Design of Lyapunov Function Based Fuzzy Logic Controller for a Class of Discrete-Time Systems

Jeng-Hann Li, Tzuu-Hseng S. Li, and Chih-Yang Chen

Abstract

In this paper, we present a new fuzzy logic controller (FLC) for discrete-time systems. All the decision rules of FLC are automatically generated by the Lyapunov stability criterion. The proposed control scheme can be easily derived with minimum information of the controlled plant. Furthermore, the fuzzy inference scheme can successfully be applied to stabilize the nonlinear discrete-time systems. We introduce three discrete-time systems, including a linear plant, a nonlinear plant, and a delayed plant, to demonstrate the effectiveness of the proposed FLC.

Keywords: Fuzzy logic control, Lyapunov stability, Rule generation.

1. Introduction

Fuzzy logic controllers have been successfully applied to many kinds of applications for almost four decades. Basically, FLC's are designed on the basis of human experiences, and the mathematical model of the controlled plant is not necessary for the design of FLC. They also possess advantages such as robustness, universal approximation, and rule-based algorithm. Designing a FLC, we usually focus on the system responses for some common operating conditions [1]. However, these methods cannot guarantee the closed-loop stability. Stability of over whole operating range is necessary as applying the FLC into controlled systems.

Tanaka and Sugeno [2] proposed a stability design approach that modeled the plant by the Takagi-Sugeno (TS) fuzzy model [3]. This fuzzy model represents the plant as a weighted sum of a set of linear state equations. Then the Lyapunov stability criterion can be directly applied to each fuzzy controlled subsystem [4], [5]. The stability of the overall system can be ensured if the required positive-definite matrix exists. However, the drawback is that it is very difficult to find the common Lyapunov function to satisfy all these fuzzy subsystems. Some other approaches [6-8] partitioned the state space into small parts, and analyzed the closed-loop stability of every part. However, if the rule number is large, the number of partitions will become large and the analyses become very time consuming. Thus, they are too complex for practical implementation.

In this paper, we propose a design method of Lyapunov function based FLC. The basic architecture of the new FLC is similar to the fuzzy reasoning proposed by Procyk and Mandani [9]. The fuzzy decision rules of the FLC are not established by expert knowledge or operator's experience but are constructed in a systematic scheme. This can help to minimize the manual time and effort involved for the synthesis of the FLC. The researches on automatically construction of fuzzy decision rules are also presented in the works [10], [11], but there are no stability analyses. We utilize the Lyapunov stability criterion to systematically generate the decision rules, thus the proposed FLC scheme can inherently stabilize the controlled plant.

The organization of the paper is shown as follows. In Section II, we firstly introduce the architecture of the FLC. The complete design methodology of the Lyapunov type discrete FLC is then presented in Section III. For demonstration, the simulations of three plants are proposed in Section IV. And finally, the conclusion is given in Section V.

2. Fuzzy Logic Control

The basic architecture of FLC is shown in Figure 1, which comprises several principle components: a normalization factor set of input variables, the fuzzification interface, the decision-making logic, the defuzzification interface, the knowledge base, and a normalization factor of output variable. In this paper, we consider an n-inputs and single-output FLC. The inputs are multiplied by their respective normalization factors, K_1, K_2, … , and K_n to transform to the normalized variables, which are thus the inputs of fuzzification process defined as ω_1, ω_2, … , and ω_n. For each variable ω_j, we can select its membership functions, usually in triangular type. Let N_j represent the number of mem-

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bership function for variable ω_j, and the membership functions of ω_j may be denoted as X_j^1, X_j^2, … , and $X_j^{N_j}$. Given a value of ω_j, the fuzzification process would output the value $\mu_j^{i_j}(\omega_j)$, which is called the membership degree of ω_j in the membership function $X_j^{i_j}$.

Assume the rule-base consist of R rules, and the rules are in the following form,

$$R^r: \text{IF } [(\omega_1 \text{ is } X_1^{i_{1r}}) \text{ and } (\omega_2 \text{ is } X_2^{i_{2r}}) \text{ and } \ldots \text{ and } (\omega_n \text{ is } X_n^{i_{nr}})] \quad \text{THEN } (u \text{ is } u_r),$$

where u_r is the associated singleton membership function of u, i.e., u_r represents the support of fuzzy singleton. Suppose the minimum inference method is used, and then the firing strength of the r-th rule becomes

$$\mu_{i_{1r},i_{2r},\ldots,i_{nr}}(\omega) = \min \cdot \left\{\mu_1^{i_{1r}}(\omega_1), \mu_2^{i_{2r}}(\omega_2), \ldots, \mu_n^{i_{nr}}(\omega_n)\right\}. \tag{1}$$

The technique for the computation of the crisp control output is the weighted average defuzzification, i.e.,

$$u = \frac{\sum_{r=1}^{R} u_r \mu_{i_{1r},i_{2r},\ldots,i_{nr}}(\omega)}{\sum_{r=1}^{R} \mu_{i_{1r},i_{2r},\ldots,i_{nr}}(\omega)}. \tag{2}$$

Then, the output of the FLC is

$$u_{fuzzy} = K_{out} \cdot u, \tag{3}$$

where K_{out} is the normalization factor of output variable and is utilized to map the normalized universe of discourse into the actual output. At present, the membership functions and fuzzy rule of the FLC can be determined by neural network [17], genetic algorithm [18], dynamic programming [19], and so on. However, these schemes are dependent on the mathematical model of the plant. In this paper, we want to propose a new design methodology to systematically generate the fuzzy decision rules with less information of the controlled plants.

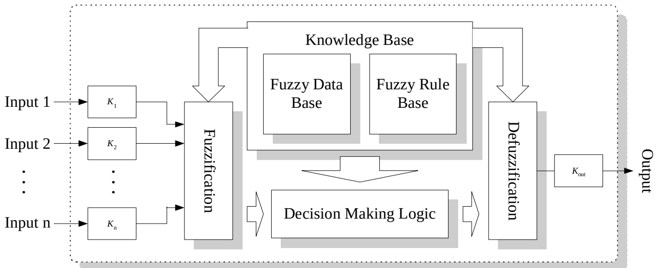

Figure 1. The fuzzy logic controller.

3. Discrete-time Lyapunov-based FLC

In this section, we would propose a new FLC that does not require the human experts and plant information. The setting of the decision rule set is a crucial problem in designing the FLC. In the proposed FLC, the fuzzy decision rules are derived from the Lyapunov stability criterion, so that the approach is inherently stable.

A. *Rule generation via Lyapunov function*

Consider a discrete-time, single input, and nonlinear system shown as follows,

$$x(k+1) = f(x(k), u(k)), \tag{4a}$$

$$y(k) = g(x(k)), \tag{4b}$$

where $u(k)$ is the control input, $x(k)$ is the state, $y(k)$ is the output, and functions $f(\bullet,\bullet)$ and $g(\bullet)$ are assumed to be sufficiently smooth within the region of interest. The control objective is to find the $u(k)$, such that the output $y(k)$ can track the desired trajectory $y_d(k)$. We consider the following Lyapunov function candidate to derive the stable fuzzy rule set,

$$V\big(e(k), \Delta e(k)\big) = \frac{1}{2}\big(\omega_e \times e^T \cdot e + \omega_c \times \Delta e^T \cdot \Delta e\big), \tag{5}$$

where $e(k) = y(k) - y_d(k)$, $\Delta e(k) = e(k) - e(k-1)$, ω_e and ω_c are positive weighting constants with respect to $e(k)$ and $\Delta e(k)$. In the tracking problem, the undesired overshoots may occur because of the plant inertia so that it is beneficial to consider the quantity of error-rate to reduce the overshoot phenomenon. In order to consider the stabilization objective, the following condition needs to be satisfied.

$$\Delta V(k) = V(k) - V(k-1) < 0. \tag{6}$$

To satisfy the stable criteria shown in equation (6), we must find the relation between $\Delta V(k)$ and $\Delta u(k)$, the change rate of the control action $u(k)$. Suppose the control law is

$$u(k+1) = u(k) + \Delta u(k+1). \tag{7}$$

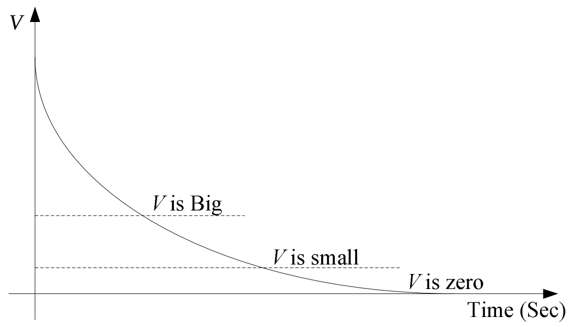

Figure 2. The desired time response of Lyapunov function.

It is assumed that the increment of control input is proportional to the variation of Lyapunov function for every time instant, that is

$$\frac{\Delta V(k+1)}{\Delta u(k+1)} = \frac{\Delta V(k)}{\Delta u(k)} . \tag{8}$$

The sign of $\Delta u(k+1)$ in (7) is determined by calculating the value of the variation of $V(k)$ with respect to $u(k)$. That is,

$$\mathrm{sign}(\Delta u(k+1)) = -\mathrm{sign}(\frac{\Delta V(k)}{\Delta u(k)}) . \tag{9}$$

This implies

$$\Delta V(k+1) = (\frac{\Delta V(k)}{\Delta u(k)}) \cdot \Delta u(k+1) < 0 . \tag{10}$$

The design target is to derive the increment of control command, $\Delta u(k+1)$, to always satisfy equation (10). Thus, above control actions can be summarized as the following linguistic rules:

$R_1 : \Delta V(k)/\Delta u(k)$ is negative then the sign of $\Delta u(k+1)$ is positive. (11a)

$R_2 : \Delta V(k)/\Delta u(k)$ is positive then the sign of $\Delta u(k+1)$ is negative. (11b)

Hence, we can adjust the values of the control action such that the value of the Lyapunov function is decreased. The control command (11) does not provide any information about the tuning magnitude of the control signal. If the fixed regulation value is adopted, the whole control strategy is similar to the variable structure control. The chattering and oscillation phenomena will then arise.

B. *Generation of fuzzy rule table*

From above discussion, we could get the relation between $\Delta V(k)/\Delta u(k)$ and $\Delta u(k+1)$, however, the relation only provides that ΔV should be negative. The magnitude of Δu is not considered yet, thus, the equation (11a) and (11b) are not good enough to control a system. For example, when $\Delta V(k)$ is negative big and $V(k)$ is almost zero, the control action determined in equation (11) will make the system response oscillate and increase the settling time. And, if $\Delta V(k)$ is negative small and $V(k)$ is big, the control action will cause the slow convergence rate. In words, the conditions of $\Delta V(k)$ and $V(k)$ could seriously effect the system response and should be taken into consideration for deriving the control strategy. From the conditions of $\Delta V(k)$ and $V(k)$, we can develop a control scheme to improve the control performance and eliminate the undesired phenomena, such as overshoots and long settling time.

The Lyapunov function V defined in equation (5) can be considered as the distance between the current and desired states, and the control goal is to drive the system states to converge to the desired ones as soon as possible. Assume the expected time response of $V(k)$ is considered as an exponentially decayed function shown in Figure 2. We now divide the exponentially decaying response into three parts and describe them in linguistic statements, as big, small, and zero. And the change rate of $V(k)$, $\Delta V(k)$, is also interpreted as positive, zero, and negative, where the sign of $\Delta V(k)$ presents the change direction of $V(k)$, which means the system responses converge to or diverge from the desired trajectory. A bigger control action must be taken to pull the undesired trajectory back and only a medium control action should be needed to maintain the system toward the desired trajectory, $y_d(k)$. When $V(k)$ is zero and $\Delta V(k)$ is small, the system is going to reach $y_d(k)$ and only a smaller control command is needed in order to reduce the settling time and avoid oscillation phenomena.

It is well known that the fuzzy logic decision is inherently a hierarchical control form. All the conceptual statements addressed above can be summarized as a rule base for the FLC. The fuzzy control action we adopted is a fuzzy PI-type controller expressed in the following form,

$$\Delta u(k+1) = F(V(k), \Delta V(k), \frac{\Delta V(k)}{\Delta u(k)}) , \tag{12}$$

where $F(\cdot,\cdot,\cdot)$ is the fuzzy relation function of the fuzzy variables $V(k)$, $\Delta V(k)$, and $\Delta V(k)/\Delta u(k)$. From equation (10), we can find that $\Delta V(k+1)$ is proportional to the product of $\Delta V(k)/\Delta u(k)$ and $\Delta u(k+1)$. In order to obtain a fast convergent regulation, the controller is designed such that $\Delta V(k+1) < -\sigma_i$, where i represents the index of the fuzzy term sets S, MS, M, MB, and B, and with the property $\sigma_B > \sigma_{MB} > \sigma_M > \sigma_{MS} > \sigma_s > 0$. For the input variables, the fuzzy term sets of $V(k)$ are $\{\text{Z, S, B}\}$, the fuzzy term sets of $\Delta V(k)$ are $\{\text{N, Z, P}\}$, and the fuzzy term sets of $\Delta V(k)/\Delta u(k)$ are $\{\text{NB, NM, NS, PS, PM, PB}\}$. The corresponding normalized membership functions are depicted in Figure 3. The fuzzy term sets of output variable, $\Delta u(k+1)$, are {NB, NBM, NM, NMS, NS, NZ, ZR, PZ, PS, PMS, PM, PBM, PB} with singleton-type membership function shown in Figure 4. Now, the complete fuzzy decision rules are tabulated in Table 1. All the 54 rules can be summarily interpreted as following nine linguistic expressions:

- If $V(k)$ is big and $\Delta V(k)$ is positive, then $\Delta u(k+1)$ is designed such that $\Delta u(k+1)\times(\Delta V(k)/\Delta u(k))$ is negative big, i.e. $\Delta V(k+1) < -\sigma_B$.
- If $V(k)$ is big and $\Delta V(k)$ is zero, then $\Delta u(k+1)$ is designed such that $\Delta u(k+1)\times(\Delta V(k)/\Delta u(k))$ is negative medium big, i.e. $\Delta V(k+1) < -\sigma_{MB}$.
- If $V(k)$ is big and $\Delta V(k)$ is negative, then $\Delta u(k+1)$ is designed such that $\Delta u(k+1)\times(\Delta V(k)/\Delta u(k))$ is negative medium, i.e. $\Delta V(k+1) < -\sigma_M$.
- If $V(k)$ is small and $\Delta V(k)$ is positive, then $\Delta u(k+1)$ is designed such that $\Delta u(k+1)\times(\Delta V(k)/\Delta u(k))$ is negative medium big, i.e. $\Delta V(k+1) < -\sigma_{MB}$.
- If $V(k)$ is small and $\Delta V(k)$ is zero, then $\Delta u(k+1)$ is designed such that $\Delta u(k+1)\times(\Delta V(k)/\Delta u(k))$ is negative medium, i.e. $\Delta V(k+1) < -\sigma_M$.
- If $V(k)$ is small and $\Delta V(k)$ is negative, then $\Delta u(k+1)$ is designed such that $\Delta u(k+1)\times(\Delta V(k)/\Delta u(k))$ is negative medium small, i.e. $\Delta V(k+1) < -\sigma_{MS}$.
- If $V(k)$ is zero and $\Delta V(k)$ is positive, then $\Delta u(k+1)$ is designed such that $\Delta u(k+1)\times(\Delta V(k)/\Delta u(k))$ is negative medium, i.e. $\Delta V(k+1) < -\sigma_M$.
- If $V(k)$ is zero and $\Delta V(k)$ is zero, then $\Delta u(k+1)$ is designed such that $\Delta u(k+1)\times(\Delta V(k)/\Delta u(k))$ is negative small, i.e. $\Delta V(k+1) < -\sigma_S$.
- If $V(k)$ is zero and $\Delta V(k)$ is negative, then $\Delta u(k+1)$ is designed such that $\Delta u(k+1)\times(\Delta V(k)/\Delta u(k))$ is negative medium small, i.e. $\Delta V(k+1) < -\sigma_{MS}$.

Since the decision rules are designed on the basis of the Lyapunov function and are independent of human expert, we can construct the fuzzy logic controller without any information of the controlled plant. That is, the derived controller can be applied to low-order or high-order, linear or nonlinear, and/or stable or unstable systems. The main constraint of the proposed control scheme is that the controlled plant must be output stabilizable.

4. Simulations

In this section, three discrete-time systems [21], including a linear plant, a nonlinear plant, and a delayed plant, are addressed to demonstrate the effectiveness of the proposed control scheme. The dynamic equations of the plants are shown as follows,

$$y(k) = y(k-1) + 0.1u(k) \tag{13}$$

$$y(k) = 0.7y(k-1) + 0.3[y(k-1)]^3 + 0.2u(k) \tag{14}$$

$$y(k) = y(k-1) + 0.02u(k-4) \tag{15}$$

where $u(k)$ is the control input and $y(k)$ is the output of the plant. For the three plants, we use all the same structure of the FLC and parameter settings, except the normalization factors. The six fuzzy subsets of $\Delta V(k)/\Delta u(k)$ are settled over the normalized interval [-1, 1] with the triangular type membership functions shown in Figure 3(a), and the parameters of (a_{-3}, a_{-2}, a_{-1}, a_1, a_2, a_3) are (-1, -0.6, -0.01, 0.01, 0.6, 1). The input variable $\Delta V(k)$ has three fuzzy subsets over the normalized interval [-1, 1] with the triangular type membership functions and $(b_{-1}, b_0, b_1) = (-1, 0, 1)$. The input variable $V(k)$ has also three fuzzy subsets over the normalized interval [0, 1] with the triangular type membership functions and $(c_0, c_1, c_2) = (0, 0.3, 1)$.

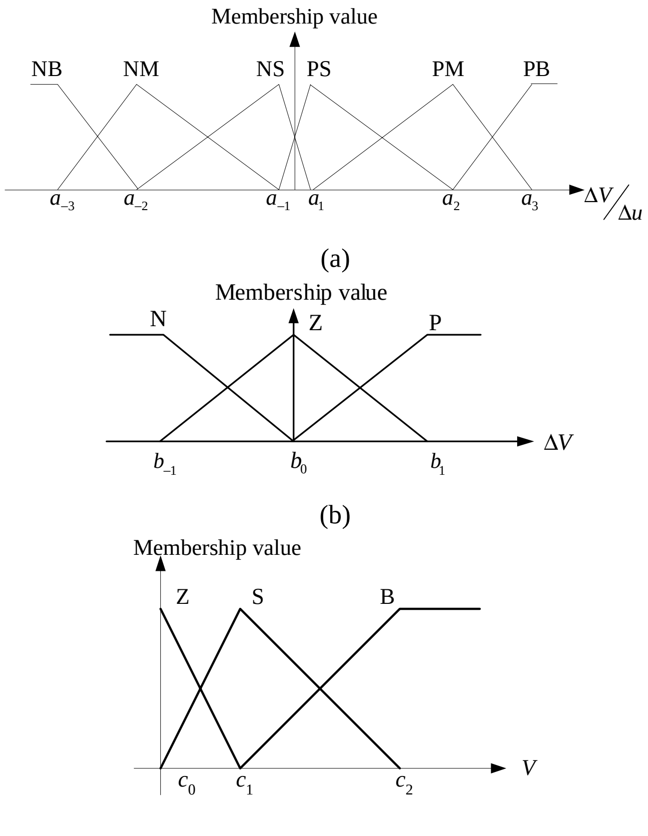

Figure 3. The normalized membership function of input variables.

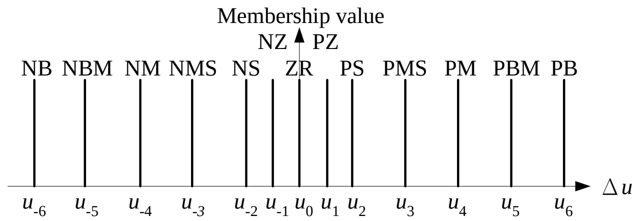

Figure 4. The normalized membership function of output variable.

Finally, the output variable Δu has 13 fuzzy subsets over [-1, 1] with the singleton type membership functions and the support values of (u_{-6}, u_{-5}, u_{-4}, u_{-3}, u_{-2}, u_{-1}, u_0, u_1, u_2, u_3, u_4, u_5, u_6) are (-1, -0.8, -0.6, -0.4, -0.2, -0.1, 0, 0.1, 0.2, 0.4, 0.6, 0.8, 1). All the applied decision rules are the same as those in Table I. The initial conditions are all set the same as $y(0)=0$ and $\Delta u(0)=0$, the desired output $y_d(k)=1$, and the weighting pair of Lyapunov function is set as $(\omega_e, \omega_c)=(1, 0.5)$. The normalization factors of $\Delta V/\Delta u$, ΔV, V, and Δu are $G_{\Delta V/\Delta u}$, $G_{\Delta V}$, G_V, and $G_{\Delta u}$, respectively. We need only to adjust these parameters to confront the differences of the plants.

Table I. Rule table of LFLC

$\Delta u(k+1)$				$\Delta V(k)/\Delta u(k)$					
				PB	PM	PS	NS	NM	NB
$V(k)$	B	$\Delta V(k)$	P	u_{-4}	u_{-5}	u_{-6}	u_6	u_5	u_4
			Z	u_{-3}	u_{-4}	u_{-5}	u_5	u_4	u_3
			N	u_{-2}	u_{-3}	u_{-4}	u_4	u_3	u_2
	S	$\Delta V(k)$	P	u_{-3}	u_{-4}	u_{-5}	u_5	u_4	u_3
			Z	u_{-2}	u_{-3}	u_{-4}	u_4	u_3	u_2
			N	u_{-1}	u_{-2}	u_{-3}	u_3	u_2	u_1
	Z	$\Delta V(k)$	P	u_{-2}	u_{-3}	u_{-4}	u_4	u_3	u_2
			Z	u_0	u_{-1}	u_{-2}	u_2	u_1	u_0
			N	u_{-1}	u_{-2}	u_{-3}	u_3	u_2	u_1

Example 1 (Linear plant): The system is described as equation (13), where the pole is located on the unit circle and hence the system is marginally stable. We set the normalization factors ($G_{\Delta V/\Delta u}$, $G_{\Delta V}$, G_V, $G_{\Delta u}$)=(0.6, 1, 1, 0.5). The time responses of the system and Lyapunov function are shown in Figure 5. One can find that the proposed FLC can drive the output to y_d with fast convergent rate, no overshoot, and zero steady-state error.

Example 2 (Nonlinear plant): The system described in equation (14) is nonlinear. We choose the normalization factors for the plant as ($G_{\Delta V/\Delta u}$, $G_{\Delta V}$, G_V, $G_{\Delta u}$)=(0.7, 1, 1, 0.5). The time responses of the system and Lyapunov function are depicted in Figure 6, where the proposed FLC can successfully stabilize the nonlinear plant.

Example 3 (Delayed plant): The system (15) has the same pole as that in plant (13), but with delayed control input. Suppose ($G_{\Delta V/\Delta u}$, $G_{\Delta V}$, G_V, $G_{\Delta u}$)=(0.8, 1, 1, 0.6), the computer simulations of the controlled system are illustrated in Figure 7. The developed FLC can still make the controlled output track the desire y_d.

5. Conclusions

In this paper, we have set up a design scheme of Lyapunov function based FLC. The new FLC possesses the following advantages: 1) the derivation does not require an accurate mathematical model of the controlled plant; 2) it is capable of designing the fuzzy decision rules by a systematic approach without relying on human experts, and 3) it can guarantee the stability of the controlled system in the sense of the Lyapunov stability. The proposed FLC have been applied to three kinds of discrete-time system, including linear, nonlinear, and delayed systems. All the simulation results demonstrate the feasibility and effectiveness of the developed FLC.

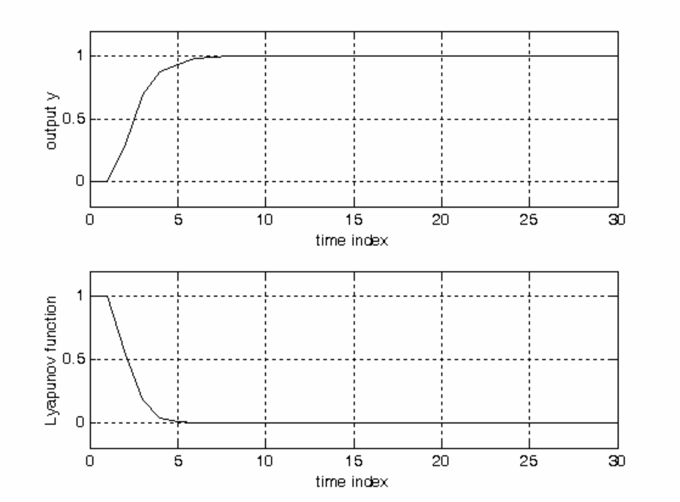

Figure 5. Time responses of the controlled system and Lyapunov function in Example 1.

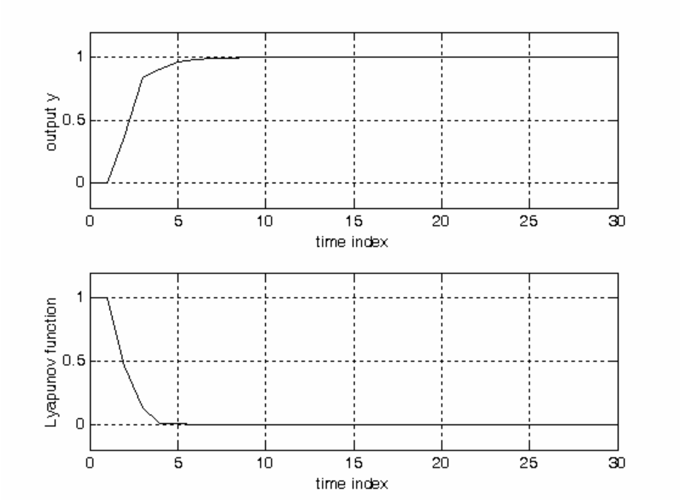

Figure 6. Time responses of the controlled system and Lyapunov function in Example 2.

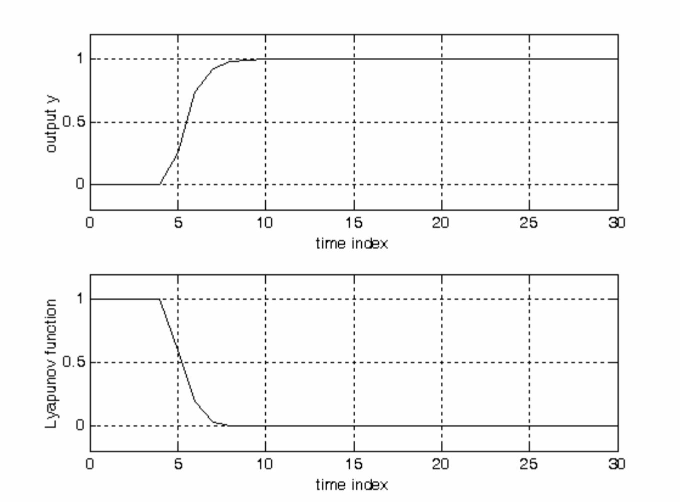

Figure 7. Time response of the controlled system and Lyapunov function in Example 3.

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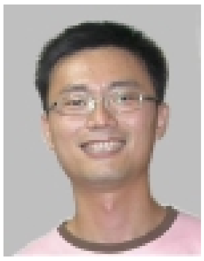

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