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Multi groups cooperation based symbiotic evolution for TSK-type neuro-fuzzy systems design

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ABSTRACT

In this paper, a TSK-type neuro-fuzzy system with multi groups cooperation based symbiotic evolution method (TNFS-MGCSE) is proposed. The TNFS-MGCSE is developed from symbiotic evolution. The symbiotic evolution is different from traditional GAs (genetic algorithms) that each chromosome in symbiotic evolution represents a rule of fuzzy model. The MGCSE is different from the traditional symbiotic evolution; with a population in MGCSE is divided into several groups. Each group formed by a set of chromosomes represents a fuzzy rule and cooperate with other groups to generate the better chromosomes by using the proposed cooperation based crossover strategy (CCS). In this paper, the proposed TNFS-MGCSE is used to evaluate by numerical examples (Mackey-Glass chaotic time series and sunspot number forecasting). The performance of the TNFS-MGCSE achieves excellently with other existing models in the simulations.

1. Introduction

In recent years, a fuzzy system uses for several problems has become a popular research topic (Jang, 1993; Juang & Lin, 1998; Lin & Lee, 1996; Lin & Lin, 1997; Lin, Lin, & Shen, 2001; Mizutani & Jang, 1995; Takagi & Sugeno, 1985; Takagi, Suzuki, Koda, & Kojima, 1992; Towell & Shavlik, 1993; Wang & Mendel, 1992). The reason is that classical control theory usually requires a mathematical model for designing controllers. Inaccurate mathematical modeling of plants usually degrades the performance of the controllers, especially for nonlinear and complex problems (Juang & Lin, 1999; Lin & Chin, 2004; Mastorocostas & Theocharis, 2002; Narendra & Parthasarathy, 1990). A fuzzy system consists of a set of fuzzy if-then rules. Conventionally, the selection of fuzzy if-then rules often relies on a substantial amount of heuristic observations to express the knowledge of proper strategies. Obviously, it is difficult for human experts to examine all the input–output data from a complex system to find proper rules for a fuzzy system. To cope with this difficulty, several approaches for generating if-then rules from numerical data have been proposed (Lin & Lin, 1997; Juang & Lin, 1998; Towell & Shavlik, 1993). These methods are developed for supervised learning; that is, the correct "target" output values are given for each input pattern to guide the network's learning.

The most well-known supervised learning algorithm is backpropagation (BP) (Jang, 1993; Juang & Lin, 1998; Lin & Lin, 1997; Lin et al., 2001; Mizutani & Jang, 1995; Takagi et al., 1992). It is a powerful training technique that can be applied to networks. Since the steepest descent technique is used in BP training to minimize the error function, the algorithm may reach the local minima but never find the global solution. In addition, the performance of BP training depends on the initial values of the system parameters, and for different network topologies one has to derive new mathematical expressions for each network layer.

Considering the disadvantages mention above, one may face with suboptimal performances, even for a suitable neural fuzzy network topology. Hence, techniques capable of training the system parameters and finding a global solution while optimizing the overall structure are needed. In that respect, evolutionary algorithms appear to be better candidates than backpropagation algorithm.

Several evolutionary algorithms, such as genetic algorithm (GA) (Goldberg, 1989), genetic programming (Koza, 1992), evolutionary programming (Fogel, 1994), and evolution strategies (Rechenberg, 1994), have been proposed. They are parallel and global search techniques. Because they simultaneously evaluate many points in the search space, they are more likely to converge toward the global solution. For this reason, an evolutionary method using for training the fuzzy model has become an important field.

The evolutionary fuzzy model generates a fuzzy system automatically by incorporating evolutionary learning procedures (Bandyopadhyay, Murthy, & Pal, 2000; Belarbi & Titel, 2000; Carse, Fogarty, & Munro, 1996; Homaifar & McCormick, 1995; Juang, 2004; Karr, 1991; Lee & Takagi, 1993; Tang, 1996; Yi-Ta Wu, Yoo Jung An, Geller, & Yih-Tyng Wu, 2006), where the well-known

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procedure is the genetic algorithms (GAs). Several genetic fuzzy models, that is, fuzzy models augment by a learning process based on GAs, have been proposed (Belarbi & Titel, 2000; Homaifar & McCormick, 1995; Juang, 2004; Lee & Takagi, 1993; Karr, 1991; Tang, 1996). Karr (1991) applied GAs to the design of the membership functions of a fuzzy controller, with the fuzzy rule set assigned in advance. Since the membership functions and rule sets are co-dependent, simultaneous design of these two approaches will be a more appropriate methodology. Based on this concept, many researchers have applied GAs to optimize both the parameters of the membership functions and the rule sets (Belarbi & Titel, 2000; Lee & Takagi, 1993; Juang, 2004; Lee & Takagi, 1993). Tang proposed a hierarchical genetic algorithm (HGA) (Tang, 1996). Carse et al.used the genetic algorithm to evolve fuzzy rule based controllers (Carse et al., 1996). The hierarchical genetic algorithm enables the optimization of the fuzzy system design for a particular application. Bandyopadhyay et al. used the variable-length genetic algorithm (VGA) that let the different lengths of the chromosomes in the population (Bandyopadhyay et al., 2000). Wu et al. proposed a data mining based GA algorithm to efficiently improve the Traditional GA by using analyzing support and confidence parameters (Wu et al., 2006).

However, these approaches encounter one or more of the following major problems: (1) all the fuzzy rules are encoded into one chromosome and (2) the population cannot evaluate each fuzzy rule locally.

Recently, Gomez and Schmidhuber proposed lots of work to solve above problems (Gomez, 2003, 2005). The proposed enforced sub-populations (ESP) used sub-populations of neurons for the fitness evaluation and overall control. As shown in Gomez's and Schmidhuber's work, the sub-populations that use to evaluate the solution locally can obtain better performance compared to systems of only one population is used to evaluate the solution.

Same with ESP, in this paper, a TSK-type neuro-fuzzy system with multi groups cooperation based symbiotic evolution (TNFS-MGCSE) is proposed for solving the problems that mention above. In TNFS-MGCSE, each chromosome represents only one fuzzy rule and an n-rules fuzzy system is constructed by selecting and combining n chromosomes from several groups. The TNFS-MGCSE is developed from symbiotic evolution. The symbiotic evolution is different from traditional GAs (genetic algorithms) that each chromosome in symbiotic evolution represents a rule of fuzzy model. In TNFS-MGCSE, compared with normal symbiotic evolution, there are several groups in the population. Each group formed by a set of chromosomes represents a fuzzy rule. Compare with the ESP, for allowing the well-performing groups of individuals cooperate to generate better generation, a cooperation based crossover strategy (CCS) is proposed in this paper. In CCS, each group will cooperate to perform the crossover steps. Therefore, the better chromosomes of each group will be selected to perform crossover in the next generation. The TNFS-MGCSE promotes both cooperation and specialization, ensures diversity and prevents a population from converging to suboptimal solutions.

The advantages of the proposed TNFS-MGCSE are summarized as follows: (1) the TNFS-MGCSE uses multi groups in a population to evaluate the fuzzy rule locally. (2) The TNFS-MGCSE uses CCS to let the better solutions form different groups can cooperate with each other for generating better solutions. (3) It indeed can obtain better performance and converge more quickly than some traditional genetic methods.

This paper is organized as follows. The TSK-type neuro-fuzzy system (TNFS) is introduced in Section 2. The group cooperation based symbiotic evolution (GCSE) is described in Section 3. The simulation results are presented in Section 4. The conclusions are summarized in the last section.

2. Structure of TSK-type neuro-fuzzy system (TNFS)

A TSK-type neuro-fuzzy system (TNFS) (Lin & Lee, 1996) employs different implication and aggregation methods from a standard Mamdani fuzzy system. Instead of using fuzzy sets, the conclusion part of a rule is a linear combination of the crisp inputs.

$$\textbf{\textit{IF }} x_1 \textbf{\textit{ is }} A_{1j}(m_{1j},\sigma_{1j}) \textbf{\textit{ and }} x_2 \textbf{\textit{ is }} A_{2j}(m_{2j},\ \sigma_{2j})\ldots \textbf{\textit{ and }} x_n \textbf{\textit{ is }} A_{nj}(m_{nj},\sigma_{nj}) \\ \textbf{\textit{THEN }} y' = w_{0j} + w_{1j}x_1 + \cdots + w_{nj}x_n \tag{1}$$

The structure of a TNFS is shown in Fig. 1, where n and R are the number of input dimensions and the number of rules, respectively. It is a five-layer network structure. In the proposed TNFS, the firing strength of a fuzzy rule is calculated by performing the following "AND" operation on the truth values of each variable to its corresponding fuzzy sets by:

$$u_{ij}^{(3)} = \prod_{i=1}^{n} \exp\left(-\frac{\left[u_i^{(1)} - m_{ij}\right]^2}{\sigma_{ij}^2}\right) \tag{2}$$

where $u_i^{(1)} = x_i$ and $u_{ij}^{(3)}$ are the output of 1th and 3th layers ; m_{ij} and σ_{ij} are the center and the width of the Gaussian membership function of the jth term of the ith input variable x_i, respectively.

The output of a fuzzy system is computed by:

$$y = u^{(5)} = \frac{\sum_{j=1}^{R} u_j^{(4)}}{\sum_{j=1}^{R} u_j^{(3)}} = \frac{\sum_{j=1}^{R} u_j^{(3)}(w_{0j} + \sum_{i=1}^{n} w_{ij}x_i)}{\sum_{j=1}^{R} u_j^{(3)}} \tag{3}$$

where $u^{(5)}$ is the output of 5th layer ; w_{ij} is the weighting value with ith dimension and jth rule node; M is the number of fuzzy rule.

3. Multi groups cooperation based symbiotic evolution

The proposed multi groups cooperation based symbiotic evolution (MGCSE) will be introduced in this section. The MGCSE is proposed for improving the symbiotic GA (Moriarty & Miikkulainen, 1996). In the proposed MGCSE, the algorithm is developed from symbiotic evolution. The idea of symbiotic evolution was first proposed in an implicit fitness-sharing algorithm that is used in an immune system model (Moriarty & Miikkulainen, 1996). The authors developed artificial antibodies to identify artificial antigens. Because each antibody can match only one antigen, a different population of antibodies is required to effectively defend against a variety of antigens. As shown in symbiotic evolution, partial solutions can be characterized as *specializations*. The specialization property ensures diversity, which prevents a population from converging to suboptimal solutions. A single partial solution cannot "take over" a population since there must be other specializations present. Unlike the standard evolutionary approach, which always causes a given population to converge, hopefully at the global optimum, but often at a local one, the symbiotic evolution find solutions in different, unconverted populations (Juang, Lin, & Lin, 2000; Moriarty & Miikkulainen, 1996). In MGCSE, compared with normal symbiotic evolution, there are several groups in the population. Each group formed by a set of chromosomes represents a fuzzy rule.

In MGCSE, each group represents a set of chromosomes that belong to a fuzzy rule. The structure of the chromosome in MGCSE is shown in Fig. 2.

In MGCSE, the coding structure of the chromosomes must be suitable for the concept of each chromosome represents only one fuzzy rule. A fuzzy rule with the form introduced in Eq. (1) is described in Fig. 3. As shown in this figure m_{ij} and σ_{ij} represent a Gaussian membership function with mean and deviation with ith dimension and jth rule node. The coding type of MGCSE is real-value code.