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A modification of Sugeno-Yasukawa Modeler to improve Structure Identification Phase

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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 middle 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 middle fuzzy models, we have highly improved the accuracy of theses middle models. The RC (Regularly Criterion) error has been reduced 53% for middle 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 parameters among input data records of a system. We have also used our new modeling method for a sample application and by modeling the system we have reduced input data needed for reasoning from 17 to 6. This caused a 60 % boost in the reasoning process of input data.

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 0. 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 parameters[1] are adjusted.

Fuzzy model was firstly introduced by Zadeh ([3],[4]) 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-modeling, based on Sugeno-Yasukawa modeling process, will be explained briefly in this section. A black-box

[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 rule as well.

system is called to a system, which the knowledge about it is restricted to a number of sampled input-output data. 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 middle models. We called the pre-final fuzzy rule-bases the middle models. Each of these middle models could be a combination of both effective and none effective input data. The error amount of these middle models is a way to determine which of them were more effective in generating the output data. By sequential combining more effective middle models the 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.
As an example assume a black-box system with N inputs and one output as illustrated in Figure 1 (a). This system can be modeled as a system of M effective inputs parameters and 1 output parameter. In modeling methods other than Fuzzy modelers such as Neural Networks[12] and Q-Learning([9]-[11]) the N and M are equal in black-box system and modeled system. This reduction in the number of input data is very beneficial in modeling process. A model with less input parameters needs less processing for calculating an output datum for each of its input data record. Additionally having no none effective parameters prevents the probable miscalculation of output data and increase the accuracy of the resulting model. These benefits make Sugeno-Yasukawa of fuzzy modeling a good choice especially for the black-box systems in which the determination of the effective parameter is only base on sampled input and output data.

3. Modified Sugeno-Yasukawa Fuzzy Modeling Method

Original and modified Sugeno-Yasukawa Fuzzy Modeling 0 Method 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 in a way which identifying effective input parameters among a large number of probable effective input parameters would be possible.

The first step of the modeling process which is the same in our modeling method and the original method is clustering training data set on the basis of output parameter y.

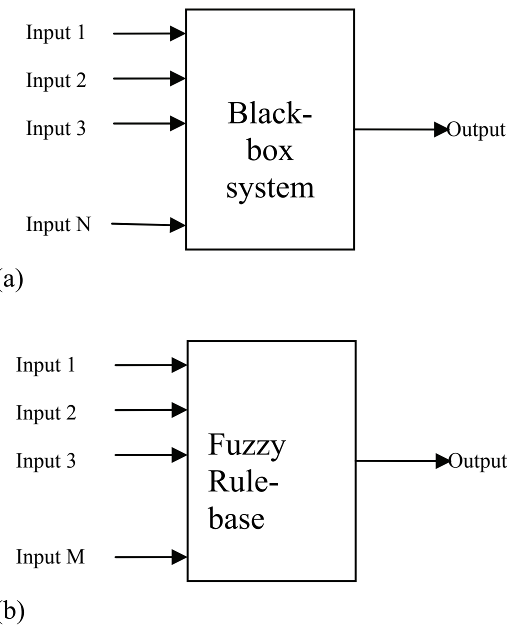

Figure 1: Fuzzy modeling of a black-box system

(a) A black-box system with N input and 1 output (b) The modeled system with M inputs and 1 output (M<=N)

The optimal number of clusters is calculated on the basis of Sc criterion[6]:

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

(2) Where:

n : $number\ data\ to\ be\ clustered;$

c : $number\ of\ clusters, c \geq 2;$

x_k : $k-th\ data, usually\ vector;$

$\bar{x}$: $average\ of\ data\ x_1, x_2, \ldots, x_n;$

$\|\cdot\|$: $norm;$

μ_{ik} : $grade\ of\ k-th\ data\ belonging\ to\ i\text{'}th\ cluster$

m : $adjustable\ weight\ (usually\ m = 1.5 \sim 3)$

In process of finding optimal number of clusters, the FCM[2] [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 2.

[2] Fuzzy C-Means Clustering

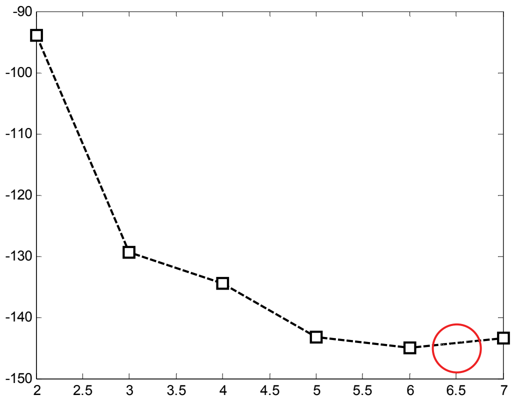

Figure 2: The optimum number of clusters for sample data

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. 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]:

$$(3)\qquad RC = \left(\sum_{i=1}^{k_A}\left(y_i^A - y_i^{AB}\right)^2 / k_A + \sum_{i=1}^{k_B}\left(y_i^B - y_i^{BA}\right)^2 / k_B\right)/2$$

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 indentification using the group B data;

y_i^{BA} : the model output for the group B input estimated by model indentification 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 middle models as for the final model. The parameter identification algorithm is as follows0:

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 $\hat{\hat{p}}_j^k = p_j^{k+1}$; else $\hat{\hat{p}}_j^k = p_j^k + f$

4) Choose the parameter which shows the best performa-nce PI in formula (1) among $\{p_j^k, \hat{p}_j^k, \hat{\hat{p}}_j^k\}$ 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 middle models their membership function parameters would be adjusted. This result in lower RC values in both effective and none effective input data middle 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:

$$(4)\qquad y = (1 + x_1^{-2} + x_2^{-1.5})^2, \quad 1 \le x_1, x_2 \le 5.$$

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

$$(5)\qquad RC\ \ improvement\,(\%) = \frac{RC_{old} - RC_{new}}{RC_{old}} \times 100$$

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

- Group I: fuzzy models which only include effective input parameters
- 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 group I is equal to 58.66% and is equal to 46.66% for group II. This comparison is presented in Table 3. 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 6. The resulting rule-base is represented in Figure 3.

[3] Regulatory Criterion

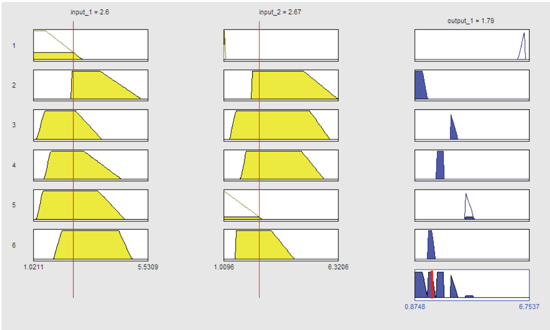

Figure 3: Resulting fuzzy Rule-base

4. Modeling the ranking of on fire building

One of the Rescue Robocup Tournaments challenges is rescue a simulated city's citizens. There are different kinds of agents in this the rescue team: Firefighter agents, Police agents and Doctor agent. The firefighter agents' duty is to rank on fire buildings in order to dump their fire. The complexity of ranking is the result of unknown parameters which cause the extension of fire in a city. In this paper we have introduced combination of human inference in first step and a modified version of Sugeno-Yasukawa modeler in second step to solve this problem. In modeling process we have generated 2426 data records using a ranking function which has 17 input parameters and 1 output which was the rank of the on-fire building. The function algorithm was created by human experience. This function was used for the first team of rescue Robocup in 2004. Feeding the modified Sugeno-Yasukawa fuzzy modeler by this training set we find only 6 effective input variables in this data set. The original Sugeno-Yasukawa fuzzy modeler was not able to come to a converged set of input parameters. Our resulting rule-base has 6 rules as its show in Figure 4.

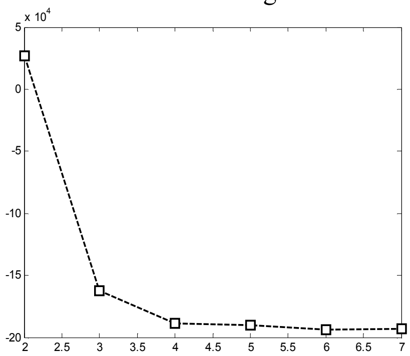

Figure 4: Rules number in fuzzy model of ranking on-fire buildings

The effective parameters are [12 13 11 3 15 8] out of 17 parameters. The process of fining these parameters is shown in Table 1. As it could be seen in Table 3 at end of this paper, in the first iteration parameter 12 is selected as effective parameter. In the second iteration parameter 13 is selected. Finally in the sixth iteration the algorithm is stopped and 5 parameters are selected. Figure 5 has illustrated a comparison between the original ranking function which has generated the ranks (the blue graph) with the resulting fuzzy rule base ranks (the green graph).

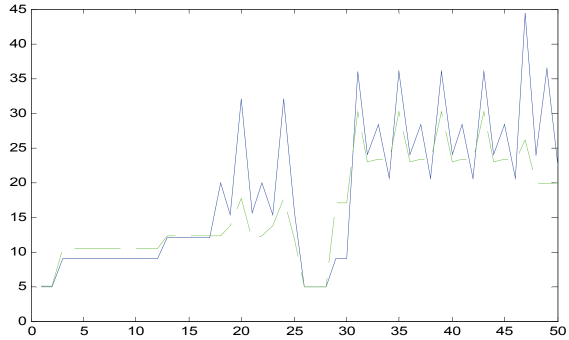

Figure 5: Comparison of original function and resulting fuzzy rule-base

5. Conclusion

We have boosted the process of structure identification strongly by doing the parameter identification phase for middle fuzzy models. As a result of this modification detecting the most effective input parameters on output data has become more accurate. This is very useful for the cases in which number of probable input parameters is large. By detecting the most effective parameters, this set will be decreased in amount and the reasoning process will be done faster. As a result, the time which is needed to calculate the result of the fuzzy model will be decreased. Our calculation of the sample application results shows that the MSE of new rule-base in comparison with original ranking function is only 10% greater while it increases the ranking process 60%. This way the firefighter agents can decide much faster to choose which of the on fire buildings and the fire can be controlled over a city.

6. References

[1] M. Sugeno, T. Yasukawa, "A Fuzzy-logic-based Approach to Qualitative Modeling", in IEEE Transactions on Fuzzy Systems, Vol. 1, No. 1, pages 7-31, February 1993.

[2] Y. Fukuyama and M. Sugeno, "A new method of choosing the number of clusters for fuzzy c-means method", in Proc. 5th Fuzzy system Symposium (in Japanese), pp. 247-250, 1989.

[3] L. A. Zadeh Towards a theory of fuzzy systems, in Aspect of Network and System Theory, R. E. Kalman and N. De Claris, Eds, New York Holt, Rinehart & Winston, 1971.

[4] L. A. Zadeh, Fuzzy sets and information granularity, in Advances in Fuzzy Set Theory and Applications, M. M. Gupra, R. K. Ragade, and R. R. Yager, Eds. Amsterdam, The Netherlands; North-Holland, pp. 3-18, 1979.
[5] J. Ihara, "Group method of data handling towards a modeling of complex systems-IV," Systems and Control (in Japanese), vol. 24, p.p .. 158-168,1980.
[6] Y. Fukuyama and M. Sugeno, "A new method of choosing the number of clusters for fuzzy c-means method," in Proc. 5th Fuzzy System Symposium (in Japanese), 1989, pp. 247-250.
[7] L.O. Chua, L. Yang, "Cellular neural networks: theory"; Circuits and Systems, IEEE Transactions on Volume 35, Issue 10, Page(s):1257 – 1272, Oct. 1988.
[8] L.O. Chua, L. Yang, "Cellular neural networks: applications"; Circuits and Systems, IEEE Transactions on Volume 35, Issue 10, Page(s):1273 - 1290, Oct. 1988.
[9] C.J.C.H. Watkins, "Learning from Delayed Rewards", PHD thesis, Kings College, Cambridge, UK, 1989.
[10] C.J.C.H Watkins, P. Dayan, "Q-earning". Machine Learning, 8(3),279-292, 1992.
[11] S. D. Whitehead, "Complexity and Cooperation Q-learning". In Proceedings of the Eighth International Workshop on Machine Learning, Evanston, IL.Morgan, Kaufmann, 1991.
[12] R. J. Williams, A Class of Gradient-estimating algorithms for reinforcement Learning in neural networks. In Proceedings of the IEEE First International Conference on Neural Networks, San Diego CA.

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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 Group I and II of Fuzzy Models

Fuzzy Models of Group I	RC improvement	Fuzzy Models of 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%

Table 3: RC values in different iteration of the algorithm

The resulted fuzzy model is to use for the decision making of the firefighter agents in the Robocup rescue team to decide which on-fire building's fire should be dumped first. Since the number of the parameters are highly decreased the decision making process will be much faster.

	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter	Parameter
	1	2	3	4	5	6	7	8	9	10	11	**12**	13	14	15	16
1	91.42	142.87	133.34	100.64	137.26	96.728	148.8	149.34	115.68	92.391	78.698	**34.623**	138.25	149.42	140.13	108.13
	12-1	12-2	12-3	12-4	12-5	12-6	12-7	12-8	12-9	12-10	12-11	**12-13**	12-14	12-15		
2	32.25	33.11	33.818	30.005	31.576	34.129	31.988	34.623	32.18	31.865	21.361	**19.086**	57.863	34.405		

...

	...-1	....-2	...-4	...-5	...-6	...-7	**...-8**	...-9	...-10	...-14	...-16
6	9.6178	22.789	12.362	11.57	8.9822	9.9538	**8.7435**	9.9442	13.201	24.031	8.9642
	...-1	....-2	...-4	...-5	...-6	...-7	...-9	...-10	...-14	**...-16**	
7	9.6178	22.789	12.362	11.57	8.9822	9.9538	9.9442	13.201	24.031	**8.9642**	

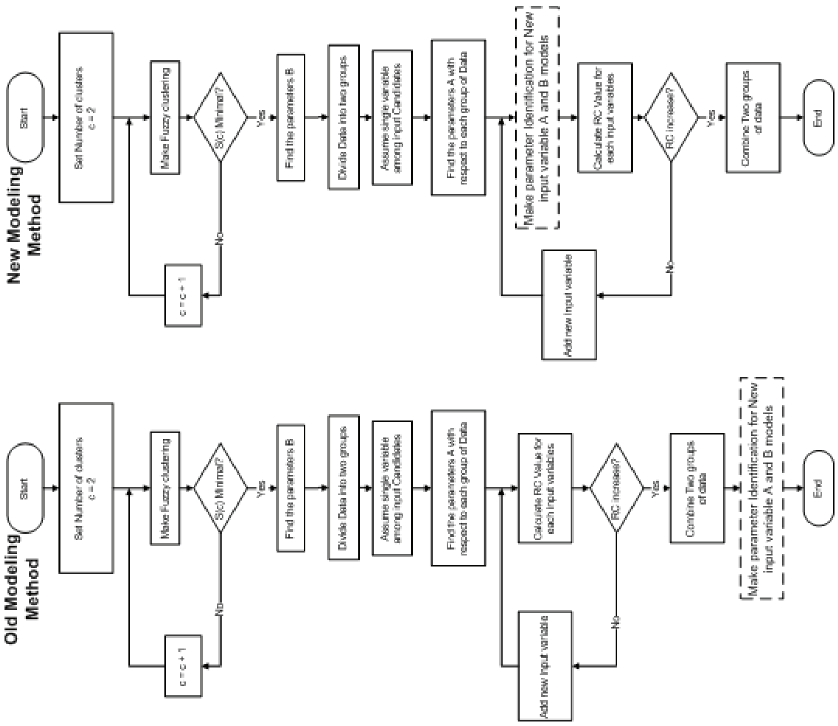

Figure 6: Modified Algorithm of fuzzy modeling