Fifth IFSA World Congress (1993), 1366-1369

Simulation Study on Self-learning Fuzzy Control of CO Concentration

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Abstract

This paper presents a simulation study on two self-learning control systems for a fuzzy prediction model of CO (carbon monoxide) concentration:linear control and fuzzy control. The self-learning control systems are realized by using Widrow-Hoff learning rule which is a basic learning method in neural networks. Simulation results show that the learning efficiency of fuzzy controller is superior to that of linear controller.

1. Introduction

CO (carbon monoxide) is one of important factors in air pollution problems. It is known that CO concentration system has
(1)high non-linearity, and
(2)many predictor variables.
On the other hand, it has been reported that fuzzy modeling techniques are useful for identification of complex systems [2,3,4,5].

In a previous paper [1], we have identified a fuzzy prediction model for CO concentration in the air at a traffic intersection point of a large city of Japan. Moreover, we have reported that the identified fuzzy model is very useful for predicting CO concentration.

In this paper, we simulate self-learning control systems of CO concentration using the identified fuzzy model. The purpose of this control is to keep CO concentration at a constant level. We adaptively adjust controller parameters by introducing Widrow-Hoff learning rule since dynamics of the real CO concentration system changes gradually over a long period of time.

2. Fuzzy modeling of CO concentration

A fuzzy model, proposed by Takagi and Sugeno [3], is described by fuzzy IF-THEN rules which locally represent linear input-output relations of a system. This fuzzy model is of the following form:

$$\text{Rule } i: \text{IF } x_1 \text{ is } A_{i1} \text{ and} \cdots \text{and } x_n \text{ is } A_{in}$$
$$\text{THEN } y_i = c_{i0}+c_{i1}x_1+\cdots+c_{in}x_n, \qquad (1)$$

where $i=1, 2, \cdots ,r$, r is the number of IF-THEN rules, yi is the output from the i-th IF-THEN rule, and Aij is a fuzzy set.

Given an input $(x1,x2,\cdots,xn)$, the final output of the fuzzy model is inferred by as follows [8]:

$$y = \sum_{i=1}^{r} w_i\, y_i \quad , \qquad (2)$$

where yi is calculated for the input by the consequent equation of the i-th implication, and the weight wi implies the overall truth value of the premise of the i-th implication for the input calculated as

$$w_i = \prod_{k=1}^{n} A_{ik}(x_k)\ , \qquad (3)$$

where $Aik(xk) = \exp(-(xk-dik)^2/bik)$, dik and bik are parameters of the membership functions.

Next, we explain outline of identification algorithm of a fuzzy model proposed by Tanaka and Sano [2]. Our method is a simplified version of a fuzzy modeling method proposed by Sugeno and Kang [4,5].

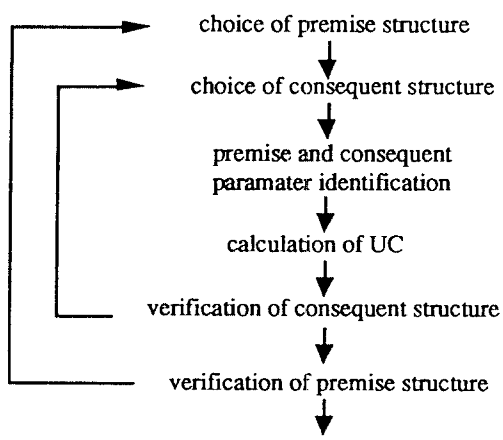

Fig.1 Identification algorithm

Fig.1 shows the identification algorithm. The identification procedure is classified into three steps:
(Step 1)choice of the premise structure and the consequent structure;
(Step 2)identification of the parameters of the structure determined in (Step 1);
(Step 3)verification of the premise structure and the consequent structure.

In a previous paper [1], we have applied this fuzzy modeling method to identification of a fuzzy prediction model for CO concentration in the air at a traffic intersection point of a large city of Japan. Inputs and an output of a fuzzy model are shown in Fig.2. x1 is wind velocity, x2 is volume of traffic, x3 is temperature, x4 is amount of sunshine, and y is CO concentration. For each variable, we perform normalization so that the mean and the variance of normalized variables equal 0 and 1, respectively. In other words, we transform the distribution to N(0,1).

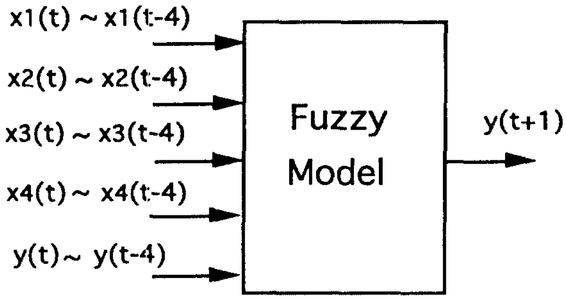

Fig.2 Inputs and an output of fuzzy model

The data used for identification and prediction of a fuzzy model are collected at the busiest traffic intersection of a large city of Japan. The number of data used for identification and prediction are 480 input-output data pairs and 253 input-output pairs, respectively. The sampling interval is 15 minutes. Of course, the prediction data is not used for identification of a fuzzy model. It is used only for checking the validity of a fuzzy model identified by using the identification data. Fig.3 shows the identification result. The fuzzy model consists of two IF-THEN rules.

Eq.(4) shows the performance index of the model.

$$J = \frac{1}{m}\sum_{t=0}^{m-1}\left|\frac{y(t+1)-y^*(t+1)}{y(t+1)}\right| \times 100 , \qquad (4)$$

where m is the number of input-output data. y*(t+1) and y(t+1) are the outputs of a fuzzy model and the real system at time instant t+1, respectively. y*(t+1) and y(t+1) are raw data and are not normalized.

Table 1 Performances of models

	Linear model	Fuzzy model
J1	5.7	4.8
J2	11.8	5.9

Table 1 shows the values of performance index for a linear model and the fuzzy model. J1 and J2 are the values of performance index for the identification data and the prediction data, respectively. The performance index J2 of the fuzzy model is superior to that of linear model. This means that the CO concentration system is essentially non-linear. Table 1 shows the usefulness of the identified fuzzy model.

Rule 1 : IF x2(t-1) is $\exp(-(x2(t-1)+1.90)^2/5.80)$
THEN y1(t+1) =
-0.008x1(t-2)+0.026x1(t-1)-0.032x1(t)
-0.205x2(t-1)+0.249x2(t)
-0.138x4(t-4)-0.181x4(t-3)+0.335x4(t-2)
+0.088x4(t-1)-0.112x4(t)
+0.090y(t-4)-0.106y(t-3)+0.011y(t-2)
-0.460y(t-1)+1.356y(t)-0.018

Rule 2 : IF x2(t-1) is $\exp(-(x2(t-1)-2.06)^2/5.72)$
THEN y2(t+1) =
-0.013x1(t-2)+0.059x1(t-1)-0.032x1(t)
-0.497x2(t-1)+0.827x2(t)
+0.006x4(t-4)+0.066x4(t-3)-0.130x4(t-2)
+0.095x4(t-1)-0.036x4(t)
-0.009y(t-4)+0.007y(t-3)-0.037y(t-2)
-0.103y(t-1)+0.748y(t)-0.002

Fig.3 Identification result

3. Self-learning controls

We simulate two self-learning control systems of keeping CO concentration at a constant level using Widrow-Hoff learning rule:linear control and fuzzy control. Fig.4 shows the self-learning control system, where x2(t) is a manipulated variable, y(t) is a controlled variable and r is a setpoint of CO concentration.

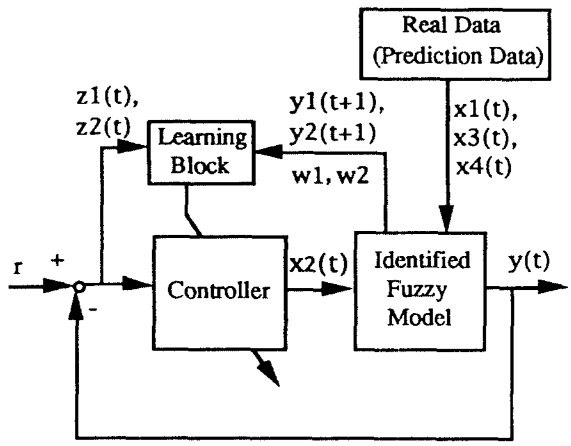

Fig.4 Self-learning control system

In this simulation,

(1)with respect to wind velocity x1, temperature x3 and amount of sunshine x4, we use real values of the prediction data,

(2)we use the identified fuzzy model as a controlled object.

Linear controller is constructed as follows.

$$\Delta x2(t) = a1\ z1(t) + a2\ z2(t),$$

$$x2(t) = x2(t-1) + \Delta x2(t),$$

where $z1(t)=r-y(t)$ and $z2(t)=z1(t)-z1(t-1)$ and ai (i=1, 2) is a parameter of the controller. As mentioned above, we adaptively adjust controller parameters by using Widrow-Hoff learning rule. The idea which adaptively optimizes parameters of fuzzy controller using Widrow-Hoff learning rule was first introduced by Ichihashi [8].

Let us consider the following performance function.

$$J = \frac{1}{2} (r - y(t+1))^2 \qquad (5)$$

By partially differentiating J with respect to each controller parameter ai, we obtain

$$\frac{\partial J}{\partial a_i} = - (r - \sum_{j=1}^{2} w_j y_j(t+1)) z_i(t) \sum_{j=1}^{2} w_j p_j , \qquad (6)$$

where wj is a membership value of j-th rule of fuzzy model at time instant t and pj is a consequent parameter of x2(t), that is, p1 = 0.249 and p2 = 0.827. We can successively adjust controller parameters using Eq.(7).

$$a_i^{NEW} = a_i^{OLD} + \varepsilon_i (r - \sum_{j=1}^{2} w_j y_j(t+1)) z_i(t) \sum_{j=1}^{2} w_j p_j , \qquad (7)$$

where ε_i is a learning factor and $\varepsilon_i = 0.003$ (i=1, 2).

On the other hand, fuzzy controller is constructed as follows.

Rule 1:IF x2(t-1) is A1 THEN

$$\Delta x12(t) = a11\ z1(t) + a12\ z2(t),$$

Rule 2:IF x2(t-1) is A2 THEN

$$\Delta x22(t) = a21\ z1(t) + a22\ z2(t),$$

where A1 and A2 are the same fuzzy sets as in the identified fuzzy model shown in Fig.3, that is,

$$A1(x2(t-1))=\exp(-(x2(t-1)+1.90)^2/5.80),$$

$$A2(x2(t-1))=\exp(-(x2(t-1)-2.06)^2/5.72).$$

The final output of the fuzzy controller is calculated as follows.

$$\Delta x2(t) = w1 \Delta x12(t) + w2 \Delta x22(t),$$

$$x2(t) = x2(t-1) + \Delta x2(t),$$

where w1 and w2 are membership values of A1 and A2, that is, w1 = A1(x2(t-1)), w2 = A2(x2(t-1)). The learning law of the fuzzy controller can be derived in the same way as the linear controller.

$$a_{ik}^{NEW} = a_{ik}^{OLD} + \varepsilon_{ik} (r - \sum_{j=1}^{2} w_j y_j(t+1)) w_k z_i(t) \sum_{j=1}^{2} w_j p_j \qquad (8)$$

where $\varepsilon_{ik} = 0.003$ (i, k=1, 2).

Fig.5 shows relations between the number of learning and summation of squared error (SE), where

$$SE = \sum_{t=1}^{m-1} (r - y(t))^2 , \qquad (9)$$

and m=253. It is found from Fig.5 that the learning efficiency of the fuzzy controller is superior to that of the linear controller. We can point out that the self-learning fuzzy controller effectively compensate non-linearity of the controlled object.

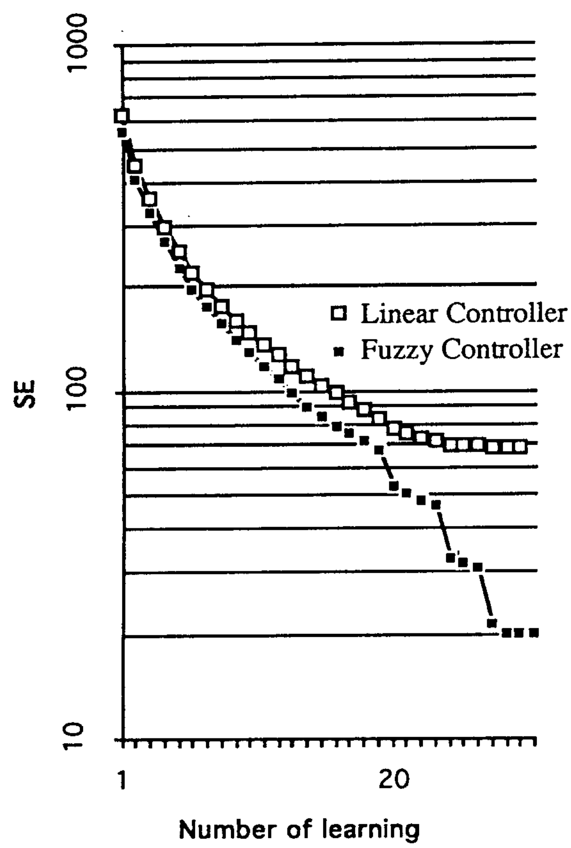

Fig.5 Learning process

Fig.6 ~ Fig.8 show simulation results of self-learning fuzzy control system. The setpoint r is set as follows. If time of a day is from 8 o'clock to 20 o'clock, then r=30, else r=5. It is found from these figures that the self-learning fuzzy control of CO concentration are effectively realized.

5. Conclusion

We have simulated two self-learning control systems for an identified fuzzy prediction model of CO concentration by using Widrow-Hoff learning rule. The purpose of this control is to keep CO concentration at a constant level. It has been assumed in this simulation that the identified fuzzy model perfectly represents real CO concentration system. Therefore, we should investigate robustness of this control system for parameter perturbation of the CO concentration model. This is a subject for future study.

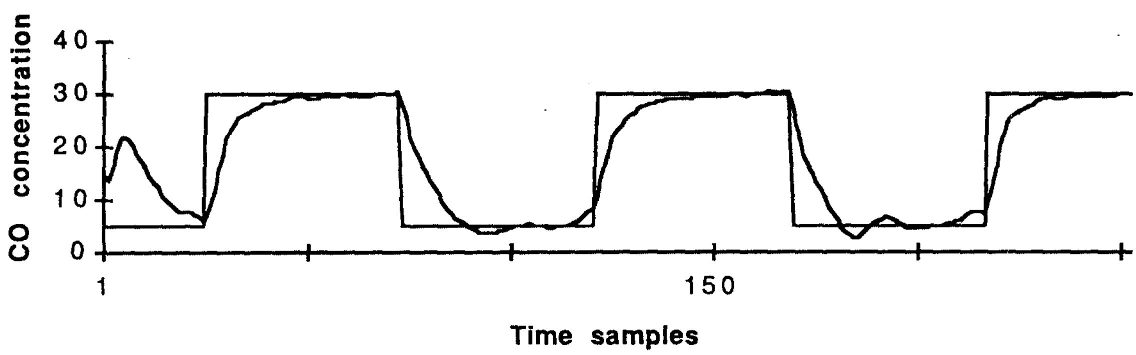

Fig.6 Control result (number of learning : 1)

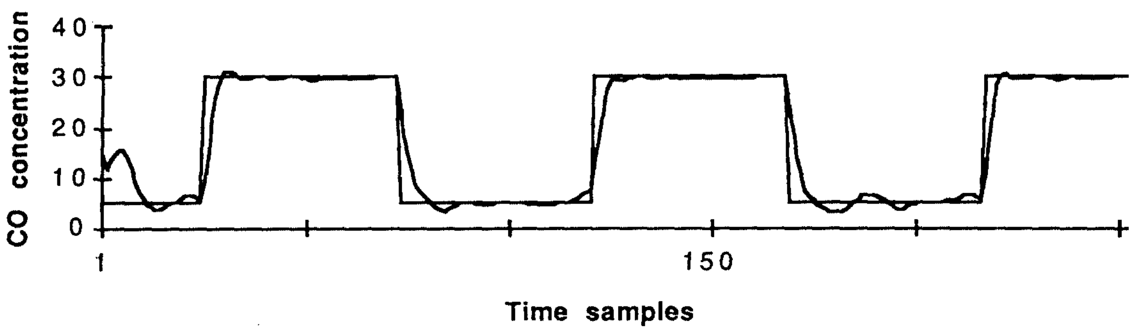

Fig.7 Control result (number of learning : 10)

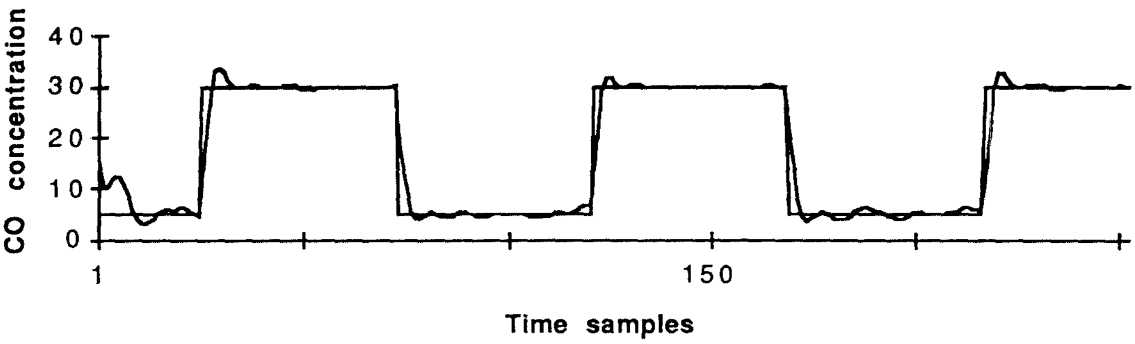

Fig.8 Control result (number of learning : 20)

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