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Parallel Interval Type-2 Subsethood Neural Fuzzy Inference System

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ABSTRACT

Neuro-fuzzy models are being increasingly employed in the domains like weather forecasting, stock market prediction, computational finance, control, planning, physics, economics and management, to name a few. These models enable one to predict system behavior in a more human-like manner than their crisp counterparts. In the present work, an interval type-2 neuro-fuzzy evolutionary subsethood based model has been proposed for its use in finding solutions to some well-known problems reported in the literature such as regression analysis, data mining and research problems relevant to expert and intelligent systems. A novel subsethood based interval type-2 fuzzy inference system, named as Interval Type-2 Subsethood Neural Fuzzy Inference System (IT2SuNFIS) is proposed in the present work. Mathematical modeling and empirical studies clearly bring out the efficacy of this model in a wide variety of practical problems such as Truck backer-upper control, Mackey–Glass time-series prediction, Narazaki–Ralescu and bell function approximation. The simulation results demonstrate intelligent decision making capability of the proposed system based on the available data. The major contribution of this work lies in identifying subsethood as an efficient measure for finding correlation in interval type-2 fuzzy sets and applying this concept to a wide variety of problems pertaining to expert and intelligent systems. Subsethood between two type-2 fuzzy sets is different from the commonly used sup-star methods. In the proposed model, this measure assists in providing better contrast between dissimilar objects. This method, coupled with the uncertainty handling capacity of type-2 fuzzy logic system, results in better trainability and improved performance of the system. The integration of subsethood with type-2 fuzzy logic system is a novel idea with several advantages, which is reported for the first time in this paper.

1. Introduction

Approximation and regression problems are encountered very frequently in many aspects of life. Human mind has an inherent capability to approximate and analyze a complex situation by converting it into a simpler one; it performs regression and approximations instinctively, effortlessly.

Scientific community has made use of soft computing tools to address some of these problems such as pattern classification, function approximation, time series prediction, optimization, pattern reconstruction from a distorted pattern and many more (Bezdek, Keller, Krishnapuram, & Pal, 1999; Jang, Sun, & Mizutani, 1997; Pal & Mitra, 1999; Simon, 1991; Tettamanzi & Tomassini, 2001). The use of neural networks (Hopfield, 1982), fuzzy systems (Zadeh, 1973), evolutionary models (Price, Storn, & Lampinen, 2005; Storn & Price, 1997) and statistical models (Fukunaga, 1972) is very popular in dealing with the aforementioned set of problems. The integration of these soft computing techniques leads to capable robust powerful systems. Neuro-fuzzy integration reaps the benefits of both neural networks and fuzzy systems. Fuzzy logic has been successfully applied to many diverse applications in past few years, mainly because of the easy and close to human reasoning capabilities and interpretability. Coupled with the parallel connectionist structure, fault tolerance, distributed computing, adaptability of neural networks, this yields a powerful integration called neuro-fuzzy system (Zadeh, 1965). Fuzzy systems have also been widely used in handling the data uncertainties which may arise due to incomplete, imprecise, contradictory, vague or partially reliable information (Klir & Yuan, 1995). In the literature, we find

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many systems using type-1 fuzzy sets (T1FS)[1] (Juang & Lin, 1998; Kasabov & Song, 2002; Paul & Kumar, 2002; Rong, Sundararajan, Huang, & Saratchandran, 2006; Subramanian & Suresh, 2012).

Type-2 fuzzy sets (T2FS) were introduced by Zadeh (1975), as extension to T1FSs. Later, detailed analysis and explanations were given by Mendel and Karnik (Karnik, Mendel, & Liang, 1999; Mendel, 2001, 2007; Mendel, Hagras, Tan, Melek, & Ying, 2014; Mendel & John, 2002). T2FSs are extension of T1FSs in that the membership function is itself fuzzy; as such one more degree of fuzziness is introduced into the system. T2FSs are gaining importance in the soft computing world due to their capability to handle uncertainties more accurately than T1FS. Based on a special case of T2FS, called as interval type-2 fuzzy set (IT2FS), various neuro-fuzzy inference systems, popularly known as interval type-2 neuro-fuzzy inference systems have been developed in the literature (Das, Subramanian, & Suresh, 2015; Gaxiola, Melin, Valdez, & Castillo, 2014; Hagras, 2006; Juang, Huang, & Cheng, 2010; Juang & Tsao, 2008a; Lee, Lin, & Lai, 2003; Liang & Mendel, 2000; Lin, Pal, Wu, Liu, & Lin, 2015; Lin, Chang, Pal, & Lin, 2013; Lin, Liao, Chang, & Lin, 2014a; Liu, Yeh, & Lee, 2012; Melin & Castillo, 2014; Subramanian, Savitha, & Suresh, 2014; Tung, Quek, & Guan, 2013; Wang, Cheng, & Lee, 2004). The use of IT2FSs have gained more attention due to their less intensive computational approach as compared to T2FSs (Liang & Mendel, 2000; Mendel, 2007; Mendel, John, & Liu, 2006).

T2FSs have an additional dimension in the membership function which is called as secondary membership function which represents the uncertainty/fuzziness in the primary membership function. One such T2FS is shown in Fig. 1. In case of IT2FSs, the secondary membership function is a unit step function.

According to Mendel (2003), some situations arise where T2FS based models perform better than their T1FS counterparts. Some of the applications include non-stationary processes, equalization of non-linear and time varying digital communication channels and unknown mathematical nature of the movement of features, described a priori by statistical attributes, such as rule-based classification of video traffic.

In this model, a subsethood measure between IT2FS inputs and IT2FS antecedent weights given by Rickard, Aisbett, and Gibbon (2009) is considered to understand the degree of overlap or containment of one set with another. Subsethood is a fundamental measure on fuzzy sets (Kosko, 1992) and is used in many applications such as analyzing auditors' fees, comparing states of patients, pre and post intervention, to converting color images to greyscale (Beynon, Peel, & Tang, 2004; Bustince, Pagola, & Barrenechea, 2007; Helgason & Jobe, 2003).

The proposed architecture is called as IT2SuNFIS and it is based on interval type-2 neuro-fuzzy architecture. IT2SuNFIS implements a hybrid approach utilizing both IT2FSs and T1FSs providing uniqueness to the model. Learning of IT2SuNFIS takes place using various differential evolution (DE) strategies including Artificial Bee Colony-differential evolution algorithm (Abraham, Jatoth, & Rajasekhar, 2012). LAM-7.1.1 (Local Area Multicomputer), which is an MPI (Message Passing Interface) environment, has been used as the parallel programming environment for all the implementations, applications and simulations. A uniform (identical CPU) cluster, having one master node (*DELL PowerEdge R610* Rack Server) and 24 compute nodes (*DELL PowerEdge M610* blade servers) connected through a *DELL PC2848* network switch, has been used for implementation of model and subsequent experimentation.

This paper is organized in 7 sections. Section 2 briefly discusses T2FSs and IT2FSs. In Section 3, proposed type-2 neuro-fuzzy architecture viz., IT2SuNFIS is presented. Section 4 deals with the learning strategy used for the training of the network. In Section 5, parallelization strategy of the model is discussed. The applications of the proposed model have been discussed in Section 6. Principal conclusions are summarized in Section 7, followed by acknowledgments.

[1] The standard fuzzy sets are referred to as T1FS to distinguish them from higher order fuzzy sets

2. Type-2 fuzzy sets

T2FSs and higher order fuzzy sets were introduced by Zadeh (1975). T2FSs were neglected until the past decade when Mendel renewed the interest in these sets and their applications (Mendel, 2001; Mendel & John, 2002). A T2FS is characterized by a fuzzy membership function; it has a region of footprint of uncertainty (FOU) (shaded area in the Fig. 1). This FOU can be divided into a set of N primary membership functions with an associated probability of occurrence of each one of them. The probability of occurrence of primary membership grades constitutes the secondary membership function, therefore enabling to capture higher order of fuzziness. For the case shown in Fig. 1, the secondary membership function is a triangular function; the probability of occurrence of the primary membership function at the center of FOU is highest and it linearly decreases on both sides. In the case of an IT2FS, secondary membership grade is a uniform distribution or a unit step function. A T2FS is distinguished from a T1FS by adding ' $\sim$ ' over the linguistic label of the set.

3. Interval Type-2 Subsethood Neural Fuzzy Inference System (IT2SuNFIS)

Interval **T**ype-**2** **Su**bsethood **N**eural **F**uzzy **I**nference **S**ystem (IT2SuNFIS) embeds the type-2 fuzzy rules of the form (Mendel, 2001):

If x_1 is $\tilde{A}_1^j$ and x_2 is $\tilde{A}_2^j \ldots$ and x_n is $\tilde{A}_n^j$ then y_k is B_k^j, $j = 1, \ldots, p$, $k = 1, \ldots, q$, where *n, p, q* respectively denote the number of inputs, rules and outputs. $\tilde{A}_i^j, i = 1, \ldots, n$ are antecedent IT2FSs with symmetric Gaussian primary membership function (GPMF) and $B_k^j, k = 1, \ldots, q$ are consequent T1FSs with Gaussian membership function defined on input and output universes of discourse (UOD) for the j^{th} rule.

IT2SuNFIS architecture is shown in the Fig. 2. It is a three layered architecture with input, hidden and output layers consisting of neurons. The input to rule layer antecedent weights are IT2FSs. The consequent weights from rule layer to output layer are T1FSs. The flow of signal from the input to output layer is discussed in detail in the following sections:

3.1. Input node signal transmission

Input nodes of the network are feature inputs. These nodes are feature specific tunable fuzzifiers which accept numeric inputs and fuzzify them using IT2FSs having GPMF with a fixed mean and uncertain standard deviations $x_i^\sigma \in [x_i^{\sigma^l}, x_i^{\sigma^u}]$. The mean of the GPMF is equal to the numeric input x_i to the network. The primary MF of input IT2FS is defined as

$$\mu_x = exp\left\{-\left(\frac{x - x_i}{x_i^\sigma}\right)^2\right\} \equiv \mathcal{F}(x_i, x_i^\sigma : x), \quad x_i^\sigma \in [x_i^{\sigma^l}, x_i^{\sigma^u}] \tag{1}$$

The membership value is in the interval $[\underline{\mu}_x, \overline{\mu}_x]$ where

$$\underline{\mu}_x = \mathcal{F}(x_i, x_i^{\sigma^l} : x)$$
$$\overline{\mu}_x = \mathcal{F}(x_i, x_i^{\sigma^u} : x) \tag{2}$$

Input fuzzified feature x_i is defined as

$$S(x_i) = \mathcal{F}(x_i, x_i^{\sigma^l}, x_i^{\sigma^u}) \tag{3}$$