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Self-generated fuzzy systems design using artificial bee colony optimization

Hacene Habbi [a,*], Yassine Boudouaoui [a], Dervis Karaboga [b], Celal Ozturk [b]

[a] Applied Automation Laboratory, University of Boumerdès, 35000 Boumerdès, Algeria
[b] Erciyes University, Engineering Faculty, Computer Engineering Department, TR-38039 Kayseri, Turkey

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ABSTRACT

In this paper, artificial bee colony (ABC) optimization based methodology is proposed for automatically extracting Takagi–Sugeno (TS) fuzzy systems with enhanced performance from data. The design procedure aims to find the structures and the parameters of the TS fuzzy systems simultaneously without knowing the rule number as a priori. In the proposed method, a fuzzy system is encoded into a food source with appropriate string representation so that the TS model is entirely specified. The encoded premise and consequent parameters of the fuzzy model evolve together through artificial bee colony optimization strategy simulating the global foraging behavior of honey bee swarm so that good solutions can be achieved. Simulations on benchmark modeling and tracking control problems are performed and compared with other existing methods. The experimental results indicate that the proposed ABC optimization based fuzzy systems design algorithms can successfully find accurate fuzzy models with appropriate number of rules. Moreover, the proposed approach outperforms the compared methods and can provide considerable improvements in tackling complex modeling and tracking control problems.

1. Introduction

Fuzzy rule-based systems have been extensively studied and applied to many engineering fields, including system identification [11,13,9], automatic control [27,7], fault detection and diagnosis [10], clustering and recognition [1], etc. Process modeling based on fuzzy reasoning provided an attractive solution to many engineering problems. Developing a fuzzy model for a given physical process does not only contribute to the better characterization of its dynamic behavior, but also it can serve as a basement for the design of efficient and robust control and monitoring strategies. On this particular issue, Habbi et al. [11] demonstrated interesting experimental results dealing with fuzzy modeling of distributed dynamics of a pilot heat exchanger process. Later on, the proposed fuzzy model has been successfully used for leak, sensor and actuator faults detection and diagnosis in the exchanger process [10,12]. It is important to notice that the experimental results presented in the above-mentioned works were obtained based on the so-called "data-driven" fuzzy modeling approach. This paradigm represents an interesting alternative to most general and classical design methods that use experts' knowledge which is not always easy to acquire and sometimes becomes impossible to obtain. This may primarily explain why building fuzzy systems automatically from numerical data is still devoting special attention with an increasing number of applications.

* Corresponding author.
E-mail address: habbi_hacene@hotmail.com (H. Habbi).

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Among many types of fuzzy systems, the Takagi–Sugeno (TS) type model attracted particular attention. As a universal approximator [3], it consists of IF–THEN fuzzy rules with linguistic antecedents and functional consequent parts. Extracting TS fuzzy models from measurements can be achieved through consecutive structure and parameter identification. The design procedure can be formulated as a nonlinear optimization problem which can be solved using clustering algorithms [30,9], partition-based methods [1], least squares and nonlinear optimization for model parameters tuning [7]. Equivalently, construction of fuzzy models can be regarded as a search problem in multidimensional space where each point corresponds to a potential fuzzy model. Obviously, the attempt is to find an optimal or near optimal location on the search space according to specific performance criteria and predefined constraints. To this end, evolutionary algorithms and swarm intelligence based techniques have been extensively investigated in recent literatures [8,31]. Swarm intelligent algorithms have been shown to outperform other algorithms in tackling the fuzzy modeling problems. Particle swarm optimization (PSO) is used in [39] to automatically extract TS fuzzy models based on a cooperative learning mechanism. Learning fuzzy system structure and parameters by clustering-aided ant colony optimization (ACO) is presented in [14]. Artificial immune system (AIS), inspired by the human immune system, is used to develop a learning algorithm for TS-type fuzzy systems in [29]. Hybridized swarm based algorithms have been also considered in recent literatures to solve the problem of automatic generation of fuzzy rule-based systems [15].

Another well-established swarm intelligent model is the artificial bee colony optimization (ABC), which was originally introduced by Karaboga based on the foraging behavior of honey bees for numerical optimization problems [16]. The ABC algorithm has been successfully applied to complex optimization problems [17,21,20] and compared with many advanced methods, such as genetic algorithms (GA), differential evolution (DE), and evolutionary programming (EP) and other swarm intelligent algorithms. However, it must be noticed that there is a few research on using ABC algorithm for automatic generation of fuzzy systems. The recent survey by Karaboga et al. [19] on the advances with ABC and applications showed only two reference links to this particular subject. We can cite, for instance, the work presented by Su et al. [33] on a novel ABC-based fuzzy c-means clustering approach to generate TS fuzzy model from numerical data. The structure and the parameters of the fuzzy model being developed by Su and co-workers were determined on different stages by means of fuzzy c-means clustering and least squares. A novel approach which finds the structure and the parameters of fuzzy systems simultaneously is presented in this paper. The present work describes a new method for automatic rule generation for fuzzy systems which is different from the study of Su et al. or other ABC based systems learning methods. According to the adopted encoding scheme, antecedent and consequent parameters of the fuzzy system evolve together through ABC optimization so that good solutions can be achieved.

Briefly, the paper is organized as follows. Section 2 introduces the basic ABC and the Gbest-guided ABC (GABC) optimization algorithms. In Section 3, the ABC-based methodology for data-driven fuzzy systems design is presented. Section 4 shows experiments on benchmark fuzzy modeling and fuzzy control problems, where the results are compared with other advanced optimization algorithms. Performance analysis of the proposed methodology is provided in Section 5. Concluding remarks are given in Section 6.

2. Artificial bee colony optimization

Artificial bee colony (ABC) optimization is a swarm intelligence based algorithm which simulates the foraging behavior of honey bees. An increasing number of modified and improved versions were described in recent literatures, such as Gbest-guided ABC [40], binary version of ABC called DisABC [22], differential ABC [32], interactive ABC [35], and cooperative ABC [41].

In ABC model, foraging honey bees are categorized into three main groups: employed bees, onlooker bees and scout bees. Based on two essential leading modes of the forages which are recruitment to a food source and abandonment of a source, the process of bees seeking for sources with high amount of nectar is the one applied to find the optimal solution for a given optimization problem. The general algorithmic structure of ABC corresponds to a three-phase framework: employed bee phase, onlooker phase and scout phase. The bee colony is equally partitioned into employed bees and onlooker bees. The number of employed bees is equal to the number of food sources. The employed bees exploit their food sources and share the nectar and the position information of these sources with the onlooker bees. Based on the information gathered, the onlooker bees will choose food sources with high profitability. The employed bee whose food source has been abandoned by the bees becomes a scout bee. In ABC algorithm, the position of a food source represents a possible solution to the optimization problem and the nectar amount of the food source corresponds to the fitness of the associated solution.

Let $x_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]$, $i = 1, 2, \ldots, SN$, denotes the ith food source in the population, where SN is the size of population and D is the number of optimization parameters. The initial population of SN solutions is generated randomly according to the following equation:

$$x_{ij} = x_j^{\min} + rand(0,1) \cdot (x_j^{\max} - x_j^{\min}) \tag{1}$$

where $x_j^{\min}$ and $x_j^{\max}$ are the lower and upper bounds of the jth parameters of the solution i.

After sending employed bees to the food source sites, an employed bee produces a modification on the position of the food source in her memory and finds a neighboring food source as follow:

$$v_{ij} = x_{ij} + \phi_{ij} \cdot (x_{ij} - x_{kj}) \tag{2}$$