21st ICIFS, 22–23 May 2017, Burgas, Bulgaria
Notes on Intuitionistic Fuzzy Sets
Print ISSN 1310–4926, Online ISSN 2367–8283
Vol. 23, 2017, No. 2, 95–102

Intuitionistic fuzzy logic adaptation of particle swarm optimization

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Received: 23 January 2017 **Revised:** 11 February 2017 **Accepted:** 21 February 2017

Abstract: In this paper a new Modular Neural Network (MNN) optimization is proposed, where a particle swarm optimization with an intuitionistic fuzzy dynamic parameter adaptation designs optimal MNNs architectures. This design consists in to find the number of hidden layers for each sub module with their respective number of neurons, learning method, error goal and the percentage of data used for the training phase. The proposed intuitionistic fuzzy adaptation seeks to avoid stagnation of error of recognition during iterations updating some PSO parameters.

Keywords: Intuitionistic fuzzy logic, Particle Swarm Optimization, Iris recognition, Human recognition.

AMS Classification: 03E72.

1 Introduction

The automated recognition of individuals based on their biological and behavioral characteristics such as face, iris, ear, voice or gait is known as biometric recognition [15]. This area allows to have a greater control about who has access to information or area. System using biometric recognition give some advantages over traditional authentication, for example a biometric measure cannot be forgotten, stolen, and are difficult to falsify as a password or a credential [20, 28]. The intelligent techniques are divided into two categories: traditional hard computing techniques and soft computing techniques. Within soft computing category, there are techniques such as fuzzy logic, neural networks, genetic algorithms, particle swarm optimization, ant colony system, and data mining among others [10, 12]. A hybrid intelligent system is combination of two or more of these techniques, this kind of systems emerge because each individual technique has limitations, for example a neural network can simulate a human brain but for its proper operation its architecture should be design by an optimization technique [1]. These systems have been proposed in a lot of works where the effectiveness that they provide is demonstrated [13, 14, 30]. In this paper Intuitionistic fuzzy logic (IFL) and particle swarm optimization are combined. There are few application of IFL in adaptation of metaheuristic algorithms parameters, namely genetic algorithms [25, 26], bat algorithms [23, 27] and Water cycle algorithm [9].

This paper is organized as follows: Section 2 contains the basic concepts used in this research work. The general architecture of the proposed method is shown in Section 3. The conclusions and further research of this work are presented in Section 4.

2 Basic concepts

2.1 Modular neural network

A mathematical representation of the human neural architecture is an artificial neural network (ANN) which can acquire, store, and utilize experimental knowledge [31, 34]. An ANN reflects human abilities such as learning and generalization. This technique belongs to the field of artificial intelligence and is widely applied in research because it can model non-linear systems [2]. A modular neural network (MNN) emerges when the computation performed by the network can be decomposed into two or more modules each module is an artificial neural network which carries out a distinct identifiable subtask, these modules are integrated together via an integrating unit [11, 29]. Different works have used MNNs showing sufficient evidence that the learning improve compared with a single ANN [19, 21].

2.2 Fuzzy logic and intuitionistic fuzzy logic

The concept of fuzzy logic (FL) was first proposed by Zadeh in 1965. Fuzzy logic allows to computers in making decisions in a way which resembles human behaviors [32, 33]. Fuzzy logic is a useful tool for modeling complex systems and deriving useful fuzzy relations or rules. However, it is often difficult for human experts to define the fuzzy sets and fuzzy rules used by these systems. 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 (or dictionary) which defines the membership functions used in the rules, and a reasoning mechanism that performs the inference procedure [16, 22]. On the other hand, intuitionistic fuzzy logic and intuitionistic fuzzy sets (IFS) [3–8] have gained recognition as a useful tool for control uncertain phenomena.

2.3 Particle Swarm Optimization

Particle Swarm Optimization (PSO) was developed by Kennedy and Eberhart in 1995 [18], this optimization technique is formerly inspired by simulation of the social behavior of animals such as fish schooling and bird flocking. This algorithm doesn't have any leader in their group or swarm, unlike other algorithms. The flocks achieve their best condition simultaneously through communication among members who already have a better situation or position. The member of the flock with better condition or position will inform it to its flocks and the others will move simultaneously to that place. Particle swarm optimization consists of a swarm of particles, where particle represent a potential solution [24]. The PSO essentially is based on animal's behavior to solve optimization problems [17].

3 General architecture of the proposed method

The proposed method design optimal MNNs architectures to pattern recognition based on iris biometric measure. The proposed method consists in the division of information (database) into 3 sub modules. Different number of persons will be learned by each sub module, besides of changing number of images for training and percentage of data for the training phase. To perform an optimal division of the information previously described and other MNNs parameters a particle swarm optimization with an intuitionistic fuzzy dynamic parameters adaptation is proposed. Figure 1 shows the architecture of the proposed method for the modular neural network. For the integration of responses the winner takes all method was used.

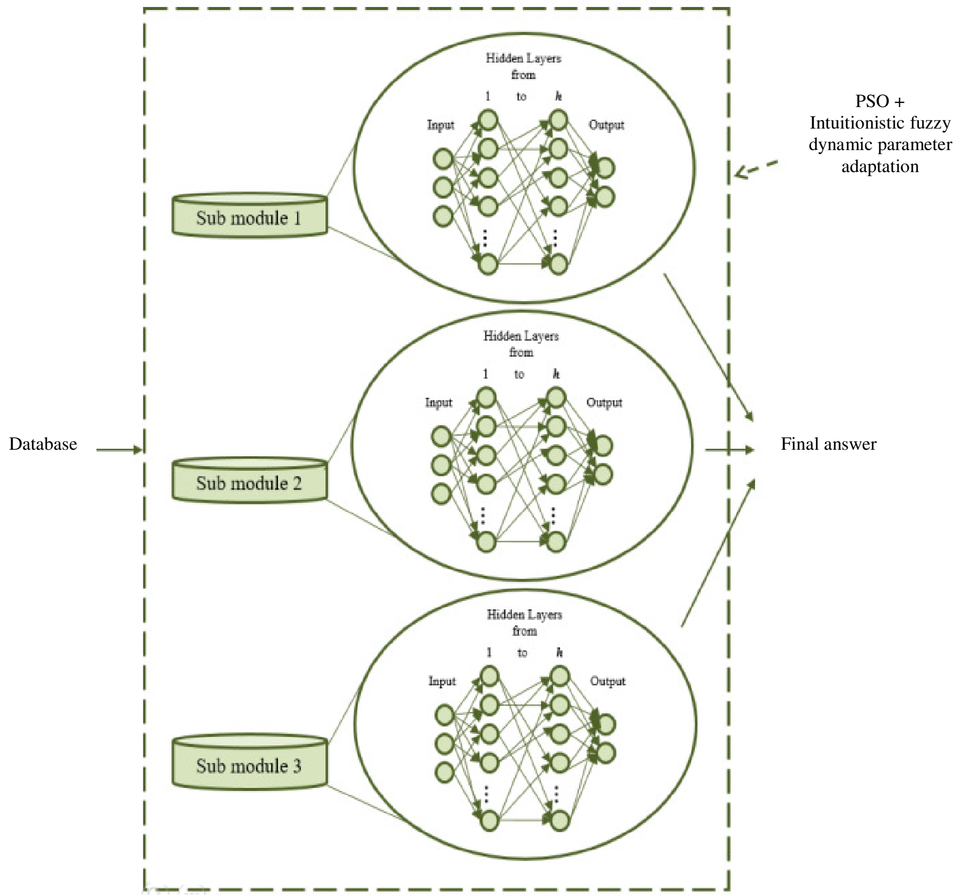

Figure 1. The architecture of proposed method for modular neural network

3.1 Description of the PSO with Intuitionistic fuzzy dynamic parameters adaptation

As any optimization technique, PSO has parameters that allow to move its population to find optimal results. This work is focused in w, C_1 and C_2. The value w can facility exploration and exploitation. The values of C_1 and C_2 are the cognitive and social components that influence the velocity of each particle. These parameters are usually initialized: to trial and error, depending of our experience or depending area of application. The proposed particle swarm optimization uses an intuitionistic fuzzy inference system (IFIS) to update these PSO parameters updating thembefore update velocity and position of the particles. In a PSO without this intuitionistic fuzzy adaptation C_1 and C_2 remain fixed throughout the evolution, meanwhile$w$ is a decreasing value during an evolution. If the parameters are not set correctly the evolution can have a stagnation in a local minimum, for this reason the proposed method also seeks to update these parameters to improve the performance of the PSO during its evolution.

The initial parameters for the PSO can be observed in Table 1, as it was previously mentioned C_1, C_2 and w are updated before update velocity and position of the particles but at the start of the evolution they have these values.

Parameter	Value
Particles	10
Maximum iterations	30
C_1	2
C_2	2
w	0.8

Table 1. Initial parameters for the PSO

The proposed IFIS is shown in Figure 2. This IFIS has 2 inputs: iterations (number of iterations without changing the recognition error) and the actual value of inertia weight (w), as outputs: update values for C_1, C_2 and w. This IFIS has 9 intuitionistic fuzzy rules. The intuitionistic fuzzy variables are shown in Figure 3.

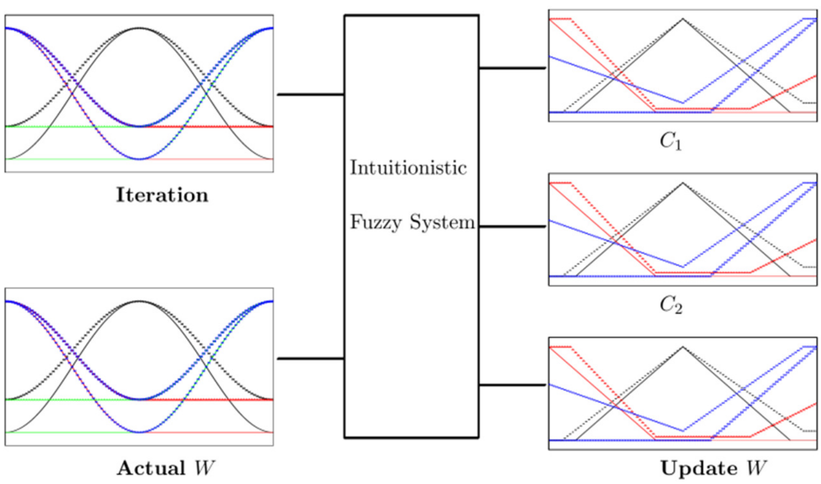

Figure 2. IFIS for the PSO with dynamic parameters adaptation

Example ranges of the variables of the IFIS are shown in Table 2.

Variable	Range
Iteration	1 to 5
Actual w	0.1 to 1
C_1	0.5 to 2
C_2	0.5 to 2
Update w	0.1 to 1

Table 2. Range of variables
for the intuitionistic fuzzy inference system

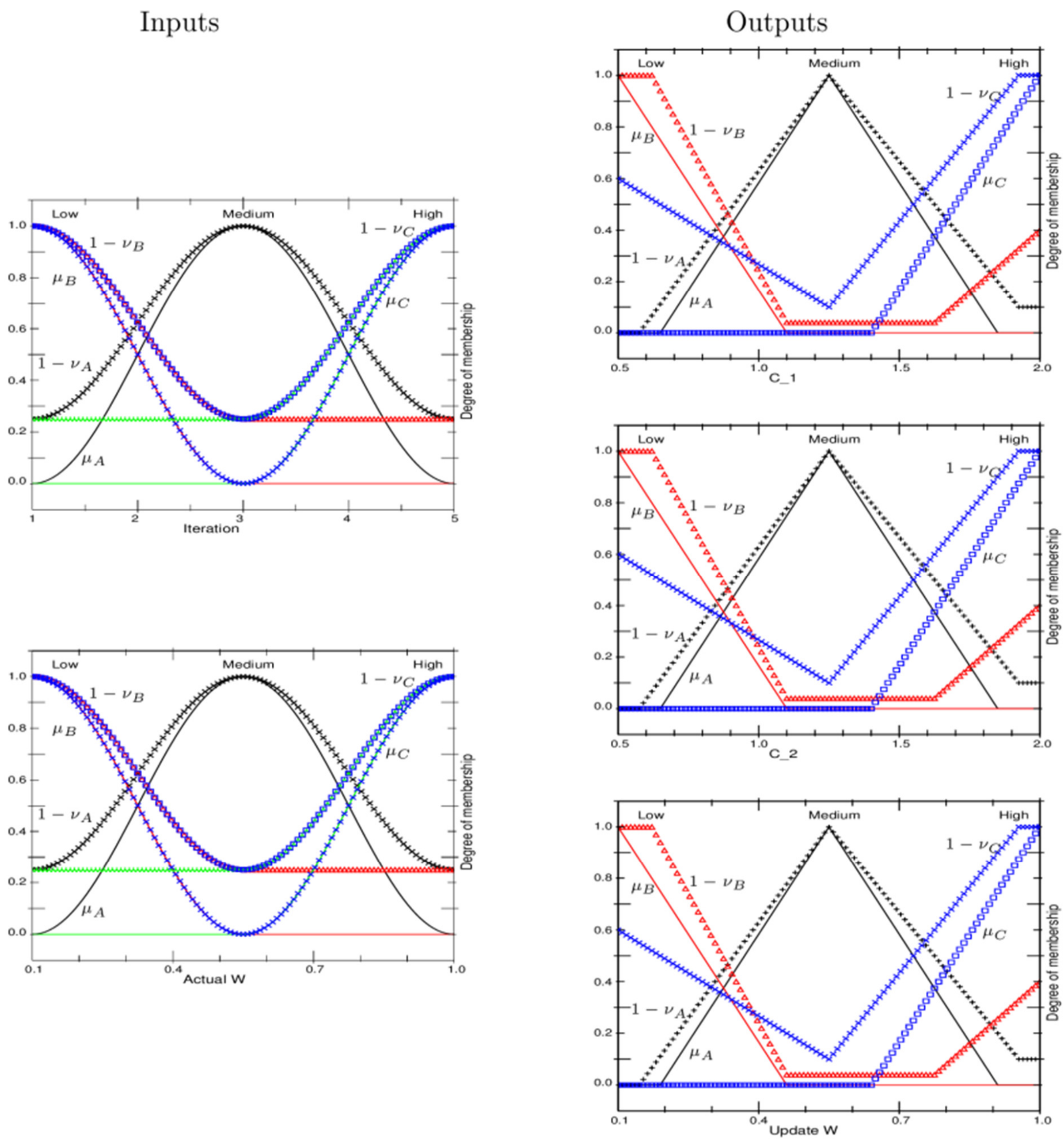

Figure 3. IFIS for the PSO with dynamic parameters adaptation

5 Conclusion

In this paper, an idea for particle swarm optimization with dynamic parameters adaptation using intuitionistic fuzzy sets was proposed. It is an alternative of the well-known fuzzy dynamic parameters adaptation.

As future work, different designs of intuitionistic fuzzy inference systems for the parameters adaptation will be proposed and applied to concrete problems.

Moreover, the described idea will be extended with applications of the specific tools from intuitionistic fuzzy sets, as the modal and topological operators that will give additional possibility for more precise evaluations. The obtained results will be compared with those already existing.

Acknowledgements

The authors are thankful for the support provided by the Bulgarian National Science Fund under Grant Ref. No. DFNI-I-02-5 "InterCriteria Analysis: A New Approach to Decision Making".

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