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Linguistic fuzzy model identification based on PSO with different length of particles

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ABSTRACT

To generate the structure and parameters of fuzzy rule base automatically, a particle swarm optimization algorithm with different length of particles (DLPPSO) is proposed in the paper. The main finding of the proposed approach is that the structure and parameters of a fuzzy rule base can be generated automatically by the proposed PSO. In this method, the best fitness (f_{gbest}) and the number (N_{gbest}) of active rules of the best particle in current generation, the best fitness (f_{pbesti}) which ith particle has achieved so far and the number (N_{pbesti}) of active rules of it when the best position emerged are utilized to determine the active rules of ith particle in each generation. To increase the diversity of structure, mutation operator is used to change the number of active rules for particles. Compared with some other PSOs with different length of particles, the algorithm has good adaptive performance. To indicate the effectiveness of the give algorithm, a nonlinear function and two time series are used in the simulation experiments. Simulation results demonstrate that the proposed method can approximate the nonlinear function and forecast the time series efficiently.

1. Introduction

Fuzzy set theory has been successfully applied in many different areas of engineering including, but not limited to, nonlinear system modeling [1], control [2,3] and image processing [4]. A major difficulty in finding an appropriate fuzzy rule base for a given task is often encountered in practice. A trial and error method is widely used in most cases but with a heavy computational burden and low efficiency, especially when there is no adequate prior assumption. Therefore, more attention has been paid to build a suitable fuzzy rule base automatically for a given task. *C*-Means clustering and searching tree methods were applied to identify the structure [5], and the complex method was used to identify the parameters of a fuzzy rule base. All samples should be used to determine centers of clusters in this algorithm and tree searching might lead to heavy computation cost. The pairwise learning approach and preference relations are used to deal with multi-class classification for linguistic fuzzy rule based classification systems, the effectiveness of this method is indicated by testing of some classification problems [6]. A spectral analysis method for fuzzy rule-based systems that performs data modeling consistently according to the symbolic relations expressed by the rules is introduced to improve the interpretability of the rules and the model's accuracy [7]. Fuzzy clustering technique and some approximate similarity measures are introduced to improve the accuracy of fuzzy model [8], the performance of TSK model is improved by it. Support vector machine is utilized to learn fuzzy rule-based classification systems [9]. With the development of evolutionary computation, Genetic algorithms (GAs) play a very important role in optimizing parameters of fuzzy rule base with the pre-defined structure. GA was adopted to identify the parameters of fuzzy rules under condition that the structure of the fuzzy rule base is predefined by *C*-means clustering algorithm [10]. GA was used to design membership functions and rule sets of fuzzy logic controllers with fuzzy domain specified in advance [11]. *C*-Means clustering algorithm with hierarchical clustering method was employed to determine the number of rules [12]. In the first stage, all samples are used to design the centers of clusters, and the total number of clusters was reduced by the hierarchical clustering method in the second stage. GAs are very useful for optimizing the parameters of a fuzzy rule base, for the crossover of the two fuzzy rule bases with different structures is very difficult, the best result of them based on the predefined structure of the fuzzy rule base [10]. To optimize the structure and parameters of fuzzy rule base simultaneously, an interactive genetic algorithm was introduced by Onisawa and Fujihara [13]. An individual is represented by a set of chromosomes and each chromosome represents a fuzzy rule. The crossover operator might occur between two chromosomes with different structures, the essential of crossover in this method

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is mutation because the genes for crossover operator are nonallelic. The efficiency of GA might be decreased in this method because the performance of GA mainly depends on the crossover operator of alleles. To avoid the difficulty in crossover operator of two chromosomes with different structures, some other methods without crossover operator are introduced to optimize fuzzy rule base. Evolutionary programming (EP) has been introduced to design an optimal fuzzy rule base [14]. Mutation is the unique genetic reinsertion operator for individuals. Some efficient results are acquired, but there are many parameters, such as two mutation probabilities α_s and α_p for structure and parameters, which are difficult to be selected. Moreover, the q tournament selection is a time dissipative operator. A systematic fuzzy modeling mechanism, without any pre-assumption about the structure of the data, which is capable of generating a fuzzy rule base automatically from numerical data and presenting a good tradeoff between the complexity and the accuracy of the model, is introduced in [15], the approach has successfully been applied to well-known benchmark datasets and real-world problems. Based on the 2-tuples linguistic representation model, a multi-objective evolutionary approach to quickly learn the associated rule base and generate a set of linguistic fuzzy-rule based systems with different tradeoffs between accuracy and interpretability in regression problems is presented in [16,17]. A decision tree method is used to extract fuzzy rules from the output of the system [18]. The bacterial evolutionary algorithm combined with Levenberg–Marquardt method is used to extract fuzzy rule base from training set was presented in [19,20].

Particle swarm optimization is a population-based heuristic search technique, each particle represents a potential solution within the searching space. PSO was first introduced by Eberhart and Kennedy in 1995 [21] and the convergence of it was studied by van den Bergh and Engelbrecht [22]. The same as other evolutionary computation methods, PSO also can be applied to optimize parameters of fuzzy rule base with the predefined or fixed structure [23–25]. Based on maximum entropy principle (MEP), PSO is utilized to optimize the centers of clusters under condition that the number of fuzzy rules has been predefined [26]. In this method, the centers of clusters are initialized randomly, then the memberships of all rules are determined by MEP, and PSO is used to modify the centers. Multi-strategy ensemble method with PSO is used for dynamic optimization [27]. The swarm in this method is divided into two parts, Gaussian local search and differential mutation are introduced into these two parts, the convergence ability of PSO is enhanced and the local convergence of the swarm is avoided. Ant and particle swarm cooperative optimization (OSAC) is designed to generate rules from on-line training data when the structure of fuzzy rule base is predefined by an on-line clustering method, the highly overlapping fuzzy sets are avoided [28]. Combined with fuzzy C-mean (FCM) clustering and recursive least-squares, a hybrid stages particle swarm optimization (HSPSO) learning method is introduced to generate evolutional fuzzy modeling systems to approach nonlinear functions [29]. In these methods, the length of genes for all particles is the same for the subtraction operators are difficult to be realized when particles with different structure. To automatically generate RBF neural network with PSO, MAX and MIN methods were introduced to optimize the structure and parameters of RBF neural network simultaneously [30]. The results indicated that the MAX method has higher convergence speed and accuracy than MIN method. The good performance of PSO is derived by choosing a special fitness function.

As previously reviewed, there are many works focus on optimizing parameters of fuzzy rule base with PSO under condition that the structure of it is predefined or assumed, all particles in these methods have the same length to satisfy the renewal equations of PSO algorithm. Clustering method is very efficient in determining the structure of fuzzy rule base, but all samples of the system are almost needed to reach high accuracy, the algorithm might involve heavy computation cost. Compared with fix structure of PSO algorithm, there are fewer PSO algorithms on determining the structure and parameters of the fuzzy rule base simultaneously with different lengths of particles. The MAX and MIN methods are the representative ones which using different lengths particles to optimize the structure and parameters of radial basis function neural networks (RBFNs) automatically. In MAX method, the maximum from the number list, which is composed by the random generated number of cells, is initially selected as the active number of cells for all particles, the length of all particles in same generation equals to the maximum. In next generation, the number list will renewed randomly between the minimum and maximum number of radial basis functions, the same procedure as the initial generation is used to determine the active number of cells for all particles till the algorithm is ended. It is obviously that the active number for some particles is redundant, and the convergence speed of algorithm might be slowed. In MIN method, the minimum from the number list which is formed as in MAX method is selected as the active number for all particles, and the number list is also renewed randomly in different generation. In this method, the information for some particles is insufficient because the minimum from the number list is selected. Moreover, the adaptive performance of these methods is not good because the active number of particles is fixed in same generation. To optimize the structure and parameters of fuzzy rule base, PSO should be modified because the fixed structure of particles cannot realize the task, and the adaptive performance of current PSO with different length of particles is insufficient. When we want to realize PSO with different length particles and sufficient adaptive performance for designing the structure and parameters of fuzzy rule base automatically, all particles in the same generation should have different length according to the current environment.

In this paper, a particle swarm optimization algorithm with different length of particles is proposed to generate fuzzy rule base automatically. In the method, if a particle wants to renew it's position, the number of active rules of it is determined by the four factors, the number of active rules and the fitness value of the best particle in current generation, the number of active rules and the fitness value of this particle when the best position of it has emerged so far. An adaptive mutation method is adopted to determine the number of rules of the fuzzy rule base [14]. In this way, the proposed algorithm has good adaptive performance. To show the effectiveness of the given method, three nonlinear systems are simulated in the paper.

The rest of the paper is organized as follows. The representation of fuzzy rule base and approximate reasoning are described in Section 2. Standard particle swarm optimization algorithm is introduced in Section 3. The PSO with different length of particles (DLPPSO) for designing fuzzy rule base is presented in Section 4. In Section 5, some simulation experiments are illustrated to show the effectiveness of the improved algorithm. Some conclusions are described in Section 6.

2. The representation of fuzzy rule base and approximate reasoning

2.1. The representation of fuzzy rule base

In general, the structure of a linguistic fuzzy rule base is determined by the number of rules and the relative importance of input fuzzy variables for the rules, and it can be represented by a connection matrix whose size is determined by the number of fuzzy rules and input variables. For a system with i rules and j input variables, the size of the connection matrix for the structure of the linguistic