Rough Set-Based Neuro-Fuzzy System

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INTRODUCTION

Neuro-fuzzy hybridization is the oldest and most popular methodology in soft computing (Mitra & Hayashi, 2000). Neuro-fuzzy hybridization is known as Fuzzy Neural Networks, or Neuro-Fuzzy Systems (NFS) in the literature (Lin & Lee, 1996; Mitra & Hayashi, 2000). NFS is capable of abstracting a fuzzy model from given numerical examples using neural learning techniques to formulate accurate predictions on unseen samples. The fuzzy model incorporates the human-like style of fuzzy reasoning through a linguistic model that comprises of if-then fuzzy rules and linguistic terms described by membership functions. Hence, the main strength of NFS in modeling data is universal approximation (Tikk, Kóczy, & Gedeon, 2003) with the ability to solicit interpretable if-then fuzzy rules (Guillaume, 2001). However, modeling data using NFS involves the contradictory requirements of interpretability versus accuracy. Prevailingly, NFS that focused on accuracy employed optimization which resulted in membership functions that derailed from human-interpretable linguistic terms, or employed large number of if-then fuzzy rules on high-dimensional data that exceeded human level interpretation.

This article presents a novel hybrid intelligent Rough set-based Neuro-Fuzzy System (RNFS). RNFS synergizes the sound concept of knowledge reduction from rough set theory with NFS. RNFS reinforces the strength of NFS by employing rough set-based techniques to perform attribute and rule reductions, thereby improving the interpretability without compromising the accuracy of the abstracted fuzzy model.

BACKGROUND

The core problem in soft computing is about bridging the gap between subjective knowledge and objective data (Dubois & Prade, 1998). There are two approaches of addressing this problem; namely, modeling data in which a function is built to accurately mimic the data, and abstracting data in which a system is built to produce articulated knowledge preferably in natural language form (Dubois & Prade, 1998). The emphasis of the former is on the ability to reproduce what has been observed. Neural networks with their prominent learning capabilities inspired from biological systems are highly suitable in this approach. On the other hand, the emphasis of the latter is on the ability to explain the data in a human interpretable way. Fuzzy systems with the ability of modeling linguistic terms that are expressions of human language are likewise highly effective in this approach. In fuzzy systems, linguistic expressions are formulated from explicit knowledge in the form of if-then fuzzy rules where the linguistic terms of the antecedents and consequents are fuzzy sets. However, the parameters of these linguistic expressions are sometimes difficult to specify and have to be manually tuned. In contrast, although neural networks are capable of learning from data, they are black box models and thus soliciting knowledge from neural networks is not a straightforward task. Hence, a neural network is capable of modeling data, but a user cannot learn from it. On the other hand, a user can learn from a fuzzy system, but it is not capable of learning from data.

Neuro-fuzzy hybridization synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks. Thus, Neuro-Fuzzy Systems (NFS) are gray-box models that are capable of abstracting a fuzzy model from given numerical examples using neural learning techniques. Hence, a Neuro-Fuzzy System learns and at the same time, a user can learn from it as well. However, the use of NFS in abstracting data involves two contradictory requirements in fuzzy modeling: interpretability versus accuracy (Casillas, Cordón, Herrera, & Magdalena, 2003). In practice, only one of the two properties prevails. Hence, they can be classified as *linguistic NFS* that are focused on interpretability, mainly using the Mamdani model (Mamdani & Assilian, 1975); and *precise NFS* that are focused on accuracy, mainly using the Takagi-Sugeno-Kang model (Takagi & Sugeno, 1985).

Prevailing research on modeling data using linguistic NFS focused on increasing accuracy as much as possible but neglected interpretability (Casillas et al., 2003). Existing linguistic NFS such as FALCON (Lin & Lee, 1996), POPFNN (Quek & Zhou, 2001) and GenSoFNN (Tung & Quek, 2002) employ the hybrid learning approach to abstract model from numerical data. In this approach, clustering is used in the first stage to generate the membership functions and competitive learning is used to identify the if-then fuzzy rules; followed by supervised learning that uses backpropagation in the final stage to optimize the membership functions. The unconstrained optimization in the final stage increases the accuracy of the abstracted model, but it resulted in membership functions that are derailed from human-interpretable linguistic terms (de Oliveira, 1999). Although the definition of interpretability and its criteria is subjected to controversial discussion, interpretable linguistic variables is often associated with the shape and mutual overlapping of the membership functions (Mikut, Jakel, & Groll, 2005). Nevertheless, formal definition on the semantic properties of interpretable linguistic variables were proposed (Mikut et al., 2005; de Oliveira, 1999); namely, coverage, normalized, convex and ordered. Interpretability is vital to NFS in modeling data because if neglected, they degenerate into black-box models in which the advantages over other methods such as neural networks are lost (Casillas et al., 2003; Mikut et al., 2005). Therefore, abstracting a fuzzy model that is not humanly interpretable derails the fundamental purpose of using NFS.

In addition, a large number of if-then fuzzy rules are required to model high dimensional data, which in turn exceeds the human interpretation capacity (Casillas et al., 2003). This interpretability issue on large number of if-then rules motivates the complexity reduction of NFS. This is similar to the problems encountered by numerical data driven techniques in data mining (Han & Kamber, 2001). These techniques rely on heuristics to guide or reduce their search space horizontally or vertically (Lin & Cercone, 1997). Horizontal reduction is realized by the merging of identical data tuples or the quantization of continuous numerical values while vertical reduction is realized by feature selection methods. In Linguistic NFS, the former corresponds to the conversion of numerical inputs from a continuous range to a finite number of linguistic terms using membership functions while the latter corresponds to fuzzy if-then rule pruning and reduction. In some existing linguistic neuro-fuzzy systems, vertical reduction is employed by identifying fewer if-then fuzzy rules using certain heuristic threshold (Quek & Zhou, 2001), or by applying pruning based on certainty factors (Tung & Quek, 2002). However, if the number of if-then rules is bounded as a practical limitation through the use of heuristic thresholds, then the universal approximation property is lost (Moser, 1999).

Recently, rough set theory (Pawlak, 1991), one of the methodologies in soft computing, has shown to provide efficient techniques of finding hidden patterns in data (Pawlak, 2002). Rough set-based methods have shown the potential for feasible feature selection with the ability to significantly reduce the pattern dimensionality in neural networks. This motivates the synergy of rough set-based methods with NFS to increase the interpretability of the abstracted model without compromising the accuracy.

ROUGH SET-BASED NEURO-FUZZY SYSTEM

This article presents the hybrid intelligent Rough set-based Neuro-Fuzzy System (RNFS) (Ang & Quek, 2006a), which synergizes the sound concept of knowledge reduction in rough set theory with the human-like reasoning style of fuzzy systems and the learning and connectionist structure of neural networks. Details on the architecture and learning process of the RNFS are described in the following sections.

Architecture of RNFS

The architecture of the RNFS is a five-layer neural network shown in Figure 1. Its architecture is developed using the Pseudo Outer-Product based Fuzzy Neural Network using the Compositional Rule of Inference and Singleton fuzzifier (POPFNN-CRI(S)) (Ang, Quek, & Pasquier, 2003) as a foundation. For simplicity, only the interconnections for the output y_m are shown. Each layer in RNFS performs a specific