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A Modified Self-Tuning Fuzzy-Neural Controller

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Abstract—**This paper presents a modified self-tuning fuzzy-neural controller in the applications nonlinear model reference control system. In order to make the controller have the adaptive control capability, the immediate system error ($e(k)$) and error change ($\Delta e(k)$) are used to be the inputs for fuzzy-neural tuning mechanism. For simplifying the construction of fuzzy system, nine rules are used in the rule table. To demonstrate the superiority of the controller we developed, several nonlinear model reference control systems are studied and simulated. The simulation results clearly show that the self-tuning fuzzy-neural controller has quite promising potential in the real control applications.**

Index Terms—**self-tuning, fuzzy-neural, controller, model reference**

I. INTRODUCTION

It is well known that conventional controller is usually designed based on a mathematical model of the system. In fact, to many real and practical control problems, the system's information is unknown or the parameters of system are uncertain and might vary with time. Thus, it is very difficult to obtain the accurate models for these systems. Generally, in order to control the time-varying system effectively, the controller must be designed to have the adaptability. The relevant control parameters can be auto-tuned in accordance with the immediate performance of the system.

Due to the simplicity and superiority in the real control applications, fuzzy controller has been widely employed into many linear and nonlinear control systems, especially for the system whose information is uncertain and unknown [1]-[5]. Fuzzy controller could incorporate the useful human knowledge in the fuzzy mechanism. Basically, fuzzy control can be classified into nonadaptive (conventional) fuzzy control and adaptive fuzzy control. In nonadaptive fuzzy control, the relevant parameters of the fuzzy controller are fixed during its real-time operation. Therefore, a good and effective fuzzy controller is very difficult to be designed for a complicated system if the highly accurate performance is desired. Usually, trail-and-error is the method well known for the parameter decision in many nonadaptive fuzzy control applications. However, such a controller needs many adjustments if the performance is not satisfactory. The fuzzy rules and relevant parameters need to be re-turned or redesigned in a number of trial-and-error cycles until the system's performance reaches the expectation.

For enhancing the capability and feasibility of fuzzy controller, the fuzzy controller with adaptability has been studied widely. Many research articles are also proposed [6]-[8]. The main advantage of adaptive fuzzy control is the better performance can be achieved because the controller's parameters could be adjusted to fit the environment changes. Since the strong learning capability and adaptability, neural network technique has been applied in the area of adaptive fuzzy control. A number of neural-fuzzy controllers with self-tuning algorithm are studied and presented [9]-[15]. However, the complicated structure and mass computations of neural network usually make the controller have the slower reaction power.

In this study, a modified self-tuning fuzzy-neural controller is developed. The controller's structure and the number of fuzzy rules are simpler than the fuzzy-neural controller proposed in article [16]. The detailed description of fuzzy-neural controller will be presented in Section II. Section III shows some control system simulations by using the fuzzy-neural controller we proposed. The discussion and conclusion will be given in Section IV.

II. THE MODIFIED FUZZY-NEURAL CONTROLLER

The fuzzy-neural controller is modified from the controller presented in [16]. In this paper, three immediate system behaviors (error $e(k)$, error change $\Delta e(k)$, and the change of error change $\Delta\Delta e(k)$) were used to be the inputs of fuzzy-neural model. However, we found that the impact of $\Delta\Delta e(k)$ on the controller is quite small. Thus, in the modified fuzzy-neural controller, only $e(k)$ and $\Delta e(k)$ are used as the inputs of fuzzy mechanism. The whole fuzzy-neural control system is presented in Fig. 1.

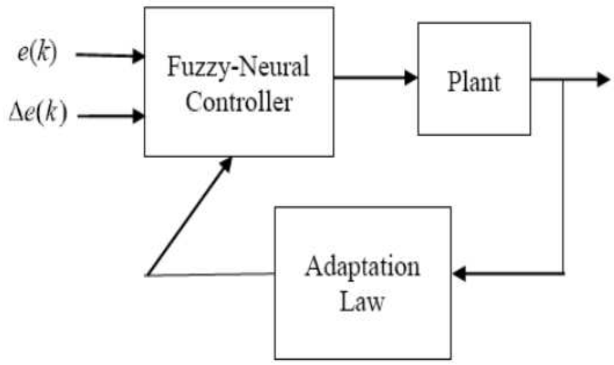

Fig. 1 The structure of fuzzy-neural control system.

In order to speed the reaction power of fuzzy-neural controller, only nine rules are taken to construct the rule table which is shown in Table 1. The membership functions of fuzzifier for $e(k)$ and $\Delta e(k)$ and defuzzifier for the force

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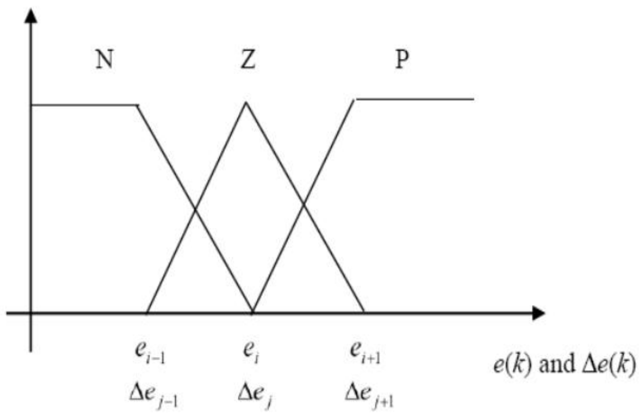
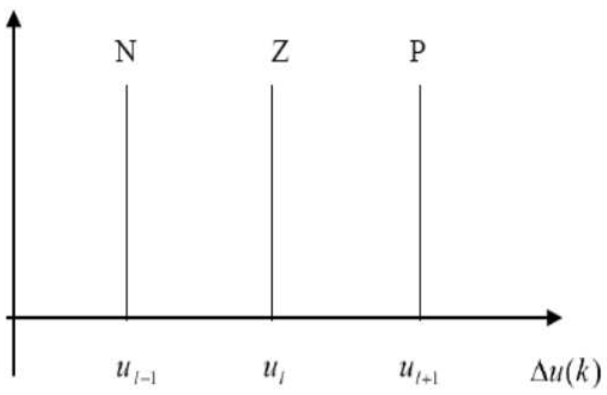
increment $\Delta u(k)$ are shown in Fig. 2 and Fig. 3.

Table 1. The rule table of neural-fuzzy controller.

$\Delta e(k)$ \ $e(k)$	N	Z	P
N	N	N	P
Z	N	Z	P
P	N	P	P

Fig. 2 The membership functions of $e(k)$ and $\Delta e(k)$.





For making the controller have the adaptability, the strength of firing rules and the singleton values of defuzzifier are designed to be adjustable. The whole fuzzy computational process is organized to be a neural model which is shown in Fig. 4. And, the steepest decent gradient method is used to derive the tuning algorithm. The adaptation law for the adjustable parameters is presented as follows [16].

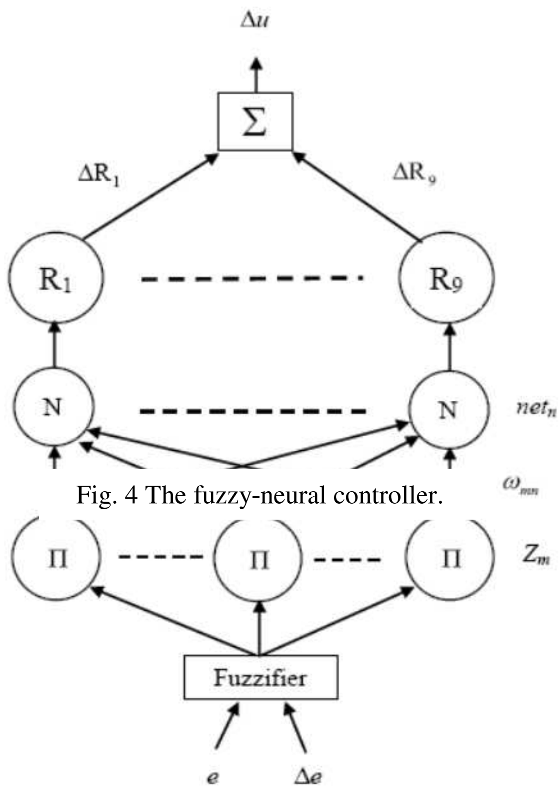


Fig. 4 The fuzzy-neural controller.

Here, we denote $O(k)$ and $Y(k)$ to be the desired and actual outputs of the system at time k. The force increment, $\Delta u(k) = u(k) - u(k-1)$ is the output of fuzzy-neural controller. $\delta_o(k)$ and $\delta_h(k)$ are the error terms of the output layer and hidden layer of fuzzy-neural model, respectively. Let η be the learning rate. Then, the adjustments of the firing rule's strength $\omega_{mn}(k)$ and the value of n-*th* rule in the defuzzier $R_n(k)$ can be derived by the chain rule.

Set the cost function as

$$E = \sum_{k=1} (O(k) - Y(k))^2 \tag{1}$$

then

$$\Delta \omega_{mn}(k) \propto -\frac{\partial E}{\partial \omega_{mn}(k)} \tag{2}$$

Fig. 3 The membership function of $\Delta u(k)$.

$$\Delta R_n(k) \propto -\frac{\partial E}{\partial R_n(k)} \tag{3}$$

$$\frac{\partial E}{\partial \omega_{mn}(k)} = \frac{\partial E}{\partial Y(k)} \frac{\partial Y(k)}{\partial u(k)} \frac{\partial u(k)}{\partial \Delta u(k)} \cdot \frac{\partial \Delta u(k)}{\partial net_n(k)} \frac{\partial net_n(k)}{\partial \omega_{mn}(k)} \tag{4}$$

$$\frac{\partial E}{\partial R_n(k)} = \frac{\partial E}{\partial Y(k)} \frac{\partial Y(k)}{\partial u(k)} \frac{\partial u(k)}{\partial \Delta u(k)} \frac{\partial \Delta u(k)}{\partial R_n(k)} \tag{5}$$

where,

$$net_n(k) = (Z_m(k) \cdot \omega_{mn}(k)) / (\sum_{m=1}^{9} Z_m(k) \cdot \omega_{mn}(k)) \cdots \tag{6}$$

is the normalization process of the firing strength.

Define the error terms

$$\delta_o(k) = -\frac{\partial E}{\partial \Delta u(k)} = \frac{\partial E}{\partial Y(k)} \frac{\partial Y(k)}{\partial u(k)} \frac{\partial u(k)}{\partial \Delta u(k)} = (O(k) - Y(k)) \cdot \operatorname{sgn}\left(\frac{Y(k) - Y(k-1)}{u(k) - u(k-1)}\right) \tag{7}$$

$$\delta_h(n) = -\frac{\partial E}{\partial net_n(k)} = \delta_o(k) \cdot R_n(k) \tag{8}$$

Thus, the adjustments of $R_n(k)$ and $\omega_{mn}(k)$ can be expressed as

$$\Delta R_n(k) = \eta \cdot \delta_o(k) \cdot net_n(k) \tag{9}$$

$$\Delta \omega_{mn}(k) = \eta \cdot \delta_h(k) \cdot \frac{(Z_m(k) \cdot \sum_{m=1}^{9} Z_m(k) \cdot \omega_{mn}(k)) - Z_m^2(k) \cdot \omega_{mn}(k)}{\left(\sum_{m-1}^{9} Z_m(k) \cdot \omega_{mn}(k)\right)^2} \tag{10}$$

III. SIMULATIONS

In this study, several model reference control systems are simulated.

Simulation 1:

A two-order unstable nonlinear system given by the following equations is considered.

$$\begin{aligned} x_1(k+1) &= x_1(k) + 0.01x_2(k) + 0.01u(k) \\ x_2(k+1) &= 0.1x_1(k) + 0.97x_2(k) \\ y(k+1) &= x_1(k+1) \end{aligned} \tag{11}$$

The system is requested to follow a model given by

$$y_m(k+1) = 0.99y_m(k) + 0.01r(k) \tag{12}$$

where, the reference input $r(k)$ is given by

$$r(k) = 0.5\sin(0.007k) + 2\cos(0.059k) \tag{13}$$

The system's initial values are $x_1(0) = 0$ $x_2(0) = 0$ and $y_m(0) = 0$.

Fig. 5 is the superposition diagram of control results by using the fuzzy-neural controller proposed. It is clearly shows the controller we developed has a quite promising performance.

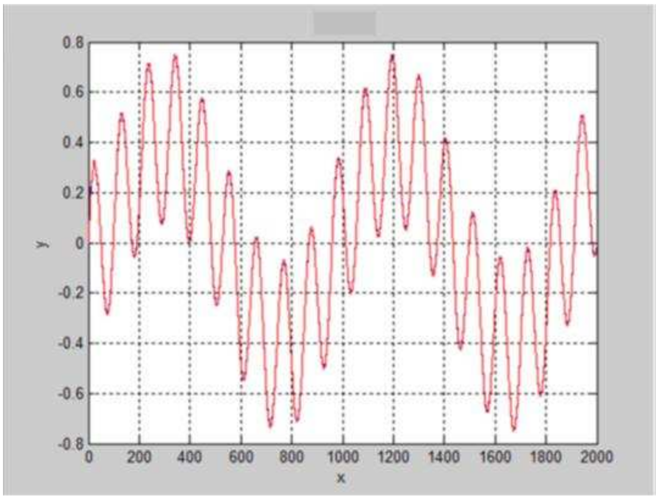


Fig. 5 The superposition diagram of control results on 1st simulation.
Dash line: the output of reference model
Solid line: actual system's output

Simulation 2:

we consider a two-order nonlinear system given by the following equation.

$$y(k+1) = 0.3y(k) + 0.6y(k-1) + u(k) \tag{14}$$

The system will follow a model given by

$$y_m(k+1) = 0.3y_m(k) + 0.6y_m(k-1) + f(u_c(k)) \tag{15}$$

where,

$$f(u_c(k)) = 0.6\sin(\pi u_c(k)) + 0.3\sin(3\pi u_c(k)) + 0.1\sin(5\pi u_c(k)) \tag{16}$$

$$u_c(k) = \sin(2\pi k / 250) \tag{17}$$

Fig. 6 shows the superposition diagram of control results.

Simulation 3:

A high-order nonlinear system is given by the following equation.

$$y(k+1) = 0.35\left[\frac{y(k)y(k-1)(y(k)+2.5)}{1+y^2(k)+y^2(k-1)}\right] + 0.35u(k) \tag{18}$$

The plant is requested to follow the model given by

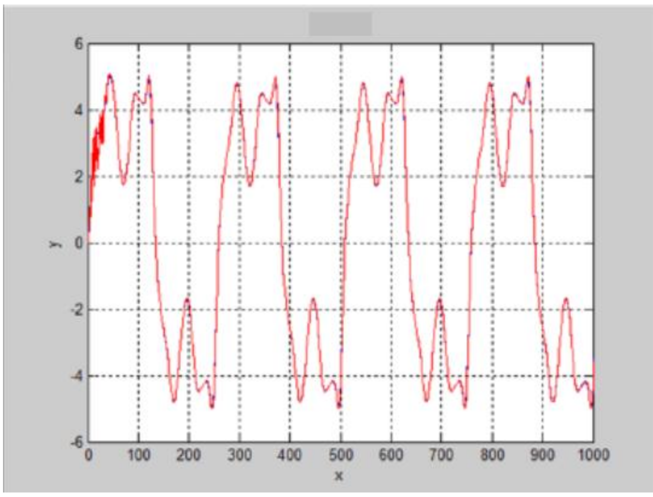
Fig. 7 The superposition diagram of control results on 3nd simulation.
Dash line: the output of reference model
Solid line: actual system's output

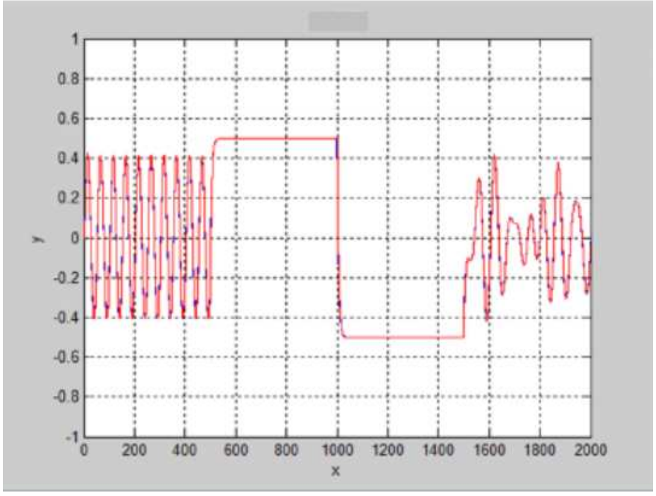
$$y_m(k+1) = 0.6y_m(k) + 0.2y_m(k-1) + 0.1r(k) \tag{19}$$

where,

$$r(k) = \begin{cases} \sin(\pi k/25) \ \text{ for } k < 500 \\ 1 \ \text{ for } 500 \le k < 1000 \\ -1 \ \text{ for } 1000 \le k < 1500 \\ 0.3\sin(\pi k/25) + 0.4\sin(\pi k/32) \\ \quad + 0.3\sin(\pi k/40) \quad \text{for } k \ge 1500 \end{cases} \tag{20}$$

Fig. 7 presents the superposition diagram of control results.





Simulation 4:

Another high-order nonlinear system is given by the following equation.

$$y(k+1) = 0.35\left[\frac{y(k)y(k)(y(k-1)+2.5}{1+y^2(k-1)}\right] + 0.35u(k) \cdots \tag{21}$$

The plant will follow the model given by

$$y_m(k+1) = 0.6y_m(k) + 0.2y_m(k-1) + 0.1r(k) \tag{22}$$

where,

$$r(k) = \begin{cases} \sin(\pi k/25) \ \text{ for } k < 500 \\ 1 \ \text{ for } 500 \le k < 1000 \\ -1 \ \text{ for } 1000 \le k < 1500 \\ 0.3\sin(\pi k/25) + 0.4\sin(\pi k/32) \\ \quad + 0.3\sin(\pi k/40) \quad \text{for } k \ge 1500 \end{cases} \tag{23}$$

Fig. 8 presents the superposition diagram of control results.

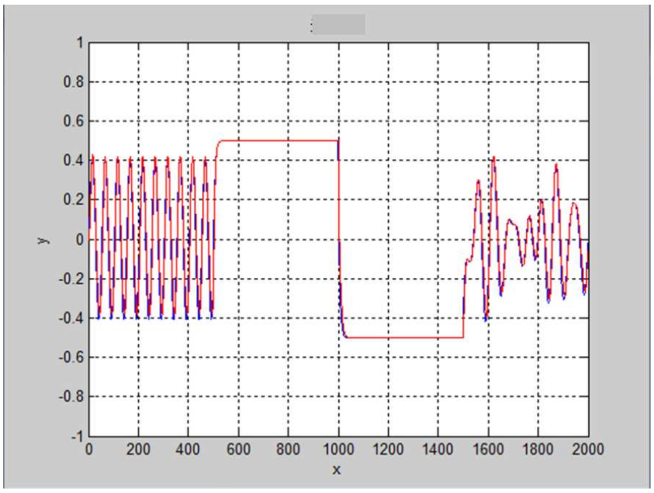


Fig. 8 The superposition diagram of control results on 4th simulation.
Dash line: the output of reference model
Solid line: actual system's output

From the results shown in Fig. 6, Fig. 7 and Fig. 8, it can be clearly found that the fuzzy-neural controller we developed has the very good performances for three nonlinear systems either.

IV. Conclusion

In this paper, a modified fuzzy-neural controller with adaptability is proposed. Two influencing factors, the system error $e(k)$ and error change $\Delta e(k)$ are used to be the inputs of fuzzy mechanism. In the fuzzy mechanism we designed, only nine rules are taken to generate the control force. Compare with the traditional fuzzy controller, the structure of the whole fuzzy mechanism and the amount of computations have been greatly simplified. In other words, the reaction power of controller can be more enhanced. In order to make the controller have the adaptability to fit the environment changes, the whole fuzzy controller is designed to be a fuzzy-neural type. The strength of firing rules and the singleton values of defuzzifier are designed to be auto-turned in accordance with the system's behaviors. Several nonlinear model reference control systems are simulated by using the fuzzy-neural controller developed. From the simulation results shown, it is clearly found that the fuzzy-neural controller do have the excellent ability to handle the complicated and nonlinear control problems. And, the controller we developed highly promotes the potential of fuzzy controller in the real adaptive control applications.

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