Genetically Optimized Self-Organizing Fuzzy Polynomial Neural Networks based on Information Granulation and Evolutionary Algorithm

박호성[1], 오성권[2]
[1]원광대학교 공과대학 정보디지털시스템학과
[2]수원대학교 공과대학 전기공학과
Ho-Sung Park[1], Sung-Kwun Oh[2]
[1]Dept.of Information and Digital System Engineering,Wonkwang University
[2]Dept.of Electrical Engineering,The University of Suwon
E-mail : ohsk@suwon.ac.kr

요 약

In this study, we proposed genetically optimized self-organizing fuzzy polynomial neural network based on information granulation and evolutionary algorithm (gdSOFPNN), develop a comprehensive design methodology involving mechanisms of genetic optimization. The proposed gdSOFPNN gives rise to a structurally and parametrically optimized network through an optimal parameters design available within FPN (viz. the number of input variables, the order of the polynomial, input variables, the number of membership functions, and the apexes of membership function). Here, with the aid of the information granulation, we determine the initial location (apexes) of membership functions and initial values of polynomial function being used in the premised and consequence part of the fuzzy rules respectively. The performance of the proposed gdSOFPNN is quantified through experimentation that exploits standard data already used in fuzzy modeling.

1. Introduction

Complex plants are difficult to control automatically due to their nonlinear, time varying behavior and imprecise measurement information. Nevertheless human operators can control these complex plants more satisfactorily than conventional automatic control systems based on their some practical experience. When the dimensionality of the model goes up (the number of system's variables increases), so do the difficulties. In the sequel, to build models with good predictive abilities as well as approximation capabilities, there is a need for advanced tools[1].

To help alleviate the problems, one among the first approaches along systematic design of nonlinear relationships between system's inputs and outputs comes under the name of a Group Method of Data Handling (GMDH). Ivakhnenko introduced GMDH in the early 1970's [2]. GMDH-type algorithms have been extensively used since the mid-1970's for prediction and modeling complex nonlinear processes. While providing with a systematic design procedure, GMDH comes with some drawbacks. To alleviate the problems associated with the GMDH, Self-Organizing Neural Networks (SONN, called "SOFPNN") were introduced by Oh and Pedrycz [3-5] as a new category of neural networks or neuro-fuzzy networks. Although the SOFPNN has a flexible architecture whose potential can be fully utilized through a systematic design, it is difficult to obtain the structurally and parametrically optimized network because of the limited design of the nodes located in each layer of the SOFPNN.

In this study, in considering the above problems coming with the conventional SOFPNN, we introduce a new structure and organization of fuzzy rules as well as a new genetic design approach. The new meaning of fuzzy rules, informationgranules melt into the fuzzy rules. In a nutshell, each fuzzy rule describes the related information granule. The determination of the optimal values of the parameters available within an individual FPN (viz. the number of input variables, the order of the polynomial, a collection of preferred nodes, the number of MF, and the apexes of membership function) leads to a structurally and parametrically optimized network through the genetic approach.

2. SOFPNN with FPN and its topology

The FPN consists of two basic functional modules. The first one, labeled by **F**, is a collection of fuzzy sets that form an interface between the input numeric variables and the processing part realized by the neuron. The second module (denoted here by **P**) is about the function based nonlinear (polynomial) processing. The detailed FPN involving a certain regression polynomial is shown in Table 1. The choice of the number of input variables, the polynomial order, input variables, and the number of MF available within each node itself helpsselect the best model with respect to the characteristics of the data, model design strategy, nonlinearity and predictive capabilities.

3. The structural optimization of gdSOFPNN

3.1 Information Granulation by means of HCM

Information granulation is defined informally as linked collections of objects (data points, in particular) drawn together by the criteria of indistinguishability, similarity or functionality [6]. Granulation of information is a procedure to extract meaningful concepts from insignificant numerical data and an inherent activity of human being carried out with intend of better understanding of the problem. We extract information for the real system with the aid of Hard C-means clustering method [7], which deals with the conventional crisp sets. Through HCM, we determine the initial location (apexes) of membership functions and initial values of polynomial function being used in the premise and consequence part of the fuzzy rules respectively. The fuzzy rules of gdSOFPNN is as followings.

$$R^j: If x_1 is A_{ji} and \cdots x_k is A_{jk} then y_j - M_j \\ = f_i(x_1 - v_{j1}), (x_2 - v_{j2}), \cdots, (x_k - v_{jk})$$

Where, A_{jk} mean the fuzzy set, the apex of which is defined as the center point of information granule (cluster). M_j and v_{jk} are the center points of new created input-output variables by information granule.

3.2 Genetic optimization of gdSOFPNN

Let us briefly recall that GAsis a stochastic search technique based on the principles of evolution, natural selection, and genetic recombination by simulating a process of "survival of the fittest" in a population of potential solutions to the given problem. The main features of genetic algorithms concern individuals viewed as strings, population-based optimization and stochastic search mechanism (selection and crossover). In order to enhance the learning of the gdSOFPNN and augment its performance, we use genetic algorithms to obtain the structural optimization of the network by optimally selecting such parameters as the number of input variables (nodes), the order of polynomial, input variables, and the number of MF within a gdSOFPNN. Here, GAs uses serial method of binary type, roulette-wheel as the selection operator, one-point crossover, and an invert operation in the mutation operator [8].

4. The algorithm and design procedure of gdSOFPNN

The framework of the design procedure of the gdSOFPNN with aid of the Information granulation (IG) comprises the following steps.

[Step1] *Determine system's input variables.*

[Step2] *Form training and testing data.*

[Step3] *Decide initial information for constructing the gdSOFPNN structure.*

[Step4] *Decide FPN structure using genetic design.*

[Step5] *Design of structurally optimized gdSOFPNN.*

[Step 6] *Identification of membership value using dynamic searching method of GAs.*

[Step 7] *Design of parametrically optimized gdSOFPNN.*

5. Experimental studies

We illustrate the performance of the network and elaborate on its development by experimenting with data coming from the NOx emission process of gas turbine power plant [9].NOx emission process is modeled using the data of gas turbine power plants. Till now, almost NOx emission processes are based on "standard" mathematical model in order to obtain regulation data from control process. However, such models do not develop the relationships between variables of the NOx emission process and parameters of its model in an effective manner. The input variables include AT, CS, LPTS, CDP, and TET. The output variable is NOx. We consider 260 pairs of the original input-output data. 130 out of 260 pairs of input-output data are used as learning set; the remaining part serves as a testing set. To come up with a quantitative evaluation of network, we use the standard MSE performance index.

	Parameters	1^{st} ~ 3^{rd} layer
GA	Maximum generation	100
	Total population size	300*No. of 1^{st} layer node
	Crossover rate	0.65
	Mutation rate	0.1
	String length	90
gdSOFPN	Maximal no.(Max) of inputs to be selected	$1 \le l \le$ Max(2~3)
N	Polynomial type(Type T)	$1 \le T^*$(or T)≤ 4
	Membership Function (MF) type	Triangular
		Gaussian
	No. of MFs per input	2 or 3

l, T, Max: integers

Table 1 Computational aspects of the genetic optimization of DS_gSOFPNN

Table 2 shows the performance index of the proposed gdSOFPNN.

Model	Layer	3rd layer			
	M.F	Triangular MF		Gaussian MF	
	Max	PI	EPI	PI	EPI
gdSOFPNN	2	0.016	0.068	0.012	0.180
	3	0.014	0.036	0.004	0.134
		Triangular MF*		Gaussian MF*	
	2	0.003	0.017	0.002	0.024
	3	0.002	0.008	0.001	0.023

Table 2 Performance index of DS_gSOFPNN for the Nox process data

Fig. 1 illustrates the detailed optimal topologies of the gdSOFPNN for 3 layers (PI=0.002, EPI=0.008).

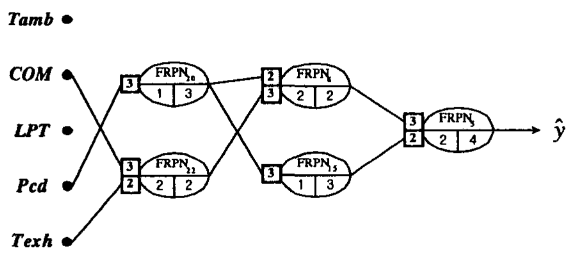

Fig. 1 gdSOFPNN architecture

Model				PI_s	EPI_s
Regression model				17.68	19.23
FNN model[10]		GA	Simplified	7.045	11.264
			Linear	4.038	6.028
		Hybrid	Simplified	6.205	8.868
			Linear	3.830	5.397
Multi-FNNs[11]		Linear		0.720	2.025
gHFPNN [12]	Max=2 (Type T*)	T	3^{rd} layer	0.008	0.082
			5^{th} layer	0.008	0.081
		G	3^{rd} layer	0.016	0.132
			5^{th} layer	0.016	0.116
[redacted]		3^{rd} layer		0.003	0.017
				0.002	0.024
				0.002	0.008
				0.001	0.023

Table 3 Comparative analysis of the performance of the network; considered are models reported in the literature(T:Triangular,

G:Gaussian-like)

6. Concluding remarks

In this study, we introduced and investigated a new architecture and comprehensive design methodology of genetically optimized self-organizing fuzzy polynomial neural networks based on information granulation and evolutionary algorithm (gdSOFPNN), and discussed their topology. The design methodology comes as a structural and parametrical optimization being viewed as two fundamental phases of the design process. In the design of gdSOFPNN, the characteristics inherent to entire experimental data being used in the construction of the IG_gSOFPNN architecture is reflected to fuzzy rules available within a FPN. Therefore Information granulation based on HCM(Hard C-Means) clustering method was adopted. With the aid of the information granulation, we determine the initial location of membership functions and initial values of polynomial function being used in the premised and consequence part of the fuzzy rules respectively.

감사의 글

본 연구는 산업자원부의 지원에 의하여 기초전력연구원(I-2004-0-074-0-00) 주관으로 수행된 과제임.

6. 참고문헌

[1] J. H. Nie and T. H. Lee, "Rule-based modeling: Fast construction and optimal manipulation", IEEE Trans. Syst., Man, Cybern. Part A, vol.26, pp. 728-738, Nov, 1996.

[2] A.G. Ivakhenko, "Polynomial theory of complex systems", IEEE Trans. Syst., Man, Cybern. SMC-1, pp. 364-378, 1971.

[3] S. K. Oh and W. Pedrycz, "The design of self-organizing Polynomial Neural Networks", Information Science, Vol. 141, pp. 237-258, 2002.

[4] S. K. Oh, W. Pedrycz, and B. J. Park, "Polynomial Neural Networks Architecture: Analysis and Design", Computers and Electrical Engineering, Vol. 29, Issue 6, pp. 703-725, 2003.

[5] S. K. Oh, W. Pedrycz, "Fuzzy Polynomial Neuron-Based Self-Organizing Neural Networks", Int. J. of General Systems, Vol. 32, pp. 237-250, 2003.

[6] L. A. Zadeh, "Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic", Fuzzy Sets and Systems, Vol. 90, pp. 111-117, 1997.

[7] J. C. BEZDEK, Pattern Recognition with Fuzzy Objective Function Algorithms, New York, Plenum, 1981.

[8] De Jong, K. A. Are Genetic Algorithms Function Optimizers?, Parallel Problem Solving from Nature 2, Manner, R. and Manderick, B. eds., North-Holland, Amsterdam, 1992.

[9] G. Vachtsevanos, V. Ramani and T. W. Hwang, "Prediction of Gas Turbine NOx Emissions using Polynomial Neural Network", Technical Report, Georgia Institute of Technology, Atlanta, 1995.

[10] S. K. Oh, W. Pedrycz and H. S. Park, "Hybrid Identification in Fuzzy-Neural Networks", Fuzzy Sets and Systems, Vol. 138, Issue 2, pp. 399-426, 2003.

[11] S. K. Oh, W. Pedrycz and H. S. Park, "Multi-FNN identification by means of HCM clustering and evolutionary fuzzy granulation", Simulation Modeling Practice and Theory, Vol. 11, pp. 627-642, 2003.

[12] S. K. Oh, W. Pedrycz and H. S. Park, "Multi-layer Hybrid Fuzzy Polynomial Neural Networks: A Design in the Framework of Computational Intelligence", Neurocomputing, 2004. (in press)