Comparison of Neural Networks with Different Membership Functions in the Type-2 Fuzzy Weights

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Abstract. In this paper a comparison of the triangular, Gaussian, trapezoidal and generalized bell membership functions used in the type-2 fuzzy inference systems, which are applied to obtain the type-2 fuzzy weights in the connection between the layers of a neural network. We used two type-2 fuzzy systems that work in the backpropagation learning method with the type-2 fuzzy weight adjustment. We change the type of membership functions of the two type-2 fuzzy systems. The mathematical analysis of the proposed learning method architecture and the adaptation of the type-2 fuzzy weights are presented. The proposed method is based on recent methods that handle weight adaptation and especially fuzzy weights. In this work neural networks with type-2 fuzzy weights are presented. The proposed approach is applied to the case of Mackey-Glass time series prediction.

1 Introduction

Neural networks have been applied in several areas of research, like in the time series prediction area, which is the study case for this paper, especially in the Mackey-Glass time series [10].

The approach presented in this paper works with type-2 fuzzy weights in the neurons of the hidden and output layers of the neural network used for prediction of the Mackey- Glass time series. These interval type-2 fuzzy weights are updated using the backpropagation learning algorithm. We used two type-2 inference systems with Triangular, Trapezoidal, Gaussian and Generalized Bell membership functions.

This paper is focused in the managing of weights, because on the practice of neural networks, when performing the training of neural networks for the same problem is initialized with different weights or the adjustment are in a different way each time it is executed, but at the end is possible to reach a similar result [5] [12] [13][14].

The next section explains the proposed method and the problem description. Section 3 describes the neural network with type-2 fuzzy weights proposed in this paper. Section 4 presents the simulation results for the proposed method. Finally, in section 5 some conclusions are presented.

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2 Proposed Method and Problem Description

The objective of this work is to use interval type-2 fuzzy sets to generalize the backpropagation algorithm to allow the neural network to handle data with uncertainty, and a comparison of the type of membership functions in the type-2 fuzzy systems, which can betriangular, Gaussian, trapezoidal and generalized bell. The Mackey-Glass time series (for τ=17) is utilized for testing the proposed approach.

The updating of the weights will be done differently to the traditional updating of the weights performed with the backpropagation algorithm (Fig. 1).

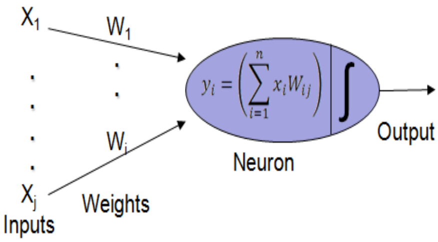

Fig. 1. Scheme of current management of numerical weights (type-0) for the inputs of each neuron

We developed a method for adjusting weights to achieve the desired result, searching for the optimal way to work with type-2 fuzzy weights [8].

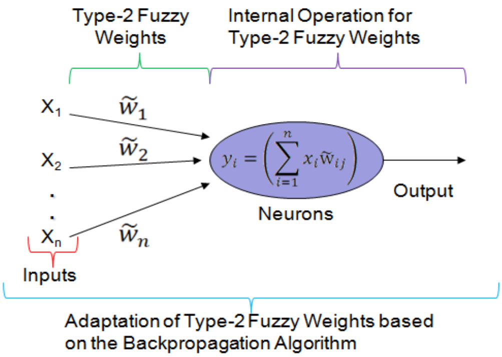

Fig. 2. Schematics of each neuron with the proposed management of weights using interval type-2 fuzzy sets

We used the sigmoid activation function for the hidden neurons and the linear activation function for the output neurons, and we utilized this activation functions because these functions have obtained good results in similar approaches.

3 Neural Network Architecture with type-2 Fuzzy Weights

The proposed neural network architecture with interval type-2 fuzzy weights (see Fig. 3) is described as follows:

Layer 0: Inputs.

$$x = [x_1, x_2, \cdots, x_n] \quad (1).$$

Phase 1: Interval type-2 fuzzy weights for the connection between the input and the hidden layer of the neural network.

$$\widetilde{w}_{ij} = [\overline{w}_{ij}, \underline{w}_{ij}] \quad (2).$$

Where $\widetilde{w}_{ij}$ are the weights of the consequents of each rule of the type-2 fuzzy system with inputs (current type-2 fuzzy weight, change of weight) and output (new fuzzy weight) [3].

Phase 2: Equations of the calculations in the hidden neurons using interval type-2 fuzzy weights.

$$Net = \sum_{i=1}^{n} x_i \widetilde{w}_{ij} \quad (3)$$

Phase 3: Equations of the calculations in the output neurons using interval type-2 fuzzy weights.

$$Out = \sum_{i=1}^{n} y_i \widetilde{w}_{ij} \quad (4)$$

Phase 4: Obtain a single output of the neural network.

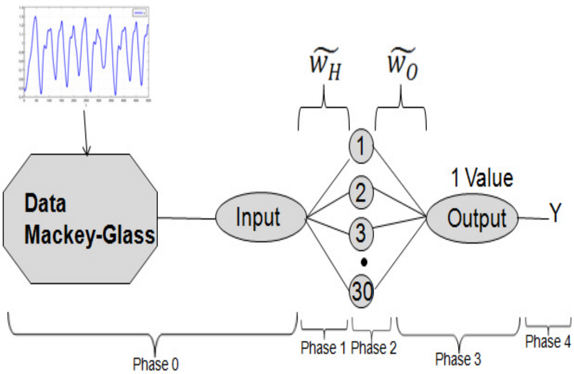

Fig. 3. Proposed neural network architecture with interval type-2 fuzzy weights

We considered a neural network architecture with 1 neuron in the output layer and 30 neurons in the hidden layer.

This neural network uses two type-2 fuzzy inference systems, one in the connections between the input neurons and the hidden neurons, and the other in the connections between the hidden neurons and the output neuron. In the hidden layer and output layer of the network we are updating the weights using the two type-2 fuzzy inference system that obtains the new weights in each epoch of the network on base at the backpropagation algorithm [6] [7].

The two type-2 fuzzy inference systems have the same structure and consist of two inputs (the current weight in the actual epoch and the change of the weight for the next epoch) and one output (the new weight for the next epoch) (see Fig. 4) [2][11][15].

We used two membership functions with their corresponding range for delimiting the inputs and outputs of the two type-2 fuzzy inference systems.

We used triangular, trapezoidal, Gaussian and generalized bell membership functions (for example, see Fig. 5 and Fig. 6).

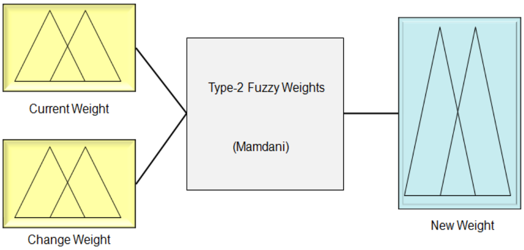

Fig. 4. Structure of the two type-2 fuzzy inference systems that were used to obtain the type-2 fuzzy weights in the hidden and output layer

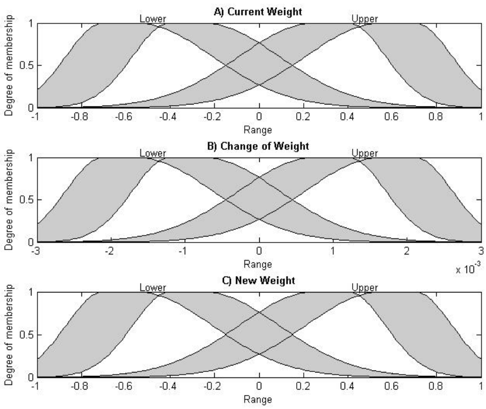

Fig. 5. Inputs (A and B) and output (C) of the type-2 fuzzy inference systems that were used to obtain the type-2 fuzzy weights in the hidden layer

We obtain the two type-2 fuzzy inference systems manually and a footprint of uncertainty of 15 % in the triangular membership functions and the others type-2 fuzzy inference systems are obtained to change the type of membership function in the inputs and output.

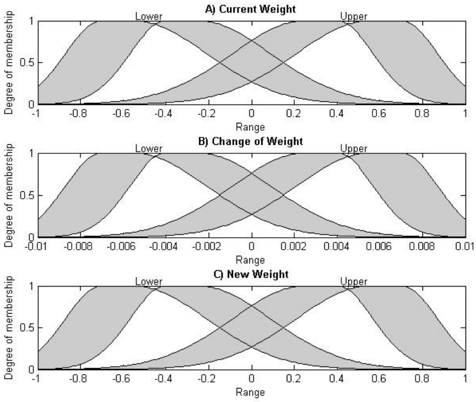

Fig. 6. Inputs (A and B) and output (C) of the type-2 fuzzy inference system that were used to obtain the type-2 fuzzy weights in the output layer

The two type-2 fuzzy inference systems used the same six rules, the four combinations of the two membership functions and two rules added for null change of the weight (see Fig. 7).

1. (Current_Weight is lower) and (Change_Weight is lower) then (New_Weight is lower)
2. (Current_Weight is lower) and (Change_Weight is upper) then (New_Weight is lower)
3. (Current_Weight is upper) and (Change_Weight is lower) then (New_Weight is upper)
4. (Current_Weight is upper) and (Change_Weight is upper) then (New_Weight is upper)
5. (Current_Weight is lower) then (New_Weight is lower)
6. (Current_Weight is upper) then (New_Weight is upper)

Fig. 7. Rules of the type-2 fuzzy inference system used in the hidden and output layer for the neural network with type-2 fuzzy weights

4 Simulation Results

We performed experiments in time-series prediction, specifically for the Mackey-Glass time series (τ=17). We used 100 epochs and $1x10^{-8}$ for network error in the experiments [1] [4] [9].

We present the obtained results of the experiments performed with the neural network with type-2 fuzzy weights (NNT2FW) in the different types: triangular, trapezoidal, two-sided Gaussian, and generalized bell; These results are achieved without optimizing of the neural network and the type-2 fuzzy systems, which means that all parameters of the neural network and the range and values of the membership functions of the type-2 fuzzy systems are established empirically. The average error was obtained of 30 experiments.

In Table 1, we present the prediction error obtained with the results achieved as output. The best prediction error is of 0.0391 and the average prediction error is of 0.0789. The APE represents the average prediction error of the experiments.

Table 1. Prediction error for the neural network with type-2 fuzzy weights for Mackey-Glass time series, with the different type and variants of membership functions

		NNT2FW		
No. Experiment	Triangular	Trapezoidal	Gaussian	Generalized Bell
1	0.0768	0.0892	0.0391	0.0947
2	0.0658	0.1133	0.0779	0.1454
3	0.0719	0.1195	0.0565	0.1772
4	0.0552	0.0799	0.0718	0.1165
5	0.0728	0.1273	**0.0355**	0.1870
6	0.0661	0.1070	0.0688	0.1356
7	0.0808	0.1511	0.0796	0.1586
8	0.0686	0.1320	0.0589	0.1156
9	0.0888	0.0927	0.0454	0.1642
10	0.0866	0.1490	0.0693	0.1275
APE	0.0789	0.1272	**0.0659**	0.1574

5 Conclusions

In this paper, we presented a comparison of learning method that updates weights (type-2 fuzzy weights) in each connection between the neurons of the layers of neural network using a type-2 fuzzy inference system with triangular, trapezoidal, Gaussians and generalized bell membership functions.

Additionally, the neurons work internally with the type-2 fuzzy weights and therefore, obtaining results at the output of each neuron of the neural network. The modifications performed in the neural network that allows working with type-2 fuzzy weights provide at the neural network greater robustness and less susceptibility at the noise in the data of the time series.

The best prediction error of 0.0391 of the neural network with type-2 fuzzy weights for the Mackey-Glass time series obtained with Gaussians membership functions is better than the best prediction error of 0.0552, 0.0799 or 0.0947 obtained with triangular, trapezoidal or generalized bell, respectively (as shown in Table 1).

This result is good considering that the used parameters for the neural networks at the moment are determined in an empirical way.

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