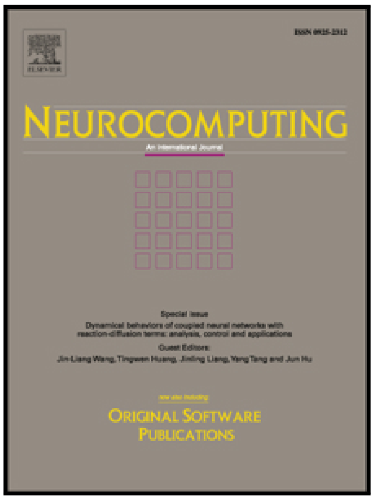

Data Driven Modelling Based on Recurrent Interval-Valued Metacognitive Scaffolding Fuzzy Neural Network

Mahardhika Pratama , Edwin Lughofer , Meng Joo Er ,
Sreenatha Anavatti , Chee-Peng Lim

PII: S0925-2312(17)30981-5
DOI: 10.1016/j.neucom.2016.10.093
Reference: NEUCOM 18511

To appear in: *Neurocomputing*

Received date: 21 April 2016
Revised date: 31 August 2016
Accepted date: 31 October 2016

Data Driven Modelling Based on Recurrent Interval-Valued Metacognitive Scaffolding Fuzzy Neural Network

Mahardhika Pratama, Edwin Lughofer, Meng Joo Er, Sreenatha Anavatti, Chee-Peng Lim

Abstract— the Metacognitive Scaffolding Learning Machine (McSLM), combining the concept of metacognition – what-to-learn, how-to-learn, and when-to-learn, and the Scaffolding theory – a tutoring theory for a learner to learn a complex task, has been successfully developed to enhance the capability of Evolving Intelligent Systems (EIS) in processing non-stationary data streams. Three issues, namely uncertainty, temporal behaviour, unknown system order, are however uncharted by any existing McSLMs and all McSLMs in the literature are designed for classification problems. This paper proposes a novel McSLM, called Recurrent Interval-Valued Metacognitive Scaffolding Fuzzy Neural Network (RIVMcSFNN) and used to solve regression and time-series modelling problems from data streams. RIVMcSFNN presents a novel recurrent network architecture as a cognitive constituent, which features double local recurrent connections at both the hidden layer and the consequent layer. The new recurrent network architecture is driven by the interval-valued multivariate Gaussian function in the hidden node and the nonlinear Wavelet function in the consequent node. As with its predecessors, the RIVMcSFNN characterises an open structure, where it can automatically grow, prune, adjust, merge, recall its hidden node and can select relevant data samples on the fly using an online active learning methodology. The RIVMcSFNN is also equipped with the online dimensionality reduction technique to cope with the *curse of dimensionality*. All learning mechanisms are carried out in the single-pass and local learning mode and actualise the plug-and-play learning principle, which aims to minimise the use of pre-and/or post-training steps. The efficacy of our algorithm was tested using numerous data-driven modelling problems and comprehensive comparisons with its counterparts. The RIVMcSFNN demonstrated substantial improvements in both accuracy and complexity against existing variants of the McSLMs and EISs.

Index Terms—fuzzy neural network, type-2 fuzzy system, online learning, metacognitive learning, evolving fuzzy system

I. Introduction

The underlying motivation of Evolving Intelligent Systems (EIS) is to cope with two main issues – large data streams and dynamic learning environments (Angelov, 2004). EIS feature a flexible working principle, where it can start its learning process from scratch with an empty knowledge base and can self-organise its structure from data streams in the single-pass learning mode (Lughofer, 2008). Such a learning trait is very relevant to deal with today's real-world big data applications, because data streams may contain various concept drifts: slow, rapid, abrupt, gradual, local, global, cyclical or otherwise (Bose, van der Aalst, Zliobaite & Pechenizkiy, 2014). In addition, EISs are computationally efficient, because their single-pass learning manner incurs a low computational burden (Angelov, 2011). Nonetheless, EIS is still cognitive in nature, because it needs to learn all the presented data streams without being able to solve the issue of what-to-learn and when-to-learn (Elwell and Polikar, 2011).

The Metacognitive Learning Machine (McLM) enhances the adaptive nature of EIS by translating the meta-memory model of Nelson and Narens (1990). In essence, the metacognition is about the ability of human beings to assess new knowledge based on previous information and the learning environment (Joysula et al., 2009; Flavell, 1979). Referring to the meta-memory model of Nelson and Narens (1990), the metacognition is composed of three fundamental components: termination of study (when to learn), selection of processing method (how to learn), and item selection (what to learn) (Isacson & Fujita, 2006). The three component are formalised in the realm of machine learning with a sample deletion strategy (what-to-learn), a sample learning strategy (how-to-learn) and a sample