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ADAPTIVE FUZZY CONTROL OF DIRECT-CURRENT MOTOR DEAD-ZONE SYSTEMS

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Abstract. *An adaptive fuzzy control scheme is studied in this paper for the direct-current (DC) motor systems with dead-zone input. The fuzzy logic systems are used to approximate the unknown functions in DC motor and based on the information of the parameters on the dead-zone, an adaptive fuzzy control approach is developed via backstepping design technique. Compared with the existing works for DC motor, less adjustable parameters are used in the approach. So, the computation load on line is reduced. The proposed scheme guarantees that the system output follows the reference signal to a small compact set and all the signals in the closed-loop are bounded. Simulation example is given to verify the effectiveness of the design method.*
Keywords: Fuzzy adaptive control, Nonlinear systems, Dead-zone input

1. **Introduction.** In recent years, the fuzzy control has attracted much attention [1-3]. Specifically, the adaptive intelligent approaches are attracted in the controller design. A great number of algorithms have been developed for nonlinear systems with unknown nonlinear functions. For example, adaptive fuzzy control techniques were given in [4-9] for a general class of nonlinear systems with uncertainties. These approaches solved the stability problem of the complex systems which can be represented as the real modeling. In these techniques, the fuzzy systems are employed to establish the modeling of the systems and the optimal fuzzy parameters are updated by the adaptive technique. Recently, two fuzzy adaptive using the observer control approaches were made in [10] for nonlinear stochastic feedback systems without the measurements of the states. A fuzzy observer was shown for estimating the unmeasured states. Based on this observer and by combining the fuzzy backstepping, a novel design was developed. To avoid the problem of "explosion of complexity" inherent in the method, the dynamic surface control technique is incorporated into the fuzzy adaptive scheme.

In the above, the continuous-time systems are stabilized by employing these approaches. Recently, the stability problem of the discrete-time systems is addressed in [11-15]. Several approaches were in turn developed for nonlinear discrete-time systems based on the neural networks which are utilized to approximate the uncertainties of the systems [11-14]. In [15], an adaptive predictive method using adaptive network-based fuzzy system and multiple models was proposed for uncertain nonlinear discrete-time systems subject to unstable zero-dynamics. The proposed controller contains a switching mechanism. By switching between the two earlier described controllers, the switching mechanism can simultaneously improve the performance of the closed-loop. These methods do not consider the effect of input nonlinearities. To this end, some good schemes were given in [16-21] for the systems with input nonlinearities. These schemes can be used to stabilize nonlinear systems with both the uncertainties and input nonlinearities.

The mentioned papers mainly addressed theory researches. In recent years, many researchers devoted much effort to study applications in the practice. An adaptive fuzzy mechanism for the position control of a traveling-wave-type ultrasonic motor was shown in [22]. The authors in [23] focused on the problem of position tracking control for the chaotic permanent magnet synchronous motor drive system with unknown nonlinear functions. The fuzzy logic systems are to approximate the unknown functions and the adaptive backstepping technique was used to design the controllers. Compared with the conventional backstepping, the designed controllers' structure is very simple. In [24], an adaptive control of DC motor system with a dead-zone was designed. The developed scheme was successfully to integrate the barrier Lyapunov function to relax the requirements on the initial conditions using the neural networks. However, the computation burden online is very heavy in [22-24]. This paper will try to solve this problem.

In this paper, a fuzzy adaptive controller is designed for a DC motor with unknown function and dead-zone input. Introduce the fuzzy systems to approximate the unknown function. Due to the presence of dead-zone input, the design procedure is difficult. A Young's inequality is used to compensate for the effect of dead-zone input. Compared with the works in [22-24], the advantage of this paper is to reduce the on-line computation burden. The proposed approach guarantees that the system output can be very good to track the reference signal and all the signals in the closed-loop system are bounded based on the Lyapunov analysis method. The simulation example is given to validate the effectiveness of the proposed method.

2. Problem Statement and Preliminaries.

Consider the systems with a DC motor which are described as

$$\begin{cases} \dot{\theta}_1 = \theta_2 \\ J\dot{\theta}_2 + F\dot{\theta}_1 + T_F + \omega = \mathrm{T} \\ y = \theta_1 \end{cases} \tag{1}$$

where $\theta_1(t)$ denotes the motor angular position; F and T_F denote unmeasured viscous friction and unmeasured friction; J is the inertia; $\omega(t)$ is unknown bounded by $\|\omega(t)\| \leq \omega_M$; $y \in R$ is the output; and $\mathrm{T} = \Gamma(\upsilon(t))$ is the motor torque, which is related to the control input $\upsilon(t)$. $\Gamma(\upsilon(t))$ is defined as

$$\mathrm{T} = \Gamma(\upsilon(t)) = \begin{cases} n_r(\upsilon(t) - c_r), & \text{if } \upsilon(t) \geq c_r \\ 0, & \text{if } -c_l < \upsilon(t) < c_r \\ n_l(\upsilon(t) - c_l), & \text{if } \upsilon(t) \leq -c_l \end{cases} \tag{2}$$

where n_r, $n_l > 0$ denote the right and left slope of the dead-zone characteristic, and c_r, $c_l > 0$ are the breakpoints of the input nonlinearity.

Further, $\Gamma(\upsilon(t))$ can be rewritten as

$$\mathrm{T} = \Gamma(\upsilon(t)) = n(t)\upsilon(t) + c(t) \tag{3}$$

where

$$n(t) = \begin{cases} n_r(t), & \text{if } \upsilon(t) > 0 \\ n_l(t), & \text{if } \upsilon(t) \leq 0 \end{cases} \tag{4}$$

and

$$c(t) = \begin{cases} -n_r(t)c_r(t), & \text{if } \upsilon(t) \geq c_r \\ -n(t)\upsilon(t), & \text{if } -c_l < \upsilon(t) < c_r \\ n_l(t)c_l(t), & \text{if } u(t) \leq -c_l \end{cases} \tag{5}$$

Here, $n(t)$ is assumed to be known and let $\bar{c} = \max(c_r, c_l)$. The design objective is to develop a fuzzy adaptive algorithm so that the system output tracks the reference signal $\theta_d(t)$ to a small compact set and all the signals in the closed-loop are bounded where $\theta_d(t)$ and $\theta_d^{(i)}(t)$, $i = 1, \ldots, n$ are known and bounded.

3. Fuzzy Adaptive Controller.

In this section, we will investigate state feedback adaptive control scheme for an actual DC motor system as described in (1). The detailed design procedure is shown in the following.

Step 1: Define the error variables $e_1 = \theta_1 - \theta_d$ and its derivative is

$$\dot{e}_1 = \dot{\theta}_1 - \dot{\theta}_d = \theta_2 - \dot{\theta}_d \tag{6}$$

Introducing the variable $e_2 = \theta_2 - \alpha_1$, we have

$$\dot{e}_1 = \dot{\theta}_1 - \dot{\theta}_d = e_2 + \alpha_1 - \dot{\theta}_d \tag{7}$$

Consider the following Lyapunov function candidate

$$V_1 = \frac{1}{2} e_1^2 \tag{8}$$

The time derivative of V_1 with (7) is

$$\dot{V}_1 = e_1 \left(e_2 + \alpha_1 - \dot{\theta}_d \right) \tag{9}$$

Design the virtual control as follows

$$\alpha_1 = -k_1 e_1 + \dot{\theta}_d \tag{10}$$

with k_1 being a positive constant.

Further, it follows that

$$\dot{V}_1 = -k_1 e_1^2 + e_1 e_2 \tag{11}$$

where the second term $e_1 e_2$ will be cancelled in the next step.

Step 2: The variable $e_2 = \theta_2 - \alpha_1$ and its time derivative is

$$\dot{e}_2 = \dot{\theta}_2 - \dot{\alpha}_1 = \frac{1}{J} \left(\mathrm{T} - F\dot{\theta}_1 - T_F - \omega \right) \tag{12}$$

Using (3), we have

$$\dot{e}_2 = \dot{\theta}_2 - \dot{\alpha}_1 = \frac{1}{J} \left(n(t) \upsilon(t) + c(t) - F\dot{\theta}_1 - T_F - \omega \right) \tag{13}$$

Consider the following Lyapunov function candidate

$$V_2 = V_1 + \frac{1}{2} e_2^2 + \frac{1}{2\gamma} \tilde{\phi}^2 \tag{14}$$

where $\tilde{\phi} = \hat{\phi} - \phi^*$ and $\hat{\phi}$ denotes the estimation of ϕ^*.

The time derivative of V_2 with (13) is

$$\dot{V}_2 = \dot{V}_1 + e_2 \left[\frac{1}{J} \left(n(t) \upsilon(t) + c(t) - F\dot{\theta}_1 - T_F - \omega \right) \right] + \frac{1}{\gamma} \tilde{\phi} \dot{\hat{\phi}} \tag{15}$$

Using the fuzzy system to approximate $H(\theta_1, \theta_2) = \left(F\dot{\theta}_1 + T_F \right) / J$, and assume that

$$H(\theta_1, \theta_2) = \psi^{*T} \xi(\theta_1, \theta_2) + \varepsilon^*(\theta_1, \theta_2) \tag{16}$$

Let $\phi^* = \|\psi^*\|$. Design the actual control as follows

$$\upsilon(t) = \frac{J}{n(t)} \left(-e_1 - k_1 e_2 - \frac{\hat{\phi}^2 e_2 \|\xi(\theta_1, \theta_2)\|^2}{\hat{\phi} |e_2| \|\xi(\theta_1, \theta_2)\| + \tau} \right) \tag{17}$$

with k_2 being a positive constant.

Substituting (16) and (17) into (15) yields

$$\begin{aligned}\dot{V}_2 = {} & \dot{V}_1 - e_1e_2 - k_2e_2^2 - \frac{\hat{\phi}^2 e_2^2 \left\| \xi\left(\theta_1, \theta_2\right) \right\|^2}{\hat{\phi}\left| e_2 \right| \left\| \xi\left(\theta_1, \theta_2\right) \right\| + \tau} \\ & - e_2\psi^{*T}\xi\left(\theta_1, \theta_2\right) + e_2\sigma + \frac{1}{\gamma}\tilde{\phi}\dot{\hat{\phi}}\end{aligned} \tag{18}$$

where $\sigma = \left(c\left(t\right) - \omega\right)/J - \varepsilon^*\left(\theta_1, \theta_2\right)$. The following inequalities can be obtained

$$\begin{aligned} & - e_2\psi^{*T}\xi\left(\theta_1, \theta_2\right) - \frac{\hat{\phi}^2 e_2^2 \left\| \xi\left(\theta_1, \theta_2\right) \right\|^2}{\hat{\phi}\left| e_2 \right| \left\| \xi\left(\theta_1, \theta_2\right) \right\| + \tau} + \frac{1}{2}\tilde{\phi}\dot{\hat{\phi}} \\ \le {} & \left| e_2 \right| \phi \left\| \xi\left(\theta_1, \theta_2\right) \right\| - \frac{\hat{\phi}^2 e_2^2 \left\| \xi\left(\theta_1, \theta_2\right) \right\|^2}{\hat{\phi}\left| e_2 \right| \left\| \xi\left(\theta_1, \theta_2\right) \right\| + \tau} + \frac{1}{2}\tilde{\phi}\dot{\hat{\phi}} \\ = {} & \hat{\phi}\left| e_2 \right| \left\| \xi\left(\theta_1, \theta_2\right) \right\| - \frac{\hat{\phi}^2 e_2^2 \left\| \xi\left(\theta_1, \theta_2\right) \right\|^2}{\hat{\phi}\left| e_2 \right| \left\| \xi\left(\theta_1, \theta_2\right) \right\| + \tau} \\ & + \frac{1}{2}\tilde{\phi}\dot{\hat{\phi}} - \tilde{\phi}\left| e_2 \right| \left\| \xi\left(\theta_1, \theta_2\right) \right\| \\ \le {} & \tau + \frac{1}{\gamma}\tilde{\phi}\dot{\hat{\phi}} - \tilde{\phi}\left| e_2 \right| \left\| \xi\left(\theta_1, \theta_2\right) \right\| \end{aligned} \tag{19}$$

and

$$e_2\sigma \le \frac{1}{2}e_2^2 + \frac{1}{2}\bar{\sigma}^2 \tag{20}$$

where $\bar{\sigma} = \omega_M + \bar{c} + \bar{\varepsilon}$.

Design the adaptation laws as follows

$$\dot{\hat{\phi}} = -\gamma\left| e_2 \right| \left\| \xi\left(\theta_1, \theta_2\right) \right\| - \gamma\hat{\phi} \tag{21}$$

Then, it has

$$\frac{1}{\gamma}\tilde{\phi}\dot{\hat{\phi}} - \tilde{\phi}\left| e_2 \right| \left\| \xi\left(\theta_1, \theta_2\right) \right\| = -\tilde{\phi}\hat{\phi} \le -\frac{1}{2}\tilde{\phi}^2 + \frac{1}{2}\phi^{*2} \tag{22}$$

Using (11), (19), (20) and (22), we obtain

$$\dot{V}_2 \le -k_1e_1^2 - \left(k_2 - 1/2\right)e_2^2 - \frac{1}{2}\tilde{\phi}^2 + \frac{1}{2}\phi^{*2} + \tau + \frac{1}{2}\bar{\sigma}^2 \tag{23}$$

Theorem 3.1. *Consider the DC motor system (1). By designing the actual control law (17), the virtual control law (10), the adaptation law (21), the proposed approach can guarantee that the tracking error converges to a small neighborhood of zero and all the signals in the closed-loop are bounded.*

Proof: From (23), it can be obtained that

$$\dot{V}_2 \le -\sum_{j=1}^{2} -k_j^*e_j^2 - \frac{1}{2}\tilde{\phi}^2 + \mu \tag{24}$$

where $k_1^* = k_1 > 0, k_2^* = k_2 - 1/2 > 0$ and $\mu = \frac{1}{2}\phi^{*2} + \tau + \frac{1}{2}\bar{\sigma}^2$.

Let $k = \min\left\{k_1^*, k_2^*, \gamma\right\}$. Then, it has

$$\dot{V}_2 \le -kV_2 + \mu \tag{25}$$

Multiplying both sides by e^{kt}, (25) can be expressed as

$$\frac{d}{dt}\left(V\left(t\right)e^{kt}\right) \le \mu e^{kt} \tag{26}$$

Integrating the above inequality over $[0, t]$, we have

$$0 \leq V(t) \leq \frac{\mu}{k} + \left[V(0) - \frac{\mu}{k}\right] e^{-kt} \tag{27}$$

Noting that $0 < e^{-kt} < 1$ and $\frac{\mu}{k} e^{-kt} > 0$, we have

$$\left[V(0) - \frac{\mu}{k}\right] e^{-kt} \leq V(0)$$

Then, (27) becomes

$$0 \leq V(t) \leq \frac{\mu}{k} + V(0) \tag{28}$$

It is easy to conclude that e_1, e_2, $\tilde{\phi}$ are bounded. Thus, it can be observed that $\tilde{\phi}$ is also bounded. From (27), we can obtain that $|e_1(t)| \leq \sqrt{\frac{\mu}{k}}$ if $V(0) = \frac{\mu}{k}$. Accordingly, the tracking error can converge to a small neighborhood of zero, i.e., $\lim\limits_{t\to\infty} |e_1(t)| = \sqrt{\frac{\mu}{k}}$.

4. **Simulation Example.** In order to validate the effectiveness, we consider DC motor system which is described in (1). Here, the inertia $J = 0.0143$ [$\mathrm{Kg} \cdot \mathrm{m}^2$], F and T_F will be approximated by using the fuzzy systems; $d = 0.01$. The non-symmetric dead-zone input is described as

$$\mathrm{T} = \Gamma(\upsilon(t)) = \begin{cases} 0.4(\upsilon(t) - 0.03), & \text{if } \upsilon(t) \geq 0.03 \\ 0, & \text{if } -0.05 < \upsilon(t) < 0.03 \\ 0.2(\upsilon(t) - 0.05), & \text{if } \upsilon(t) \leq -0.05 \end{cases} \tag{29}$$

The control objective is to ensure that $y = \theta_1$ follows the desired trajectory $\theta_d = 0.5 \sin t - 0.7$ to a small neighborhood of zero and that all the signals of the closed-loop system are bounded.

The design parameter is chosen as $k_1 = 5$, $k_2 = 5$, $\gamma = 15$, $\tau = 0.1$ and the initial condition for the system states is chosen as $\theta_1(0) = -0.5$, $\theta_2(0) = 1$, $\hat{\phi}(0) = 0.2$.

The simulation results are obtained by applying the presented control approach to the DC motor system. The tracking performance is given in Figures 1 and 2. It can be shown

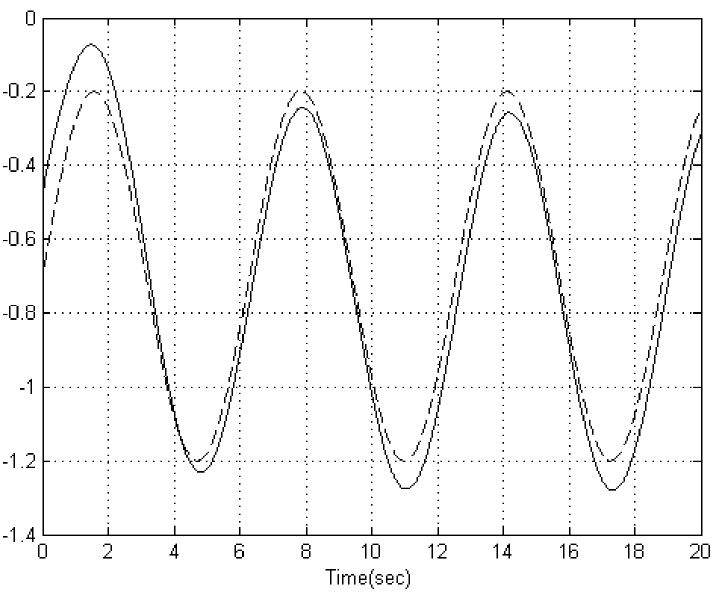

Figure 1. The system output θ_1 (solid line) and the reference signal $\theta_d(t)$ (dashed line)

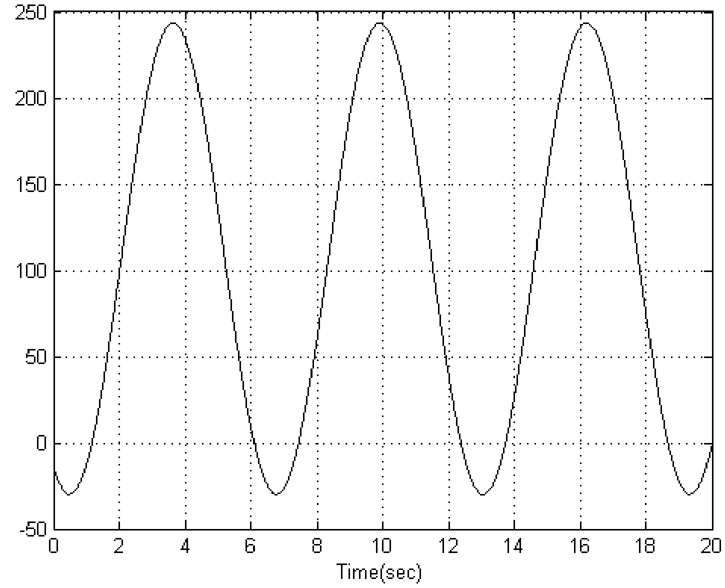

FIGURE 2. The trajectory of the tracking error $e_1(t)$

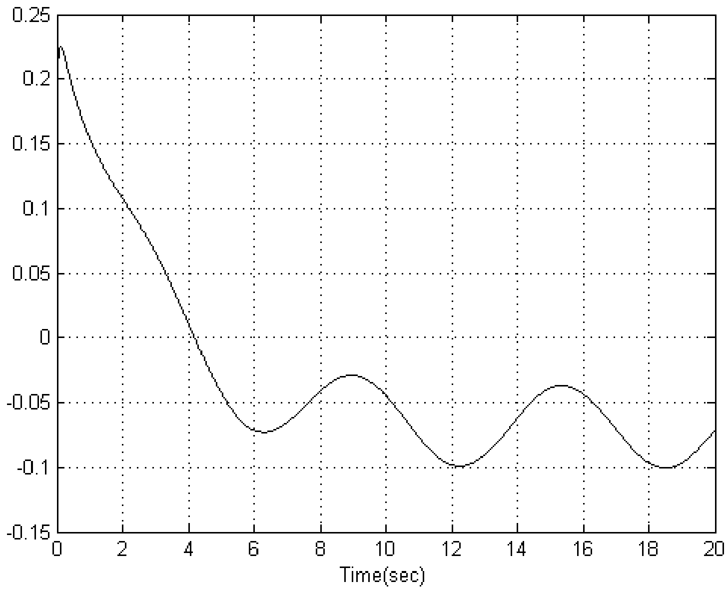

FIGURE 3. The trajectory of the control input $v(t)$

that a good tracking performance is obtained. Figure 3 shows the boundedness of the control input. Figures 4 and 5 illustrate the trajectories of the state θ_2 and the adaptation law and they are bounded. Thus, we can conclude that a good tracking performance is obtained and all the signals in the closed-loop system are bounded. To further illustrate the control performance of the proposed control method, the proposed method in [4] is used to control the system (1). It can be seen from Figure 6 that a poor tracking performance is obtained. This implies that the approach in [4] cannot compensate the dead-zone effectively.

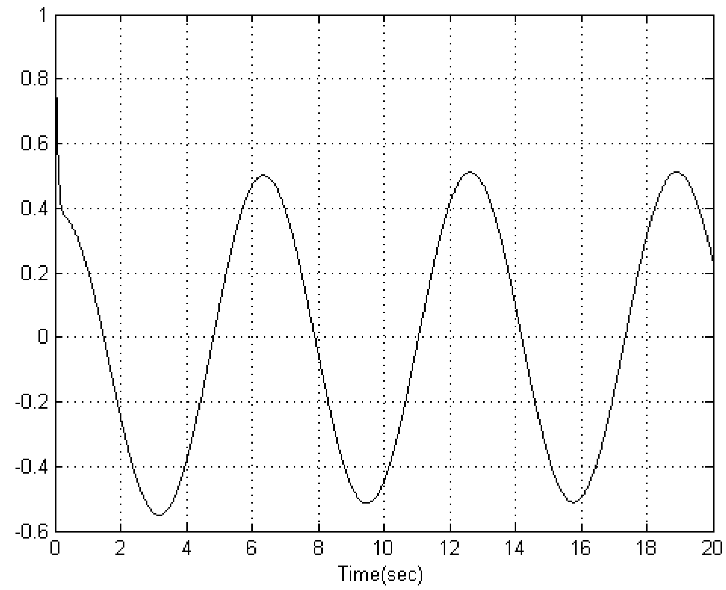

FIGURE 4. The trajectory of the state θ_2

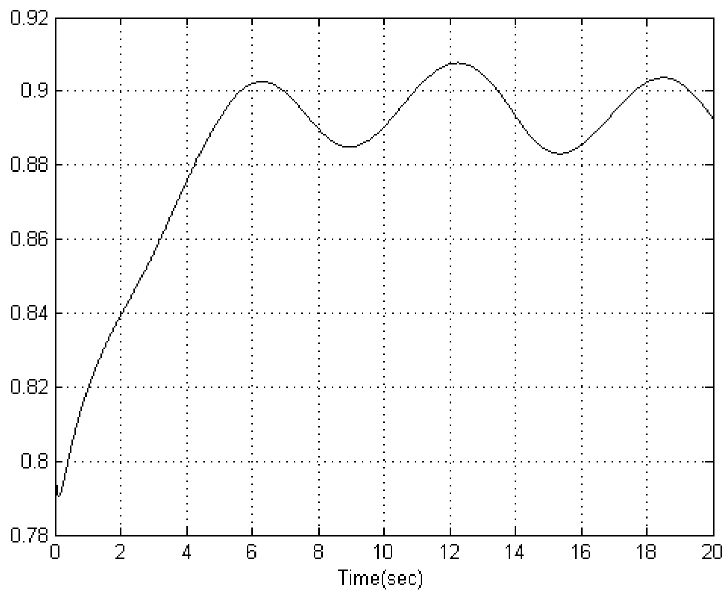

FIGURE 5. The trajectory of the adaptation law $\hat{\phi}$

5. **Conclusions.** In this paper, an adaptive fuzzy control scheme has been developed for DC motor system to solve the tracking control problem. The considered control DC motor contains the non-symmetric dead-zone and uncertainties. By utilizing the information on the parameters of the dead-zone and using fuzzy logic systems to approximate the uncertainties. A robust adaptive fuzzy control scheme has been constructed. It is proven that all the signals of the closed-loop system are bounded and the tracking error of the system can be reduced to a small compact set. A simulation example is studied to verify the effectiveness of the proposed approach.

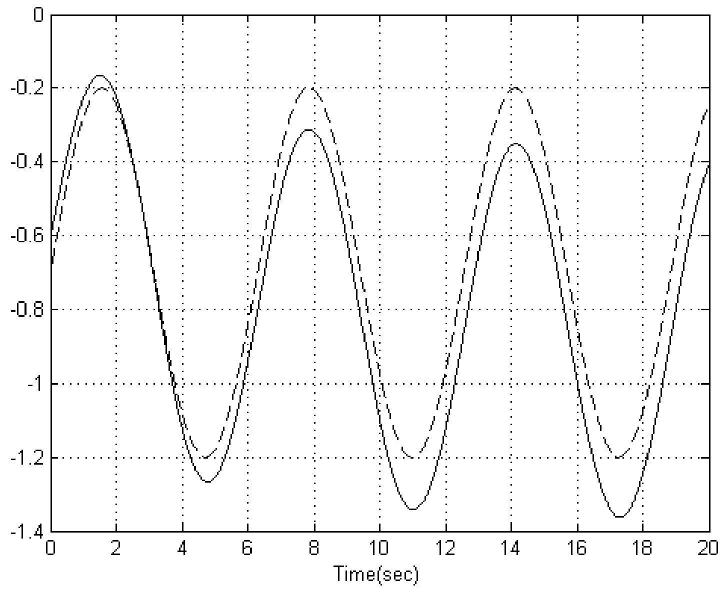

FIGURE 6. The system output θ_1 (solid line) and the reference signal $\theta_d(t)$ (dashed line) without dead-zone

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