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Fuzzy Radial Basis Function Neural Networks with information granulation and its parallel genetic optimization

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Abstract

Fuzzy modeling of complex systems is a challenging task, which involves important problems of dimensionality reduction and calls for various ways of improving the accuracy of modeling. The IG-FRBFNN, a hybrid architecture of the IG-FIS (Fuzzy Inference System) and FRBFNN (Fuzzy Radial Basis Function Neural Networks), is proposed to address these problems. The paper is concerned with the analysis and design of IG-FRBFNNs and their optimization by means of the Hierarchical Fair Competition-based Parallel Genetic Algorithm (HFC-PGA). In the proposed network, the membership functions of the premise part of the fuzzy rules of the IG-based FRBFNN model directly rely on the computation of the relevant distance between data points and the use of four types of polynomials such as constant, linear, quadratic and modified quadratic are considered for the consequent part of fuzzy rules. Moreover, the weighted Least Square (WLS) learning is exploited to estimate the coefficients of the polynomial forming the conclusion part of the rules. Since the performance of the IG-RBFNN model is affected by some key design parameters, such as a specific subset of input variables, the fuzzification coefficient of the FCM, the number of rules, and the order of polynomial of the consequent part of fuzzy rules, it becomes beneficial to carry out both structural as well as parametric optimization of the network. In this study, the HFC-PGA is used as a comprehensive optimization vehicle. The performance of the proposed model is illustrated by means of several representative numerical examples.

Keywords: Fuzzy radial basis function neural network; Fuzzy C-Means clustering; Hierarchical fair competition parallel genetic algorithm; Weighted least squares method

1. Introduction

Recently, a great deal of attention in the realm of fuzzy sets has been paid to advanced techniques of system modeling and design of fuzzy models. In the early 1980s, linguistic modeling [1] and fuzzy relation equation-based

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approach [2] were proposed as primordial identification schemes of fuzzy models. The general class of Sugeno–Takagi models [3] gave rise to more sophisticated yet more complex rule-based systems where the rules were equipped with conclusions being formed as local linear regression models. Some enhanced fuzzy models that incorporate high-order polynomials as local models were presented by Bikdash [4].

The performance of fuzzy models depends on structure and learning algorithm of the models. While being appealing with respect to their generic topology, these models still await formal solutions as far as their structural optimization is concerned.

Clustering is a process of dividing data elements into groups (clusters) and as such is widely used to build information granule from data. Specifically, C-Means clustering (C-Means) and Fuzzy C-Means (FCM) clustering have been used to construct information granules [5–7], Mountain clustering [8] and subtractive clustering [9] were proposed to automatically determine the number of rules (where the number of rules is equal to the number of information granules). There have been many studies related to the identification of fuzzy models using evolutionary optimization such as Genetic Algorithms (GAs) and Genetic Programming (GP) [10–17,39,45].

When using fuzzy logic for system modeling, two main approaches are sought: (a) clustering techniques perform a subdivision of the input space, depending on the number of rules used to reach the objective and (b) considered are grid-based fuzzy systems (GBFS), which provide a thorough coverage of the entire input space [18,19]. However GBFS comes with a significant drawback; the number of rules increases exponentially with the number of input variables and the number of membership functions (MFs) per variable, the effect well-known as the curse of dimensionality [20]. More importantly, the transparency of fuzzy logic becomes very much reduced. The understandability of the system vanishes and the advantage of using fuzzy logic disappears [21].

Fuzzy Radial Basis Function Neural Networks (FRBFNNs) are designed by integrating the ideas of a Radial Basis Function Neural Network (RBFNN) and the Fuzzy C-Means (FCM) algorithm [22,44]. The visible advantage of the FRBFNN is that it does not suffer from the curse of dimensionality in comparison with other networks based on grid portioning. However the accuracy of the model might get worse due to use of zero-order polynomials treated as local models which represent the input–output mappings existing in each sub-space.

In this paper, we present an Information Granule-based Fuzzy RBF Neural Network (IG-FRBFNN) to address the drawbacks of the conventional FRBFNN. The proposed IG-FRBFNN has following features. (1) The membership functions of the premise part of fuzzy rules do not assume any explicit forms such as e.g., Gaussian, ellipsoidal, triangular, etc. but the degrees of membership directly rely on the computation of the relevant distance between data points and the prototypes. (2) FCM clustering algorithm is used to construct information granules. (3) While the consequent parts of the conventional FRBFNN are only constants (viz. zero-order polynomial), four orders of polynomials such as constant (zero-order), linear (first-order), quadratic (second-order) and modified quadratic (modified second-order) are provided in the proposed IG-FRBFNN. (4) The weighted least squares (WLS) method, which is a learning algorithm, is considered to estimate the values of the coefficients of the consequent's polynomials. The WLS can reduce computing overload and enhance interpretability of local models (each rule) when compared with the ordinary least squares (OLS) method that forms a learning algorithm of a global nature. The interpretability because of this method estimates coefficients of local models independently. In particular, these benefits manifest significantly in case when dealing with a large number of fuzzy rules. (5) The structural and parametric optimization for IG-FRBFNN is carried out by means of the Hierarchical Fair Competition-based Parallel Genetic Algorithm (HFC-PGA). The structure optimization includes the selection of input variables to be used in the model, the number of the rules and the order of the polynomials in the consequent parts. The parametric optimization involves the fuzzification coefficient which is used in the FCM algorithm.

Section 2 presents an architecture of the model and elaborates on a learning method applied to the construction of the FRBFNN. Section 3 deals with the optimization of IG-FRBFNN using the HFC-PGA. Section 4 presents the experimental results. Finally, conclusions are drawn in Section 5.

2. Architecture and learning of the IG-FRBFNN

In the architecture of the conventional RBFNN, the transfer function of a hidden node is represented in the form of some Gaussian function. Here, one has to decide on the number of neurons of the hidden layer and the form of the RBFs. In general, any RBF is uniquely specified by its center and width. The output of the RBFNN is a weighted sum of the activation levels of the RBFs. The learning algorithm of the RBFNN is used to adjust the weights of the