Research Article

Fuzzy PD Control of Networked Control Systems Based on CMAC Neural Network

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The network and plant can be regarded as a controlled time-varying system because of the random induced delay in the networked control systems. The cerebellar model articulation controller (CMAC) neural network and a PD controller are combined to achieve the forward feedback control. The PD controller parameters are adjusted adaptively by fuzzy reasoning mechanism, which can optimize the control effect by reducing the uncertainty caused by the network-induced delay. Finally, the simulations show that the control method proposed can improve the performance effectively.

1. Introduction

Networked control system (NCS) is a distributed and networked real-time feedback control system which combine communication network and control system [1]. Due to the irregularly multiple nodes shared network and data flowing change, information exchange time delay occurred inevitably, which is the network-induced delay [2]. The network-induced delay will cause system poor control quality and bad performance, even unstable [3–5]. Therefore, the induced delay is one of the most issues in the network control system [6–9].

Based on the influence of the induced delay in the network control system, a cycle time delay network using augmented deterministic discrete time model method is proposed by [10] to control the linear continuous controlled object. In [11] based on the queue management network, the queuing methodology is put forward to turn random time delay into fixed-length time delay. The buffer queue method is designed based on probability predictor delay compensation, according to the problem of random delay in the network

control system [12]. Zhang et al. [13] studied the stability of network control system with constant delay. Wu et al. [14] propose a delay-dependent sufficient condition by applying the delay partitioning approach for the asymptotic stability with an $H\infty$ error performance for the error system. Wu and Zheng [15] addressed the L_2-L_∞ dynamic output feedback (DOF) control problem for a class of nonlinear fuzzy ItO stochastic systems with time-varying delay. Yue et al. [16] established the new network control system model considering network-varying delay, packet loss, and wrong sequence. Peng et al. [17] researched on network control system with interval variable delay and reduced complexity by introducing Jessen inequality. Wu et al. [18] investigated the problems of stability analysis and stabilization for a class of discrete-time Takagi-Sugeno fuzzy systems with time-varying state delay. Wu et al. [19] proposed sufficient conditions to guarantee the exponential stability for the switched neural networks with constant and time-varying delays by using the average dwell time approach together with the piecewise Lyapunov function technique and by combining a novel Lyapunov-Krasovskii functional, which benefits from the delay partitioning method, with the free-weighting matrix technique. In [20] the impact of the network-induced delay is described as a system of continuous-time nonlinear perturbation using nonlinear perturbation theory by assuming no observation noise. Yang et al. introduced a new class of discrete-time networked nonlinear systems with mixed random delays and packet dropouts [21] and discussed the problem of feedback control for networked systems with discrete and distributed delays subject to quantization and packet dropout [22]. Xie et al. [23] discussed the problem of robust $H\infty$ fault-tolerant control for uncertain networked control system with random delays and actuator faults.

In this paper, the PD control with CMAC (cerebellar model articulation controller, CMAC) is proposed. The transmission network and the controlled object are regarded as the time-varying controlled system, in which CMAC neural network implements the forward feedback, while the fuzzy PD composite switching model is applied and adaptive on-line parameters by using fuzzy inference engine are set. The method proposed can reduce the impact of network-induced delay and the uncertainties, so it optimize the control effect and improve the control performance of the system.

The rest of the paper is organized as follows. In Section 2, the problem of time delay in NCS is described. The CMAC neural network-based fuzzy PD controller is put forward in Section 3. Simulation results are shown in Section 4. Finally, a conclusion is provided in Section 5.

2. The Description of Network Control System with Time Delay

In network control system, there are three kinds of delay, namely, sensor-controller delay τ_{sc}, controller computation delay τ_c, and controller-actuator delay τ_{ca}, where the τ_{sc} and τ_{ca} are caused by the transmission delay generated by the forward channel and feedback channel, and the τ_c is caused by the hardware structure and software code. The controller computation delay τ_c used is to be neglected because it is smaller than τ_{sc} and τ_{ca}. So the total delay of the kth sampling period can be represented as $\tau^k = \tau_{\text{sc}}^k + \tau_{\text{ca}}^k$ [24]. The network control system block diagram is shown in Figure 1.

3. The Design of CMAC Neural Network-Based Fuzzy PD Controller

Network control system is time varying because of the network random delay, and the general PID controller will make the control performance worse. But intelligent control has
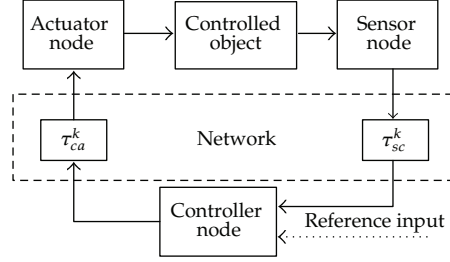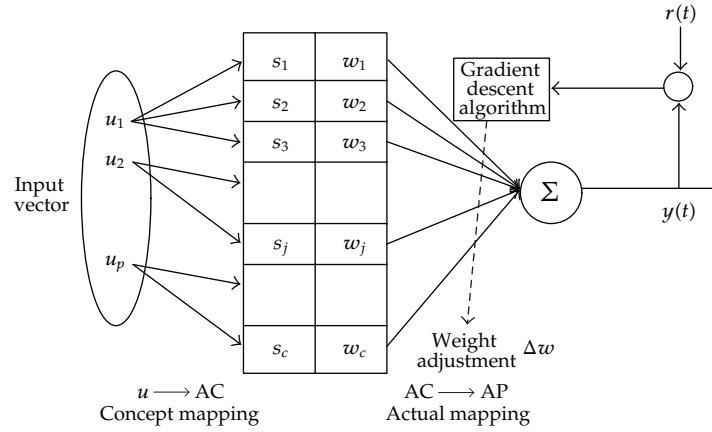
Figure 1: Networked control system.

Figure 2: Structure of CMAC network.

a better adaptive ability and is an effective method to improve the system performance [25–28], therefore intelligent control is applied to improve the robustness of the system [29–33]. In this paper, CMAC neural network-based fuzzy PD is applied to control the system. We use the PD algorithm instead of the PID, so that the learning of CMAC neural network only depends on the measured and varying values of errors.

3.1. CMAC Neural Network

CMAC is a neural network model which can simulate the function of the cerebellar and has the ability to express and inquire complex nonlinear forms adaptively. The network can change the form's information through the learning algorithm and can also store information by category [34]. CMAC consists of input layer, middle layer, and output layer, and its structure is shown in Figure 2.

$\mathbf{u}_p = [\mathbf{u}_{1p}, \mathbf{u}_{2p}, \ldots, \mathbf{u}_{np}]^T$ and $[u_p]$ are respectively input space vector and quantization coding, and the input space is mapped to the c memory cells, and c is generalization parameters. The mapping vector is as follows:

$$\mathbf{R}_p = S([u_p]) = [s_1(u_p), s_2(u_p), \ldots, s_c(u_p)]^T, \tag{3.1}$$
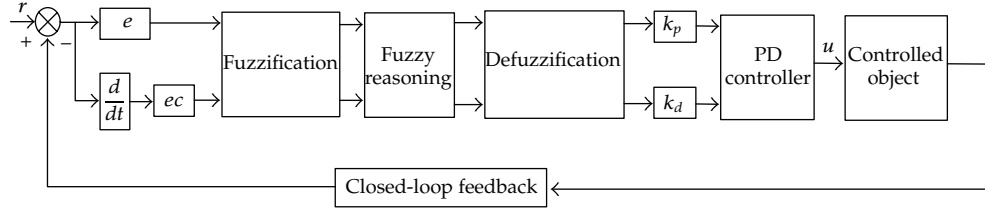
Figure 3: Diagram of fuzzy PD controller.

where $s_j([u_p]) = 1, j = 1, 2, \ldots, c$. The network's output is the sum of the weights of the c units.

Now only thinking of the single input, the output is

$$y = \sum_{j=1}^{c} w_j s_j([u_p]),\tag{3.2}$$

so

$$y = \sum_{j=1}^{c} w_j.\tag{3.3}$$

The learning algorithm is as follows.

The δ learning rule is adapted to adjust the weights, and the norm of weight adjustment is

$$E = \frac{1}{2c} e(t)^2,\tag{3.4}$$

where $e(t) = r(t) - y(t)$.

According to the gradient descent, the weights are adjusted as follows:

$$\Delta w_j(k) = -\eta \frac{\partial E}{\partial w} = \eta \frac{r(t) - y(t)}{c} \cdot \frac{\partial y}{\partial w} = \eta \frac{e(t)}{c},$$
$$w_j(t) = w_j(t-1) + \Delta w_j(t) + \beta(w_j(t-1) - w_j(t-2)),\tag{3.5}$$

where $w = [w_1, w_2, \ldots, w_c]^T$, and β is inertial coefficient.

3.2. Fuzzy PD Controller

Fuzzy PD controller takes fuzzy reasoning to adjust the real-time PD parameters. The design of the fuzzy controller includes the fuzzy rules, fuzzy domain, and defuzzification. In this paper, fuzzy algorithm applies the dual-input-output, where signal difference e and difference rate ec are the input, meanwhile, the PD controller proportion coefficient k_p and differential coefficient k_d are the output, respectively. The structure is shown in Figure 3.
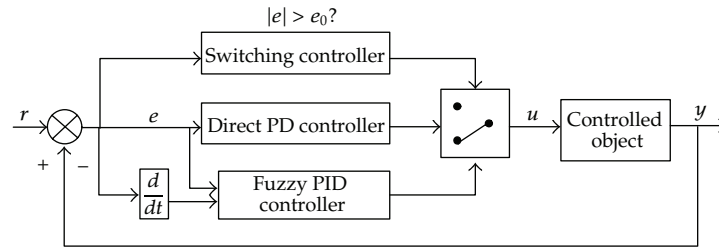
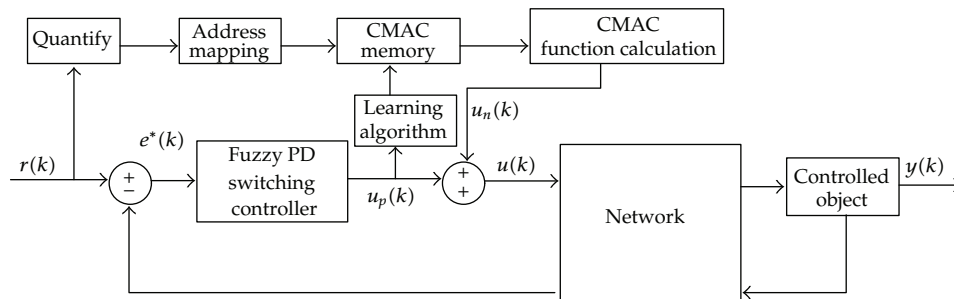**Figure 4:** Structure of fuzzy PD switching controller.

Figure 5: Compound control structure based on CMAC and fuzzy PD.

The fuzzy PD control in a wide range can improve the dynamic response speed, while PD control in a small scale can improve the static control accuracy. So in this paper switching control system between fuzzy PD and PD control is proposed, PD control in the small deviation is applied to obtain higher static control accuracy, and fuzzy PD control in large deviations is applied to obtain faster dynamic response and smaller overshoot. Its structure is shown in Figure 4. The PD control is applied when $|e| \leq e_0$ and the fuzzy PD control is applied when $|e| > e_0$, where e_0 is threshold value.

3.3. Fuzzy PD Composite Controller Based on CMAC Neural Network

In general, CMAC network is a nonlinear mapping, which is very suitable for online applications because it takes a simple δ algorithm as learning algorithm. This algorithm has a fast convergence speed and avoids local minimum value problem. The fuzzy PD switching controller is a nonlinear control, which has faster dynamic response, smaller overshoot, and strong robustness. So the CAMC-fuzzy PD controller is designed, which has the advantages of CMAC neural network and fuzzy PD controller. Also it is applied in the network control system with delay. The structure is shown in Figure 5.

The input of CMAC neural network is command signal $\text{rin}(k)$. Using the study algorithm with tutor, calculate the relative neural network output $u_n(k)$ of CMAC, compare with the total control input $u(k)$ at the end of each control cycle, then correct weights, and go to the process of learning.

At the beginning of the operating system, fuzzy PD controller plays a major role, while the neural network of CMAC does not work. After a while, the output of CMAC neural network gradually plays a key role by continuous learning the actual output and the expected output values to modify weights.
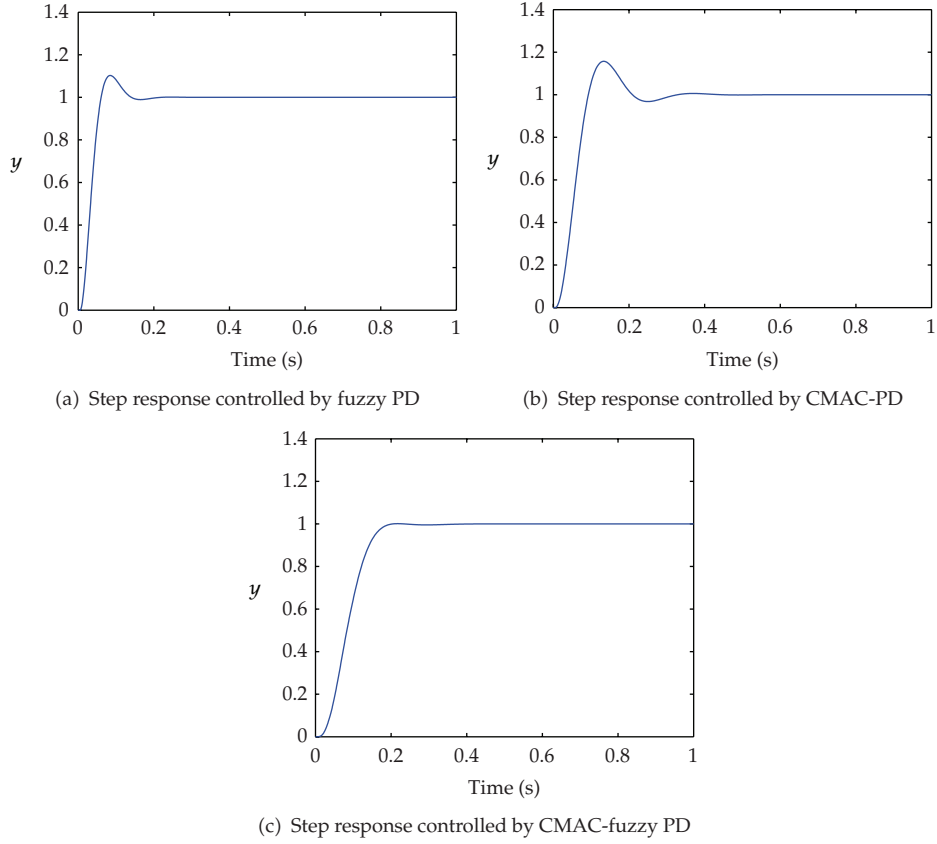
(a) Step response controlled by fuzzy PD

(b) Step response controlled by CMAC-PD

(c) Step response controlled by CMAC-fuzzy PD

Figure 6: Step responses when the mean of time delay is 5 ms.

The control algorithm is

$$u_n(k) = \sum_{i=1}^{c} w_i \mathbf{a}_i, \tag{3.6}$$

where $\mathbf{a}_i$ is binary choice vector, and c is a generalization parameter.

Consider the following:

$$u_p(k) = \begin{cases} k_P * e(k) + k_d * ec(k), & |e| \leq e_0, \\ k'_p * e(k) + k'_d * ec(k), & |e| > e_0, \end{cases} \tag{3.7}$$

where k_P and k_d are parameters preset by PD controller, meanwhile k'_p and k'_d are parameters adjusted online by fuzzy PD controller.

The output of system is

$$u(k) = u_n(k) + u_p(k), \tag{3.8}$$

(a) Step response controlled by fuzzy PD

(b) Step response controlled by CMAC-PD
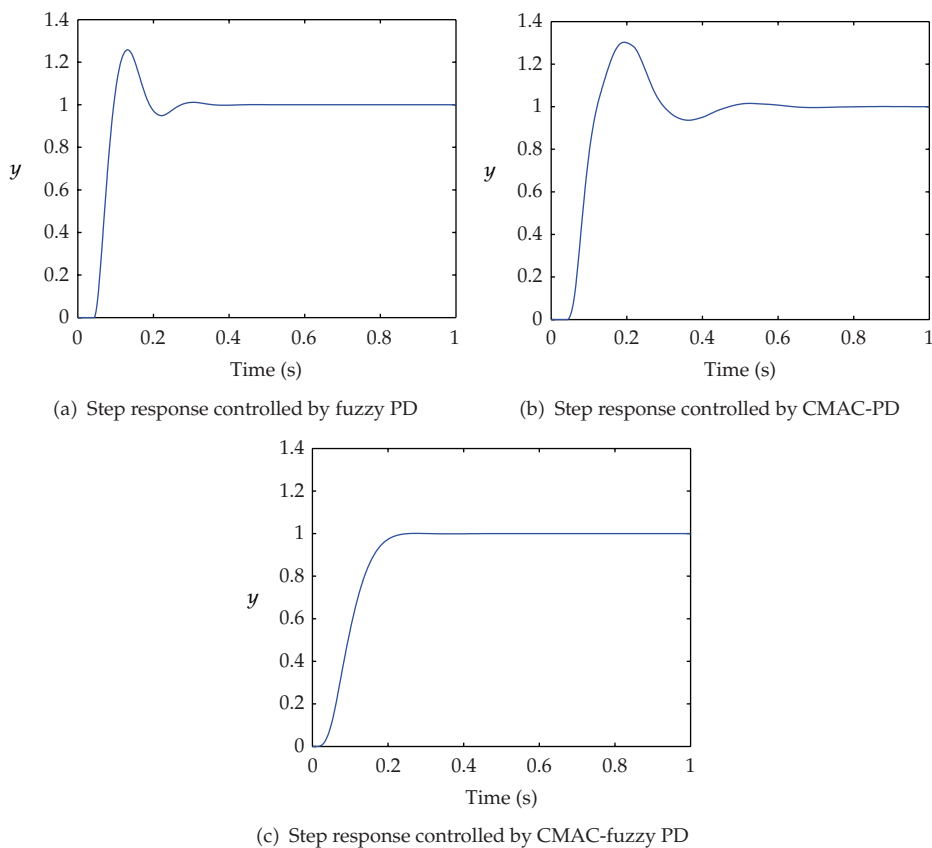

(c) Step response controlled by CMAC-fuzzy PD

Figure 7: Step responses when the mean of time delay is 50 ms.

where $u_n(k)$ is the output of CMAC neural network, and $u_p(k)$ is the output of the fuzzy PD composites switching controller.

The mapping of CMAC neural network is that the input space is S and the range of $[S_{min}, S_{max}]$ is divided into $N + 2c$ quantization intervals, that is,

$$v_1 \cdots v_c = S_{min},$$

$$v_j = v_{j-1} + \Delta v_j \quad (j = c + 1, \ldots, c + N), \tag{3.9}$$

$$v_{N+c+1} \cdots v_{N+2c} = S_{max}.$$

The mapping of CMAC is

$$a_j = \begin{cases} 1, & \text{if } S_j \in [v_j v_{j+c}], j = c + 1, \ldots, c + N, \\ 0, & \text{other}. \end{cases} \tag{3.10}$$

Adjusted index in the learning process is

$$E = \frac{1}{2c}(u_n(k) - u(k))^2,$$

$$\Delta w(k) = -\eta \frac{\partial E}{\partial w} = \eta \frac{u(k) - u_n(k)}{c} \cdot a_i = \eta \frac{u_p(k)}{c} a_i, \tag{3.11}$$

$$w(k) = w(k-1) + \Delta w(k) + \beta(w(k-1) - w(k-2)),$$

where η is the rate of network learning, $\eta \in (0,1)$, and β is inertial, $\beta \in (0,1)$.

4. Simulation

In simulation, the input is the unit step, and the transfer function of controlled object is $(0.0008674z + 0.0008503)/(z^2 - 1.94z + 0.9418)$. Parameters $N = 100$, $c = 5$, $\eta = 0.1$, $\beta = 0.04$, and $k_p = 0.02$, $k_d = 0.06$, and switching threshold e is 0.2.

The domain of fuzzy algorithm input e and ec is, respectively, $[-6, 6]$ and $[-30, 30]$. If the actual value of e exceeds the set domain, the value will be limited. The membership function is Gaussian bell-shaped function, which is N, Z, P (negative, zero, positive), respectively; the domain of k'_p and k'_d is, respectively, $[0, 0.001]$ and $[0, 0.1]$, and membership function is also Gaussian bell-shaped function, which is Z, S, M, P (zero, small, medium, large) respectively; Mamdani-type reasoning is adopted and gravity method is defuzzification. Fuzzy lut of k'_p and k'_d is, respectively, shown as Tables 1 and 2.

Due to the network delay varies randomly during continuous-time. In simulation, system network delay is generated by Gaussian random signal source, and step responses means for 5 ms and 50 ms under Gaussian distribution random delay network. Compared with the traditional CMAC-PD composite control and fuzzy PD control, step response charts are shown in Figures 6 and 7, where sampling time is 1 ms.

From Figure 6(a), we can see that the result is not very good because of the time delay. Under traditional fuzzy PD controller, the step responses of the system show great overshot, long rising time, and large steady state error. In Figure 7(a) especially, when the time delay increases, the fuzzy PD control overshoot of the system is also increased. Otherwise, the result is not ideal under traditional CMAC-PD controller from Figures 6–7(b). Compared with the first two kinds of methods, the CMAC-fuzzy PD controller proposed in this paper is more ideal, especially in the long-delay network. Figures 6–7(c) show that the system has the virtue of stability, precision, fastness, and strong robustness.

5. Conclusions

Network control system is the time varying because of the random-induced delay, which results in worse control effects. But the intelligent control has better adaptation and can be used to improve the control performance. This paper regards transmission network and the controlled objects as a time-varying system, combines CMAC neural network algorithm with PD controller to achieve forward feedback control, and adopts the intelligent control strategy. The PD controller introduces fuzzy PD complex switching model. According to the size of the error signal, switching-controller switches between directly PD controller and fuzzy PD

Table 1: Fuzzy lut of k_p'.

e/ec	N	Z	P
N	S	M	Z
Z	P	P	P
P	P	P	P

Table 2: Fuzzy lut of k_d'.

e/ec	N	Z	P
N	Z	M	M
Z	P	Z	P
P	M	Z	S

controller, in order to improve the speed of dynamic response of the system and accuracy of steady-state control. Simulation results show that the system has the virtue of stability, precision, fastness, and strong robustness. So that this method can achieve a better effect and can also improve the system's performance effectively.

Acknowledgments

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