership functions, the validation of this integrator was on average a recognition of 99.52%. In the optimized cases, for the validation with triangular type MFs the average recognition was 99.64%, and for the validation with Gaussian type MFs the average recognition was 99.76%. Since initially the results with fuzzy integration were not satisfactory, it was decided to apply an evolutionary approach to optimize the membership functions of this response integrator of the modular neural network. The evolutionary method chosen to optimize this integration system was a genetic algorithm. After applying the genetic algorithm a better recognition rate was achieved, because better results with the optimized integration system were obtained in the modular neural network.

References

[1] Bastys A, Kranauskas J, Krüger V. Iris recognition by fusing different representations of multi-scale Taylor expansion, *Computer Vision and Image Understanding.* 2011; 115(6): 804-816.

[2] Boddeti VN, Kumar BV. Extended depth of field iris recognition using unrestored wave front coded imagery, *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans.* 2009; 40(3): 495-508.

[3] Dey S, Samanta D, Fast and accurate personal identification based on iris biometric, *International Journal of Biometrics.* 2010; 2(3): 250-281.

[4] Du Y, Arslanturk E, Zhou Z, Belcher C. Video-based noncooperative iris image segmentation, *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics.* 2011; 41(1): 64-74.

[5] Melin P, Castillo O. Hybrid Intelligent Systems for Pattern Recognition. Heidelberg: Springer-Verlag. 2005.

[6] Chumklin S, Auephanwiriyakul S, Theera-Umpon N. *Microcalcification detection in mammograms using interval type-2 fuzzy logic system with automatic membership function generation*, 2010 Proceedings of the IEEE World Congress on Computational Intelligence (WCCI 2010). Barcelona. 2010; art. no. 5584896.

[7] Gaxiola F, Melin P, López M. Modular neural networks for person recognition using the contour segmentation of the human iris biometric measurement, *Studies in Computational Intelligence*. 2010; 312(1): 137-153.

[8] Sibai FN, Hosani HI, Naqbi RM, Dhanhani S, Shehhi S. Iris recognition using artificial neural networks, *Expert Systems with Applications.* 2011; 38(5): 5940-5946.

[9] Zuo J, Schmid NA. On a methodology for robust segmentation of non ideal iris images, *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics.* 2010; 40(3): 703-718.

[10] Hidalgo D, Castillo O Melin P. Type-1 and type-2 fuzzy inference systems as integration methods in modular neural networks for multimodal biometry and its optimization with genetic algorithms, *Information Sciences.* 2009; 179(13): 2123-2145.

[11] Jarjes AA, Wang K, Mohammed GJ. A new Iris segmentation method based on improved snake model and angular integral projection, *Research Journal of Applied Sciences, Engineering and Technology.* 2011; 3(6): 558-568.

[12] Kalka ND, Zuo J, Schmid NA, Cukic B. Estimating and fusing quality factors for iris biometric images, *IEEE Trans. Syst., Man, Cybern., A, Syst., Humans.* 2009; 40(3): 509-524.

[13] Köse C, Ikibaşs C. A personal identification system using retinal vasculature in retinal fundus images, *Expert Systems with Applications*. 2011; 38(11): 13670-13681.

[14] Liau HF, Isa D. Feature selection for support vector machine-based face-iris multimodal biometric system, *Expert Systems with Applications.* 2011; 38(9): 11105-11111.

[15] Pimenta AHM, Camargo H. A. Interval type-2 fuzzy classifier design using genetic algorithms, 2010 IEEE World Congress on Computational Intelligence (WCCI), Barcelona. 2010: art. no. 5584520.

[16] Lopez M, Melin P. *Topology optimization of fuzzy systems for response integration in ensemble neural networks: The case of fingerprint recognition*, Proceedings of the Annual Conference of the North American Fuzzy Information Processing Society (NAFIPS). New York. 2008: art. no. 4531334.

[17] Lopez M, Melin P, Castillo O. Comparative study of feature extraction methods of fuzzy logic type 1 and type-2 for pattern recognition system based on the mean pixels, *Studies in Computational Intelligence*. 2010; 312(1): 171-188.

[18] Mat Isa NA, Mamat WMFW. Clustered-Hybrid Multilayer Perceptron network for pattern recognition application, *Applied Soft Computing Journal*. 2011; 11(1): 1457-1466.

[19] Melin P. *Interval type-2 fuzzy logic applications in image processing and pattern recognition*, Proceedings of the 2010 IEEE International Conference on Granular Computing (GrC 2010). San Jose. 2010: 728-731.

[20] Mendoza O, Melin P, Castillo O. Interval type-2 fuzzy logic and modular neural networks for face recognition applications, *Applied Soft Computing Journal.* 2009; 9(4): 1377-1387.

[21] Perez C.A., Aravena C.M., Vallejos J.I., Estevez P.A., Held C.M. Face and iris localization using templates designed by particle swarm optimization, *Pattern Recognition Letters.* 2010; 31(9): 857-868.

[22] Lopez M, Melin P, Castillo O. Optimization of response integration with fuzzy logic in ensemble neural networks using genetic algorithms, *Studies in Computational Intelligence*. 2008; 154(1): 129-150.

[23] Sánchez D, Melin P. Modular neural network with fuzzy integration and its optimization using genetic algorithms for human recognition based on iris, ear and voice biometrics, *Studies in Computational Intelligence.* 2010; 312(1): 85-102.

[24] Zeng J, Liu ZQ. *Type-2 fuzzy hidden Markov models to phoneme recognition*, Proceedings of the International Conference on Pattern Recognition (ICRP), Cambridge 2004: 192-195,.

[25] Chua TW, Tan WW. Genetically evolved fuzzy rule based classifiers and application to automotive classification, *Lecture Notes in Computer Science*. 2008; 5361(1): 101-110.

[26] Hosseini R, Dehmeshki J, Barman S, Mazinani M. Qanadli S., *A genetic type-2 fuzzy logic system for pattern recognition in computer aided detection systems*, Proceedings of 2010 IEEE World Congress on Computational Intelligence (WCCI 2010). Barcelona. 2010: art. no. 5584773.
[27] Puhan NB, Sudha N, Sivaraman Kaushalram A. Efficient segmentation technique for noisy frontal view iris images using Fourier spectral density, *Signal, Image and Video Processing.* 2011; 5(1): 105-119.
[28] Sanz J, Fernandez A, Bustince H, Herrera F. *A genetic algorithm for tuning fuzzy rule based classification systems with interval valued fuzzy sets*, 2010 IEEE World Congress on Computational Intelligence (WCCI), Barcelona. 2010: art. no. 5584097.
[29] Fallahnezhad M, Moradi MH, Zaferanlouei S. A Hybrid Higher Order Neural Classifier for handling classification problems, *Expert Systems with Applications.* 2011; 38(1): 386-393.
[30] Wade JJ, McDaid LJ, Santos JA, Sayers HM. SWAT: A spiking neural network training algorithm for classification problems, *IEEE Transactions on Neural Networks.* 2010; 21(11): 1817-1830.
[31] Castillo O, Melin P. Type-2 Fuzzy Logic: Theory and Applications. Heidelberg: Springer-Verlag. 2008.
[32] Karnik NN, Mendel JM*. An Introduction to Type-2 Fuzzy Logic Systems*. University of Southern California. Technical Report, 1998.
[33] Chen X, Li Y, Harrison R, Zhang YQ. Type-2 fuzzy logic based classifier fusion for support vector machines, *Applied Soft Computing Journal.* 2008; 8(1): 1222-1231.
[34] Farouk RM. Iris recognition based on elastic graph matching and Gabor wavelets, *Computer Vision and Image Understanding.* 2011; 115(8): 1239-1244.
[35] Herman P, Prasad G, McGinnity TM. *Support vector-enhanced design of a T2FL approach to motor imagery-related EEG pattern recognition*, Proceedings of the IEEE International Conference on Fuzzy Systems (FUZZ 2007). London. 2007: art. no. 4295661.
[36] Herman P, Prasad G, McGinnity TM. *Design and on-line evaluation of type-2 fuzzy logic system based framework for handling uncertainties in BCI classification*, Proceedings of the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS'08), Vancouver. 2008: 4242-4245.
[37] Lucas LA, Centeno TM., Delgado MR. *General type-2 fuzzy classifiers to land cover classification*, Proceedings of the ACM Symposium on Applied Computing. Fortaleza, Ceará, Brazil. 2008; 1743-1747.
[38] Madasu VK, Hanmandlu M, Vasikarla S. A novel approach for fuzzy edge detection using type II fuzzy sets, *Proceedings of SPIE - The International Society for Optical Engineering.* 2008; 7075(1): art. no. 70750I.
[39] Mitchell HB. Pattern recognition using type-II fuzzy sets, *Information Sciences.* 2005; 170(1): 409-418.
[40] Own CM. Switching between type-2 fuzzy sets and intuitionistic fuzzy sets: An application in medical diagnosis, *Applied Intelligence*. 2009; 31(1): 283-291.
[41] Zhang WB, Hu HZ, Liu WJ. *Rules extraction of interval type-2 fuzzy logic system based on fuzzy c-means clustering*, Proceedings of the Fourth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), Hainan. 2007: 256-260.
[42] Zheng G, Xiao J, Wang J, Wei Z. *A similarity measure between general type-2 fuzzy sets and its application in clustering*, Proceedings of the World Congress on Intelligent Control and Automation, Jinan. 2010: 6383-6387.
[43] Kalka ND, Zuo J, Schmid NA, Cukic B. Estimating and fusing quality factors for iris biometric images, *IEEE Trans. Syst., Man, Cybern., A, Syst., Humans.* 2009; 40(3): 509-524.
[44] Qun R, Baron L, Balazinski M, *Type-2 Takagi-Sugeno-Kang fuzzy logic modeling using subtractive clustering*, Proceedings of the Annual Conference of the North American Fuzzy Information Processing Society (NAFIPS), Toronto. 2010: art. no. 4216787.
[45] Ren Q, Baron L, Balazinski M. *High order type-2 TSK fuzzy logic system*, Proceedings of the NAFIPS 2010 Conference, Toronto. 2010: art. no. 4531215.
[46] Rhee FCH, Choi BI. *Interval type-2 fuzzy membership function design and its application to radial basis function neural networks*, Proceedings of the IEEE International Conference on Fuzzy Systems (FUZZ), London. 2007: art. no. 4295680.
[47] Wu H, Mendel JM. Classification of battlefield ground vehicles based on the acoustic emissions, *Studies in Computational Intelligence.* 2010; 304(1): 55-77.
[48] L Yu, J Xiao, G Zheng. *Robust interval type-2 possibilistic c-means clustering and its application for fuzzy modeling*, Proceedings of the 6th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), Tianjin. 2009: 360-365.
[49] Ozkan I, Türkşen IB. *Entropy assessment for type-2 fuzziness*, Proceedings of the IEEE International Conference on Fuzzy Systems (FUZZ), Budapest. 2004: 1111-1115.
[50] Ozkan I, Turksen B. *MiniMax ε-stable cluster validity index for type-2 fuzziness*, Proceedings of the NAFIPS 2010 Conference, Toronto. 2010: art. no. 5548183.

[51] Phong PA, Thien KQ. *Classification of cardiac arrhythmias using interval type-2 TSK fuzzy system*, Proceedings of the 1st International Conference on Knowledge and Systems Engineering, Hanoi. 2009: 1-6.
[52] Qin K, Kong L, Liu Y, Xiao Q. *Sea surface temperature clustering based on type-2 fuzzy theory*, Proceedings of the 18th International Conference on Geoinformatics, Beijing. 2010: art. no. 5567484.
[53] Santiago-Sanchez K, Reyes-Garcia CA, Gomez-Gil P. Type-2 fuzzy sets applied to pattern matching for the classification of cries of infants under neurological risk, *Lecture Notes in Computer Science*. 2009; 5754(1): 201-210.
[54] Sharma P, Bajaj P. *Performance analysis of vehicle classification system using type-1 fuzzy, adaptive neuro-fuzzy and type-2 fuzzy inference system*, Proceedings of the 2nd International Conference on Emerging Trends in Engineering and Technology (ICETET), Nagpur. 2009: 581-584.
[55] Sharma P, Bajaj P. *Accuracy comparison of vehicle classification system using interval type-2 fuzzy inference system*, Proceedings of the 3rd International Conference on Emerging Trends in Engineering and Technology (ICETET), Goa. 2010: 85-90.
[56] Tan WW, Foo CL, Chua TW. *Type-2 fuzzy system for ECG arrhythmic classification*, Proceedings of IEEE International Conference on Fuzzy Systems (FUZZ), London. 2007: art. no. 4295478.
[57] Database of Human Iris. Institute of Automation of Chinese Academy of Sciences (CASIA). Available on the Web page: http://www.cbsr.ia.ac.cn/english/IrisDatabase.asp (2011)
[58] Tizhoosh HR. Image thresholding using type II fuzzy sets, *Pattern Recognition.* 2005; 38(1): 2363-2372.