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Improved Adaptive Dynamic Surface Control for a Class of Uncertain Nonlinear Systems

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ABSTRACT An improved dynamic surface control (IDSC) approach is presented for a class of strict-feedback nonlinear systems with unknown functions. The proposed method makes the state errors get rid of the influence of first-order filters, which simplifies the design of control. By employing neural networks to account for system uncertainties, the virtual control signal of the IDSC is directly used to construct the state error instead of the signal generated by the first-order filter in the dynamic surface control (DSC) method. The stability of the method is proved by Lyapunov stability theory, and the semi-global uniform ultimate boundedness of all signals in the closed-loop system is guaranteed. Simulation results demonstrate the IDSC method has better tracking performance and stability than traditional DSC method.

INDEX TERMS Neural networks, improved dynamic surface control (IDSC), strict-feedback nonlinear system, virtual control signal.

I. INTRODUCTION

During the past decades, Approximation-based adaptive control for uncertain nonlinear systems has received much attentions [1]–[15]. In these articles, neural networks (NNs) and fuzzy-logic systems (FLS) are used to approximate uncertain nonlinear functions without superfluous knowledge about controlled system, which has effectively removed the restrictive conditions for system uncertainties. In addition, as a very powerful control method for nonlinear systems, backstepping method has been widely used in the existing achievements [15]–[18]. Abundant remarkable results have been obtained by combining backstepping method with the neural networks or logic fuzzy systems [19]–[21]. In these approaches, backstepping method is used as the basic frame of control design, and they can always achieve satisfactory control performances and robustness. Nevertheless, these aforementioned schemes suffered from the major limitation of the ‘‘explosion of complexity’’. Because of the recursive control design of the backstepping method, the design complexity of the aforementioned method is always unbearable when facing the repeated differential of nonlinear functions. Therefore, a low pass filter was firstly introduced in each design step of backstepping method, and the semi-globally boundedness of all the signals in the controlled system is proved. This method is popular known as ‘DSC’ method since dynamic surfaces are introduced by using low pass filters. Based on the DSC method, many approximation-based adaptive backstepping approaches have been proposed [22]–[30]. A DSC-based robust adaptive neural control approach has been proposed for strict-feedback nonlinear systems in [30]. However, the bounds of control gain functions are always assumed to be constants while using DSC method. This restrictive condition has been weakened that the control gain functions can be unbounded functions in [31], where a DSC-based adaptive neural control method is designed for a class of non-strict-feedback nonlinear systems. Meanwhile, the DSC method has already been successfully used for much nonlinear systems by combining the universal approximations [32]. Thus far, the DSC method has been widely used in various types of systems, from linear systems to strict feedback uncertain systems, to pure-feedback or nonaffine systems, as well as constrained systems [33], [34] and other complex systems [35]–[39].

However, with the wide application of DSC, its inherent problems become more and more obvious. Many articles about improved DSC method has been concerned. [40] proposed a novel modular neural dynamic surface control

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method for the position tracking control of PMSMs. A second-order nonlinear tracking differentiator (NLTD) instead of a first-order filter is used to extract the time derivatives of virtual control law, which makes the derivative of virtual control input more accurate. There are still three deficiencies in this improvement. Firstly, phase delay reduces system performance. Secondly, due to the problem of switching function, there is high frequency chatter after the system enters the steady state. Although the maximum speed control functions can be introduced to eliminate the chatter, it is difficult to use it in practical engineering due to the introduction of too many parameters. Thirdly, it is difficult to adjust its velocity factor to a proper value. In [41], an improved adaptive DSC approach has been presented for the tracking control of a class of semi-strict feedback systems. The improved algorithm introduces nonlinear adaptive filters instead of the first-order low pass ones to avoid repeatedly differentiating the virtual control signals. It can realize global tracking instead of semi global tracking. But it introduces a large number of adaptive law design, which makes the structure more complex, meanwhile, if any adaptive parameter is not selected properly, the stability of the system cannot be guaranteed. An improved adaptive neural dynamic surface control for pure-feedback systems with full state constraints and disturbance have been researched in [42]. A command filter instead of a first-order filter was presented, where the effects of filtering error were reduced by introducing a serial of error compensating variables in the controller designing. And it is extended to a class of uncertain state constrained systems. In [43], author proposed an improved DSC method, which introduces a first-order sliding mode differentiator to realize global dynamic surface control. [44] proposed a nonlinear adaptive robust controller is based on the improved dynamic surface control method. The sliding mode control is introduced to the dynamic surface design procedure, and the parameter update laws are designed using the uncertainty equivalence criterion which not only reduces the complexity of the controller but also improves the system robustness, speed and accuracy.

The above improvement of DSC is to replace the first-order filter with other methods, while lack of research on the improvement of DSC first-order filter. When we turn our attention back to DSC method, it should be noted that the state errors and actual controller for the DSC method are constructed based on the signals produced by passing virtual control signals through first-order filters, which implies the convergence of state errors heavily depends on the first-order filters. This fact will result in the problem that the tracking performance or even the stability of system may degrade rapidly when the time constants are changed.

Motivated by the above discussion, an improved dynamic surface control (IDSC) method is proposed in this article for a class of nonlinear systems. Though the basic idea of DSC method is utilized, we use the original virtual control signals to construct the state errors and actual controller in this article, which is very different from the standard DSC method. In the IDSC, first order filtering error is replaced and independent of the design of control. Then, the stability of the closed-loop system controlled by IDSC method has been proved based on Lyapunov theorem. Finally, simulation results are given for the comparison of DSC and IDSC methods to show the advantage of the method in our article.

The remainder of this article is organized as follows. Section II gives the problem formulation and preliminaries. In Section III, the improved dynamic surface control design is described in detail. The stability analysis of the closed-loop system is given in Section IV. The simulation examples are given to demonstrate the effectiveness of the proposed method in Section V and followed by Section VI which concludes this article.

II. PROBLEM STATEMENT

Consider a class of nonlinear systems investigated in [7] as follows

$$\begin{cases} \dot{x}_i = x_{i+1} + f_i(\bar{x}_i), \quad i = 1, 2..., n-1 \\ \dot{x}_n = u + f_n(\bar{x}_n) \\ y = x_1 \end{cases} \tag{1}$$

where $\bar{x}_i = [x_1, x_2, \ldots, x_i]^T \in R^i$ denotes the state vector of the system; $u \in R$ is system control input; $y \in R$ is system output; $f_i(\cdot)$ are unknown continuous functions, $i = 1, \ldots, n$.

We make the same assumptions as [7] as follow:

Assumption 1: f_i is a smooth function in its arguments, and $f_i(0, \ldots, 0) = 0$.

The control objective is to design a controller to make the output y of the system track the desired trajectory y_d. By properly selecting the design parameters, the tracking error can converge to any small neighborhood of the origin.

Assumption 2: The desired trajectory y_d is sufficiently smooth function of t, and y_d, $\dot{y}_d$ and $\ddot{y}_d$ are bounded, that is, there exists a positive constant B_0 such that $\Omega_0 := \left\{(y_d, \dot{y}_d, \ddot{y}_d) : (y_d)^2 + (\dot{y}_d)^2 + (\ddot{y}_d)^2 \le B_0\right\}$.

Assumption 3: The powerful approximation function of artificial neural networks is often used to construct approximators for nonlinear systems, and is widely used to solve the control problems of nonlinear systems. We design a neural network to approximate the unknown nonlinear continuous function $f_i(\bar{x}_i)$.

$$f_i(\bar{x}_i) = W_i^{*T} \Psi(\bar{x}_i) + \varepsilon_i \tag{2}$$

where $x \in \Omega_x \subset R$, W_i^{*T} is a neural network weight vector, ε_i is an approximation error and meets $|\varepsilon| \le \varepsilon^*$, $\varepsilon^* > 0$ is an unknown constant. Cause W_i^{*T} is unknown, it's estimated value $\hat{W}$ whose adaptive updating law was designed to

$$\dot{\hat{W}}_i = \gamma_i \Gamma_i \left[e_i \Psi(\bar{x}_i) - \sigma_i \hat{W}_i \right] \tag{3}$$

where $\Gamma_i = \Gamma_i^T > 0$ are the adaptive gain matrices, $\gamma_i > 0$, $\sigma_i > 0$ are parameters.

III. IMPROVED DYNAMIC SURFACE CONTROL DESIGN

Firstly, we present a standard dynamic surface control method for the addressed control problem. From the standard dynamic surface control method proposed in [7], the stable tracking controller for system (1) is as follows, for $1 \leq i \leq n-1$

$$S_i = x_i - x_{id} \tag{4}$$
$$\alpha_i = -\hat{W}_i^T \Psi(\bar{x}_i) - K_i S_i + \dot{x}_{id} \tag{5}$$
$$\tau_{i+1}\dot{x}_{i+1d} + x_{i+1d} = -\hat{W}_i^T \Psi(\bar{x}_i) - K_i S_i + \dot{x}_{id} \tag{6}$$
$$S_n = x_n - x_{nd} \tag{7}$$
$$u = \dot{x}_{nd} - \hat{W}_n^T \Psi(\bar{x}_n) - K_n S_n \tag{8}$$

where $x_{1d} = y_d$, and $\Psi(\bar{x}_i)$, K_i and τ_i are design parameters.

It can be seen from [7] that the stability of the system can be guaranteed and the tracking error can be adjusted under the condition that the initial values of S_i and y_i are bounded and compact, where $y_i = x_{id} - \alpha_{i-1}$.

According to the basic idea of DSC method, the controller we proposed, i.e. 'IDSC', is given as follows:

$$e_1 = x_1 - y_d \tag{9}$$
$$e_i = x_i - \alpha_{i-1}, \quad for\ i = 2, \ldots, n \tag{10}$$
$$\alpha_i = -\hat{W}_i^T \Psi(\bar{x}_i) - K_i e_i + \dot{x}_{id}, \quad for\ i = 1, \ldots, n-1 \tag{11}$$
$$\tau_{i+1}\dot{x}_{i+1d} + x_{i+1d} = -\hat{W}_i^T \Psi(\bar{x}_i) - K_i e_i + \dot{x}_{id} \quad for\ i = 1, \ldots, n-1 \tag{12}$$
$$u = -k_n e_n - \hat{W}_n^T \Psi(\bar{x}_n) + \dot{x}_{nd} \tag{13}$$

Comparing the controllers of DSC method and IDSC method, it is easy to see that the main difference between the two methods is that the state error term e_i (see (10) and (11)) of IDSC method is constructed directly by α_i, while the error term S_i of DSC method is constructed by x_{i+1d} generated by α_i through first-order filter (see (6) to (8)).

The reasons why we use α_i to construct the state errors are listed as follows.

1). The purposes of control designs are confining S_i and e_i to zero. However, it should be known that actually the idea values for x_i is α_{i-1}, rather than x_{id}, since there will be no residual terms in the dynamics of e_{i-1}-subsystems. The signals, α_{i-1}, are called the 'ideal control input' of e_{i-1}-subsystems dynamics.

2). When τ_{i+1} are chosen not small enough, the error for x_{id} and α_{i-1} may make the controlled system unstable.

3). x_{id} is a signal produced by α_{i-1} passing through a first-order filter. Therefore, there must be an error for x_{id} and α_{i-1}. This error is actually unnecessary for the control design, and it is cancelled in IDSC method. This fact makes the IDSC more efficiently to confine the state errors.

IV. STABILITY ANALYSIS FOR IDSC METHOD

As for the IDSC given in this article, we will give the main result in this section. Define the Lyapunov function as follows:

$$V = \sum_{i=1}^{n} V_i + \sum_{i=2}^{n} \frac{y_i^2}{2} \tag{14}$$
$$V_i = \frac{e_i^2}{2} + \frac{1}{2}\tilde{W}_i^T \Gamma_i^{-1} \tilde{W}_i, \quad i = 1, 2, \ldots, n \tag{15}$$

where $y_i = x_{id} - \alpha_{i-1}$. estimation error is $\tilde{W}_i = W_i^* - \hat{W}_i$.

We have the following theorem for system (1) with the IDSC method.

Theorem 1: Consider the nonlinear system (1), and the virtual controllers (11), the controller (13) and the first-order filters (12). Given any $p > 0$, if $V(0) < p$, then there exist K_i and τ_i such that all of the signals in the closed-loop system are bounded. Furthermore, the tracking error $e_1 = x_1 - y_d$ converges to a small neighborhood of the origin by appropriately choosing design parameters.

Proof: Firstly, we will analysis the stabilities of e_i, respectively, by consider the time derivative of V_i. Secondly, the stability of the whole closed-control system will be analyzed by using the analysis for each e_i.

Noting (11) and (15), the time derivative of V_1 is

$$\dot{V}_1 = e_1\dot{e}_1 + \tilde{W}_1^T \Gamma_1 \dot{\tilde{W}}_1 = e_1(\dot{x}_1 - \dot{y}_d) - \tilde{W}_1^T \Gamma_1^{-1} \dot{\hat{W}}_1 \tag{16}$$

Substituting (1) into (16), and then using (11), we have, for $1 \leq i \leq n-1$

$$\begin{aligned}\dot{V}_1 &= e_1\left(x_2 + W_1^{*T}\Psi(x_1) + \varepsilon_1 - \dot{x}_{1d}\right) - \tilde{W}_1 \Gamma_1^{-1} \dot{\hat{W}}_1 \\ &= e_1\left(e_2 + \alpha_1 + W_1^{*T}\Psi(x_1) + \varepsilon_1 - \dot{x}_{1d}\right) - \tilde{W}_1^T \Gamma_1^{-1} \dot{\hat{W}}_1 \\ &= e_1\left(e_2 - K_1 e_1 + \tilde{W}_1^T \Psi(x_1) + \varepsilon_1\right) - \tilde{W}_1^T \Gamma_1^{-1} \dot{\hat{W}}_1 \\ &\leq e_1 e_2 - K_1 e_1^2 + \tilde{W}_1^T \Gamma_1^{-1}\left(e_1 \Gamma_1 \Psi(x_1) - \dot{\hat{W}}_1\right) + e_1 \varepsilon_1\end{aligned} \tag{17}$$

which implies that the boundedness of e_1 depends on e_2. Design the adaptive law for $\hat{W}_1$ as follows

$$\dot{\hat{W}}_1 = \gamma_1 \Gamma_1 \left(e_1 \Psi(x_1) - \sigma_1 \hat{W}_1\right) \tag{18}$$

Then, substituting (18) into (17) yields

$$\dot{V}_1 \leq e_1 e_2 - K_1 e_1^2 + \sigma_1 \tilde{W}_1^T \hat{W}_1 + e_1 \varepsilon_1 \tag{19}$$

In the sequel, the boundedness of e_i, $(2 \leq i \leq n-1)$ will be investigated by consider Lyapunov candidate functions V_i. The time derivative of V_i for $2 \leq i \leq n-1$ is

$$\dot{V}_i = e_i \dot{e}_i = e_i(\dot{x}_i - \dot{\alpha}_{i-1}) - \tilde{W}_i^T \Gamma_i^{-1} \dot{\hat{W}}_i, 2 \leq i \leq n-1 \tag{20}$$

Noting $y_i = x_{id} - \alpha_{i-1}$, $i = 2, \ldots, n$, then we have

$$\dot{V}_i = e_i \dot{e}_i = e_i(\dot{x}_i - \dot{x}_{id} + \dot{y}_i) - \tilde{W}_i^T \Gamma_i^{-1} \dot{\hat{W}}_i, 2 \leq i \leq n-1 \tag{21}$$

In view of (11) and (12), we have

$$\dot{x}_{id} = \frac{1}{\tau_i}(\alpha_i - x_{id}) = -\frac{y_i}{\tau_i} \tag{22}$$

$$\dot{y}_i = -\frac{y_i}{\tau_i} - \dot{\alpha}_{i-1} \tag{23}$$

and by noting (11) and (23), we have

$$\dot{y}_{i+1} = -\frac{y_{i+1}}{\tau_{i+1}} + k_i\dot{e}_i + \dot{\hat{W}}_i^T\psi(\bar{x}_i) + \hat{W}_i^T\frac{\partial\psi(\bar{x}_i)}{\partial\bar{x}_i}\dot{\bar{x}}_i^T + \frac{\dot{y}_i}{\tau_i}, \quad i = 1,\ldots,n-1 \tag{24}$$

Define

$$B_{i+1}\left(e_1,\ldots,e_{i+1},y_2,\ldots,y_{i+1},\hat{W}_1^T,\ldots,\hat{W}_i^T,y_d,\dot{y}_d,\ddot{y}_d\right) = k_i\dot{e}_i + \dot{\hat{W}}_i^T\psi(\bar{x}_i) + \hat{W}_i^T\frac{\partial\psi(\bar{x}_i)}{\partial\bar{x}_i}\dot{\bar{x}}_i^T + \frac{\dot{y}_i}{\tau_i} \tag{25}$$

where $\bar{e}_i = [e_1,\ldots,e_i]^T$, $\bar{y}_i = [y_2,\ldots,y_i]^T$, $\bar{K}_i = [K_1,\ldots,K_i]^T$ and $\bar{\tau}_i = [\tau_2,\ldots,\tau_i]^T$.

It can be easily known from [7] that the arguments of $B_{i+1}(\cdot)$ are the ones show in (25) and there exist unknown continuous functions η_{i+1}, $i = 1,\ldots,n-1$ satisfying

$$\left|y_{i+1} + \frac{y_{i+1}}{\tau_{i+1}}\right| = \left|B_{i+1}(\bar{e}_{i+1}^T,\bar{y}_{i+1}^T,\bar{K}_i,\bar{\tau}_i,\hat{W}_i^T y_d,\dot{y}_d,\ddot{y}_d)\right| \le \eta_{i+1}(\bar{e}_{i+1}^T,\bar{y}_{i+1}^T,\bar{K}_i,\bar{\tau}_i,\hat{W}_i^T y_d,\dot{y}_d,\ddot{y}_d) \tag{26}$$

Substituting (1) and (10) into (20), and then using (11), we have, for $2 \le i \le n-1$

$$\begin{aligned}\dot{V}_i &= e_i\left(x_{i+1} + W_i^{*T}\Psi(\bar{x}_i) + \varepsilon_i - \dot{x}_{id} + \dot{y}_i\right) - \tilde{W}_i^T\Gamma_i^{-1}\dot{\hat{W}}_i\\ &= e_i\left(e_{i+1} + \alpha_i + W_i^{*T}\Psi(\bar{x}_i) + \varepsilon_i - \dot{x}_{id} + \dot{y}_i\right)\\ &\quad - \tilde{W}_i^T\Gamma_i^{-1}\dot{\hat{W}}_i\\ &= e_i\left(e_{i+1} - K_ie_i + \tilde{W}_i^T\Psi(\bar{x}_i) + \varepsilon_i + \dot{y}_i\right) - \tilde{W}_i^T\Gamma_i^{-1}\dot{\hat{W}}_i\\ &\le e_i(e_{i+1} + \dot{y}_i) - K_ie_i^2 + \tilde{W}_i^T\Gamma_i^{-1}\left(e_i\Gamma_i\Psi(\bar{x}_i) - \dot{\hat{W}}_i\right)\\ &\quad + e_i\varepsilon_i\end{aligned} \tag{27}$$

Design the adaptive law for $\hat{W}_i$ as follows:

$$\dot{\hat{W}}_i = \gamma_i\Gamma_i\left(e_i\Psi(\bar{x}_i) - \sigma_i\hat{W}_i\right) \tag{28}$$

Then, substituting (28) into (27) yields

$$\dot{V}_i \le e_i(e_{i+1} + \dot{y}_i) - K_ie_i^2 - \sigma_i\tilde{W}_i^T\hat{W}_i + e_i\varepsilon_i \tag{29}$$

And, similarly, we can obtain

$$\begin{aligned}\dot{V}_n &= e_n\left(u - \dot{x}_{nd} + W_n^{*T}\Psi(\bar{x}_n) + \varepsilon_n + \dot{y}_n\right) - \tilde{W}_n^T\Gamma_n^{-1}\dot{\hat{W}}_n\\ &= -K_ne_n^2 + e_n\dot{y}_n + \tilde{W}_n^T\Gamma_n^{-1}\left(e_n\Gamma_n\Psi(\bar{x}_n) - \dot{\hat{W}}_n\right) + e_n\varepsilon_n\end{aligned} \tag{30}$$

Design the adaptive law for $\hat{W}_n$ as follows

$$\dot{\hat{W}}_n = \gamma_n\left(e_n\Gamma_n\Psi(\bar{x}_n) - \sigma_n\hat{W}_n\right) \tag{31}$$

Then, substituting (31) into (30) yields

$$\dot{V}_i \le +e_n\dot{y}_n - K_ne_n^2 - \sigma_n\tilde{W}_n^T\hat{W}_n + e_n\varepsilon_n \tag{32}$$

By using (25) and (26), we can know that the time derivative of V defined in (14) satisfies

$$\dot{V} \le \sum_{i=1}^{n-1}e_ie_{i+1} + \sum_{i=2}^{n}e_i\dot{y}_i - \sum_{i=1}^{n}K_ie_i^2 + \sum_{i=1}^{n}\left(e_i\varepsilon_i - \sigma_i\tilde{W}_i^T\Gamma_i^{-1}\hat{W}_i\right) + \sum_{i=2}^{n}y_i\dot{y}_i \tag{33}$$

Using (26) and (33),

$$-\sigma_i\tilde{W}_i^T\hat{W}_i \le -\frac{\sigma_i}{2}\left\|\tilde{W}_i\right\|^2 + \frac{\sigma_i}{2}\left\|W_i^*\right\|^2 \tag{34}$$

$$e_i\varepsilon_i \le \frac{1}{2}e_i^2 + \frac{1}{2}\varepsilon_i^{*2} \tag{35}$$

we have

$$\dot{V} \le \sum_{i=1}^{n-1}e_ie_{i+1} + \sum_{i=2}^{n}e_i\dot{y}_i - \sum_{i=1}^{n}\left(K_i - \frac{1}{2}\right)e_i^2 + \sum_{i=1}^{n}\left(-\frac{\sigma_i}{2}\left\|\tilde{W}_i\right\|^2 + \frac{\sigma_i}{2}\left\|W_i^*\right\|^2\right) + \sum_{i=2}^{n}y_i\dot{y}_i + \frac{1}{2}\sum_{i=1}^{n}\varepsilon_i^{*2} \tag{36}$$

From the definition of $B_{i+1}(\cdot)$, we have $\dot{y}_{i+1} = -y_{i+1}/\tau_{i+1} + B_{i+1}(\cdot)$. Therefore, (33) can be further rewritten as

$$\begin{aligned}\dot{V} \le &\sum_{i=1}^{n-1}e_ie_{i+1} + \sum_{i=2}^{n}e_i\left(-\frac{y_i}{\tau_i} + B_i(\cdot)\right) - \sum_{i=1}^{n}K_ie_i^2\\ &+ \sum_{i=1}^{n}\left(-\frac{\sigma_i}{2}\left\|\tilde{W}_i\right\|^2 + \frac{\sigma_i}{2}\left\|W_i^*\right\|^2\right)\\ &+ \sum_{i=2}^{n}\left(-\frac{y_i^2}{\tau_i} + y_iB_i(\cdot)\right) + \frac{1}{2}\sum_{i=1}^{n}\varepsilon_i^{*2}\end{aligned} \tag{37}$$

Noting (26) and using Young's inequality, one obtains

$$e_i\left(-\frac{y_i}{\tau_i} + B_i(\cdot)\right) \le \left(\frac{1}{2\tau_i} + \frac{\eta_i^2(\cdot)}{b}\right)e_i^2 + \frac{1}{2\tau_i}y_i^2 + \frac{b}{4} \tag{38}$$

$$y_iB_i(\cdot) \le \frac{y_i^2\eta_i^2(\cdot)}{b} + \frac{b}{4} \tag{39}$$

$$e_ie_{i+1} \le \frac{e_i^2}{2} + \frac{e_{i+1}^2}{2} \tag{40}$$

where b is any positive constant.

Using (38), (39) and (40), we can rewrite (37) as

$$\dot{V} \le -(K_1 - 1)e_1^2 - \sum_{i=2}^{n}\left(K_i - \frac{3}{2} - \frac{1}{2\tau_i} - \frac{\eta_i^2(\cdot)}{b}\right)e_i^2 - \sum_{i=2}^{n}\left(\frac{1}{2\tau_i} - \frac{\eta_i^2(\cdot)}{b}\right)y_i^2 + C_0 - \frac{\sigma_i}{2}\sum_{i=1}^{n}\left\|\tilde{W}_i\right\|^2 \tag{41}$$

where $C_0 = \sum_{i=1}^{n}\frac{\sigma_i}{2}\left\|W_i^*\right\|^2 + \frac{1}{2}\sum_{i=1}^{n}\varepsilon_i^{*2}$.

Consider the sets

$$\Omega_i := \left\{ \left(e_1, .., e_i, y_2, .., y_i, \hat{W}_1^T, .., \hat{W}_i^T\right) \times \left| \sum_{j=1}^{i} e_j^2 + \sum_{j=1}^{i} \left(\tilde{W}_i^T \Gamma_i^{-1} \tilde{W}_i\right) + \sum_{j=2}^{i} y_j^2 \le 2p \right. \right\}, \quad i = 2, 3, \ldots, n \tag{42}$$

It is obviously that Ω_i and $\Omega_i \times \Omega_0$ are compact sets. Notice that η_i is a continuous function on $\Omega_i \times \Omega_0$, therefore, η_i has a maximum, say M_i on $\Omega_i \times \Omega_0$. Select $K_1 = 1 + a_0$, $K_i = 1.5 + \frac{1}{2\tau_i} + \frac{M_i^2}{b} + a_1$, where $a_0 > C_0/2p$ and $a_1 > C_0/2p$. Choose $1/\tau_i = 2\left(M_i^2/b + a_2\right)$, where $a_2 > C_0/2p$. Therefore

$$\dot{V} \le -2a_{\min} V + C_0 - \sum_{i=2}^{n} \left(1 - \frac{\eta_i^2(\cdot)}{M_i^2}\right) \frac{M_i^2}{b} \left(e_i^2 + y_i^2\right) \tag{43}$$

where $a_{\min} = \min\{a_0, a_1, a_2, \sigma_i/2\lambda_{\max}\{\Gamma_i^{-1}\}\}$ and $a_{\min} > C_0/2p$. It is easily known from (43) that on $V(e_1, \ldots, e_n, y_2, \ldots, y_n) = p$, $\eta_i \le M_i$. Therefore, $\dot{V} \le -2a_{\min} V + C_0$. Since $a_{\min} > C_0/2p$, it follows that $\dot{V} \le 0$ on $V = p$. Therefore, $V \le p$ is an invariant set, namely, if $V(0) \le p$, then $V(t) \le p$ for all $t > 0$. Thus, $e_1, \ldots, e_n, y_2, \ldots, y_n$ are bounded, and it is easily to conclude that α_i and u are bounded. Additionally, From (33), it can be seen that

$$\dot{V} \le -2a_{\min} V + C_0 \tag{44}$$

on $\Omega_i \times \Omega_0$. This implies

$$V(t) \le (V(0) - C_1)\, e^{-2a_{\min} t} + C_1 \tag{45}$$

which yields

$$\lim_{t\to+\infty} |e_1| \le \lim_{t\to+\infty} \left|\sqrt{2V(t)}\right| \le \sqrt{2C_1} \tag{46}$$

where $C_1 = C_0/2a_{\min}$. Noticing that C_1 can be adjusted to arbitrary small by increasing K_1, K_i and $1/\tau_i$, therefore, the tracking error can be confined to arbitrary small. This completes the proof.

V. SIMULATION RESULTS

In this section, a simulation example is presented to demonstrate the advantages of our method by comparing DSC method. Consider the following non-affine pure-feedback nonlinear system:

$$\begin{cases} \dot{x}_1 = x_2 + x_1 + x_1 \cos(x_1) \\ \dot{x}_2 = u \\ y = x_1 \end{cases} \tag{47}$$

In (47), $f_1(x_1) = x_1 + x_1 \cos(x_1)$,. Therefore, based on the standard DSC method in [7], the tracking controller is proposed as follows

$$\begin{aligned} S_1 &= x_1 - y_d \\ \alpha_1 &= -\hat{W}_1^T \Psi(\bar{x}_1) - K_1 S_1 + \dot{y}_d \\ \tau_2 \dot{x}_{2d} + x_{2d} &= \alpha_1 \\ S_2 &= x_2 - x_{2d} \\ u &= \dot{x}_{2d} - 15 S_2 \end{aligned} \tag{48}$$

According the IDSC method in our article and noting Theorem 1, the controller of IDSC is proposed as follows

$$\begin{aligned} e_1 &= x_1 - y_d \\ e_2 &= x_2 - \alpha_1 \\ \alpha_1 &= -\hat{W}_1^T \Psi(\bar{x}_1) - K_1 e_1 + \dot{y}_d \\ \tau_2 \dot{x}_{2d} + x_{2d} &= \alpha_1 \\ u &= -15 e_2 - \hat{W}_2^T \Psi(\bar{x}_2) + \dot{x}_{2d} \end{aligned} \tag{49}$$

The time constants in both methods are $\tau_2 = 0.1$. The weight vector of neural network in both methods are $\hat{W} = 0.1$. It can be seen that, for the purpose of comparison, all the design parameters of two method are the same. Moreover, we set the initial conditions of two methods to be the same as well. Specially, let the initial conditions of both methods to be $(x_1(0), x_2(0))^T = (0, 0)^T$ and $x_{2d}(0) = 0$. Let $y_d = \sin t$. Then, the simulation results are shown in Figs. 1-3.

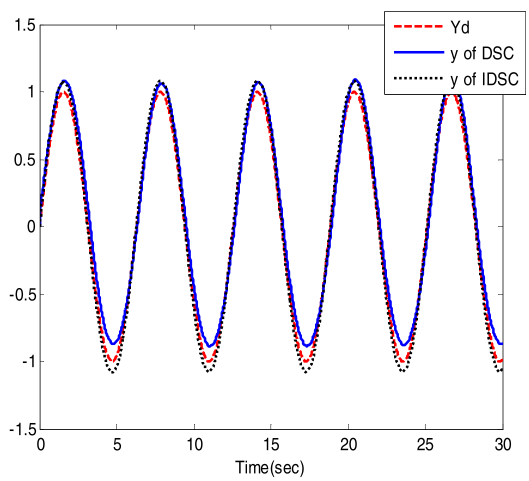

FIGURE 1. System output y and desired signal y_d with $\tau_2 = 0.1$.

It can be seen from Fig. 2 that IDSC has smaller tracking error than DSC under the same conditions. It can be seen from Fig. 1-3, that both methods can achieve the control target, and the IDSC method has better tracking performance than the DSC method under the same conditions.

In order to further illustrate the advantages of the IDSC method proposed in this article, we change the design parameters τ_2 to be $\tau_2 = 0.2$, and all the other design parameters and conditions are still the same and not changed. The simulation results of DSC method with $\tau_2 = 0.2$ are shown in Fig. 4-6. It can be seen from Fig. 4 and Fig. 5 that under the control of DSC method, the system output y is unable to be tracked, and the tracking error e_1 is getting larger and larger. When τ_2 of DSC only changes from 0.1 to 0.2, the system becomes unstable.

In the following article, we use the IDSC method to deal with $\tau_2 = 0.2$ conditions. All other design parameters and

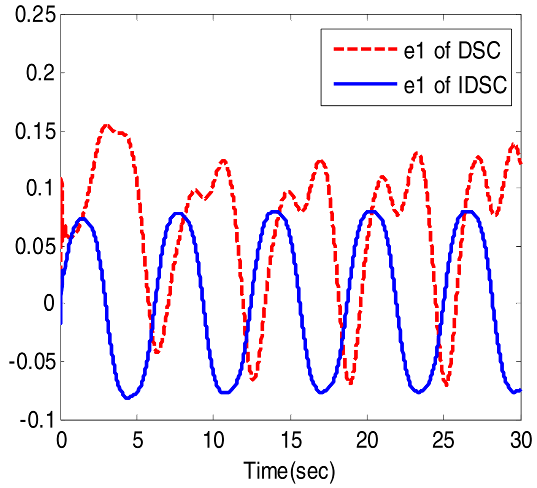

FIGURE 2. Tracking errors with $\tau_2 = 0.1$.

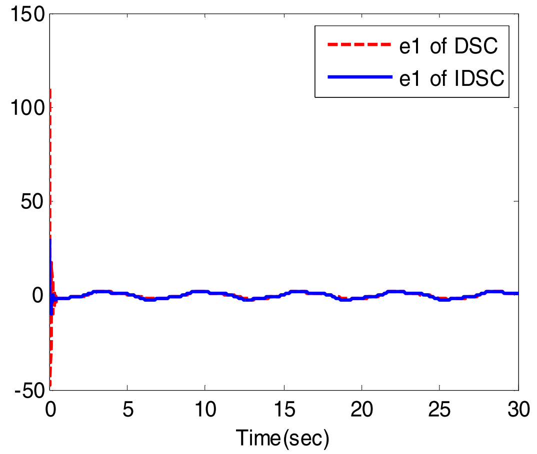

FIGURE 3. Control input u with $\tau_2 = 0.1$.

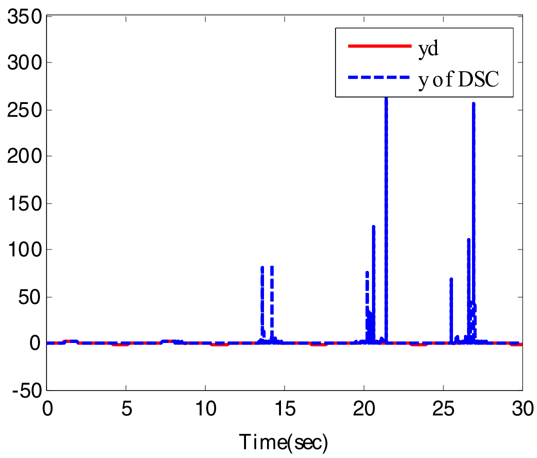

FIGURE 4. System output y of DSC and desired signal y_d with $\tau_2 = 0.2$.

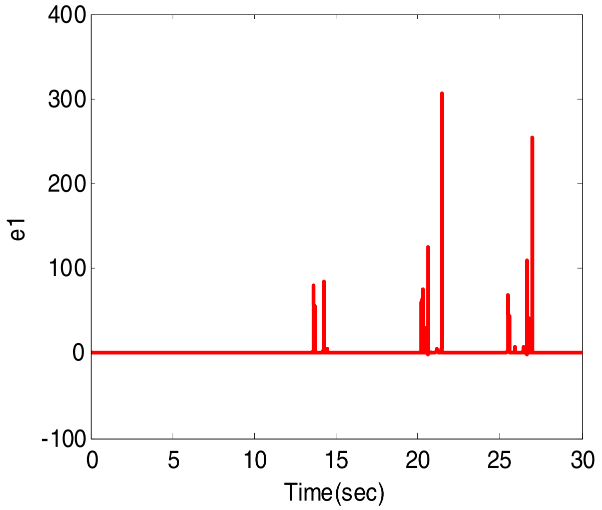

FIGURE 5. Tracking error of DSC with $\tau_2 = 0.2$.

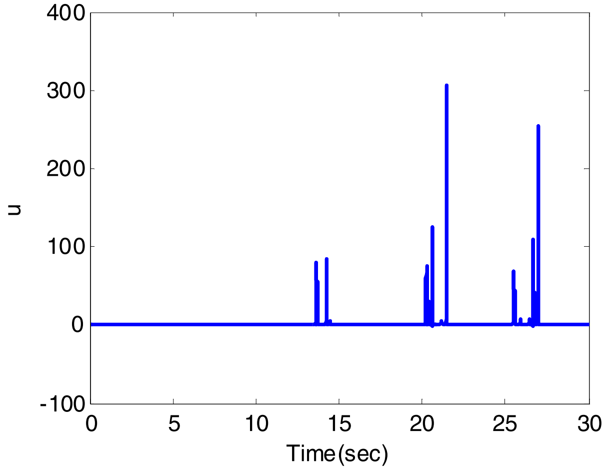

FIGURE 6. Control input u of DSC with $\tau_2 = 0.2$.

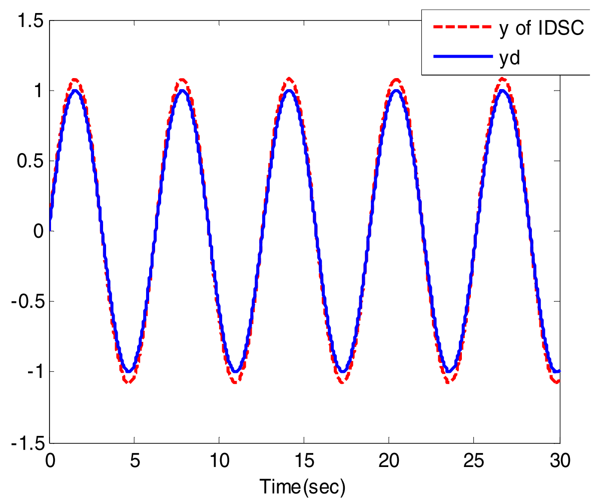

FIGURE 7. System output y of IDSC and desired signal y_d with $\tau_2 = 0.2$.

conditions remain unchanged. Figure 7-9 reports the simulation results of DSC method under $\tau_2 = 0.2$ condition. It can be seen from Fig. 7 and Fig. 8 that the system output y still tracks y_d well under $\tau_2 = 0.2$, and the tracking error is limited to a satisfactory range. Under the method of IDSC with $\tau_2 = 0.2$, all signals of the system are stable.

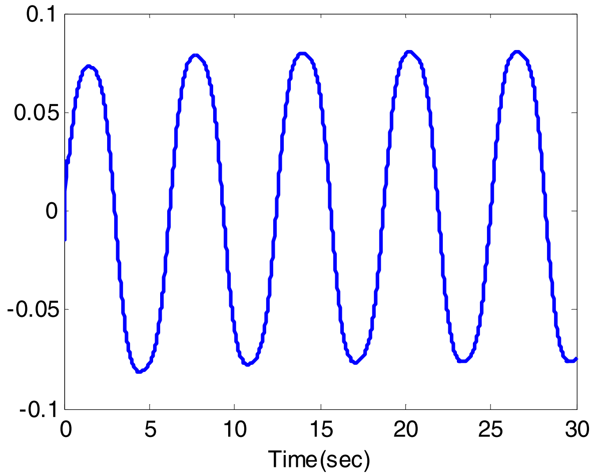

FIGURE 8. Tracking error of IDSC with $\tau_2 = 0.2$.

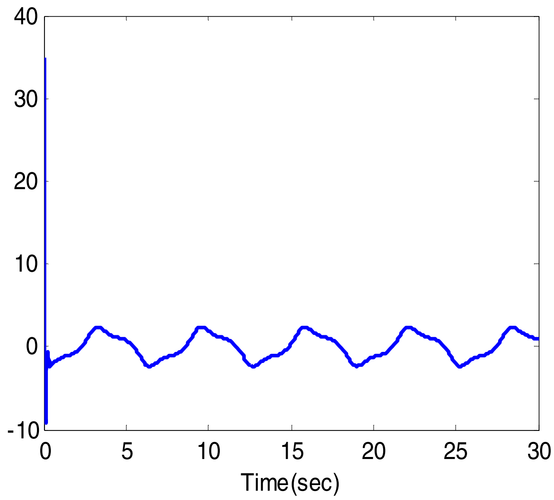

FIGURE 9. Control input u of IDSC $\tau_2 = 0.2$.

The simulation results show that IDSC method has better tracking performance than DSC method under the same conditions. When τ_i changes from 0.1 to 0.2, IDSC control system is more stable than DSC control system. It should be noted that τ_i is a key design parameter of DSC method because it always affects the stability of the controlled system. For example, the stability of the controlled system is always weakening, while τ_i is decreasing. Therefore, we propose IDSC method to achieve better tracking performance and improve the stability of the controlled system.

VI. CONCLUSION

In this article, based on the traditional DSC method, an improved DSC method is proposed, in which the virtual control law is used to construct the system error directly. The neural network is used to approximate the unknown nonlinear system function, and the adaptive rate of the system control rate and unknown parameters is derived. Based on Lyapunov theorem, the stability of the closed-loop system controlled by IDSC method is proved. Finally, the simulation results have been given. Simulation results show that, compared with DSC method, IDSC method can obtain more stable control system, and has better tracking performance.

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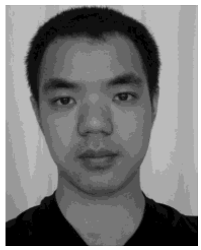

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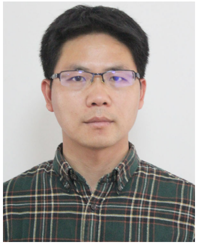

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