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Nonlinear system identification based on a self-organizing type-2 fuzzy RBFN

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ABSTRACT

This paper presents a new self-evolving recurrent Type-2 Fuzzy Radial Basis Function Network (T2FRBFN) in which the weights are considered Gaussian type-2 fuzzy sets and uncertain mean in each RBF neuron. The capability of the proposed T2FRBFN for function approximation and dynamical system identification perform better than the conventional RBFN. A novel type-2 fuzzy clustering is presented to add or remove the hidden RBF neurons. For parameter learning, back-propagation with adaptive learning rate is used. Finally the proposed T2FRBFN is applied to identification of three nonlinear systems as case studies. A comparison between T2FRBFN and the conventional RBFN as well as the method of Rubio-Solis and Panoutsos (2015) is presented. Simulation results and their statistical description show that the proposed T2FRBFN perform better than the conventional RBFN.

1. Introduction

Computational intelligence is one of the effective and high performance methods in modeling and identification of some classes of nonlinear systems. High computation ability, adaptability and parallel processing are the important advantages of neural networks. A neural network can create a mapping between its input and output spaces by a set of connection weights and activation functions. Nowadays RBFNs have attracted much attention because of they have simple topological structure, they have locally tuned neurons and they have ability to have a fast learning algorithm in comparison with other multi-layer feed forward neural networks.

It is clear that a mathematical model is very important and necessary in some areas of control, prediction and simulation that in these areas the model is essentially used such as MPC, inverse control etc. With feeding input signals to a physical system, output corresponding to this input can be obtained, after that by using input–output data and different methods of system identification, the mathematical equations can be achieved. In recent years, many papers have been presented in neural network based identification and modeling. RBFNs are more complex than other types of neural networks because of in addition to network weights, the center and width of RBF neuron effect on performance of RBFN (Yu et al., 2014). Capability and advantages of RBFN have been expressed in many papers (Varvak, 2015; Ha et al., 2015; Buhmanna and Dai, 2015; Lei et al., 2015; Knauer et al., 2015). In recent 10 years, type-2 fuzzy logic with more capabilities and more flexibility than type-1 fuzzy logic has been investigated (Olatunji et al., 2015; Tavoosi et al., 2015, 2016; Zhou et al., 2015; Lu, 2015; Doostparast Torshizi and Fazel Zarandi, 2014; Sun et al., 2015).

Not much study has been done about neural networks with type-1 (or type-2) fuzzy sets as weights up to now. In continue some of the works in this area are reviewed. Gaxiola et al. (2014) proposed a neural network with fuzzy weight for time series prediction. They used both type-1 and type-2 fuzzy sets as weight of three different perceptron neural networks. They showed that the neural network with type-2 fuzzy weights perform better than neural network with type-1 fuzzy or crisp weights. Kuo et al. (2002) presented a fuzzy neural network that its weights are type-1 fuzzy sets. They used left and right widths of fuzzy sets to mathematical description of the fuzzy neural network. Combining RBFN and fuzzy system has raised academic interest (Tsekouras et al., 2015; Al Gizi et al., 2015; Alam et al., 2015). Tsekouras et al. (2015) used fuzzy clustering to input space partitioning of a RBFN. Al Gizi et al. (2015) used a combination of fuzzy system, RBFN and genetic algorithm to find the optimal parameters of PID. Alam et al. (2015) used fuzzy *c*-mean to update the hidden layer weights of RBFN. After successful combination of type-1 fuzzy and RBFN, it looks the combination of type-2 fuzzy and RBFN will be fruitful. In this case, few studies have been conducted (Rubio-Solis and Panoutsos, 2015; Rhee and Choi, 2007). In continue some of the works in this area are reviewed. Rubio-Solis and Panoutsos (2015) proposed a type-2 fuzzy RBFN that it uses type-2 fuzzy neuron as RBF neuron and centroid interval sets as weights. Their proposed

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structure is very similar to type-2 fuzzy systems because it has fuzzy rules and the consequent part of fuzzy rules is interval sets like (Lu, 2015). Rhee and Choi (2007) used type-1 fuzzy memberships which are computed from the centroid of the interval type-2 fuzzy memberships were incorporated into the RBF neural network. Karnik et al. (1999) proposed a method called Karnik–Mendel (KM) for type reduction (Karnik et al., 1999).

Self-evolving RBFN uses online learning for the definition of the number of hidden neuron. Self-evolving RBFN is a network that initially there is one RBF neuron and it is added one by one until to reach desired performance. Some strategies have proposed to self-evolving RBFN (Qiao and Han, 2012; Qiao et al., 2014; Lian, 2014; El-Sousy, 2014).

The proposed T2FRBFN in this paper is similar to Rubio-Solis and Panoutsos (2015) with the exception that:

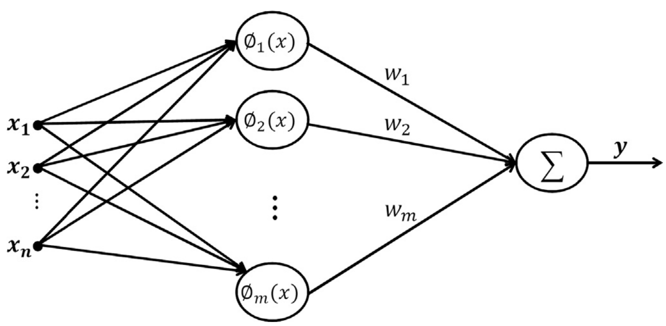

Fig. 1. Structure of RBFN.

1. In the proposed T2FRBFN the weight between hidden neurons and output layer is interval type-2 fuzzy.
2. We propose a RBFN with type-2 fuzzy parameters, so there is not any fuzzy rule.
3. We use modified KM algorithm to accelerate the training.
4. We use a novel type-2 fuzzy clustering method to find the number of RBF neuron in hidden layer.

This paper is extended version of our previous papers (Tavoosi and badamchizadeh 2013; Jahangiri et al., 2012; Suratgar and Nikravesh, 2009) that it presents a novel recurrent self-evolving type-2 fuzzy RBFN for nonlinear systems identification. The paper is organized as follows. In Section 2.1, an RBF network is reviewed. In Section 2.2, a brief description of type-2 fuzzy sets is given. The proposed T2FRBFN is described in Section 3. In Section 4, the simulation studies are presented for identification of three nonlinear systems. Finally, Section 5 gives the conclusions of the advocated design methodology.

2. A review on RBFN and type-2 fuzzy systems

In this section, a brief review of RBFN and type-2 fuzzy is presented.

2.1. A review on RBF network

Standard RBFN has three layers (Sharifian et al., 2011) (Fig. 1).

The first layer is input layer, the second layer is hidden layer and the third layer is output layer. The response of a neuron in

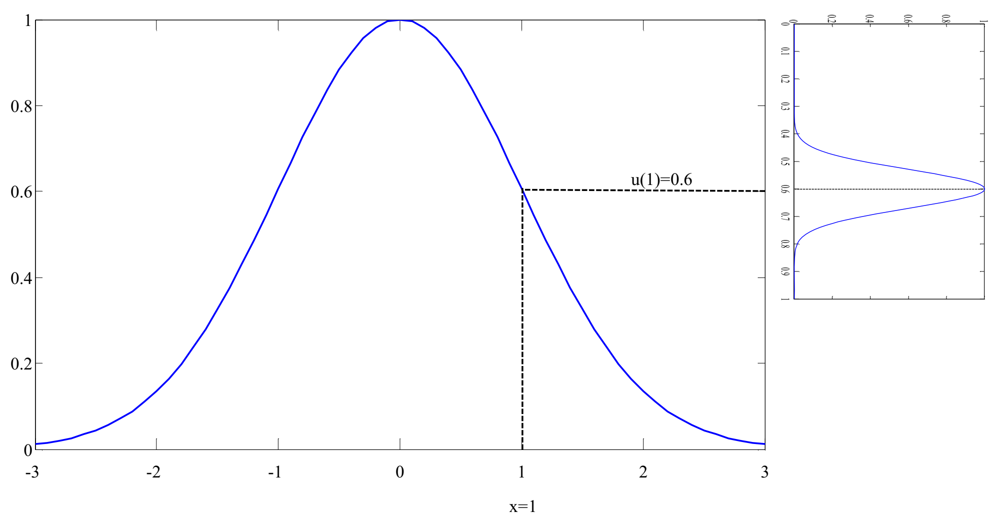

Fig. 2. Gaussian primary and secondary membership functions.

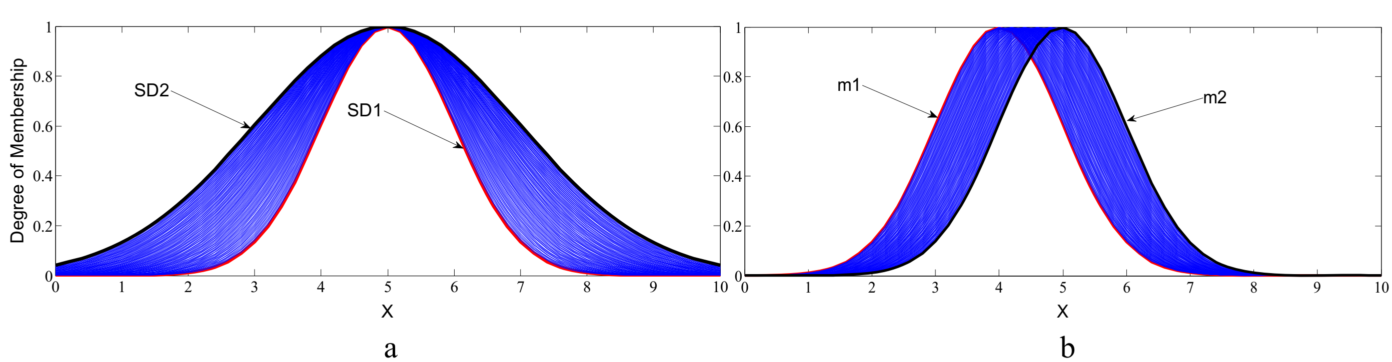

Fig. 3. (a) Uncertainty in standard deviation and (b) uncertainty in mean.