System Identification Based on Dynamical Training for Recurrent Interval Type-2 Fuzzy Neural Network

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ABSTRACT

This paper proposes a novel fuzzy modeling approach for identification of dynamic systems. A fuzzy model, recurrent interval type-2 fuzzy neural network (RIT2FNN), is constructed by using a recurrent neural network which recurrent weights, mean and standard deviation of the membership functions are updated. The complete back propagation (BP) algorithm tuning equations used to tune the antecedent and consequent parameters for the interval type-2 fuzzy neural networks (IT2FNNs) are developed to handle the training data corrupted by noise or rule uncertainties for nonlinear system identification involving external disturbances. Only by using the current inputs and most recent outputs of the input layers, the system can be completely identified based on RIT2FNNs. In order to show that the interval IT2FNNs can handle the measurement uncertainties, training data are corrupted by white Gaussian noise with signal-to-noise ratio (SNR) 20 dB. Simulation results are obtained for the identification of nonlinear system, which yield more improved performance than those using recurrent type-1 fuzzy neural networks (RT1FNNs).

Keywords: *Back Propagation, Fuzzy Controllers, Interval Type-2 Fuzzy Neural Network, Measurement Uncertainties, Recurrent Fuzzy Neural Network*

INTRODUCTION

In the past decades, fuzzy sets and their associated fuzzy logic have supplanted conventional technologies in many scientific applications and engineering systems, especially in control systems, pattern recognition and system identification. We have also witnessed a rapid growth in the use of fuzzy logic in a wide variety of consumer products and industrial systems. Since 1985, there has been a strong growth in their use for dealing with the control of, especially nonlinear, time varying systems. For instance, fuzzy controllers have generated a great deal of excitement in various scientific and engineering areas, because they allow for

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ill-defined and complex systems rather than requiring exact mathematical models (Narendra & Parthasarathy, 1990; Wang 1993; Wang, 1994; Rovithakis & Christodoulou, 1994; Castro et al., 1995; Chen et al., 1996). The most important issue for fuzzy control systems is how to deal with the guarantee of stability and control performance, and recently there have been significant research efforts on the issue of stability in fuzzy control systems (Spooner & Passino, 1996; Ma & Sun, 2000).

Quite often, the information that is used to construct the rules in a fuzzy logic system (FLS) is uncertain. At least, there are four possible ways of rule uncertainties in type-1 FLS (Mendel 2004; Liang & Mendel, 2000): (1) Being words mean different things to different people, the meanings of the words that are used in antecedents and consequents of rules can be uncertain; (2) consequents may have a histogram of values associated with them, especially when knowledge is extracted from a group of experts who do not all agree; (3) measurements that activate a type-1 FLS may be noisy and therefore uncertain; (4) finally, the data that are used to tune the parameters of a type-1 FLS may also be noisy. Therefore, antecedent or consequent uncertainties translate into uncertain antecedent or consequent membership functions (MFs). Type-1 FLSs are unable to directly handle rule uncertainties, since their membership functions are type-1 fuzzy sets. On the other hand, type-2 FLSs involved in this paper whose antecedent or consequent membership functions are type-2 fuzzy sets can handle rule uncertainties (Hagras, 2004; Hagras, 2007; Martinez et al., 2009; Sepulveda et al., 2009; Castro et al., 2009). A type-2 FLS is characterized by IF-THEN rules, but its antecedent or consequent sets are type-2. Hence, type-2 FLSs can be used when the circumstances are too uncertain to determine exact membership grades such as when training data is corrupted by noise.

Type-2 FLSs have been applied successfully to deal with decision making (Yager, 1980), time-series forecasting (Karnik & Mendel, 1999), time varying channel equalization (Liang & Mendel, 2000), fuzzy controller designs (Wang, 1994; Lin et al., 2009, 2010; Lin, 2010b), VLSI fault diagnosis (Lin, 2010a) and control of mobile robots (Wu, 1996), due to the type-2 FLSs ability to handle uncertainties. Further, genetic algorithm (GA) was adopted to fine tune the Gaussian MFs in the antecedent part of type-1 FNN (Wang et al., 2001). The dynamical optimal training algorithm for the two-layer consequent part of interval TFNN (Wang et al., 2004), was proposed to learn the parameters of the antecedent type-2 MFs as well as of the consequent weighting factors of the consequent part of the T2FNN. The back propagation (BP) equations proposed by Wang et al. (2004) are not correct and were modified by Hagras (2006).

However, the BP algorithm presented in Hagras (2006) was the only one of the sixteen possible combinations for the different permutations what active branch x_k and the status of rule i compared to numbers R and L used to compute y_r and y_l, respectively. Based on the presented generalized analysis for the computing derivatives in interval type-2 FLSs (Mendel, 2004), in this paper, the all sixteen possible combinations of the specific BP equation used to tune the antecedent and consequent parameters of the interval T2FNN will be developed.

This paper is organized as follows. First, a brief description of interval type-2 fuzzy logic system is introduced. The construction of RIT2FNN is described and the BP algorithm for RIT2FNN is presented. Finally, a simulation example to demonstrate the performance of the proposed method is provided and the conclusions of the advocated design methodology are given.

BRIEF DESCRIPTION OF INTERVAL TYPE-2 FUZZY LOGIC SYSTEM

Due to the complexity of type reduction, the general type-2 FLS becomes computationally intensive. In order to make things simpler and easier to compute meet and join operations, the secondary MFs of an interval type-2 FLS are