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Information Granulation-based Fuzzy Inference Systems by Means of Genetic Optimization and Polynomial Fuzzy Inference Method

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Abstract

In this study, we introduce a new category of fuzzy inference systems based on information granulation to carry out the model identification of complex and nonlinear systems. Informal speaking, information granules are viewed as linked collections of objects (data, in particular) drawn together by the criteria of proximity, similarity, or functionality. To identify the structure of fuzzy rules we use genetic algorithms (GAs). Granulation of information with the aid of Hard C-Means (HCM) clustering algorithm help determine the initial parameters of fuzzy model such as the initial apexes of the membership functions and the initial values of polynomial functions being used in the premise and consequence part of the fuzzy rules. And the initial parameters are tuned effectively with the aid of the genetic algorithms and the least square method (LSM). The proposed model is contrasted with the performance of the conventional fuzzy models in the literature.

Key Words : fuzzy inference systems, information granulation, genetic algorithms, Hard C-Means clustering, optimization

1. Introduction

There has been a diversity of approaches to fuzzy modeling. To enumerate a few representative trends, it is essential to refer to some developments that have happened over time. In the early 1980s, linguistic modeling[1,2] and fuzzy relation equation-based approach[3,4] were proposed as primordial identification methods for fuzzy models. In the linguistic approach, Tong identified a gas furnace process by means of a logical examination of data[7]. Next, C. W. Xu reported good results obtained through the modified Tongs method[8] and proposed an algorithm for an adaptive model based on decision tables. The main drawback of the method was apparent when dealing with high-order multivariable systems[5] where issues of memory requirements and computation time started to become serious stumbling blocks. Pedrycz introduced an idea of identification of fuzzy systems realized in a formal framework of fuzzy relation equations. The proposed methodology dwelled on a concept of referential fuzzy sets regarded as modeling landmarks[2]. C. W. Xu and others presented a self-learning algorithm for the simple SISO fuzzy model[5]. In the fuzzy relation equation-based approach, Pedrycz identified fuzzy systems, using the referential fuzzy set and Zadeh's conditional possibility distributions[3]. Xu constructed and identified the fuzzy relations of a model using referential fuzzy sets[5,6]. The general class of Sugeno-Takagi models[9] gave rise to more sophisticated rule-based systems where the rules come with conclusions forming local regression models. While appealing with respect to the basic topology (a modular fuzzy model composed of a series of rules)[8,10], these models still await formal solutions as far as the structure optimization of the model is concerned, say a construction of the underlying fuzzy sets-information granules being viewed as basic building blocks of any fuzzy model. Some enhancements to the model have been proposed by Oh and Pedrycz[11], yet the problem of finding "good" initial parameters of the fuzzy sets in the rules remains open.

This study concentrates on the central problem of fuzzy modeling that is a development of information granules-fuzzy sets. Taking into consideration the essence of the granulation process, we propose to cast the problem in the setting of clustering techniques and genetic algorithms. The design methodology emerges as a hybrid structural optimization and parametric optimization. Information granulation with the aid of HCM clustering help determine the initial parameters of fuzzy model such as the initial apexes of the membership functions and the initial values of polynomial function being used in the premise and consequence part of the fuzzy rules. And the initial parameters are tuned (adjusted) effectively with the aid of the genetic algorithms and the least square method. The proposed model is evaluated with using numerical example and is contrasted with the performance of conventional models in the literature

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2. Information Granulation (IG)

Informal speaking, information granules[12,13] are viewed as linked collections of objects (data point, in particular) drawn together by the criteria of proximity, similarity, or functionality. Granulation of information is an inherent and omnipresent activity of human beings carried out with intent of better understanding of the problem. In particular, granulation of information is aimed at splitting the problem into several manageable chunks. In this way, we partition this problem into a series of well-defined subproblems of a far lower computational complexity than the original one. The form of information granulation (IG) themselves becomes an important design feature of the fuzzy model, which are geared toward capturing relationships between information granules.

It is worth emphasizing that the HCM clustering has been used extensively not only to organize and categorize data, but it becomes useful in data compression and model identification. For the sake of completeness of the entire discussion, let us briefly recall the essence of the HCM algorithm[14].

[Step 1] Fix the number of clusters ($2 \le c < n$) and initialize the partition matrix $U^{(0)} \in M_c$

$$M_c = \left\{ U \mid u_{ik} \in \{0,1\},\ \sum_{i=1}^{c} u_{ik} = 1,\ 0 < \sum_{k=1}^{n} u_{ik} < n \right\} \quad (1)$$

[Step 2] Calculate the center vectors v_i of each cluster:

$$v_i^{(r)} = \{v_{i1}, v_{i2}, \cdots, v_{ij}\},\quad v_{ij} = \frac{\sum_{k=1}^{n} u_{ik} \cdot x_{kj}}{\sum_{k=1}^{n} u_{ik}} \quad (2)$$

Where, $[u_{ik}] = U^{(r)}$, $i = 1, 2, \ldots, c$, $j = 1, 2, \ldots, m$.

[Step 3] Update the partition matrix $U^{(r)}$; these modifications are based on the standard Euclidean distance function between the data points and the prototypes,

$$d_{ik} = d(x_k - v_i) = \| x_k - v_i \| = \left[\sum_{j=1}^{m} (x_{kj} - v_{ij})^2 \right]^{1/2} \quad (3)$$

$$u_{ik}^{(r+1)} = \begin{cases} 1 & d_{ik}^{(r)} = \min\{d_{jk}^{(r)}\} \text{ for } all\ j \in c \\ 0 & otherwise \end{cases} \quad (4)$$

[Step 4] Check a termination criterion. If

$$\| U^{(r+1)} - U^{(r)} \| \le \varepsilon (\text{tolerance level}) \quad (5)$$

Stop ; otherwise set $r = r+1$ and return to **[Step 2]**.

3. IG-based Fuzzy Inference Systems

The identification procedure for fuzzy models is usually split into the identification activities dealing with the premise and consequence parts of the rules. The identification completed at the premise level consists of two main steps. First, we select the input variables $x_1, x_2, \ldots, x_k$ of the rules. Second, we form fuzzy partitions (Low, High, etc.) of the spaces over which these individual variables are defined. In such a sense, this phase is all about information granulation as the elements of the fuzzy partitions we are interested in when developing any rule-based model. The number of the fuzzy sets constructed there implies the number of rules of the model. In addition, one has to construct detailed membership functions of the information granules. The identification of the consequence part of the rules embraces two phases, namely 1) a selection of the consequence variables of the fuzzy rules, and 2) determination of the parameters of the consequence (conclusion part). And the least square error (LSE) method used at the parametric optimization of the consequence parts of the successive rules.

In this study we carry out the modeling using characteristics of input-output data set. Therefore, it is important to understand the characteristics of data. To find this we use HCM clustering. By classifying data as characteristics through HCM clustering, we design the fuzzy model by means of center of classified clusters.

3.1 Premise Identification

For the triangular membership functions we have parameters to optimize. In the simplest scenario as illustrated in Figure 1, the minimal and maximal initial values of the vertical points of the membership functions depend on the range of experimental data encountered in the data set. Note that in this case fuzzy sets are distributed uniformly across the entire universe of discourse (space). Owing to the properties of those fuzzy sets (uniform distribution), only the boundaries of the entire space are subject to optimization. The situation shown in figure 2 is quite different from the uniform distribution of the information granules. The HCM clustering helps us organize the data into cluster, and in this way we take into account the characteristics of the experimental data.

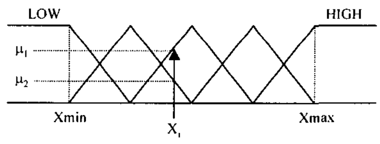


Fig. 1. Fuzzy partition composed of uniformly distributed fuzzy sets

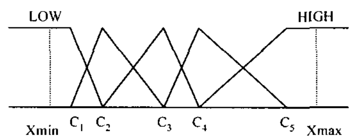


Fig. 2. Fuzzy partition composed of nonuniformly distributed fuzzy sets constructed with aid of clustering technique

To determine the initial membership parameters in premise part we are

[Step 1] Find the center values of each cluster from input-output data set using HCM clustering.

$$(x_1 ; y) \rightarrow (v_{1c} ; m_{1c}),\ \cdots,\ (x_k ; y) \rightarrow (v_{kc} ; m_{kc}) \quad (6)$$

here, c is the number of clusters, v_{kc} and m_{kc} are center values of k-th input and output data respectively.

[Step 2] Divide the correlational fuzzy space between input variables by center values. At this time, those values become the initial values of the vertical points of the membership functions.

3.2 Consequence Identification

The characteristics of input-output data is also involved in the conclusion parts as follows:

[Step 1] Find input data set (x_1, x_2, ..., x_k) that is included the respective fuzzy space because the fuzzy rules is formed by correlation between input variables.

[Step 2] Seek the corresponding output data at this time and find input-output data set (x_1, x_2, ..., x_k ; y) that is contained the each fuzzy space. In this way, the center values of input-output variables in the rules of the conclusion parts are determined and these values become the initial values of the consequence polynomial functions.

$$(x_1, \cdots, x_k \ ; \ y) \rightarrow (V_{1j}, \cdots, V_{kj} \ ; \ M_j) \tag{7}$$

The identification of the conclusion parts of the rules deals with a selection of their structure that is followed by the determination of the respective parameters of the local functions occurring there.

3.2.1 Type 1: Simplified Fuzzy Inference

The consequence part of the simplified inference mechanism is a constant. The rules read in the form

$$\begin{aligned} &R^j\text{: } IF\ x_1\ is\ A_{1c} \text{ and } \cdots \text{ and } x_k\ is\ A_{kc} \\ &Then\ y_j - M_j = f_i(x_1, \cdots, x_k) \end{aligned} \tag{8}$$

The calculations of the numeric output of the model, based on the activation (matching) levels of the rules there, are carried out in the well known format

$$y^* = \frac{\sum_{j=1}^{n} w_{ji} y_j}{\sum_{j=1}^{n} w_{ji}} = \sum_{j=1}^{n} \hat{w}_{ji}(a_{j0} + M_j) \tag{9}$$

Here, as the normalized value of w_{ji}, we use an abbreviated notation to describe an activation level of rule R^j to be in the form

$$\hat{w}_{ji} = \frac{w_{ji}}{\sum_{j=1}^{n} w_{ji}} \tag{10}$$

where R^j is the j-th fuzzy rule, x_k represents the input variables, A_{kc} is a membership function of fuzzy sets, a_{j0} is a constant, M_j is a center value of output data, n is the number of fuzzy rules, y^* is the inferred output value, w_{ji} is the premise fitness matching R^j (activation level).

If the input variables of the premise and parameters are given in consequence parameter identification, the optimal consequence parameters that minimize the assumed performance index can be determined. In what follows, we define the performance index as the root mean squared error (RMSE).

$$PI = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (y_i - y_i^*)^2} \tag{11}$$

where y^* is the output of the fuzzy model, m is the total number of data, and i is the data number. Furthermore, x_{1i}, x_{2i}, ..., x_{ki}, y_i (i=1, 2, ..., m) are pairs of input-output data sets. The consequence parameters a_{j0} can be determined by the standard least-squares method. In the fuzzy model of Type 1, the parameters can be estimated by solving the optimization problem.

$$\hat{a} = (X^T X)^{-1} X^T Y \tag{12}$$

where,

$$Y = [y_1 - (\sum_{j=1}^{n} M_j \hat{w}_{j1}) \ \ y_2 - (\sum_{j=1}^{n} M_j \hat{w}_{j2}) \ \cdots \ y_m - (\sum_{j=1}^{n} M_j \hat{w}_{jm})]^T,$$

$$X = [x_1 \ x_2 \ \cdots \ x_m]^T, \ x_i^T = [\hat{w}_{1i} \ \cdots \ \hat{w}_{ni}], \ \hat{a} = [a_{10} \ \cdots \ a_{n0}]^T$$

3.2.2 Type 2: Linear Fuzzy Inference

The conclusion is expressed in the form of a linear relationship between inputs and output variable. This gives rise to the rules in the form

$$\begin{aligned} &R^j\text{: } IF\ x_1\ is\ A_{1c} \text{ and } \cdots \text{ and } x_k\ is\ A_{kc} \\ &Then\ y_j - M_j = f_i(x_1, \cdots, x_k) \end{aligned} \tag{13}$$

where f_j is a linear function of the input variables;

$$f_i(x_1, \cdots, x_k) = a_{j0} + a_{j1}(x_1 - V_{1j}) + \cdots + a_{jk}(x_k - V_{kj}) \tag{14}$$

here, V_{kj} is a center value of input data. The numeric output y^* is determined in the same way as in the previous type of rule; that is, by taking a weighted sum of the activation levels of the individual rules;

$$\begin{aligned} y_i^* &= \frac{\sum_{j=1}^{n} w_{ji}\ y_j}{\sum_{j=1}^{n} w_{ji}} = \frac{\sum_{j=1}^{n} w_{ji}\ (f_i(x_1, \cdots, x_k) + M_j)}{\sum_{j=1}^{n} w_{ji}} \\ &= \sum_{j=1}^{n} \hat{w}_{ji}\ (a_{j0} + a_{j1}(x_{1i} - V_{1j}) + \cdots + a_{jk}(x_{ki} - V_{kj}) + M_j) \end{aligned} \tag{15}$$

The consequence parameters are produced by the standard least-squares method.

3.2.3 Type 3: Quadratic Fuzzy Inference

The consequence part of the quadratic inference mechanism is a quadratic polynomial. The rules read in the form

$$\begin{aligned} &R^j\text{: } IF\ x_1\ is\ A_{1c} \text{ and } \cdots \text{ and } x_k\ is\ A_{kc} \\ &Then\ y_j - M_j = f_i(x_1, \cdots, x_k) \end{aligned} \tag{16}$$

where f_j is a polynomial function of the input variables; namely:

$$\begin{aligned} f_j(x_1, \cdots, x_k) = &a_{j0} + a_{j1}(x_1 - V_{1j}) + \cdots + a_{jk}(x_k - V_{kj}) \\ &+ a_{j(k+1)}(x_1 - V_{1j})^2 + \cdots + a_{j(2k)}(x_k - V_{kj})^2 \\ &+ a_{j(2k+1)}(x_1 - V_{1j})(x_2 - V_{2j}) + \cdots \\ &+ a_{j((k+2)(k+1)/2)}(x_{k-1} - V_{(k-1)j})(x_k - V_{kj}) \end{aligned} \tag{17}$$

The numeric output y^* is determined in the same way as in the previous type of rule.

3.2.4 Type 4: Modified Quadratic Fuzzy Inference

The conclusion is expressed in the form of the quadratic polynomial omitted square terms between inputs and output variable. This gives rise to the rules in the form

$$R^j:\ IF\ x_1\ is\ A_{1c}\ \text{and}\ \cdots\ \text{and}\ x_k\ is\ A_{kc} \quad (18)$$
$$Then\ y_j - M_j = f_i(x_1, \cdots, x_k)$$

where f_j is a polynomial function of the input variables; namely:

$$\begin{aligned} f_j(x_1, \cdots, x_k) = a_{j0} + a_{j1}(x_1 - V_{1j}) + \cdots + a_{jk}(x_k - V_{kj}) \\ + a_{j(k+1)}(x_1 - V_{1j})(x_2 - V_{2j}) + \cdots \\ + a_{j(k(k+1)/2)}(x_{k-1} - V_{(k-1)j})(x_k - V_{kj}) \end{aligned} \quad (19)$$

4. Optimization of IG-based FIS

The need to solve optimization problems arises in many fields and is especially dominant in the engineering environment. There are several analytic and numerical optimization techniques, but there are still large classes of functions that are fully addressed by these techniques. Especially, the standard gradient-based optimization techniques that are being used mostly at the present time are augmented by a differential method of solving search problems for optimization processes. Therefore, the optimization of fuzzy models may not be fully supported by the standard gradient-based optimization techniques, because of the nonlinearity of fuzzy models represented by rules based on linguistic levels. This forces us to explore other optimization techniques such as genetic algorithms. First of all, to identify the fuzzy model we determine such an initial structure as the number of input variables, input variables being selected and the number of membership functions in premise part and the order of polynomial (Type) in conclusion. And then the membership parameters of the premise are optimally tuned by GAs.

Genetic algorithms[15] have proven to be useful in optimization of such problems because of their ability to efficiently use historical information to obtain new solutions with enhanced performance and a global nature of search supported there. GAs are also theoretically and empirically proven to support robust searches in complex search spaces. Moreover, they do not get trapped in local minima, as opposed to gradient-descent techniques being quite susceptible to this shortcoming.

In this study, for the optimization of the fuzzy model, genetic algorithms use the serial method of binary type, roulette-wheel in the selection operator, one-point crossover in the crossover operator, and invert in the mutation operator. Here, we use 1000 generations, 60populations, 10bits per string, crossover rate equal to 0.6, and mutation probability equal to 0.1.

5. Experimental Studies

This section includes comprehensive numeric studies illustrating the design of the fuzzy model. We demonstrate how IG-based FIS can be utilized to predict future values of a chaotic time series. The performance of the proposed model is also contrasted with some other models existing in the literature. The time series is generated by the chaotic Mackey-Glass differential delay equation [16] of the form:

$$\dot{x}(t) = \frac{0.2x(t-\tau)}{1+x^{10}(t-\tau)} - 0.1x(t) \quad (20)$$

The prediction of future values of this series arises is a benchmark problem that has been used and reported by a number of researchers. From the Mackey-Glass time series $x(t)$, we extracted 1000 input-output data pairs for the type from the following the type of vector format such as: $[x(t-30), x(t-24), x(t-18), x(t-12), x(t-6), x(t); x(t+6)]$ where t = 118-1117. The first 500 pairs were used as the training data set while the remaining 500 pairs were the testing data set for assessing the predictive performance.

We carried out the structure identification from experimental data using GAs to design Max_Min -based and IG-based fuzzy model. The number of input variables was set to be selected maximum up to four from above the type of vector format. The corresponding input variables was picked up $x(t-30)$, $x(t-18)$, $x(t-12)$, $x(t)$ both of two. The number of membership functions assigned to each input of Max_Min-based fuzzy model was set to two, three, three, and two, and the other hand, the number of membership functions of IG-based fuzzy model was selected to two, so the number of rules is 36 and 16, respectively. In the conclusion, both of two models were set to consequence type 3. And then for each fuzzy model, we conducted optimally by auto-tuning the parameters of the premise membership functions.

Table 1 shows the performance index for Max_Min -based and IG-based fuzzy model with four input variables, which consist of consequence type 3.

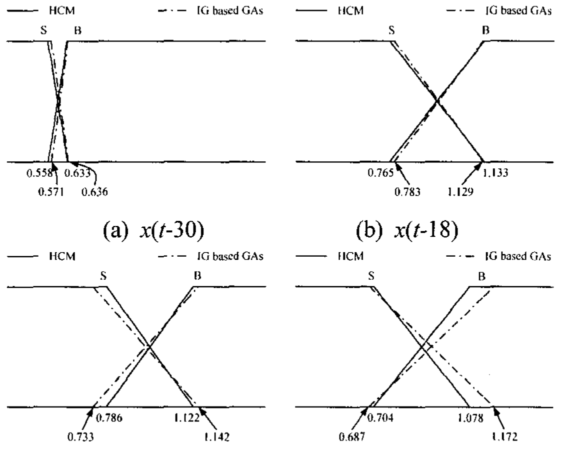
Table 1. Performance index of Max_Min-based and IG-based fuzzy model(θ=0.0)

Model	Identification	input variable	No. of MFs	Type	PI	E_PI
Max/Min _FIS	Structure	$x(t-30)$ $x(t-18)$ $x(t-12)$ $x(t)$	2x3x3x2	Type 3	0.0094	0.0091
	Parameters				0.0021	0.0020
IG_FIS	Structure	$x(t-30)$ $x(t-18)$ $x(t-12)$ $x(t)$	2x2x2x2	Type 3	0.0007	0.0070
	Parameters				0.0005	0.0005

From the table 1 it is clear that the performance of a IG-based fuzzy model is better than that of a Max_Min-based fuzzy model not only after identifying the structure but also after identifying optimally the parameters.

The IG-based fuzzy model comes with sixteen rules with two membership functions for four input variables. Figure 3 is partitioned into two fuzzy input spaces for the input variables.

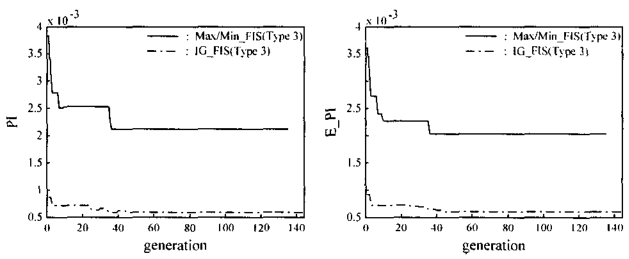
The same figure shows membership functions of each input variable according to the partition of fuzzy input spaces using HCM clustering and GAs.



(a) $x(t\text{-}30)$ (b) $x(t\text{-}18)$

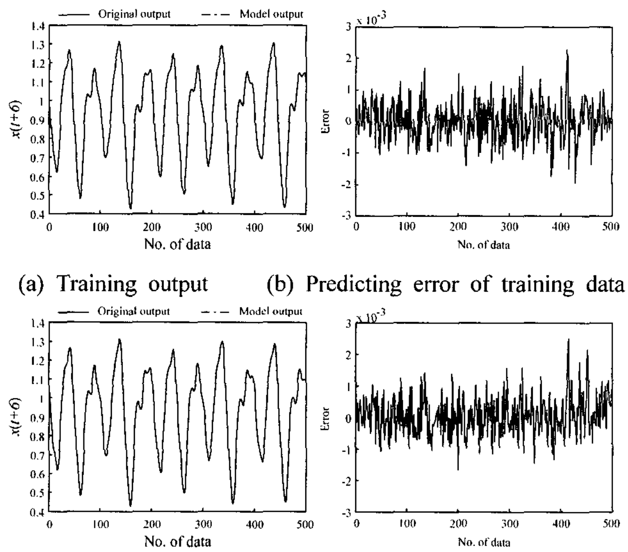
(c) $x(t\text{-}12)$ (d) $x(t)$

Fig. 3. Initial and optimized membership parameters for IG-based fuzzy model



(a) PI (b) E_PI

Fig. 4. Optimal convergence process of performance index for Max_Min-based and IG-based fuzzy model



(a) Training output (b) Predicting error of training data

(c) Testing output (d) Predicting error of testing data

Fig. 5. Model output and predicting error of training and testing data for IG-based fuzzy model

Figure 4 depicts the values of the performance index produced in successive generation of the GAs. It is obvious that the performance of an IG-based fuzzy model is good from initial generation due to the characteristics of input-output data.

Model output and predicting error of training and testing data for IG-based fuzzy model is presented in figure 5.

The identification error (performance index) of the proposed model is also compared to the performance of some other models in table 2. Here the non-dimensional error index (NDEI) is defined as the root mean square errors divided by the standard deviation of the target series.

Table 2. Comparison of identification error with previous fuzzy models

Model	N0.of rules	PIt	PI	E_PI	NDEI
Wang's model[17]	7	0.004			
	23	0.013			
	31	0.010			
Cascaded-correlation NN[18]					0.06
Backpropagation MLP[18]					0.02
6th-order polynomial[18]					0.04
ANFIS[19]	16		0.0016	0.0015	0.007
FNN model[20]			0.014	0.009	
Recurrent neural network[21]		0.0138			
Our model	16		0.0005	0.0005	0.0022

6. Concluding Remarks

In this paper, we have developed a comprehensive identification framework for fuzzy model based on information granulation. The underlying idea deals with an optimization of information granules by exploiting techniques of clustering and genetic algorithms. The experimental study showed that the model is compact (realized through a small number of rules), and their performance is superb in comparison to other models. The proposed model is effective for nonlinear complex systems, so we can construct a well-organized model.

While the detailed discussion was focused on triangular fuzzy sets, the developed methodology applies equally well to any other class of fuzzy sets as well as a type of nonlinear local model. Moreover, the models scale up quite easily and do not suffer from the curse of dimensionality encountered in other identification techniques of rule-based systems.

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