Expert Systems With Applications 79 (2017) 140–152

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

# Interval type-2 neuro-fuzzy system with implication-based inference mechanism

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ARTICLE INFO

*Article history:*
Received 25 August 2016
Revised 19 February 2017
Accepted 28 February 2017

*Keywords:*
Implication-based rules
Fuzzy inference systems
Neuro-fuzzy systems
Interval type-2 fuzzy sets

ABSTRACT

Neuro-fuzzy systems have been proved to be an efficient tool for modelling real life systems. They are precise and have ability to generalise knowledge from presented data. Neuro-fuzzy systems use fuzzy sets – most commonly type-1 fuzzy sets. Type-2 fuzzy sets model uncertainties better than type-1 fuzzy sets because of their fuzzy membership function. Unfortunately computational complexity of type reduction in general type-2 systems is high enough to hinder their practical application. This burden can be alleviated by application of interval type-2 fuzzy sets. The paper presents an interval type-2 neuro-fuzzy system with interval type-2 fuzzy sets both in premises (Gaussian interval type-2 fuzzy sets with uncertain fuzziness) and consequences (trapezoid interval type-2 fuzzy set). The inference mechanism is based on the interval type-2 fuzzy Łukasiewicz, Reichenbach, Kleene-Dienes, or Brouwer–Gödel implications. The paper is accompanied by numerical examples. The system can elaborate models with lower error rate than type-1 neuro-fuzzy system with implication-based inference mechanism. The system outperforms some known type-2 neuro-fuzzy systems.

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## 1. Introduction

Neuro-fuzzy systems have been proved to be an efficient tool for modelling real life systems. They are precise and have ability to generalise knowledge from presented data. Their important advantage is interpretability of created models. Some kinds of neuro-fuzzy systems have been proved to be universal approximators that satisfy the Stone–Weierstrass theorem (Kosko, 1994). Neuro-fuzzy systems use fuzzy sets to handle vagueness. Mendel and John (2002) list noise and uncertainty of data among main sources of uncertainties in fuzzy systems with type-1 fuzzy sets. The membership function of type-1 fuzzy sets has strictly crisp values. That deteriorates the ability to represent noisy or uncertain data. Type-2 fuzzy sets (Zadeh, 1975) model better such uncertainties because of their fuzzy membership function.

Type-1 and type-2 fuzzy systems share the same architecture, they have four main components: fuzzifier, inference engine with a rule base, and output processor. In type-2 fuzzy systems the output processor has two tasks: type-reduction and defuzzification. Type reduction is the main cause of high computation burden of the type-2 fuzzy systems. It is their main disadvantage and can be mitigated by application of interval type-2 (IT2) fuzzy sets. An interval type-2 fuzzy set is a kind of type-2 fuzzy set. A secondary membership function of an interval type-2 (IT2) fuzzy sets can have only two values: 0 or 1. A system is called an interval type-2 fuzzy system when it has interval type-2 sets in some part (mostly in rule premises).

Interval type-2 neuro-fuzzy systems have been profoundly theoretically analysed by Liang and Mendel (2000), Karnik, Mendel, and Liang (1999), and Mendel and Rajati (2014). These papers present the theory and design patterns. Mendel (2004) provides mathematical formulae for steepest-descent parameter tuning of type-2 fuzzy systems with a Karnik–Mendel type reducer. The Karnik–Mendel algorithm (Karnik & Mendel, 2001) is consistent with an extension principle. Unfortunately this complicates the theoretical analysis and implementation of systems. To avoid this Wu and Mendel (2002), Nie and Tan (2008), Du and Ying (2010) formulate type-reducers in a closed-form formulae. These solutions do not satisfy the requirements of the fuzzy theory, but are easier to analyse than the Karnik–Mendel algorithm. Neuro-fuzzy systems can be ordered starting with type-1 (T1) through interval type-2 (IT2) to general type-2 systems. This sequence presents both increase in ability to handle uncertainties and computational burden. Computational complexity of type reduction in general type-2 systems is high enough to hinder their practical application. Interval type-2 systems have lower computational overhead than general type-2 fuzzy systems. They can better handle uncertainties and can model more complex surfaces than type-1 systems with similar number of rules. An interval type-2 fuzzy sys-

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http://dx.doi.org/10.1016/j.eswa.2017.02.046
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tem with the KM type reducer cannot be implemented by a type-1 fuzzy system using the same rule base (Wu, 2012).

There have been proposed many interval type-2 neuro-fuzzy systems. Most systems have interval type-2 fuzzy sets only in premises. The DIT2LIFR-IP system (Juang & Chen, 2013) uses interval type-2 sets in premises and zero-order TSK interval type-2 consequences (interval constants). The initial rule base is generated by a self-splitting clustering algorithm in the input–output space. Aliasghary, Eksin, Guzelkaya, and Kumbasar (2015) describe an interval type-2 fuzzy system with diamond-shaped type-2 fuzzy sets in premises and singletons in consequences and Nie–Tan type reduction. Melin, Mendoza, and Castillo (2010) present an interval type-2 fuzzy inference system with interval fuzzy constants in consequences. Starczewski and Rutkowski (2003) propose a type-2 neuro-fuzzy system with interval fuzzy membership grades in rule antecedents and intervals in consequents. Chen and Chang (2011a) apply interval type-2 Gaussian fuzzy sets with fuzzy cores in premises for sparse fuzzy rule-based system. Juang and Tsao (2008a) propose a self-evolving interval type-2 fuzzy neural network with online structure and parameter learning. The premises of the rules are built with interval type-2 fuzzy sets with uncertain means. The consequences follow a TSK pattern. The rules are generated with an online clustering method.

Non interval type-2 fuzzy systems are not as popular as interval type-2 systems. One of the examples may be a system with type-2 fuzzy set in premises (with triangular secondary membership function) and Mamdani type consequences (Starczewski, Scherer, Korytkowski, & Nowicki, 2008).

Tuning of (interval) type-2 neuro-fuzzy system is a challenging task in spite of wide research (Starczewski et al., 2008). Many techniques are applied, eg: gradient descent and the rule-ordered recursive least squares algorithm (Juang & Chen, 2013), hybrid backpropagation (Castro, Castillo, Melin, & Rodríguez-Díaz, 2009), genetic algorithm (Park & Lee, 2013), backpropagation and AdaBoost algorithms (Starczewski et al., 2008).

A fuzzy IF-THEN rule is a kind of fuzzy implication. Fuzzy implications have been deeply analysed from mathematical point of view. In the proposed system is an implication-based (Dubois & Prade, 1996) fuzzy inference system where fuzzy rules are evaluated as fuzzy implication. This approach is also called an implicative or deductive approach (Štěpnička & Baets, 2013).

The novelty of this paper is a neuro-fuzzy system with two features: (1) it is an interval type-2 neuro-fuzzy system (with IT2 sets both in premises and consequences of rules) with (2) implication-based inference mechanism. To the best of our knowledge this is the first attempt at creation of an interval type-2 (IT2) fuzzy system with an implication-based inference mechanism and IT2 fuzzy sets both in premises and consequences of the rules.

Our system is an extension of the ANNBFIS (Artificial Neural Network Based Fuzzy Inference System) system (Czogała & Łęski, 2000). This type-1 system has been proved to be precise and fast in calculations and has many applications and modifications as $\varepsilon$-insensitive learning (Leski, 2003), rough-fuzzy paradigm (Siminski, 2015), deterministic annealing optimisation (Czabański, 2006), subspace approach (Siminski, 2017), hybrid system with SVM (Siminski, 2014a; 2014b), incomplete data mining (Siminski, 2016a), and inversion of neuro-fuzzy system (Siminski, 2016b).

The paper is organized as follows: Section 2 describes the interval type-2 fuzzy implications. Section 3 describes the proposed interval type-2 neuro-fuzzy system with implication-based inference mechanism. Section 4 shortly presents the creation of rules from train data. Section 5 describes datasets and experiments. Finally Section 6 summarizes the paper. The calculation of derivatives is moved to Appendix to keep the text clearer.

## 2. Interval type-2 implication

The paper describes an interval type-2 neuro-fuzzy system with implication-based inference mechanism (IT2NFSIB). Each rule in rule base is a fuzzy interval type-2 implication. Alcalde, Burusco, and Fuentes-González (2005) discuss the construction and features of interval type-2 fuzzy implications based on known type-1 fuzzy implications. The authors propose methods for construction of internal type-2 fuzzy implications from continuous T-norms for interval type-2 fuzzy numbers (denoted as $[l, u]$, where $l$ and $u$ are lower and upper limits of the fuzzy set) as:

- Łukasiewicz implication:

$$I_L([a,b],[c,d]) = \begin{cases} [\min\{(1-a+c),(1-b+d)\}, & \\ \quad (1-b+d)], & a > c \text{ and } b > d \\ [1-a+c, 1], & a > c \text{ and } \leqslant d \\ [1,1], & a \leqslant c \text{ and } \leqslant d \\ [1-b+d, 1-b+d], & a \leqslant c \text{ and } b > d \end{cases} \tag{1}$$

- Brouwer–Gödel implication

$$I_{BG}([a,b],[c,d]) = \begin{cases} [c,d], & a > c \text{ and } b > d \\ [c,1], & a > c \text{ and } b \leqslant d \\ [1,1], & a \leqslant c \text{ and } b \leqslant d \\ [d,d], & a \leqslant c \text{ and } b > d \end{cases} \tag{2}$$

- Kleene-Dienes implication

$$I_{KD}([a,b],[c,d]) = [\max\{(1-b),c\}, \max\{(1-a),d\}]. \tag{3}$$

In similar way we construct an interval type-2 $S$-implication from the probabilistic T-conorm (dual to the product T-norm):

- Reichenbach implication:

$$I_R([a,b],[c,d]) = [1-b+bc, 1-a+ad]. \tag{4}$$

## 3. IT2 neuro-fuzzy system with implication-based inference mechanism

Interval type-2 neuro-fuzzy system with implication-based inference mechanism is a multiple input single output (MISO) system. Fuzzy rule base is a crucial part of the system. Each fuzzy rule is an interval type-2 fuzzy logical implication. The value of the rule is a value of fuzzy implication of premise and consequence.

Rule base $\mathbb{L}$ contains fuzzy rules $l$ (fuzzy implications)

$$l : \boldsymbol{x} \text{ is } \mathfrak{a} \rightsquigarrow y \text{ is } \mathfrak{b}, \tag{5}$$

where $\boldsymbol{x} = [x_1, x_2, \ldots, x_D]^{\mathrm{T}}$ and $y$ are linguistic variables, $\mathfrak{a}$ and $\mathfrak{b}$ are fuzzy linguistic terms. The squiggle arrow ($\rightsquigarrow$) stands for an interval type-2 fuzzy implication.

### 3.1. Premise

The premise is built with a Gaussian function. That has two main advantages: (1) Membership to a fuzzy set with a Gaussian function is never zero. It prevents from a situation when a data item is not recognized by any rule. (2) A Gaussian function is differentiable in its whole domain. That enables gradient optimisation.

The rule's premise denoted by $\mathfrak{a}$ (cf. Eq. (5)) is built with an interval type-2 Gaussian fuzzy set $\mathbb{A}$ with uncertain fuzziness $s$ in $D$-dimensional space. For each dimension $d$ the set $\mathbb{A}$ is described with an interval whose limits are Gaussian membership functions:

$$\underline{\mu}_d(x_d) = \exp\left(-\frac{(x_d - v_d)^2}{2\underline{s}_d^2}\right), \tag{6}$$

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