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An Adaptive Fuzzy Controller Using Fuzzy Neural Networks

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Abstracts

This paper presents an adaptive fuzzy controller using fuzzy neural networks(FNNs). The adaptive controller uses two FNNs. One FNN is used to identify a fuzzy model of controlled object. The other FNN is used as a fuzzy controller. The fuzzy controller is designed with the linguistic rules of the fuzzy model. The response of the designed control system is checked with a linguistic response analysis proposed by the authors. An adaptive tuning of the control rules of the FNN controller is made possible utilizing the fuzzy model.

Simulations using nonlinear controlled objects were done to verify the proposed control system.

1. INTRODUCTION

Fuzzy control has a distinguishing feature in that it can incorporate expert's control rules using linguistic expressions. One of the main problems of the fuzzy control is the difficulty of acquiring the fuzzy rules and tuning the membership functions. There have been many researches on applications of neural networks to fuzzy reasonings[1]~[8]. The authors have also proposed three types of fuzzy neural networks and have studied an automatic identification method of fuzzy models of controlled objects/controllers[9]~[12].

Another main problem of the fuzzy controller is that the stability is hard to guarantee. Many research works have been done on the stability analysis[15]~[21]. These works have been done describing the control system in numerical equations. These method do not make use of the distinguishing feature of the fuzzy controls, i.e. easily understandable linguistic expressions.

Yasukawa and Sugeno proposed a novel method of designing linguistic fuzzy controllers[22]. This method fully utilizes the feature of fuzzy controllers. The paper, however, does not study stability and adaptive tuning of the controller.

This paper presents a new designing method of fuzzy controller with checked response using linguistic rules of identified model of the controlled object. This method enables us to design the controller without requiring profound knowledge of control theory. Type I of the fuzzy neural networks (FNNs)[11][12] is used for the fuzzy modeling of the controlled object. The FNN with the back propagation learning can identify fuzzy models of nonlinear systems. The response of the designed control system, i.e. whether the response settles or oscillates, can be checked linguistically with the method proposed by the authors[23]. An adaptive tuning method of the control rules is also proposed in this paper. The adaptive tuning is realized with the derivative feedback from the fuzzy model of the controlled object. Simulations using a nonlinear object are done to show the feasibility of the proposed designing method.

2. FUZZY CONTROLLER

Figure 1 shows the configuration of the proposed control system. The fuzzy controller controls the output of the controlled object y to follow the command r with the manipulated variable u. The FNNs are used for the fuzzy model and the fuzzy controller. The fuzzy control system is designed in the following process:

(i) The fuzzy model is identified from the input-output data of the controlled object.

(ii) The fuzzy controller is designed with the linguistic fuzzy rules. The response of the control system is checked.

(iii) The adaptive tuning of the control rules is done using the fuzzy model of the controlled object.

In the following chapters, the FNN and the detailed design of the controller will be described

3. FUZZY NEURAL NETWORK

The FNNs presented by the authors are the multi-layered back-propagation(BP) models of which the structures are designed to realize the processes of fuzzy reasoning and to make the connection weights of the networks correspond to the parameters of the fuzzy reasoning. Through the learning with the BP algorithm, the FNNs can identify the fuzzy rules and tune the membership functions of fuzzy reasoning automatically. The fuzzy model of the controlled object as well as the fuzzy controller are to be made with the FNNs. This paper uses "Type I" of the FNNs in [11][12].

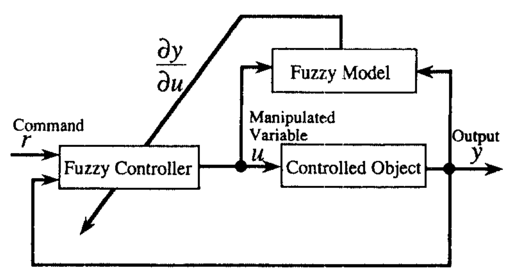


Fig.1 Adaptive control system

4.2 DESIGN OF FUZZY CONTROLLER

This paper presents a linguistic design method of the fuzzy controller using the obtained fuzzy model of the controlled object.

The fuzzy models of the controlled objects with single input and single output are described with the simplified fuzzy inference as:

$$
\begin{aligned}
R^{i}_{P}: &\text{ If } y_t \text{ is } A_{i1} \text{ and } y_{t-1} \text{ is } A_{i2} \text{ and } \dots \\
&\text{and } u_t \text{ is } B_{i1} \text{ and } u_{t-1} \text{ is } B_{i2} \text{ and } \dots \\
&\text{then } y_{t+1} = f_i
\end{aligned} \tag{7}
$$

where $A_{i1}, A_{i2}, B_{i1}, B_{i2}$ are fuzzy variables and f_i is a constant. The fuzzy controller can be designed from this fuzzy model as:

$$
\begin{aligned}
R^{i}_{C}: &\text{ If } r_{t+1} \text{ is } F_i \\
&\text{and } y_t \text{ is } A_{i1} \text{ and } y_{t-1} \text{ is } A_{i2} \text{ and } \dots \\
&\text{and } u_{t-1} \text{ is } B_{i2} \text{ and } u_{t-2} \text{ is } B_{i3} \text{ and } \dots \\
&\text{then } u_t = B_{i1}
\end{aligned} \tag{8}
$$

where F_i is the fuzzy variable representing the constant f_i. The rule on Table 1, for example:

"If y_t is NB and u_t is NM then y_{t+1} is -0.91(NB)".

can be a control rule expressed as:

"If y_t is NB and r_{t+1} is NB then u_t is NM".

Other fuzzy control rules from Table 1 are

"If y_t is NM and r_{t+1} is NM then u_t is NB"
"If y_t is NS and r_{t+1} is NS then u_t is NB"
"If y_t is ZO and r_{t+1} is ZO then u_t is ZO"
"If y_t is PS and r_{t+1} is PS then u_t is PB" (9)
"If y_t is PM and r_{t+1} is PM then u_t is PB"
"If y_t is PB and r_{t+1} is PB then u_t is PM"

There are many undefined control rules on the rule table. These rules are derived from the input-output characteristics of the controlled object. The obtained control rules are listed on Table 2.

The response of the designed fuzzy control system can be analyzed linguistically using the method proposed by the authors[23]. The method is briefly explained as follows:

This method first defines the fired fuzzy rules for making the correspondence between the total inferred value of the fuzzy inference and the linguistic description of the rules.

Def.1: (Fired Fuzzy Rule)
The rule R^i is said to be the fired fuzzy rule at the t-th time if the truth value of the rule is the highest at t, i.e.

$$(\mu_i = \max_j \mu_j,\ j = 1, \cdots, n). \tag{10}$$

The fired fuzzy rule at the t-th time is denoted by R^{i_t}

A sequence of the fired fuzzy rules is described using the fired fuzzy rule of the fuzzy controller at the t-th time $R^{i_t}_C$ and the fired fuzzy rule of the fuzzy model of the plant P at the t-th time $R^{i_t}_P$ as

$$R^{i_t}_C \rightarrow R^{i_t}_P \rightarrow R^{i_t+1}_C \rightarrow R^{i_t+1}_P \tag{11}$$

The fired fuzzy rules at the t-th time can be described as the following:

$$R^{i_t} = R^{i_t}_C * R^{i_t}_P \tag{12}$$

where $*$ is a composition operation with which $x*y$ means that the rule y will be fired after the rule x. With the above fired fuzzy rules, the response of the control system can be easily analyzed. It is also possible to define stability of the control system.

Def.2: (Stability)
The fuzzy control system is stable if there exists a positive integer τ such that:

$$R^{i_{t+\tau}} = R^{i_t} \tag{13}$$

where t is an integer and $t \geq T_0 \geq 0$. T_0 is also an integer and is determined depending on the initial condition of the control system.

Def.3: (Asymptotic Stability)
The fuzzy control system is asymptotically stable if there exists R^{i_∞} such that:

$$\lim_{t \to \infty} R^{i_t} = R^{i_\infty} \tag{14}$$

In practice, it is not so easy to verify the stability of the control system. The fired fuzzy rules enable us to check the response of the designed fuzzy control system.

Figure 4 shows an example of the response analysis using the above fired fuzzy rules. The figure shows portions of the fuzzy control rules and the fuzzy model of the controlled object. Assuming that the command is "PB" and the initial state of the object y_0 is "ZO". The manipulated variable u_0 is, then, "PB".Then the output of the controlled object y_{t+1} is 0.06 and is becoming greater. The states of the fuzzy controller and the controlled object shift along (i), (ii), (iii) and to (iv) as indicated on the tables. The control system settles in the fuzzy subspace where r_t is PB, u_t is PM, and y_t is PB. Figure 5 shows the corresponding step response of the control system. This response was obtained with the FNN controller of which the labels in the consequent potion of the control rules are replaced with constants as: PB = 0.9, PM = 0.6, PS = 0.3, ZO = 0, NS = -0.3, NM = -0.6 and NB = -0.9.

Table 2 Fuzzy rules of conrroller

u_t		y_t NB	NM	NS	ZO	PS	PM	PB
r_t (y_{t+1})	NB	NM	NB	NB	NB	NB	NB	NB
	NM	PB	NB	NB	NB	NB	NB	NB
	NS	PB	PB	NB	NB	NB	NB	NB
	ZO	PB	PB	PB	ZO	NB	NB	NB
	PS	PB	PB	PB	PB	PB	NB	NB
	PM	PB	PB	PB	PB	PB	PB	NB
	PB	PB	PB	PB	PB	PB	PB	PM

Controller

u_t		y_t ZO 0.0	PS 0.3	PM 0.6	PB 0.9
r_t	ZO 0.0	ZO	NB	NB	NB
	PS 0.3	PB	PB	NB	NB
	PM 0.6	PB	PB	PB	NB
	PB 0.9	PB (i)	PB (ii)	PB (iii)	PM (iv)

Controlled object

y_{t+1}		y_t ZO 0.0	PS 0.3	PM 0.6	PB 0.9
u_t	ZO 0.0	0	0.18	0.50	0.85
	PS 0.3	0.01	0.20	0.53	0.87
	PM 0.6	0.04	0.24	0.56	0.91 (iv)
	PB 0.9	0.06 (i)	0.26 (ii)	0.59 (iii)	0.94

Fig.4 Stability analysis

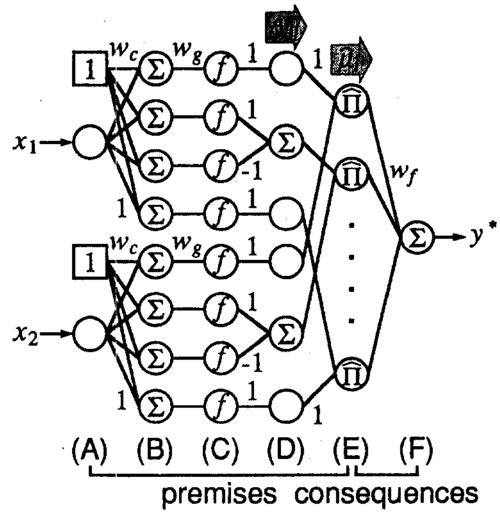


Fig.2 Fuzzy neural network

Figure 2 shows an example of the configuration of the FNN. The FNN realizes a simplified fuzzy inference of which the consequences are described with singletons. The BP algorithm can be applied for adjusting the weights in the neural networks. The inputs are non-fuzzy numbers. The simplified fuzzy inference with two inputs x_1, x_2 and one output y is written as follows:

$$R^i : \text{If } x_1 \text{ is } A_{i,1} \text{ and } x_2 \text{ is } A_{i,2} \text{ then } y = f_i \quad (i = 1,2,\cdots,n) \qquad (1)$$

$$\mu_i = A_{i,1}(x_1)A_{i,2}(x_2) \qquad (2)$$

$$y^* = \frac{\sum_{i=1}^{n} \mu_i f_i}{\sum_{i=1}^{n} \mu_i} = \sum_{i=1}^{n} \hat{\mu}_i f_i \qquad \hat{\mu}_i = \frac{\mu_i}{\sum_k \mu_k} \qquad (3)$$

where R^i is the i-th fuzzy rule. $A_{i,1}, A_{i,2}$ are fuzzy variables. f_i is a constant. n is the number of fuzzy rules. μ_i is the truth value of R^i. $\hat{\mu}_i$ is the normalized truth value so that the sum of $\hat{\mu}_i$ is unity. y^* is the inferred value.

The FNN in Fig.2 has two inputs x_1, x_2 and one out put y* and three membership functions in each premise. The circles and squares in the figure mean units of the neural network and the denotation w_c, w_g, w_f and 1, -1 are the connection weights.

The FNN realizes the inference in (1)- (3) in the neural network structure. The connection weights of the network w_c, w_g, w_f corresponding to the parameters of fuzzy inference are updated with the BP learning algorithm. The output of the unit in (C)-layer $O^{(C)}$ is given by

$$O^{(C)} = \frac{1}{1 = exp\{-w_g(x_j + w_c)\}}. \qquad (4)$$

The connection weights w_c, w_g determine the positions and gradients of the sigmoid functions in the units in (C)-layer, respectively. Figure 3 shows the membership functions in the premise $A_{1j}(x_j)$, $A_{2j}(x_j)$, $A_{3j}(x_j)$ realized in (A)-(D)-layers. Each membership function consists of one or two sigmoid functions. The outputs of the units in (D)-layer are the grades of membership functions. The products of the grades are fed to the units in (E)-layer and the outputs of the units are normalized truth values in the premises $\hat{\mu}_i$. The output of the unit in (F)-layer is the sum of the products of the connection weights w_f and $\hat{\mu}_i$. The connection weights w_f correspond to the singletons in the consequence f_i. The output in (F)-layer is, therefore, the inferred value y^*.

The FNN tunes the membership functions in the premises and identifies the fuzzy rules by adjusting the connection weights w_c, w_g and w_f, respectively. w_f are initialized to be zero. The FNN has no rules at the beginning of the learning.

Since the center-of-gravity method is used in (E)-layer, the updating method of connection weights, i.e. BP algorithm, needs some modifications. The learning algorithm for the FNN is well described in [11].

4. DESIGNING OF FUZZY CONTROLLER

The controlled object used in this paper is simple and is expressed as

$$T \cdot \frac{dy}{dt} + y^{1/3} = u \qquad (5)$$

where u is the input and y is the output. T is the time constant. The system has a small nonlinearity.

4.1 FUZZY MODELING

The controlled object is a first order system. Thus the system can be described with fuzzy rules as:

$$R^i_p : \text{If } y_t \text{ is } A_i \text{ and } u_t \text{ is } B_i \text{ then } y_{t+1} = f_i \qquad (6)$$

where t is the sampled time. The membership functions in each premise are seven labeled as: "PB (Positive Big)", "PM (Positive Medium)", "PS (Positive Small)", "ZO (Zero)", "NS (Negative Small)", "NM (Negative Medium)", NB (Negative Big)". The time constant of the controlled object T is set to be 10 while the sampling time is 1. The number of input-output data of the controlled object are 121 evenly distributed in the input space of y_t and u_t ([-1 1]*[-1 1]). The iteration of the learning of the FNN is 1000.

Table 1 shows the obtained fuzzy rules of the controlled object. The rules on the table can be read, for example, as:

"If y_t is NB and u_t is NM then y_{t+1} is -0.91(NB)".

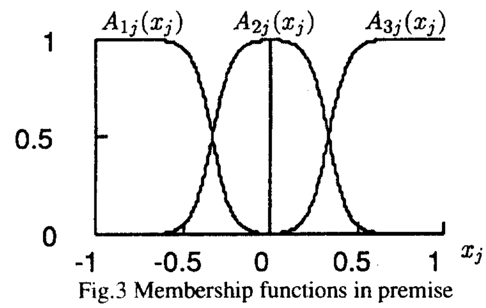


Fig.3 Membership functions in premise

Table 1 Fuzzy rules of controlled object

y_{t+1}		y_t: NB	NM	NS	ZO	PS	PM	PB
u_t	NB	−0.94	−0.59	−0.26	−0.06	0.09	0.41	0.76
	NM	−0.91	−0.56	−0.24	−0.04	0.12	0.44	0.79
	NS	−0.87	−0.53	−0.20	−0.01	0.15	0.48	0.82
	ZO	−0.85	−0.50	−0.18	0	0.18	0.50	0.85
	PS	−0.82	−0.48	−0.15	0.01	0.20	0.53	0.88
	PM	−0.79	−0.44	−0.12	0.04	0.24	0.56	0.91
	PB	−0.76	−0.41	−0.09	0.06	0.27	0.59	0.94

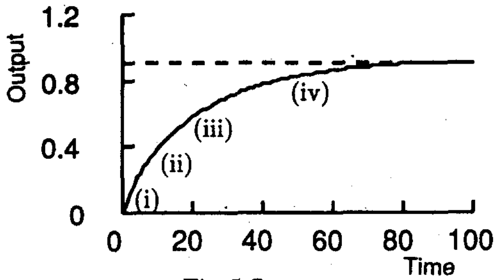


Fig.5 Step response

4.3 ADAPTIVE TUNING OF CONTROL RULES

The control rules on Table 2 are designed based on the fired fuzzy rules. Steady state errors are observed in the responses to some command values. In this section, an adaptive tuning method for the control rules is presented. The FNN controller is tuned with the BP algorithm while controlling the object. The error function can be defined by

$$E = \frac{(r-y)^2}{2} . \qquad (15)$$

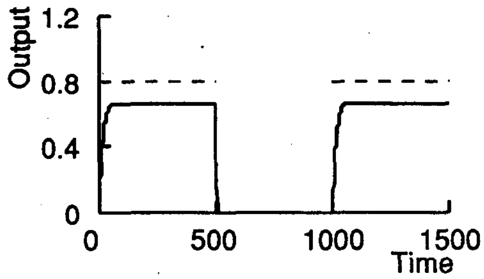
The error signal of the output unit of the FNN δ is derived as:

$$\delta = -\frac{\partial E}{\partial y} = -\frac{\partial E}{\partial y}\frac{\partial y}{\partial u} = (r-y)\frac{\partial y}{\partial u} . \qquad (16)$$

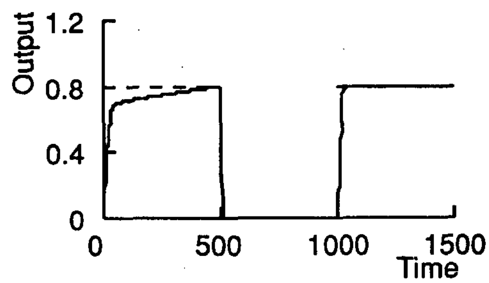
The term $\frac{\partial y}{\partial u}$ can not be known directly from the controlled object. This value is obtained from the fuzzy model. Figure 6 shows the responses of the control systems. Fig.6(a) is the case with the fuzzy controller on Table 2 without the adaptive scheme. Fig. 6(b) shows the result with the adaptive tuning of fuzzy control rules.

5. CONCLUSIONS

This paper presented a new designing method of control system with FNNs. The fuzzy controller was linguistically designed from the fuzzy model of the controlled object. The response of the fuzzy controller was checked through a linguistic response analysis. An adaptive tuning method for fuzzy control rules was also presented.



(a)Fuzzy controller



(b)Fuzzy adaptive controller

Fig.6 Responses of control systems

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