A Genetic Fuzzy System with Inconsistent Rule Removal and Decision Tree Initialization

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Abstract. This paper presents a genetic fuzzy system for identification of Pareto-optimal Mamdani fuzzy models (FMs) for function estimation problems. The method simultaneously optimizes the parameters of fuzzy sets and selects rules and rule conditions. Selection of rules and rule conditions does not rely only on genetic operators, but it is aided by heuristic rule and rule conditions removal. Instead of initializing the population by commonly used Wang-Mendel algorithm, we propose a modification to decision tree initialization. Experimental results reveal that our FMs are more accurate and consist of less rules and rule conditions than the FMs obtained by two recently published genetic fuzzy systems [2, 3].

1 Introduction

One reason for the popularity of fuzzy models (FMs) is that they can be transparent if identified adequately. Recent trend has been the application of multiobjective evolutionary algorithms (MOEAs) to find FMs presenting trade-off between accuracy and interpretability criteria (see for example [2, 3, 11, 14, 16]). Those methods are also called genetic fuzzy systems (GFS) [4]. It was stated in [2] that most of MOEA based methods in literature consider only classification problems, that is, the output belongs to a set of pre-specified labels. Only few have covered function estimation problems, that is, the value of output is continuous (see for example

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Some of these \cite{14,16}, however, applied Takagi-Sugeno (TS) FM, which may be harder to interpret than Mamdani FM due to linear function in its consequent part.

In \cite{2,3} MOEAs were applied to find a Pareto-optimal set of Mamdani FMs. In \cite{2}, the number of rules and parameters of fuzzy sets were optimized by MOEA, but the rule conditions were kept fixed. Thus, optimal rules can not be found. In \cite{3}, the number of rules and rule conditions were optimized by MOEA, however, the parameters of fuzzy sets were fixed and pre-specified. Therefore, fuzzy partitions may not present the real distribution of data and the accuracy of FMs is deteriorated \cite{7}. On the other hand, it was pointed out in \cite{8} that if the fuzzy partitions of each variable are available by a priori knowledge, modification of them can impair the interpretability of FMs.

When function estimation problems are considered, the initial population is usually obtained randomly or by Wang and Mendel (WM) method \cite{15}. Naturally random initialization does not guarantee a good starting point for further optimization. WM method also has several drawbacks. First, it leads to high number of rules when high dimensional problems are considered. Second, it requires that the each variable is partitioned with fuzzy sets a priori. Third, it uses all available variables in all rules, thus leading to unnecessary complexity of the rule base.

DT based initialization algorithm was introduced in \cite{1}. Because it can automatically select the relevant variables and partition the input space, it makes it a desirable initialization algorithm. In \cite{1} it was applied to classification problems and here we modify it to suit for function estimation problems.

The further optimization is performed by MOEA, which selects the adequate rules and rule conditions and optimizes the parameters of fuzzy sets. Rule selection is not solely based on genetic operators but aided by heuristic removal of inconsistent rules and rule conditions. Our method is validated by identifying FMs for four well known problems and comparing our results to other MOEA based approaches \cite{2,3}. Our results show that our method obtains more compact and accurate FMs than in the comparative studies.

This paper is organized as follows. First, Mamdani FMs are defined. Then, in section \ref{section:identification} our identification method is introduced. After that, in section \ref{section:results} the results comparison is performed. Finally, conclusions are given in section \ref{section:conclusions}.

2 Mamdani Fuzzy Models

Let the dataset with \( D \) data points and \( n \) input variables be denoted as \( \mathbf{Z} = [\mathbf{X} \, \mathbf{y}] \), where \( \mathbf{X} \) is \( D \times n \) input matrix and \( \mathbf{y} \) is \( D \times 1 \) output vector. Mamdani fuzzy rules are denoted as:

\[
R_i : \text{If } x_1 \text{ is } A_{i,1} \ldots \text{ and } x_n \text{ is } A_{i,n} \text{ then } B_i,
\]

where \( A_{i,j}, \ j = 1, \ldots, n, i = 1, \ldots, R \), is an input membership function (MF), \( B_i \) is an output MF, and \( R \) is the number of rules. In order to reduce the computational costs, the output of FMs is computed here by approximation of centroid method \cite{17,3}: