An Improvement in Sugeno-Yasukawa Modeler

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Abstract

Structure identification is one of the most significant steps in Fuzzy modeling of a complex system. Efficient structure identification requires good approximation of the effective input data. Misclassification of effective input data can highly degrade the efficiency of the inference of the fuzzy model. In this paper we present a modification to Sugeno-Yasukawa modeler to improve structure identification by increasing the accuracy of effective input data detection. There exist some intermediate models in the Sugeno-Yasukawa modeling process which a combination of them will result in the final fuzzy model of the system. In the original modeling process parameter identification is only done for the final fuzzy model. By doing the parameter identification for the intermediate fuzzy models, we have highly improved the accuracy of theses intermediate models. The RC (Regularly Criterion) error has been reduced 53% for intermediate fuzzy models and 67% in the final model for the sample function in formula (3). This accuracy increase, result in a better detection of effective input data among input data records of a system.

Keywords: Fuzzy Logic, Fuzzy Modeling, Structure Identification, Parameter Identification, Black-box systems

1. Introduction

A natural life problem which mankind encounters is to find the effective input parameters for each new environment on the basis of required outputs and create a relationship between these input/output parameters to be able to react appropriately in different situation. After creating these relationships, the rules and the way input/output are parameters related to each other should be adjusted. The whole process is called modeling or identifying a model [1]. It is divided into two kinds: structure identification and parameter identification. Structure identification is of two types. The first type which is to find the effective parameters is called structure identification type I and can be separated into two steps:

- Find a restricted subset of effective parameters out of nearly infinite and unknown number of parameters.

- Find a more restricted subset of parameters out of the found parameters in the previous step.

The second type is called structure identification type II. In this type the relationships and the rules are created. Finally in parameter identification the created model parameters¹ are adjusted.

Fuzzy model was firstly introduced by Zadeh ([3], **Error! Reference source not found.**) and is a good choice to model a nearly unknown environment as human does. In this paper we have used a modified version of Sugeno-Yasukawa modeling process for identifying a fuzzy model.

In section two of this paper, the fuzzy modeling concept for black box system will be discussed. Afterwards, the modified version of Sugeno-Yasukawa modeling process will be explained in section three. Finally in the last part of the paper the result of the modifications in the original modeling process and the benefits of using this modified version of modeling process will be presented.

2. Sugeno-Yasukawa Fuzzy modeling of a black-box system

The concept of fuzzy modeling of a black box system, based on Sugeno-Yasukawa modeling process, will be explained briefly in this section. A system, which the knowledge about it is restricted to a number of sampled input-output data, is called a black box system. These data reflect the system behavior. A Fuzzy modeler tries to detect a subset of input data which is engaged in producing the output data. This subset is called the effective input data. Fuzzy modeling of a block box system detects the effective input data by introducing intermediate models. We called the pre-final fuzzy rule-bases the intermediate models. Each of these intermediate models could be a combination of both effective and none effective input data. The error amount of these intermediate models is a way to determine which of them were more effective in generating the output data. By sequential combining more effective intermediate models the

¹ This should be recalled here that model parameters are not the input/output parameters. For example in a fuzzy model the parameters which are defining the membership functions in each rule are the model parameters. Meanwhile in this model there exists some input and output parameters for each of the rules as well.

final fuzzy model of the system would be achieved. This final model is a rule base showing the most accurate relationship between effective inputs and the output data. In this paper, as it will be explain in more details in section 3, we improved the accuracy of intermediate models in order to improve the detection of effective input data.

3. Modified Sugeno-Yasukawa Fuzzy Modeling Method

Original and modified Sugeno-Yasukawa Fuzzy Modeling Method [1] will be explained in this section. The original modeling fuzzy method has some restriction in recognizing effective parameters when the number of initial black box system parameters is large. We have modified the modeling process steps so that identifying effective input parameters among a larger number of probable effective input parameters would be possible.

The first step of the modeling process is clustering training data set on the basis of output parameter y . This step in our method is the same as the original method. The optimal number of clusters is calculated on the basis of Sc criterion[6]:

$$(1) \quad S(c) = \sum_{k=1}^n \sum_{i=1}^c (\mu_{ik})^m (\|x_k - v_i\|^2 - \|v_i - \bar{x}\|^2)$$

Where:

- n : number data to be clustered;
- c : number of clusters, $c \geq 2$;
- x_k : k -th data, usually vector;
- $\bar{x}$: average of data $x_1, x_2, \dots, x_n$;
- $\|\cdot\|$: norm;
- μ_{ik} : grade of k -th data belonging to i -th cluster
- m : adjustable weight (usually $m = 1.5 \sim 3$)

In process of finding optimal number of clusters, the FCM² [2] algorithm is running for output data to cluster them into two clusters. The Sc criterion is calculated for the resulting clusters. This division goes on until a first local minimum is achieved. As a result the optimal number of clusters is assumed equal to this local minimum. For example, the optimal number of clusters for a sample data is six as it is illustrated in Figure-1.

Figure-1: The optimum number of clusters for sample data

Cluster numbers represents the number of rules in the final rule-base. As a result of FCM each of output data will have its own membership degree. Number of membership value is equal to number of clusters for each of the output data. Each of membership values explains the belief of its membership to each of the clusters.

Our main modification is in the process of the recognizing the effective parameters of the black-box system (Structure Identification Type I). In the original process there is only one parameter identification phase for the final detected parameters. But in our method in each of the phases in detecting effective parameters we run the parameter adjustment phase for the membership function of the input and output parameter(s). Afterwards the RC^3 criterion is calculated on the basis of the following formula[5]:

$$(2) \quad RC = \left[\sum_{i=1}^{k_A} (y_i^A - y_i^{AB})^2 / k_A + \sum_{i=1}^{k_B} (y_i^B - y_i^{BA})^2 / k_B \right] / 2.$$

Where:

- k_A and k_B : the number of data of the groups A and B;
- y_i^A and y_i^B : the output data of the groups A and B;
- y_i^{AB} : the model output for the group A input estimated by model identification using the group B data;
- y_i^{BA} : the model output for the group B input estimated by model identification using the group A data;

In the Parameter Identification phase the value of system model parameters are determined. We use the same parameter identification algorithm for our intermediate models as for the final model. The parameter identification algorithm is as follows[1]:

² Fuzzy C-Means Clustering

³ Regulatory Criterion

- 1) Set the value f of adjustment
(f is a constraint for adjusting parameters)
- 2) Assume that the k 'th parameter of the j 'th fuzzy set is p_j^k .
- 3) Calculate $p_j^k + f$ and $p_j^k - f$. If $k = 2, 3, 4$, and $p_j^k - f$ is smaller than p_j^{k-1} , then $\hat{p}_j^k = p_j^{k-1}$; else $\hat{p}_j^k = p_j^k - f$. Also if $k = 1, 2, 3$ and $p_j^k + f$ is bigger than p_j^{k+1} , then $\hat{p}_j^k = p_j^{k+1}$; else $\hat{p}_j^k = p_j^k + f$
- 4) Choose the parameter which shows the best performance PI in formula (1) among $\{p_j^k, \hat{p}_j^k, \hat{p}_j^k\}$ and replace p_j^k with it.
- 5) Go to step 2 while unadjusted parameters exist.
- 6) Repeat step 2 until we are satisfied with the result.

By applying this algorithm on the intermediate models their membership function parameters would be adjusted. This result in lower RC values in both effective and none effective input data intermediate models.

As it could be seen in Table 1 that RC values have decreased in comparison with the RC values in [1] by using the modified modeling method for the following sample function:

$$(3) \quad y = (1 + x_1^{-2} + x_2^{-1.5})^2, \quad 1 \leq x_1, x_2 \leq 5.$$

RC improvement values are calculated on the basis of the following formula:

$$(4) \quad RC \text{ improvement } (\%) = \frac{RC_{old} - RC_{new}}{RC_{old}} \times 100$$

To make it more clear how our modification improves the structure identification phase, we have divided the intermediate fuzzy models into two groups:

- The group I: fuzzy models which only include effective input parameters
- The group II: fuzzy models which include both effective and none effective input parameters

We did a comparison between the average improvements in RC values of these two groups. The average RC improvement value for the group I is equal to 58.66%, while it is equal to 46.66% for the group II. This comparison is presented in Table 2. As a result, the detection of the effective parameters will be much improved and the probability of detecting none effective parameters as effective for noisy sample data will be decreased. The refined state diagram of the modeling process is represented in Figure 3.

The resulting rule-base is represented in Figure 2.

Figure 2: Resulting fuzzy Rule-base

4. Conclusion

We have boosted the process of structure identification strongly by doing the parameter identification process for intermediate fuzzy models. This way we have decreased RC error of intermediate models for both intermediate models with only effective input parameters (The group I) and intermediate models with both effective and non-effective input parameters (The group II). What makes our modified process more accurate in detecting effective input parameters from non-effective input parameters is that RC values reduction in models of the group I is more than that of the group II. As it's shown in Table 2 this value for the group I intermediate models is 58.66% while it is 46.66% for intermediate models of the group II.

This makes our modified method very useful for cases in which number of probable effective input parameters is large. In such cases detection of real effective parameters would be harder and needs a more clarified boundary between effective and none effective input parameters. By increasing the difference between intermediate models of the group I and II the resulting fuzzy rule base will contain truly effective input parameters and will be more accurate.

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[8]

Table 1: Comparison of *RC* values in different iterations of Modeling

Modeling Iterations	Our Method	Old Method	RC Improvement	Our Method	Old Method	RC Improvement	Our Method	Old Method	RC Improvement
1	RC 1 = 0.33283	RC 1 = 0.630	47%	RC 2 = 0.33116	RC 2 = 0.863	62%	RC 3 = 0.56849	RC 3 = 0.830	32%
2	RC 2-1 = 0.147	RC 2-1 = 0.424	65%	RC 3-1 = 0.33847	RC 3-1 = 0.571	41%			
3	RC 3-2-1 = 0.15832	RC 3-2-1 = 0.483	67%						

Table 2: Comparison of *RC* improvement for the group I and II of Fuzzy Models

Fuzzy Models of the group I	RC improvement	Fuzzy Models of the group II	RC improvement
RC 1	47%	RC 3	32%
RC 2	62%	RC 3-1	41%
RC 2-1	65%	RC 3-2-1	67%
Average Improvement	58.66%	Average Improvement	46.66%

Figure 3: Modified Algorithm of fuzzy modeling