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Real-time fuzzy system identification using uncertainty bounds

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ABSTRACT

In this paper, a novel embedded real-time interval type-2 fuzzy neural network (FNN) system identification is presented using intelligent algorithms, back propagation (BP) algorithms. Interval type-2 FNN is introduced to handle uncertainties which arise from the noisy training data, noisy measurements used to activate the fuzzy logic system (FLS) and linguistic uncertainties. In order to overcome the iterative type-reduction overhead, the intelligent algorithms are proposed to learn the parameters of interval type-2 FLS using uncertainty bounds, inner- and outer-bound sets, which provide estimates of the uncertainties contained in the output of an interval type-2 FLS without having to perform the costly computations of type-reduction. Two nonlinear systems, namely, Duffing forced oscillation system and inverted pendulum system, are fully illustrated to be identified and simulation results show that not only similar identification performance to one that use type-reduction can be achieved but also significantly faster real-time identification can be performed.

1. Introduction

Many engineering applications need a compact and accurate description, i.e., mathematical description, of the dynamic behavior of the system under consideration, so that we are able to control it. Unfortunately, the exact mathematical model of the plant, especially when this is highly nonlinear and complex, is rarely known and thus appropriate identification schemes have to be applied which will provide us with an approximate model of the plant [10,11]. Although the structure is well known, numerical model expressions usually become unrelated and computationally inefficient as the complexity increases. Furthermore, it is highly probable that many system uncertainties, unpredictable dynamics and other unknown phenomena cannot be mathematically modeled at all.

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 thanks to their properties of universal approximator. We have also witnessed a rapid growth in the use of fuzzy logic in a wide variety of consumer products and industrial systems. 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 [12–17]. Unfortunately, there are many sources of uncertainties existing in the knowledge used to construct a FLS, such as uncertainties associated with the use of noisy training data, linguistic uncertainties and uncertainties in inputs and outputs of the FLS. Hence, interval type-2 FLS is recommended to overcome the limitations of type-1 FLS which cannot directly handle those uncertainties [1,2,5–9,12,13,15–18].

Zadeh [32] proposed the concept of type-2 fuzzy set as an extension of the concept of type-1 fuzzy sets. The grades of membership are themselves fuzzy of type-2 fuzzy sets. Type-2 fuzzy sets allow us to handle uncertainties due to uncertain linguistic knowledge and uncertain numerical values. A theory and design technique for interval type-2 fuzzy logic systems is proposed [8,9,19–27] and a comparable theory and design technique for normalized output interval type-2 TSK fuzzy logic systems is introduced [28,29]. Moreover, a type-2 FLS is again characterized by IF-THEN rules, but its antecedent or consequent sets are now of type-2 [19–27]. The type-2 FLS has been successfully applied to fuzzy neural network, VLSI testing [17] and fuzzy controller designs. The neural-network based fuzzy logic control and decision system is presented [30] and system identification based on dynamical training for recurrent interval type-2 fuzzy neural network is introduced [31].

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However, interval type-2 FLS real-time performance can be diminished by a computational overhead associated with the iterative type-reduction algorithms. In order to overcome the iterative type-reduction overhead, a method to approximate the type-reduced set by the inner- and outer-bound sets is introduced by Wu and Mendel [3] to replace the use of the iterative Karnik–Mendel algorithm [7–9,15–17] In this paper, a novel embedded real-time interval type-2 fuzzy neural system identification is presented by using the BP method to tune all parameters, i.e., centers, widths and end points of the centroid of the consequent type-2 fuzzy sets, of interval type-2 fuzzy membership functions in interval type-2 FNN.

This paper is organized as follows. First, a brief description of inner- and outer- bound sets for a type-reduced set of an interval type-2 FLS is introduced in Section 2. The construction of the real-time interval type-2 FNN is described in Section 3. Based on inner- and outer-bound sets, BP algorithms of real-time system identification for the interval type-2 FNN are presented in Section 4. Two simulation examples to demonstrate the performance of the proposed method are provided in Section 5. Section 6 gives the conclusions of the advocated system identification methodology.

2. Brief description of inner- and outer-bound sets for a type-reduced set of an interval type-2 FLS [3]

In this section, inner- and outer-bound sets for the type-reduced set of an interval type-2 FLS are introduced without the computation of $L^*(\mathrm{x})$and $R^*(\mathrm{x})$, the numbers used to decide the point to separate two sides (one side using lower firing strengths $\underline{f}^i$ and another side using upper firing strengths $\overline{f}^i$), to eliminate a major bottleneck of the time-consuming Karnil–Mendel (KM) iterative algorithm to the use of an interval type-2 FLS in real-time applications, where $L^*(\mathrm{x})$and $R^*(\mathrm{x})$ are very important switching numbers which depend on the input x for type-reduction of interval type-2 defuzzification. A collection of embedded type-1 FLS [3,4] is equivalent to an interval type-2 FLS. By incorporating with the left (or right) end points of the centroids of the consequents denoted as boundary type-1 FLSs for an interval type-2 FLS, the following embedded type-1 FLSs only use the Lower and upper membership functions (LMFs, UMFs) of the input and antecedent fuzzy sets given as follows [3]:

$$\{\text{LMFs, left}\}: y_l^{(0)}(\mathrm{x}) = \frac{\sum_{i=1}^{M} \underline{f}^i w_l^i}{\sum_{i=1}^{M} \underline{f}^i} \tag{1}$$

$$\{\text{UMFs, left}\}: y_l^{(M)}(\mathrm{x}) = \frac{\sum_{i=1}^{M} \underline{f}^i w_l^i}{\sum_{i=1}^{M} \underline{f}^i} \tag{2}$$

$$\{\text{LMFs, right}\}: y_r^{(M)}(\mathrm{x}) = \frac{\sum_{i=1}^{M} \underline{f}^i w_r^i}{\sum_{i=1}^{M} \underline{f}^i} \tag{3}$$

$$\{\text{UMFs, right}\}: y_r^{(0)}(\mathrm{x}) = \frac{\sum_{i=1}^{M} \underline{f}^i w_r^i}{\sum_{i=1}^{M} \underline{f}^i} \tag{4}$$

where w_l^i and w_r^i represent the end points of the centroid of the consequent type-2 fuzzy sets, the lower and upper firing strength of the ith rule can be obtained as [2]

$$\underline{f}^i = \underline{u}_{\tilde{F}_1^i}(x_1) * \cdots * \underline{u}_{\tilde{F}_n^i}(x_n) = \prod_{j=1}^{N} \underline{u}_{F_j^i}(x_j) \tag{5}$$

and

$$\overline{f}^i = \overline{u}_{\tilde{F}_1^i}(x_1) * \cdots * \overline{u}_{\tilde{F}_n^i}(x_n) = \prod_{j=1}^{N} \overline{u}_{F_j^i}(x_j) \tag{6}$$

and $*$ represent t-norm operators. In order to predict the inner- and outer-bound sets, $[\overline{y}_l(\mathrm{x}), \underline{y}_r(\mathrm{x})]$ and $[\underline{y}_l(\mathrm{x}), \overline{y}_r(\mathrm{x})]$, respectively for the type-reduced set $[y_l(\mathrm{x}), y_r(\mathrm{x})]$ of an interval type-2 FLS, the following theorem is considered.

Theorem 1. Mendel [2] *The end points $y_l(\mathrm{x})$ and $y_r(\mathrm{x})$ of the type-reduced set of an interval type-2 FLS for the input* x, *bounded from below and above by*

$$\underline{y}_l(\mathrm{x}) \le y_l(\mathrm{x}) \le \overline{y}_l(\mathrm{x}) \tag{7}$$

$$\underline{y}_r(\mathrm{x}) \le y_r(\mathrm{x}) \le \overline{y}_r(\mathrm{x}) \tag{8}$$

where

$$\overline{y}_l(\mathrm{x}) = \min\left\{ y_l^{(0)}(\mathrm{x}), y_l^{(M)}(\mathrm{x}) \right\} \tag{9}$$

$$\underline{y}_r(\mathrm{x}) = \max\left\{ y_r^{(0)}(\mathrm{x}), y_r^{(M)}(\mathrm{x}) \right\} \tag{10}$$

and

$$\underline{y}_l(\mathrm{x}) = \overline{y}_l(\mathrm{x}) - \left[\frac{\sum_{i=1}^{M}(\overline{f}^i - \underline{f}^i)}{\sum_{i=1}^{M}\overline{f}^i \sum_{i=1}^{M}\underline{f}^i} \times \frac{\sum_{i=1}^{M}\underline{f}^i(w_l^i - w_l^1)\sum_{i=1}^{M}\overline{f}^i(w_l^M - w_l^i)}{\sum_{i=1}^{M}\underline{f}^i(w_l^i - w_l^1) + \sum_{i=1}^{M}\overline{f}^i(w_l^M - w_l^i)} \right] \tag{11}$$