A Self-tuning Fuzzy Controller for Networked Control System

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Summary

This paper mainly deals with the controller design for a class of networked control system (NCS) with the presence of network-induced delay and data packet dropout. Aiming at the stochastic and time-varying characteristics of delay and dropout, a NCS model with uncertain linear parameters was established by converting the uncertainties of delay and dropout into the uncertainties of the coefficient matrixes of system state equation. Based on the mathematical model, a self-tuning fuzzy controller composed with two basic fuzzy controllers for NCS was proposed. The first-level fuzzy controller was used to control the controlled plant directly. In addition, in order to solve the influences of the uncertainties on the system stability effectively, a second-level fuzzy controller was designed to adjust the quantification and the scaling factors of the first-level fuzzy controller in an on-line and adaptive way according to the system error and the change of the error. Simulation results based on Truetime simulation platform verify the validity of the self-tuning fuzzy controller for NCS.

Key words:
networked control system, network-induced delay, data packet dropout, fuzzy controller.

1. Introduction

The development trend of the distributed control system is to adopt serial communication network as the information exchange channel between controllers, sensors and actuators. This kind of feedback control system using a real-time network to realize a closed control loop is called networked control system (NCS) [1]. Compared with the traditional control systems, NCS has many advantages such as reduced system wiring, high reliability, ease of system maintenance, and share of information resource, etc. Therefore, NCS has been widely used in manufacturing, aircraft and remote robot systems [2, 3]. However, NCS also has some distinct disadvantages such as network-induced delay and data packet dropout [4]. Generally speaking, the network-induced delay and the data packet dropout change randomly along with the change of data transmission, which will further complicate the analysis and the synthesis of NCS. Therefore, how to design a satisfactory NCS controller with the presence of stochastic delay and dropout has become a very important problem.

There are mainly three controller design methods for networked control system with stochastic delay, i.e., stochastic control method, certainty method, and intelligent control method. From the point of the view of stochastic control and dynamic planning, [5] and [6] proposed a controller design method for NCS with network-induced delay respectively, which requires the statistical property of delay is known beforehand. Because large amount of calculation of mean and variance are needed during the stochastic NCS controller design course, the calculation will become rather complex. Aiming at the problem of being unable to determine the statistical property of networked induced-delay, [7, 8] proposed a method of converting a stochastic delay into a certain delay through a queue buffer area. The advantage of this method is that the present design methods of certainty system can be applied directly for NCS controller design, while the disadvantage is that the delay is enlarged artificially due to each delay being converted into a maximal delay. Intelligent control technique imitates the process of human thinking. Therefore, it can fulfill effective control for nonlinear systems with unknown dynamics model. Lee utilized the optimizational function of genetic algorithm to adjust Proportional, Integral, and Derivative (PID) parameters [9]. Based on the continuous networked control system model described in [10], Peng and Yue viewed a fuzzy controller as the internal model part of Smith control and integrated the Smith pre-estimation part with the controlled object, which can reduce the transformation of redundant information and compensates the network-induced delay [11].

Compared with the research of network-induced delay, the analysis and the research of the data packet dropout are quite limited. In order to improve the whole performance of NCS, this paper deals with the controller design for a class of networked control system with the presence of network-induced delay and data packet dropout. Because it’s very difficult to build an exact mathematical model for NCS due to the stochastic and time-varying properties of delay and dropout, we could not obtain satisfactory control effects through the conventional model-based control methods. Fuzzy control does not need the exact mathematical model of the controlled plant, and it has strong adaptive capability to uncertain and time-varying model. Based on the above analysis, a fuzzy controller

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with parameter self-tuning for NCS was proposed.

The paper is organized as follows. The dynamic model of NCS with delay and dropout was given in Section 2. In Section 3, the idea and the algorithm steps of designing self-tuning fuzzy controller were described. In order to verify the validity of the proposed control method, some simulation results were presented and analyzed in Section 4. Finally, conclusions were drawn in Section 5.

2. NCS Model

There are several major assumptions made during the establishment of NCS model under the precondition that the controlled plant is continuous, constant and stabilizable, and that the system noise is negligible [11]. Most of these assumptions are valid and acceptable. As long as one works within the constraints of these assumptions, the mathematical model will provide valuable information about NCS.

A1 Sensor is clock-driven, and sampling interval h is equal;

A2 Controller and actuator are event-driven;

A3 Lump together τ_{ca} (controller-to-actuator delay) and τ_{sc} (sensor-to-controller delay). Networked-induced delay τ is the sum of τ_{ca} and τ_{sc}, that is, $\tau = \tau_{sc} + \tau_{ca}$;

A4 Data packet is transferred separately.

Based on the above assumptions, the mathematical model of NCS can be established as the following equation through viewing the delay and dropout as the change of the parameters of NCS model.

$$\begin{cases} \dot{x}(t) = (A + \Delta A)x(t - \tau_0) + (B + \Delta B)u(t - \tau) \\ y(t) = Cx(t) \end{cases}$$

(1)

where, $t \in (i_k h + \tau_k, i_{k+1}h + \tau_{k+1})$, $x(t) \in R^n$ is the state vector, $u(t) \in R^m$ is the control input vector, $y(t) \in R^p$ is the output vector. $A \in R^{n\times n}$, $B \in R^{n\times m}$, and $C \in R^{p\times n}$ are constant matrixes. $\Delta A \in R^{n\times n}$ and $\Delta B \in R^{n\times m}$ are uncertain linear parameter matrixes that are used to describe the network-induced delay and data packet dropout, which meet $\|\Delta A\| \le \alpha$ and $\|\Delta B\| \le \beta$. $\|\cdot\|$ denotes Euclidean norm. α and β are constants that are relative with the maximum allowable delay and the rate of dropout. τ_0 is the inherent delay of the controlled plant.

In the paper, suppose that $u(t) = 0$ before the first control signal arrive the controlled plant and that the delay is bounded, i.e., there exists a constant $\eta > 0$ that can make $(i_{k+1} - i_k)h + \tau_{k+1} \le \eta$ ($k = 1, 2, 3, \cdots$). τ_k and τ_{k+1} denote the delay at time k and $(k+1)$ respectively. $\tau_k \ne \tau_{k+1}$ means that the network-induced delay is stochastic and uncertain. $\{i_1, i_2, i_3, \cdots\}$ is the subset of $\{0, 1, 2, 3, \cdots\}$. It does not require $i_k < i_{k+1}$, which means that there may exist the data packet dropout phenomenon during the course of data transmission. Therefore, the networked-induced delay and the data packet dropout are both considered in the NCS model shown in Eq. (1), which can be viewed as a universal model of NCS.

3. Self-tuning Fuzzy Controller for NCS

Generally speaking, the plant of the NCS includes not only the physical system to be controlled but also the network that connects the system components. This network part of the plant is quite difficult to handle because the network system is stochastic in nature and there is no differential or difference equation to describe its behavior. Because fuzzy control technique can be used for control of a plant where the plant modeling is difficult or conventional control methods have shown limited success, fuzzy control is a very attractive method for NCS whose modeling is very difficult because of the uncertainties of delay and dropout.

The structure of the proposed networked control system is sketched in Fig.1, which includes a self-tuning fuzzy controller composed with a first-level fuzzy controller and a second-level fuzzy controller, a controlled plant, and a control network. The controller and the plant are connected via the network, and the control input and the plant output are transmitted through the network. Due to the use of the control network, the control input and the plant output inevitably contain the network-induced delay. For complex networked control systems, it's generally difficult to obtain satisfactory control effects through a common fuzzy controller with a group of fixed quantification and scaling factors. Therefore, a second-level fuzzy controller was designed to adjust the quantification and scaling factors of the first-level fuzzy controller according to the system error and the change of the error in real-time.

In Fig.1, $y(t)$ is the actual output of the controlled plant, $r(t)$ is the reference input, $e(t) = r(t) - y(t)$ is the error between $r(t)$ and $y(t)$, $c(t)$ is the change of error, and $u(t)$ is the control input. k_e, k_c, and k_u are the quantification and scaling factors of the first-level fuzzy controller. If the output of a fuzzy controller is control variable $u(t)$, the fuzzy controller is similar to a nonlinear PD controller. If the output of a fuzzy controller is the increment of control variable $\Delta u(t)$, the fuzzy controller is similar to a nonlinear PID controller that can eliminate system steady error and oscillation. Therefore, the output of the first-level fuzzy controller is set as the increment of control variable $\Delta u(t)$.

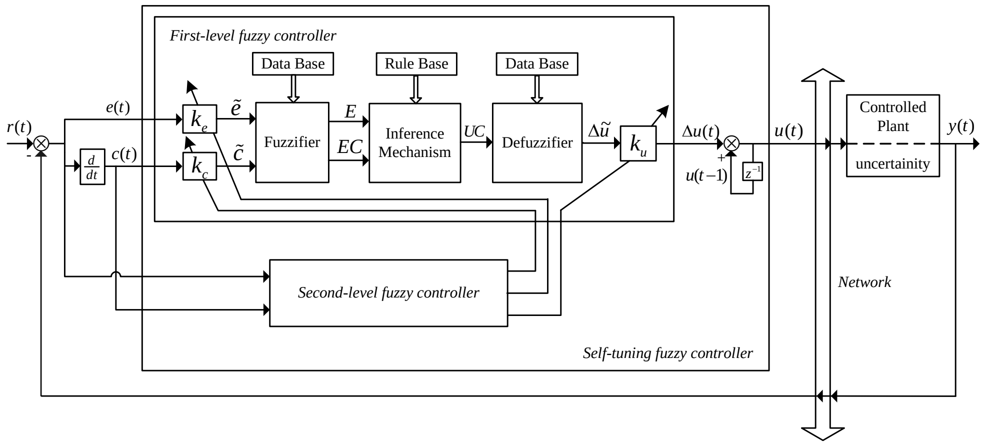

Fig. 1 The structure of self-tuning fuzzy controller for NCS

3.1 The First-level Fuzzy Controller Design

The first-level fuzzy controller is a two-dimension fuzzy logic controller with two inputs and single output. Its function is to make the actual system output $y(t)$ track the eference input $r(t)$ through adjusting control variable. It mainly composed of three modules such as a fuzzifier, a fuzzy inference mechanism, and a defuzzifier.

The fuzzifier module converts the crisp variables e, c, and Δu into the linguistic variables E, EC, and UC. Suppose the basic universes of discourses are $e \in [-|e_{\max}|, |e_{\max}|]$, $c \in [-|c_{\max}|, |c_{\max}|]$, and $\Delta u \in [-|\Delta u_{\max}|, |\Delta u_{\max}|]$, the fuzzy universes of discourses are $E \in [-M, M]$, $EC \in [-N, N]$, and $UC \in [-L, L]$. Based on the above hypothesis, the quantification and scaling factors are defined as the follows.

$$K_e = \frac{M}{|e_{\max}|} \quad , \quad K_c = \frac{N}{|c_{\max}|} \quad , \quad K_u = \frac{|\Delta u_{\max}|}{L}$$

(2)

where M, N, and L are natural numbers.

There are seven linguistic values for each linguistic variable are defined on the fuzzy universes of discourses, such as Positive Big (PB), Positive Middle (PM), Positive Small (PS), Zero (ZE), Negative Small (NS), Negative Middle (NM), and Negative Big (NB). The choice of membership functions has definite influence on the control performance. Generally speaking, the steeper the membership function is, the higher the resolution is and the higher the control sensitiveness is. On the contrary, the flatter the membership function is, the better the stability is and the stronger the robustness is. Because triangular membership function has advantages of simple computation, ease of realization and good control performance, it is adopted to represent the membership functions of the inputs and the output of the first-level fuzzy controller, which are shown in Fig.2.

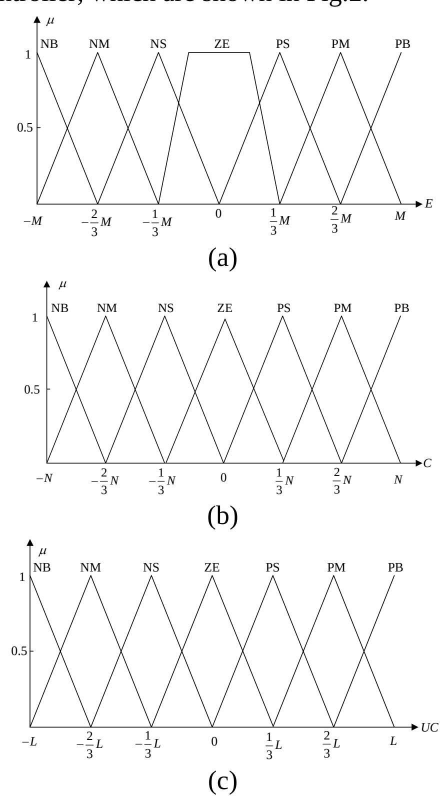

Fig. 2 The membership functions of the first-level FLC: (a) Membership function of E. (b) Membership function of EC. (c) Membership function of UC

Fuzzy control rule is the core of the design of fuzzy controller, which is in fact a set including a series of fuzzy condition statements. The principle of determining fuzzy rules is to ensure the static and the dynamic performances of the system output are optimal through the action of the output of fuzzy controller. It's well-known that the fuzzy control rules for a single-input–single-output (SISO) controller can be derived from step response. Fig.3 shows the typical step response curve of a closed-loop system. In Fig.3, characteristic points are classified into four groups, i.e., a_j, b_j, c_j, and d_j, and fuzzy control rules can be formulated by examining these characteristic points.

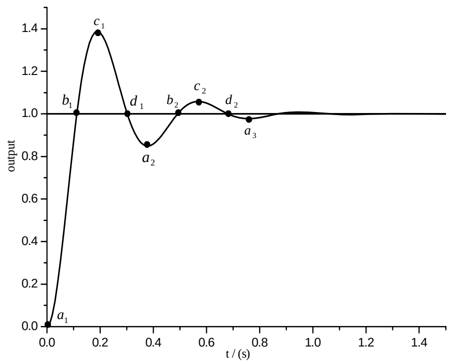

Fig. 3 Typical step response of a closed-loop system

As an example, at the first characteristic point a_j, $\tilde{e}$ is positive and $\tilde{c}$ is zero. Hence, the plant output should be increased in order to decrease the error between the reference input and the plant output, and $\Delta\tilde{u}$ should be positive. From this reason, when a_j varies, fuzzy control rules are described as follows:

Rule 1: If E is PB and EC is ZE then UC is PB
Rule 2: If E is PM and EC is ZE then UC is PM
Rule 3: If E is PS and EC is ZE then UC is PS
Rule 4: If E is ZE and EC is ZE then UC is ZE

By similar reasoning, we can formulate the control rule for b_j, c_j, and d_j, resulting in a primary rule base that consist of only the cases where either the error or the error change is close to zero, another rule base is formulated to encompass all the cases for better control performance. The first-level rule base consisting of 49 rules are shown in Table 1.

Table 1: Fuzzy control rules for the first-level fuzzy controller

EC \ E	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	ZE
NM	NB	NB	NB	NM	NS	ZE	PS
NS	NB	NB	NM	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PM	PB	PB
PM	NS	ZE	PS	PM	PB	PB	PB
PB	ZE	PS	PM	PB	PB	PB	PB

The fuzzy linguistic value obtained from fuzzy logic inference can be used to control the controlled plant only after it has been converted into a crisp output through the defuzzifier module. Specially, the commonly used centroid method is adopted to calculate the crisp output by taking an average of vertex values of the triangular membership functions weighted by their firing strength.

3.2 The Second-level Fuzzy Controller Design

The second-level fuzzy controller is a two-dimension fuzzy logic controller with two inputs and three outputs. The inputs are the error e and the change of the error c, while the outputs are the quantification factors k_e and k_c, and the scaling factor k_u. The definitions of linguistic values for e and c of the second-level fuzzy controller are similar to that of the first-level fuzzy controller. The linguistic values for these factors are defined as Very Big (VB), Quite Big (QB), A Little Big (LB), Moderate (M), A Little Small (LS), Quite Small (QS), and Very Small (VS). All of the fuzzy subsets of the inputs and the outputs of the second-level fuzzy controller are all represented by triangular membership functions.

In order to improve the control performance of the first-level fuzzy controller, the quantification and the scaling factors should be adjusted in on-line. As an example, at the beginning phase of the control process, both e and c are bigger, therefore, k_e and k_c should be smaller to reduce the resolution of e and c, and k_u should be bigger to increase the control variable so as to quick the system response speed. On the contrary, when e and c are smaller, k_e and k_c should be bigger to increase the resolution of e and c, and k_u should be smaller to reduce the control variable so as to suppress the overshoot and make the system stable. Based on the above analysis, the fuzzy control rules for the second-level fuzzy controller can be summarized and Table 2 shows the fuzzy control rules of the quantization factor k_e.

Table 2: Fuzzy control rules of the quantization factor k_e

EC \ E	NB	NM	NS	ZE	PS	PM	PB
NB	VS	QS	LS	M	LS	QS	VS
NM	QS	LS	M	M	M	LS	QS
NS	LS	M	M	LB	M	M	LS
ZE	M	M	QB	VB	QB	M	M
PS	LS	M	M	LB	M	M	LS
PM	QS	LS	M	M	M	LS	QS
PB	VS	QS	LS	M	LS	QS	VS

4. Simulation Research

In order to verify the superiority of the proposed controller, the authors applied the self-tuning fuzzy control method in this paper and the conventional fuzzy control method to control the following controlled plant.

$$\begin{cases} \dot{x}(t) = \begin{bmatrix} 0 & 1 \\ -2 & 3 \end{bmatrix} x(t-\tau_0) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(t-\tau) \\ y(t) = [1 \quad 0] x(t) \end{cases} \quad (3)$$

where, $\tau_0 = 2\,s$ is the inherent delay of the controlled plant, τ is the network-induced delay.

During the simulation process, as shown in Table 3, the dynamic simulation platform Truetime was used to realize the configuration of the network environment. The sampling period is 0.01 s, the network-induced delay follows a uniform distribution within the range of [0, 0.015] s, and the rate of the data packet dropout is 0.6.

Table 3: The configuration of the network environment

Type of network	Minimum frame size (bytes)	Data rate (bit/s)
CSMA/AMP (CAN)	5	80000

Pre-processing delay (s)	Post-processing delay (s)	Number of network
0	0	1

Fig.4 shows the step response curves through these two kinds of fuzzy controllers. The detailed performance comparison of the self-tuning and the conventional fuzzy control methods on the networked control system are tabulated in Table 4. The performance indexes considered here include overshoot, settling time, and steady-state error. It can be seen from Fig. 4 and Table 4 that the networked control system has much better dynamic and static performances through the self-tuning fuzzy controller than that of the conventional fuzzy controller.

Table 4: Performance comparison of the conventional and the self-tuning fuzzy controllers

Controller	Overshoot (%)	Settling time (s)	Steady-state error
Conventional fuzzy controller	14.5	3.2	0.088
Self-tuning fuzzy controller	4.92	3.1	0

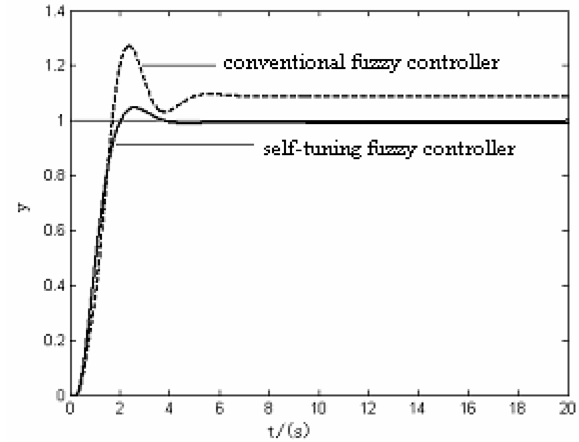

Fig. 4 The step response curves with delay and dropout

5. Conclusions

There is inevitably exists the network-induced delay and the data packet dropout phenomena during the information transmission process. The delay and the dropout have stochastic and time-varying characteristics due to the influences of the communication protocol, the load fluctuation, the network transmission speed, and the data packet, which will deteriorate the system performance and even destabilize the system. The conventional model-based control methods are difficult to be suitable for complex networked control systems. Because fuzzy control can be used for control of a plant where the plant modeling is difficult or conventional control methods have shown limited success, a self-tuning fuzzy controller was designed to control a kind of NCS with the presence of delay and the dropout. The NCS model with uncertain linear parameters, the structure of NCS fuzzy control system, the detailed design steps of the first-level and the second-level fuzzy controllers are given in the paper. Simulation results verify the validity of the proposed fuzzy controller for NCS.

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