IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received April 25, 2021, accepted May 17, 2021, date of publication May 25, 2021, date of current version June 2, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3083567

High-Order Disturbance Observer-Based Neural Adaptive Control for Space Unmanned Systems With Stochastic and High-Dynamic Uncertainties

YAO ZHANG[1,2], XIN NING[1,2], ZHENG WANG[1,3,4], AND DENGXIU YU[4], (Member, IEEE)

[1]National Key Laboratory of Aerospace Flight Dynamics, Northwestern Polytechnical University, Xi'an 710072, China
[2]School of Astronautics, Northwestern Polytechnical University, Xi'an 710072, China
[3]Research Center for Unmanned System Strategy Development, Northwestern Polytechnical University, Xi'an 710072, China
[4]Unmanned System Research Institute, Northwestern Polytechnical University, Xi'an 710072, China

Corresponding author: Zheng Wang (wz_nwpu@126.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 11772256.

ABSTRACT In this paper, a high order disturbance observer based stochastic adaptive anti-disturbance control algorithm has been designed for the space unmanned systems (SUSs) with high dynamic disturbances and stochastic uncertainties. Firstly, to suppress the adverse influence of the high dynamic disturbances, a high order disturbance observer is designed for the SUSs to maintain the accurate approximation. Secondly, to overcome the infaust effects of the stochastic uncertainties, a novel variable has been introduced and the corresponding adaptive law has been proposed. Moreover, the neural networks have been employed to enhance the adaptability with respect to the nonlinearities and modeling errors. Based on the stochastic control theory and the fourth-order Lyapunov function, the stochastic stability of the closed-loop control system has been proved. Finally, the performance of high-order disturbance observer has been verified in two cases of simulations, and the effectiveness of the stochastic adaptive anti-disturbance control strategy has been demonstrated simultaneously.

INDEX TERMS Adaptive backstepping control, disturbance observer, stochastic uncertainties, stochastic control, space unmanned systems.

I. INTRODUCTION

The space unmanned systems are the space systems those can complete space operations autonomously through advanced control theory, artificial intelligence and communication technology without manual intervention. The SUS plays a significant role in complicated space missions such as space rendezvous, on-orbit service, space pursuit-escape games, including the space stations, space robots, and satellites, etc. Multiple space engineering projects have been carried out since the 1960s, the researchers found that the frequent manual space work is not only high-cost but also inefficient. Therefore, the SUS came into existence. Generally speaking, the SUS are designed to meet the rapidly growing task quantity, highly depending on the advanced control technology and intelligence methods. However, there are still a prohibitive amount of difficulties to be solved in the SUS control design process [1]–[3].

In recent decades, there has been a tremendous interest in SUS, and many significant technological achievements have emerged within the aera of its control design [4]–[7]. Specifically, for one of the hotspot spacecraft formation flying (SFF) mission, a purposeful, large-scale formation needs to be designed, constructed, and maintained using a sparse separation of spacecraft. The typical linearized orbital system model, the Clohessy-Wiltshire (CW) model was once widely used in formation missions because of its favorable compatibility with various mature linear control methods [8]–[10]. But the convenience brought by the linearization comes at the cost of losing modeling accuracy. With the consummation of nonlinear system theory, plenty delicate nonlinear controllers were introduced into the SUS. Researchers in [11], [12] studied the relative position adaptive control for SFF and proved asymptotical stability of the system subjected to uncertainties. For the promotion of parametric linear regression, the external disturbances in [11], [12] were assumed to be constant which rarely exist in the physical world. Moreover, the simple combination of

The associate editor coordinating the review of this manuscript and approving it for publication was Bidyadhar Subudhi.

backstepping and the certainty-equivalence (CE) based adaptive law was proposed to stabilize the compositive formation system while ignoring the convergence and boundness of the parameter estimation. In [13], a novel output feedback frame based on a filtered velocity observer provided a semi-global, asymptotically convergent, relative position tracking controller with desired adaptive compensation. It is worth mentioning that the application of partial integration within the design of adaptive law greatly improves the flexibility of using unmeasurable state information. In addition, another noticeable aspect in the SUS is space robot, which is one of the main realization methods of autonomous on-orbit services and had set off a research boom on a global scale in the last thirty years [14]. Huang *et al.* [15] proposed an adaptive controller constructed by a dynamic and a kinematic adaption law for the tethered space robot (TSR), taking the attitude motions of both base and target satellites and the elasticity of tether into account. In [16], a CE based adaptive controller with desirable separation property has been proposed to improve the performance of robot manipulators with both the uncertain kinematics and dynamics. Besides, to highly restore the sophisticated nonlinear terms in the system, the adaptive theory was also organically combined with many well-known intelligent frameworks such as Reinforcement Learning (RL) and Neural Network (NN) [17], [18]. Unfortunately, in the above literatures, although the CE-based adaptive law was adopted without exception, the vulnerability of the parameter estimation values convergence and robustness remains unresolved, and they scarcely concentrated on the high dynamic disturbance suppression problem of closed-loop SUS [19], [20].

With the rapid development of intelligent theories and methods, a number of reliable approaches has been proposed to approximate and compensate the uncertainties in the control systems. Broad Learning System (BLS), which can make full use of the self-adjusting mechanism of node number to achieve better learning performance, has been firstly proposed in [4]. Compared with the traditional fusion method, a framework that can learn and fuse two modal characteristics based on the broad learning method constructed in [5] has better stability and rapidity. By fusing the Takagi-Sugeno (T-S) fuzzy system into BLS, the fuzzy broad learning system (FBLS) is proposed in [6]. In [8], the quaternion broad learning system (QBLS) has been constructed to achieve tremor estimation and suppression. By combing a fully convolutional network with broad learning system, a framework for license plate recognition has been introduced in [9]. Furthermore, BLS has been used to solve practical engineering problems. In [12], BLS has been introduced into hyperspectral image analysis algorithm, which providing new ideas and technical reserves for a variety of hyperspectral image analysis problems. [13] proposed a method of landscape capacity allocation based on BLS, and obtained a capacity allocation result that met the total investment cost and minimized network active power loss.

Since various uncertain factors, such as unknown external interference, widely exist in the actual engineering system, the stability of the control system is affected to a certain extent [14]. In order to solve the uncertain dynamic and external disturbance in the nonlinear uncertain system and ensure the high precision tracking performance, the intelligent control methods such as adaptive control [15], sliding mode control [16] and neural network [17] have been widely paid attention by the researchers. Because of the clear physical significance and relatively simple engineering implementation, the disturbance observer is widely used to estimate disturbances in uncertain systems, receiving extensive attention in the academic and engineering fields [18], [21], [22].In disturbance observer-based (DOB) control, disturbances are observed by using identified dynamics and measurable states of plants, and the robustness of systems is easily achieved by feeding back the observed disturbances [23]. In [24], a high-order disturbance observer has been proposed to observe the disturbances and its high-order derivatives, which can increase the observation accuracy. [25] uses a disturbance observer with an additional nonlinear term to adjust the observer's steady-state performance. In [26], the decentralized adaptive output feedback saturated control problem has been researched for interconnected nonlinear systems with strong interconnections; In [27], the problem of disturbance attenuation and rejection has been investigated for stochastic Markovian jump system with multiple disturbances. In [28], a disturbance observer based resilient control algorithm has been proposed for Markovian jump nonlinear systems with multiple disturbances. In [29], the refined anti-disturbance control problem has been investigated for the switched linear parameter-varying systems, by using a parameter-dependent discontinuous Lyapunov function. Meanwhile, the active disturbance rejection control (ADRC) methods have also widely utilized to ensure the control performance under disturbances [25], [30], [31]. Because of the low reliability for accurate information, the ADRC controllers have been designed for many of the engineering systems [30], [31].In [32], the ADRC has been investigated for the quadrotor with winds. In [33], by a combination of back-stepping and ADRC, an integrated controller is devised to tackle multiple uncertainties. In [34], an ADRC controller which can reduce the control gains and the bandwidth has been designed. Besides, several output feedback anti-disturbance control algorithm can be found in [35], [36] and [37]. Although fruitful results have been obtained in the area of the control design for SUSs, the high dynamic disturbances have been rarely taken into consideration. Furthermore, the control method which can handle the high dynamic disturbances and the stochastic uncertainties simultaneously has never been designed for the SUSs. However, the high dynamic disturbances are often encountered when achieving the attitude stability and tracking of the SUSs, and the stochastic uncertainties are unavoidable in the control process. The adverse influence of those stochastic and high dynamic uncertainties may result in the task failure of on orbit service. Therefore, it is of important urgency and significance to carry out the study of the stochastic anti-disturbance control methods for the SUSs.

Based on the above-mentioned analysis, this paper investigates the neural adaptive control for SUSs with stochastic and high-dynamic uncertainties. By utilizing the high order disturbance observer and several new variables, the infaust effects of the high dynamic disturbances and stochastic uncertainties can be suppressed. By using the neural networks, the adaptability with respect to the nonlinearities and modeling errors can be enhanced. Based on the stochastic control theory, it has been proven that the closed-loop stochastic anti-disturbance control system is stable. Compared with the existing results, the proposed method possesses the following features:

- To the best of the authors knowledge, it is the first stochastic adaptive anti-disturbance control structure for the SUSs suffering from the stochastic and high-dynamic uncertainties.
- The proposed method possesses strong robustness and can achieve better performance. By using the proposed method, the adverse influence of the high dynamic disturbances and stochastic uncertainties can be suppressed.
- According to the stability criteria of the proposed stochastic anti-disturbance control structure, the control gains and the adaptive parameters can be preliminarily determined.

The structure of this paper is arranged as follows. In section 2, the problem statement and preliminaries for the stochastic anti-disturbance control of the SUSs are formulated. In section 3, high-order disturbance observer and stochastic adaptive anti-disturbance controller is designed for SUSs. Simulation studies are shown in section 4 with two cases of disturbances. Some conclusions are drawn in section 5. Throughout this paper, for any vector $a = [a_1, a_2, a_3]^T \in \mathbb{R}^3$, $a^\times \in \mathbb{R}^{3\times 3}$ is defined by

$$a^\times = \begin{bmatrix} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{bmatrix}$$

$\forall b \in R^3$, it follows that $a^\times b = a \times b$. $\|a\|$ represents the Euclidean norm of the vector a and $Tr(\cdot)$ represents the trace of a matrix. Besides, I_n is $n \times n$ identity matrix.

II. PROBLEM FORMULATION AND PRELIMINARIES

A. SYSTEM MODEL

Define $\sigma = \begin{bmatrix} \sigma_1 & \sigma_2 & \sigma_3 \end{bmatrix}^T \in \mathbb{R}^3, \omega = \begin{bmatrix} \omega_x & \omega_y & \omega_z \end{bmatrix}^T \in \mathbb{R}^3$ in the inertia frame, which represent the absolute attitude and angular velocity of the spacecraft, respectively. The attitude kinematics and dynamics model of the SUS can be described by the MRPs:

$$\begin{aligned} \dot{\sigma} &= G(\sigma)\left[\omega + \omega_0 C_2(\sigma)\right] \\ J\dot{\omega} &= \omega^\times J\omega + \tau + f(\sigma, \omega) + d_\tau + \Delta\xi \end{aligned} \tag{1}$$

where J represents the inertia matrix, $f(\sigma, \omega)$ denotes the unknown nonlinear moment, is the external disturbances. ω_0 is the orbital angular rate value, which can be denoted as $\omega_0 = \sqrt{\mu_g / r_0^3}$, where μ_g, r_0 represent the gravitational constant of the Earth and orbital radius, respectively. Besides, the attitude motion system is commonly influenced by stochastic uncertainties. $\xi \in \mathbb{R}$ is define as white noises, and $\Delta \in \mathbb{R}^3$ represents the amplitudes of the stochastic uncertainties. The Jacobian matrix $G(\sigma) \in \mathbb{R}^{3\times 3}$ can be given by

$$\begin{aligned} G(\sigma) &= \frac{1}{4}\left[\left(1 - \sigma^T\sigma\right) I_3 + 2\sigma^\times + 2\sigma\sigma^T\right] \\ &= \frac{1}{4}\begin{bmatrix} G_1(\sigma) & G_2(\sigma) & G_3(\sigma) \end{bmatrix} \end{aligned} \tag{2}$$

where

$$G_1(\sigma) = \begin{bmatrix} 1 + \sigma_1^2 - \sigma_2^2 - \sigma_3^2 \\ 2(\sigma_1\sigma_2 + \sigma_3) \\ 2(\sigma_1\sigma_3 - \sigma_2) \end{bmatrix}$$
$$G_2(\sigma) = \begin{bmatrix} 2(\sigma_1\sigma_2 - \sigma_3) \\ 1 + \sigma_2^2 - \sigma_1^2 - \sigma_3^2 \\ 2(\sigma_2\sigma_3 + \sigma_1) \end{bmatrix}$$
$$G_3(\sigma) = \begin{bmatrix} 2(\sigma_1\sigma_3 + \sigma_2) \\ 2(\sigma_2\sigma_3 - \sigma_1) \\ 1 + \sigma_3^2 - \sigma_1^2 - \sigma_2^2 \end{bmatrix}$$

$C_2(\sigma)$ is the second column vector of the direction cosine matrix $C(\sigma)$ and equals to

$$C_2(\sigma) = \frac{1}{\left(1 + \sigma^T\sigma\right)^2}\begin{bmatrix} 8\sigma_1\sigma_2 + 4\sigma_3\left(1 - \sigma^T\sigma\right) \\ 4\left(\sigma_2^2 - \sigma_1^2 - \sigma_3^2\right) + \left(1 - \sigma^T\sigma\right)^2 \\ 8\sigma_2\sigma_3 - 4\sigma_1\left(1 - \sigma^T\sigma\right) \end{bmatrix} \tag{3}$$

According to [38], the kinematic and dynamic equations in (1) can be rewritten into a Lagrange-like form as

$$\bar{H}(\sigma)\ddot{\sigma} + C(\sigma, \dot{\sigma})\dot{\sigma} + \bar{g}(\sigma) = \bar{\tau} + \bar{f}(\sigma, \dot{\sigma}) + \bar{d}_\tau + \bar{\Delta}\xi \tag{4}$$

where

$$\begin{aligned} \bar{H}(\sigma) &= G^{-T}(\sigma) J G^{-1}(\sigma) \\ \bar{g}(\sigma) &= G^{-T}(\sigma) \\ &\quad \times \left[\omega_0^2 C_2^\times(\sigma) J C_2(\sigma) - 3\omega_0^2 C_3^\times(\sigma) J C_3(\sigma)\right] \\ \bar{\tau} &= G^{-T}(\sigma)\tau \\ \bar{f} &= G^{-T}(\sigma) f(\sigma, \dot{\sigma}) \\ \bar{d}_\tau &= G^{-T}(\sigma) d_\tau \\ \bar{\Delta} &= G^{-T}(\sigma)\Delta \end{aligned} \tag{5}$$

$C_3(\sigma)$ denotes the third column vector of $C(\sigma)$, which equals to

$$C_3(\sigma) = \frac{1}{\left(1 + \sigma^T\sigma\right)^2}\begin{bmatrix} 8\sigma_1\sigma_3 - 4\sigma_2\left(1 - \sigma^T\sigma\right) \\ 8\sigma_2\sigma_3 + 4\sigma_1\left(1 - \sigma^T\sigma\right) \\ 4\left(-\sigma_1^2 - \sigma_2^2 + \sigma_3^2\right) + \left(1 - \sigma^T\sigma\right)^2 \end{bmatrix} \tag{6}$$

Besides, the vector of Coriolis and centripetal torque $C(\sigma, \dot{\sigma})$ equaled to

$$C(\sigma,\dot{\sigma}) = G^{-T}(\sigma)\begin{bmatrix} -JG^{-1}(\sigma)\dot{G}(\sigma)G^{-1}(\sigma) \\ -\omega_0 JC_2^{\times}(\sigma)G^{-1}(\sigma) \\ +\left(G^{-1}(\sigma)\dot{\sigma}\right)^{\times}JG^{-1}(\sigma) \\ +(J\omega_0 C_2(\sigma))^{\times}G^{-1}(\sigma) \\ -(\omega_0 C_2(\sigma))^{\times}JG^{-1}(\sigma) \end{bmatrix} \quad (7)$$

where

$$\dot{G}(\sigma) = \frac{8}{\left(1+\sigma^T\sigma\right)^2}\left[\dot{\sigma}\sigma^T + \sigma\dot{\sigma}^T - \dot{\sigma}^T\sigma I_3 - \dot{\sigma}^{\times}\right] - \frac{16\sigma^T\dot{\sigma}}{\left(1+\sigma^T\sigma\right)^3}\left[\left(1-\sigma^T\sigma\right)I_3 - 2\sigma^{\times} + 2\sigma\sigma^T\right] \quad (8)$$

Our control objective is to develop a dynamic controller such that the attitude of SUS can track the desired attitude signal σ_d in the presence of the unknown nonlinearities, complex external disturbances and stochastic uncertainties.

In this paper, we make the following assumptions:

Assumption 1: The external disturbance d_τ is unknown and continuously differentiable. Also, the i-th order derivatives of d_τ is unknown and bounded, that is $\left\| d_\tau^{(i-1)} \right\| \leq \delta_d$.

Assumption 2: The inertia matrix J is a known positive definite, symmetric and bounded. Therefore, the inverse of J is bounded, which satisfies $\left\|J^{-1}\right\| \leq \delta_J$.

Assumption 3: The amplitudes of the stochastic uncertainties $\Delta \in \mathbb{R}^3$ is bounded, which satisfies $\left\|\Delta^T\Delta\right\| \leq \bar{\psi}$.

Moreover, the following properties of the spacecraft have to be recalled.

Property 1: The matrix $G(\sigma)$ is positive definite and bounded, which satisfies $1/4 \leq \|G(\sigma)\| \leq 1/2$. Therefore, on the basis of **Assumption 2**, the newly defined matrix H is bounded, that is,

$$\|H(\sigma)\| = \left\|G(\sigma)J^{-1}\right\| \leq \|G(\sigma)\|\left\|J^{-1}\right\| \leq \frac{1}{2}\delta_J$$

Remark 1: For practical systems, the i-th order derivatives of the external disturbance are usually bounded. The similar assumptions can be found in [39], and the reasonability of Assumption 1 can be known.

B. SUPPORTING DEFINITIONS AND LEMMAS

Consider the stochastic system below

$$dx = f(x,u)\,dt + g(x,u)\,d\omega \quad (9)$$

where $u \in \mathbb{R}^m$ and $x \in \mathbb{R}^n$ denote the input and the system state (9), respectively. $f(\cdot) : \mathbb{R}^{m+n} \rightarrow \mathbb{R}^n$ and $g(\cdot) : \mathbb{R}^{m+n} \rightarrow \mathbb{R}^{n\times r}$ are locally Lipschitz functions and satisfy $f(0,0) = 0, g(0,0) = 0$. $\omega \in \mathbb{R}^r$ is an independent standard Wiener process.

Definition 1 [40]: Given any Lyapunov function $V(x) \in C^{2,1}$ along with (9), the differential operator is defined as:

$$\mathcal{L}V(x) = \frac{tialV}{\partial x}f + \frac{1}{2}Tr\left\{g^T\frac{\partial^2 V}{\partial x^2}g\right\} \quad (10)$$

where $Tr(\cdot)$ is the matrix trace.

Lemma 1 [41]: For any real variables x, y any constant $\delta > 0$, $1 < p, q < \infty$ as well as $1/p + 1/q = 1$, the following inequality holds:

$$xy \leq \delta\frac{x^p}{p} + \delta^{-\frac{q}{p}}\frac{y^q}{q}$$

C. RADIAL BASIS FUNCTION NEURAL NETWORKS (RBFNNs)

According to [42] and [43], the uncertainties in SUSs can be approximated with the help of the RBFNNs. For any continuous function $f(x) : \mathbb{R}^n \rightarrow \mathbb{R}$, we can find a RBFNN $\Theta^T\Phi(x)$ such that

$$\sup_{x\in U}\left|f(x) - \Theta^T\Phi(x)\right| < \varepsilon \quad (11)$$

where $\Theta \in \mathbb{R}^l$ denotes the NN weights, l denotes the number of the NN nodes, $S(x) = [s_1(x), \cdots, s_l(x)]^T$ is a Gaussian function.

$$s_i(x) = \exp\left(-\frac{\|x-\pi_i\|^2}{\omega_i^2}\right), \quad i = 1,\ldots,l \quad (12)$$

where $\pi_i = \left[\pi_{i,1},\cdots,\pi_{i,n}\right]^T$.

Lemma 2 [44]: Let Ω_x denotes a compact set. Define $f(x)$ as a continuous function on Ω_x, the following equality holds

$$f(x) = \left(\Theta^*\right)^T\Phi(x) + \varepsilon^* \quad (13)$$

where Θ^* is the optimal NN weight and ε^* is the minimum approximation error. Note that Θ^* and ε^* are both bounded.

III. MAIN RESULTS

In this section, the high-order disturbance observer is designed for the SUSs to suppress the adverse influence of the high dynamic disturbances. Meanwhile, to overcome the infaust effects of the stochastic uncertainties, a novel variable has been introduced and the corresponding adaptive law has been proposed. Moreover, the neural networks have been employed to enhance the adaptability with respect to the nonlinearities and modeling errors. **Fig. 1** shows the block of the proposed stochastic adaptive anti-disturbance control scheme for the SUSs suffering from the stochastic and high-dynamic uncertainties.

A. HIGH-ORDER DISTURBANCE OBSERVER AND STOCHASTIC ADAPTIVE ANTI-DISTURBANCE CONTROLLER DESIGN

Define $z_1(t) = \sigma(t) - \sigma_d(t)$, $z_2(t) = \dot{\sigma}(t) - \beta(t)$, where $\beta(t)$ is the inner loop virtual control signal satisfying that

$$\beta(t) = -k_1 z_1(t) \quad (14)$$

Based on RBFNNs, we can get $f(z_1, z_2) = W^T\Phi(z_1,z_2) + \varepsilon$, then from (4) it is easy to get that

$$\begin{aligned} \dot{z}_1 &= z_2 - k_1 z_1 \\ \dot{z}_2 &= H(\sigma)\begin{bmatrix} -F(\sigma,\dot{\sigma})z_2 + k_1 F(\sigma,\dot{\sigma})z_1 - g(\sigma) \\ +W^T\Phi(z_1,z_2) + \varepsilon + \tau + d_\tau + \Delta\xi \end{bmatrix} - \dot{\beta} \end{aligned} \quad (15)$$

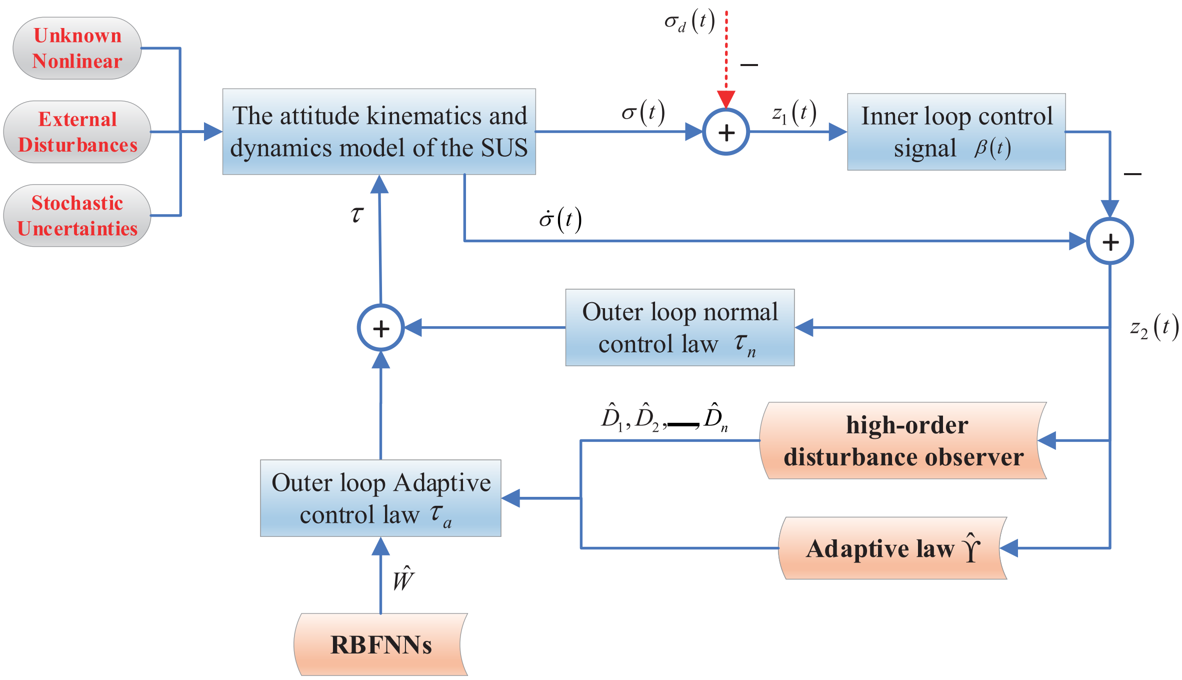

FIGURE 1. The structure of the proposed control scheme for SUSs.

where

$$H(\sigma) = \bar{H}^{-1}G^{-T}(\sigma) = G(\sigma)J^{-1}$$
$$g(\sigma) = \omega_0^2 C_2^{\times}(\sigma)JC_2(\sigma) - 3\omega_0^2 C_3^{\times}(\sigma)JC_3(\sigma)$$
$$F(\sigma,\dot{\sigma}) = \begin{bmatrix} -JG^{-1}(\sigma)\dot{G}(\sigma)G^{-1}(\sigma) \\ -\omega_0 JC_2^{\times}(\sigma)G^{-1}(\sigma) \\ +\left(G^{-1}(\sigma)\dot{\sigma}\right)^{\times}JG^{-1}(\sigma) \\ +(J\omega_0 C_2(\sigma))^{\times}G^{-1}(\sigma) \\ -(\omega_0 C_2(\sigma))^{\times}JG^{-1}(\sigma) \end{bmatrix} \tag{16}$$

Then from [45], substituting ξ with $d\zeta/dt$ respectively, we finally obtain that

$$\begin{aligned} &dz_1 \\ &= [z_2 - k_1 z_1]\,dt \\ &dz_2 \\ &= H(\sigma)\begin{bmatrix} -F(\sigma,\dot{\sigma})z_2 + k_1 F(\sigma,\dot{\sigma})z_1 - g(\sigma) \\ +W^T\Phi(z_1,z_2) + \varepsilon + \tau + d_\tau - H^{-1}(\sigma)\dot{\beta} \end{bmatrix} dt \\ &\quad + H(\sigma)\Delta d\zeta \end{aligned} \tag{17}$$

Aiming at the disturbance d_τ, define $\hat{D}_1, \hat{D}_2, \cdots, \hat{D}_n$ as the estimation of $d_\tau, \dot{d}_\tau \cdots d_\tau^{(n-1)}$ and $p_1, p_2 \cdots p_n$ as auxiliary variables, then the first order of high-order disturbance observer is designed as

$$\begin{aligned} \hat{D}_1 &= p_1 + L_1 H^{-1}(\sigma)z_2 \\ \dot{p}_1 &= -L_1\begin{bmatrix} -F(\sigma,\dot{\sigma})z_2 + k_1 F(\sigma,\dot{\sigma})z_1 - g(\sigma) \\ +\hat{W}^T\Phi(z_1,z_2) + \tau + \hat{D}_1 - H^{-1}(\sigma)\dot{\beta} \end{bmatrix} \\ &\quad - L_1\dot{H}^{-1}(\sigma)z_2 + \hat{D}_2 \end{aligned} \tag{18}$$

the i-order ($i = 2, \cdots, n-1$) is designed as

$$\begin{aligned} \hat{D}_i &= p_i + L_i H^{-1}(\sigma)z_2 \\ \dot{p}_i &= -L_i\begin{bmatrix} -F(\sigma,\dot{\sigma})z_2 + k_1 F(\sigma,\dot{\sigma})z_1 - g(\sigma) \\ +\hat{W}^T\Phi(z_1,z_2) + \tau + \hat{D}_{i-1} - H^{-1}(\sigma)\dot{\beta} \end{bmatrix} \\ &\quad - L_i\dot{H}^{-1}(\sigma)z_2 + \hat{D}_{i+1} \end{aligned} \tag{19}$$

the n-order is designed as

$$\begin{aligned} \hat{D}_n &= p_n + L_n H^{-1}(\sigma)z_2 \\ \dot{p}_n &= -L_n\begin{bmatrix} -F(\sigma,\dot{\sigma})z_2 + k_1 F(\sigma,\dot{\sigma})z_1 - g(\sigma) \\ +\hat{W}^T\Phi(z_1,z_2) + \tau + \hat{D}_1 - H^{-1}(\sigma)\dot{\beta} \end{bmatrix} \\ &\quad - L_n\dot{H}^{-1}(\sigma)z_2 \end{aligned} \tag{20}$$

where $L_1, L_2 \cdots L_n \in \mathbb{R}$ denote the designed gains of the disturbance observer. Besides, $\hat{W}$ denotes the estimation of W.

Define the estimation errors as $\tilde{D}_1 = \hat{D}_1 - d_\tau, \tilde{D}_2 = \hat{D}_2 - \dot{d}_\tau, \cdots, \tilde{D}_n = \hat{D}_n - d_\tau{}^{(n-1)}, \tilde{W} = \hat{W} - W$. Integrating the system equation (17), we can get

$$\begin{aligned} d\tilde{D}_1 &= \left(-L_1\tilde{D}_1 + \tilde{D}_2 - L_1\tilde{W}^T\Phi + L_1\varepsilon\right)dt - L_1\Delta d\zeta \\ d\tilde{D}_2 &= \left(-L_1\tilde{D}_2 + \tilde{D}_3 - L_2\tilde{W}^T\Phi + L_2\varepsilon\right)dt - L_2\Delta d\zeta \\ &\;\vdots \\ d\tilde{D}_n &= \left(-L_n\tilde{D}_n - L_n\tilde{W}^T\Phi + L_n\varepsilon + d^{(n-1)}\right)dt - L_n\Delta d\zeta \end{aligned} \tag{21}$$

Define

$$\Upsilon = \frac{3}{2}\sup_{t\geq 0}\left\| H(\sigma)\Delta\Delta^T H^T(\sigma)\right\| \tag{22}$$

In view of SUSs (17) subjected to disturbance and stochastic uncertainties, define design the controller as

$$\tau = \tau_n + \tau_a \tag{23}$$

where the normal control law is

$$\begin{aligned}\tau_n = F(\sigma,\dot{\sigma})z_2 - k_1 F(\sigma,\dot{\sigma})z_1 + g(\sigma)\\ +H^{-1}(\sigma)\dot{\beta} - k_2 H^{-1}(\sigma)z_2\end{aligned} \tag{24}$$

the adaptive control law is

$$\tau_a = -\hat{W}^T\Phi(z_1,z_2) - \hat{D}_1 - \hat{\Upsilon}\delta_\Upsilon H^{-1}(\sigma)z_2 \tag{25}$$

$\hat{W}, \hat{D}_1$ denotes the same meaning as before and $\hat{\Upsilon}$ denotes the estimation of Υ. The update laws of $\hat{W}$, $\hat{\Upsilon}$ is designed as

$$\begin{aligned}\dot{\hat{W}} &= \Gamma_W\left[\begin{array}{l}\left(\begin{array}{l}-\Phi(z_1,z_2)\cdot\Phi^T(z_1,z_2)\cdot\Phi(z_1,z_2)\cdot\\ \Lambda^T\cdot H(\sigma)\cdot H^T(\sigma)\cdot\Lambda\cdot\Lambda^T\cdot H(\sigma)\end{array}\right)\\ -\sigma_W\hat{W}\end{array}\right]\\ \dot{\hat{\Upsilon}} &= \Gamma_\Upsilon\left(\delta_\Upsilon\Lambda^T z_2 - \sigma_\Upsilon\hat{\Upsilon}\right)\end{aligned} \tag{26}$$

Remark 2: It should be noticed that the symmetric, positive definite inertia matrix H is invertible. According to the result in [38], the following equalities can be obtained:

$$\begin{aligned}\dot{H}^{-1}(\sigma) &= -H^{-1}(\sigma)\dot{H}(\sigma)H^{-1}(\sigma)\\ H^{-1}(\sigma) &= JG^{-1}(\sigma)\\ \dot{H}(\sigma) &= \dot{G}(\sigma)\end{aligned} \tag{27}$$

B. STABILITY ANALYSIS

Theorem 1: Consider the attitude dynamic equation of the SUS (1). Design the high-order disturbance observer as (18) $\sim$ (20) and select the adaptive controller as (23) $\sim$ (25), and the adaptive laws as (26). Suppose the RBFNNs approximation errors are all bounded. Then the closed-loop system (28) related to (1), (18) $\sim$ (20), (23) $\sim$ (25) as well as (26) will be uniformly ultimately bounded, that is all the signals will converge to a compact set as time goes to infinite. The closed-loop stability of SUS under the complex disturbance and stochastic uncertainties is guaranteed and the control objective can be achieved.

Proof: The closed-loop attitude control system of the SUS can be formulated by:

$$\begin{aligned}\dot{z}_1 &= z_2 - k_1 z_1\\ dz_2 &= \left[\begin{array}{l}-k_2 z_2 - H(\sigma)\tilde{W}^T\Phi(z_1,z_2)\\ +H(\sigma)\varepsilon - H(\sigma)\tilde{D}_1 - \hat{\Upsilon}\delta_\Upsilon z_2\end{array}\right]dt\\ &\quad +H(\sigma)\Delta d\zeta\end{aligned} \tag{28}$$

Construct the Lyapunov function candidate as:

$$\begin{aligned}V(t) &= V_1(t) + V_2(t)\\ V_1(t) &= \frac{1}{2}z_1^T z_1 + \frac{1}{4}\left(z_2^T z_2\right)^2\\ V_2(t) &= \frac{1}{4\Gamma_W}Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right) + \frac{1}{4}\sum_{i=1}^{n}\left(\tilde{D}_i^T\tilde{D}_i\right)^2\\ &\quad +\frac{1}{2\Gamma_\Upsilon}\tilde{\Upsilon}^2\end{aligned} \tag{29}$$

According to **Definition 1** and closed-loop attitude system (28), we obtain the derivation of V_1 is

$$\begin{aligned}\dot{V}_1(t) = z_1^T\dot{z}_1 + z_2^T z_2 z_2^T\left[\begin{array}{l}-k_2 z_2 - H(\sigma)\tilde{W}^T\Phi(z_1,z_2)\\ +H(\sigma)\varepsilon - H(\sigma)\tilde{D}_1 - \hat{\Upsilon}\delta_\Upsilon z_2\end{array}\right]\\ +\frac{3}{2}Tr\left(\Delta^T H^T(\sigma)z_2 z_2^T H(\sigma)\Delta\right)\end{aligned} \tag{30}$$

From (21), the derivative of V_2 is

$$\begin{aligned}\dot{V}_2(t) &= \frac{1}{\Gamma_W}Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\dot{\hat{W}}\right)\\ &\quad +\tilde{D}_1^T\tilde{D}_1\tilde{D}_1^T\left(-L_1\tilde{D}_1 + \tilde{D}_2 - L_1\tilde{W}^T\Phi\right)\\ &\quad -\frac{3}{2}Tr\left(\Delta^T L_1^T\tilde{D}_1\tilde{D}_1^T L_1\Delta\right)\\ &\quad +\tilde{D}_2^T\tilde{D}_2\tilde{D}_2^T\left(-L_1\tilde{D}_2 + \tilde{D}_3 - L_2\tilde{W}^T\Phi\right)\\ &\quad -\frac{3}{2}Tr\left(\Delta^T L_2^T\tilde{D}_2\tilde{D}_2^T L_2\Delta\right) + \cdots\\ &\quad +\tilde{D}_n^T\tilde{D}_n\tilde{D}_n^T\left(-L_n\tilde{D}_n - L_n\tilde{W}^T\Phi + d^{(n-1)}\right)\\ &\quad -\frac{3}{2}Tr\left(\Delta^T L_n^T\tilde{D}_n\tilde{D}_n^T L_n\Delta\right) + \frac{1}{\Gamma_\Upsilon}\tilde{\Upsilon}\dot{\hat{\Upsilon}}\\ &= \frac{1}{\Gamma_W}Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\dot{\hat{W}}\right)\\ &\quad +\sum_{i=1}^{n-1}\tilde{D}_i^T\tilde{D}_i\tilde{D}_i^T\left(-L_i\tilde{D}_i + \tilde{D}_{i+1} - L_i\tilde{W}^T\Phi\right)\\ &\quad +\tilde{D}_n^T\tilde{D}_n\tilde{D}_n^T\left(-L_n\tilde{D}_n - L_n\tilde{W}^T\Phi + d^{(n-1)}\right)\\ &\quad -\frac{3}{2}\sum_{i=1}^{n}\tilde{D}_i^T L_i\Delta\Delta^T L_i^T\tilde{D}_i + \frac{1}{\Gamma_\Upsilon}\tilde{\Upsilon}\dot{\hat{\Upsilon}}\end{aligned} \tag{31}$$

Define $\Lambda^T = z_2^T z_2 z_2^T$, $\Xi_i^T = \tilde{D}_i^T\tilde{D}_i\tilde{D}_i^T \quad i = 1,\cdots,n$, the derivative of V_1 in (30) can be rewritten as

$$\begin{aligned}\dot{V}_1(t) &= -k_1 z_1^T z_1 + z_1^T z_2\\ &\quad +\Lambda^T\left[\begin{array}{l}-k_2 z_2 - H(\sigma)\tilde{W}^T\Phi(z_1,z_2)\\ +H(\sigma)\varepsilon - H(\sigma)\tilde{D}_1 - \hat{\Upsilon}\delta_\Upsilon z_2\end{array}\right]\\ &\quad +\frac{3}{2}z_2^T H(\sigma)\Delta\Delta^T H^T(\sigma)z_2\end{aligned} \tag{32}$$

and V_2 in (31) is

$$\begin{aligned}\dot{V}_2(t) &= \frac{1}{\Gamma_W}Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\dot{\hat{W}}\right)\\ &\quad +\sum_{i=1}^{n-1}\Xi_i^T\left(-L_i\tilde{D}_i + \tilde{D}_{i+1} - L_i\tilde{W}^T\Phi\right)\\ &\quad +\Xi_n^T\left(-L_n\tilde{D}_n - L_n\tilde{W}^T\Phi + d^{(n-1)}\right)\\ &\quad -\frac{3}{2}\sum_{i=1}^{n}\tilde{D}_i^T L_i\Delta\Delta^T L_i^T\tilde{D}_i + \frac{1}{\Gamma_\Upsilon}\tilde{\Upsilon}\dot{\hat{\Upsilon}}\end{aligned} \tag{33}$$

According to **Lemma 2**, we know that

$$z_1^T z_2 \le \frac{1}{2} z_1^T z_1 + \frac{1}{2} z_2^T z_2 \le \frac{1}{2} z_1^T z_1 + \frac{1}{8\delta_z}\left(z_2^T z_2\right)^2 + \frac{1}{2}\delta_z \tag{34}$$

And from (22), we obtain

$$\frac{3}{2} z_2^T H(\sigma)\Delta\Delta^T H^T(\sigma) z_2 \le \Upsilon z_2^T z_2 \le \Upsilon \delta_\Upsilon \Lambda^T z_2 + \frac{\Upsilon}{4\delta_\Upsilon} \tag{35}$$

Hence, it can obtain that

$$\begin{aligned}\dot{V}_1(t) &= -k_1 z_1^T z_1 + \frac{1}{2} z_1^T z_1 + \frac{1}{8\delta_z}\left(z_2^T z_2\right)^2 + \frac{1}{2}\delta_z \\ &\quad + \Lambda^T \begin{bmatrix} -k_2 z_2 - H(\sigma)\tilde{W}^T \Phi(z_1, z_2) \\ + H(\sigma)\varepsilon - H(\sigma)\tilde{D}_1 - \hat{\Upsilon}\delta_\Upsilon z_2 \end{bmatrix} \\ &\quad + \Upsilon\delta_\Upsilon\Lambda^T z_2 + \frac{\Upsilon}{4\delta_\Upsilon} \\ &= -k_1 z_1^T z_1 + \frac{1}{2} z_1^T z_1 + \frac{1}{8\delta_z}\left(z_2^T z_2\right)^2 + \frac{1}{2}\delta_z \\ &\quad - k_2\Lambda^T z_2 - \Lambda^T H(\sigma)\tilde{W}^T\Phi(z_1, z_2) \\ &\quad + \Lambda^T H(\sigma)\varepsilon - \Lambda^T H(\sigma)\tilde{D}_1 - \tilde{\Upsilon}\delta_\Upsilon\Lambda^T z_2 + \frac{\Upsilon}{4\delta_\Upsilon}\end{aligned} \tag{36}$$

According to **Property 1**, we get that

$$\begin{aligned}-\Lambda H(\sigma)\tilde{D}_1 &\le \frac{1}{2}\left(z_2^T z_2\right)^2 + \frac{1}{2} z_2^T H(\sigma)\tilde{D}_1\tilde{D}_1^T H^T(\sigma) z_2 \\ &\le \frac{1}{2}\left(z_2^T z_2\right)^2 \\ &\quad + \frac{1}{4}\left(z_2^T H(\sigma) H^T(\sigma) z_2\right)^2 + \frac{1}{4}\left(\tilde{D}_1^T\tilde{D}_1\right)^2 \\ &\le \left(\frac{1}{2} + \frac{\delta_J{}^4}{64}\right)\left(z_2^T z_2\right)^2 + \frac{1}{4}\left(\tilde{D}_1^T\tilde{D}_1\right)^2\end{aligned} \tag{37}$$

and

$$\begin{aligned}\Lambda^T H(\sigma)\varepsilon &\le \frac{1}{2}\left(z_2^T z_2\right)^2 + \frac{\varepsilon^2}{2} z_2^T H(\sigma) H^T(\sigma) z_2 \\ &\le \left(\frac{1}{2} + \frac{\delta_J^4}{64}\right)\left(z_2^T z_2\right)^2 + \frac{1}{4}\varepsilon^4\end{aligned} \tag{38}$$

Further, we have the items that

$$\begin{aligned}&-\Lambda^T H(\sigma)\tilde{W}^T\Phi(z_1, z_2) \\ &\le \begin{pmatrix} \Lambda^T \cdot H(\sigma) \cdot H^T(\sigma) \cdot \Lambda \cdot \Lambda^T \cdot H(\sigma) \cdot \tilde{W}^T \cdot \\ \tilde{W} \cdot \tilde{W}^T \cdot \Phi(z_1, z_2) \cdot \Phi^T \cdot (z_1, z_2) \cdot \Phi(z_1, z_2) \end{pmatrix}\end{aligned} \tag{39}$$

Integrating (37), (38) and (39), then the derivative of $V_1(t)$ in (36) is expressed as

$$\begin{aligned}\dot{V}_1(t) &= -k_1 z_1^T z_1 + \frac{1}{2} z_1^T z_1 + \frac{1}{8\delta_z}\left(z_2^T z_2\right)^2 + \frac{1}{2}\delta_z \\ &\quad - k_2\Lambda^T z_2 - \Lambda^T H(\sigma)\tilde{W}^T\Phi(z_1, z_2) \\ &\quad + \Lambda^T H(\sigma)\varepsilon - \Lambda^T H(\sigma)\tilde{D}_1 - \tilde{\Upsilon}\delta_\Upsilon\Lambda^T z_2 + \frac{\Upsilon}{4\delta_\Upsilon} \\ &= -\left(k_1 - \frac{1}{2}\right) z_1^T z_1 \\ &\quad - \left(k_2 - \frac{1}{8\varepsilon_z} - \left(1 + \frac{\delta_J^4}{32}\right)\right)\left(z_2^T z_2\right)^2 \\ &\quad + \begin{bmatrix} \Lambda^T \cdot H(\sigma) \cdot H^T(\sigma) \cdot \Lambda \cdot \Lambda^T \cdot H(\sigma) \cdot \tilde{W}^T \cdot \\ \tilde{W} \cdot \tilde{W}^T \cdot \Phi(z_1, z_2) \cdot \Phi^T \cdot (z_1, z_2) \cdot \Phi(z_1, z_2) \end{bmatrix} \\ &\quad - \tilde{\Upsilon}\delta_\Upsilon\Lambda^T z_2 + \frac{1}{4}\left(\tilde{D}_1^T\tilde{D}_1\right)^2 \\ &\quad + \frac{1}{2}\delta_z + \frac{1}{4}\varepsilon^4 + \frac{\Upsilon}{4\delta_\Upsilon}\end{aligned} \tag{40}$$

Based on **Assumption 3**, we can define

$$T_i = \frac{3}{2}\sup_{t\ge 0}\left\| L_i\Delta\Delta^T L_i^T \right\| \tag{41}$$

By choosing limited DOB gains, it can obtained that

$$\begin{aligned}-\frac{3}{2}\sum_{i=1}^{n}\tilde{D}_i^T L_i\Delta\Delta^T L_i^T\tilde{D}_i &\le \sum_{i=1}^{n} T_i\tilde{D}_i^T\tilde{D}_i \\ &\le \sum_{i=1}^{n}\delta_{T_i}\Xi_i^T\tilde{D}_i + \sum_{i=1}^{n}\frac{T_i^2}{4\delta_{T_i}}\end{aligned} \tag{42}$$

And using the inequality in **Lemma 1**, we can obtain

$$\begin{aligned}\sum_{i=1}^{n-1}\Xi_i^T\tilde{D}_{i+1} &\le \frac{1}{2}\sum_{i=1}^{n-1}\left(\tilde{D}_i^T\tilde{D}_i\right)^2 + \frac{1}{2}\sum_{i=1}^{n-1}\tilde{D}_i^T\tilde{D}_{i+1}\tilde{D}_{i+1}^T\tilde{D}_i \\ &\le \frac{1}{2}\sum_{i=1}^{n-1}\left(\tilde{D}_i^T\tilde{D}_i\right)^2 + \frac{1}{4}\sum_{i=1}^{n-1}\left(\tilde{D}_i^T\tilde{D}_i\right)^2 \\ &\quad + \frac{1}{4}\sum_{i=1}^{n-1}\left(\tilde{D}_{i+1}^T\tilde{D}_{i+1}\right)^2 \\ &\le \frac{3}{4}\left(\tilde{D}_1^T\tilde{D}_1\right)^2 + \sum_{i=2}^{n-1}\left(\tilde{D}_i^T\tilde{D}_i\right)^2 + \frac{1}{4}\left(\tilde{D}_n^T\tilde{D}_n\right)^2\end{aligned} \tag{43}$$

as well as

$$\begin{aligned}-\sum_{i=1}^{n}\Xi_i^T L_i\tilde{W}^T\Phi &\le \sum_{i=1}^{n}(\tilde{D}_i^T\tilde{D}_i\tilde{D}_i^T\tilde{D}_i \\ &\quad + L_i^4\left(\Phi^T\Phi\right)^2\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}) \\ &\le \sum_{i=1}^{n}(\left(\tilde{D}_i^T\tilde{D}_i\right)^2 \\ &\quad + L_i^4\left(\Phi^T\Phi\right)^2 Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right)) \\ &\le \sum_{i=1}^{n}(\left(\tilde{D}_i^T\tilde{D}_i\right)^2 \\ &\quad + L_i^4\varphi^2 Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right))\end{aligned} \tag{44}$$

Then substituting the (42), (43), (44) into (33), the derivative of $V_2(t)$ is represented as

$$\dot{V}_2(t) \le \frac{1}{\Gamma_W} Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\dot{\hat{W}}\right) - \sum_{i=1}^{n} L_i\Xi_i^T\tilde{D}_i$$

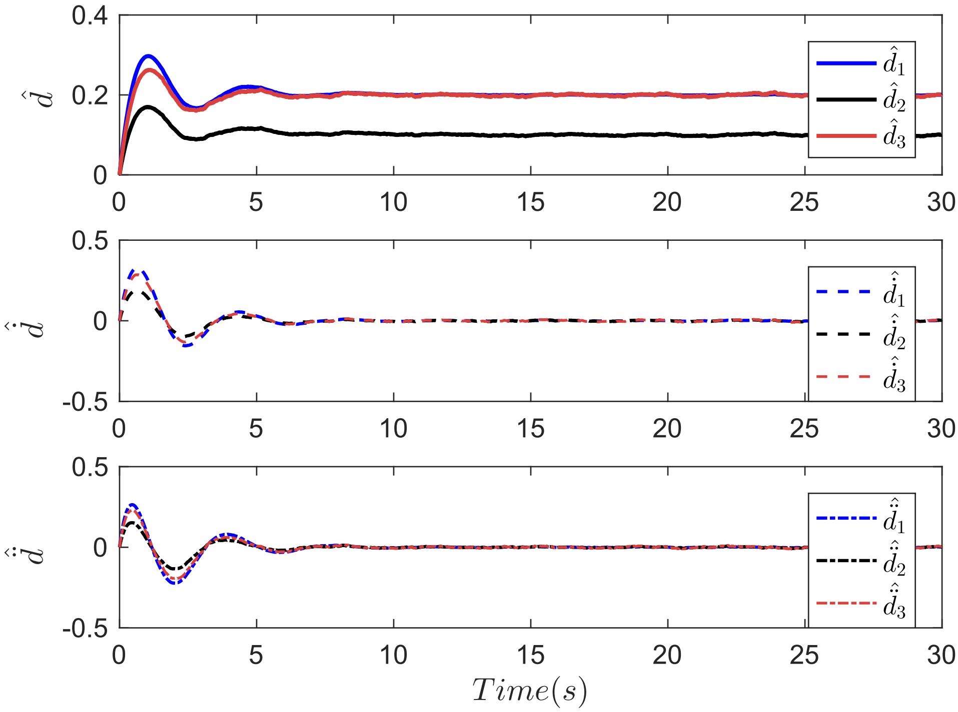

FIGURE 2. **The estimation effects for constant disturbances.**

$$
\begin{aligned}
&+\frac{3}{4}\left(\tilde{D}_1^T\tilde{D}_1\right)^2+\sum_{i=2}^{n-1}\left(\tilde{D}_i^T\tilde{D}_i\right)^2+\frac{1}{4}\left(\tilde{D}_n^T\tilde{D}_n\right)^2\\
&+\sum_{i=1}^{n}\left(\tilde{D}_i^T\tilde{D}_i\right)^2+\frac{1}{\Gamma_\Upsilon}\tilde{\Upsilon}\dot{\hat{\Upsilon}}\\
&+\sum_{i=1}^{n}\left(\begin{array}{l}L_i^4\varphi^2 Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right)\\ +\Xi_n^T d^{(n-1)}+\sum\limits_{i=1}^{n}\delta_{T_i}\Xi_i^T\tilde{D}_i+\sum\limits_{i=1}^{n}\frac{T_i^2}{4\delta_{T_i}}\end{array}\right)
\end{aligned}
$$

Further,

$$
\begin{aligned}
\dot{V}_2(t)\leq&\frac{1}{\Gamma_W}Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\dot{\hat{W}}\right)\\
&+\frac{3}{4}\left(\tilde{D}_1^T\tilde{D}_1\right)^2+\sum_{i=2}^{n-1}\left(\tilde{D}_i^T\tilde{D}_i\right)^2+\frac{1}{4}\left(\tilde{D}_n^T\tilde{D}_n\right)^2\\
&+\sum_{i=1}^{n}\left(\tilde{D}_i^T\tilde{D}_i\right)^2+\Xi_n^T d^{(n-1)}+\sum_{i=1}^{n}\frac{T_i^2}{4\delta_{T_i}}+\frac{1}{\Gamma_\Upsilon}\tilde{\Upsilon}\dot{\hat{\Upsilon}}\\
&+\left(\sum_{i=1}^{n}\begin{array}{l}L_i^4\varphi^2 Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right)\\ -\sum\limits_{i=1}^{n}L_i\Xi_i^T\tilde{D}_i+\sum\limits_{i=1}^{n}\delta_{T_i}\Xi_i^T\tilde{D}_i\end{array}\right)
\end{aligned}
\tag{45}
$$

Besides, from **Assumption 1**, the following inequality holds

$$
\begin{aligned}
\Xi_n^T d^{(n-1)}&\leq\frac{1}{2}\left(\tilde{D}_n^T\tilde{D}_n\right)^2+\frac{1}{2}\tilde{D}_n^T d^{(n-1)}d^{(n-1)T}\tilde{D}_n\\
&\leq\frac{3}{4}\left(\tilde{D}_n^T\tilde{D}_n\right)^2+\frac{1}{4}\delta_d^2
\end{aligned}
\tag{46}
$$

$V_2(t)$ in (45) is rewritten as

$$
\begin{aligned}
\dot{V}_2(t)\leq&\frac{1}{\Gamma_W}Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\dot{\hat{W}}\right)\\
&+\sum_{i=1}^{n}L_i^4\varphi^2 Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right)\\
&-\sum_{i=1}^{n}L_i\Xi_i^T\tilde{D}_i+\sum_{i=1}^{n}\delta_{T_i}\Xi_i^T\tilde{D}_i\\
&+\frac{1}{4}\delta_d^2+\sum_{i=1}^{n}\frac{T_i^2}{4\delta_{T_i}}+\frac{1}{\Gamma_\Upsilon}\tilde{\Upsilon}\dot{\hat{\Upsilon}}\\
&+\frac{3}{4}\left(\tilde{D}_1^T\tilde{D}_1\right)^2+\sum_{i=2}^{n-1}\left(\tilde{D}_i^T\tilde{D}_i\right)^2+\frac{1}{4}\left(\tilde{D}_n^T\tilde{D}_n\right)^2\\
&+\sum_{i=1}^{n}\left(\tilde{D}_i^T\tilde{D}_i\right)^2+\frac{3}{4}\left(\tilde{D}_n^T\tilde{D}_n\right)^2\\
\leq&\frac{1}{\Gamma_W}Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\dot{\hat{W}}\right)+\sum_{i=1}^{n}L_i^4\varphi^2 Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right)\\
&-\sum_{i=1}^{n}L_i\Xi_i^T\tilde{D}_i+\sum_{i=1}^{n}\delta_{T_i}\Xi_i^T\tilde{D}_i\\
&-\frac{1}{4}\left(\tilde{D}_1^T\tilde{D}_1\right)^2+2\sum_{i=1}^{n}\left(\tilde{D}_i^T\tilde{D}_i\right)^2\\
&+\frac{1}{4}\delta_d^2+\sum_{i=1}^{n}\frac{T_i^2}{4\delta_{T_i}}+\frac{1}{\Gamma_\Upsilon}\tilde{\Upsilon}\dot{\hat{\Upsilon}}
\end{aligned}
\tag{47}
$$

Substitute the adaptive laws (26) into (40) and (47) yields

$\dot{V}(t)$

$$\begin{aligned}
&\leq -\left(k_1-\frac{1}{2}\right)z_1^T z_1-\left(k_2-\frac{1}{8\varepsilon_z}-\left(1+\frac{\delta_J^4}{32}\right)\right)\left(z_2^T z_2\right)^2\\
&\quad+\left[\begin{array}{l}\Lambda^T H(\sigma)H^T(\sigma)\Lambda\Lambda^T H(\sigma)\tilde{W}^T\cdot\\ \tilde{W}\tilde{W}^T\Phi(z_1,z_2)\Phi^T(z_1,z_2)\Phi(z_1,z_2)\end{array}\right]\\
&\quad-\tilde{\Upsilon}\delta_\Upsilon\Lambda^T z_2+\frac{1}{4}\left(\tilde{D}_1^T\tilde{D}_1\right)^2+\frac{1}{2}\delta_z+\frac{1}{4}\varepsilon^4+\frac{\Upsilon}{4\delta_\Upsilon}\\
&\quad-Tr\left[\begin{array}{l}\tilde{W}^T\tilde{W}\tilde{W}^T\Phi(z_1,z_2)\cdot\\ \Phi^T(z_1,z_2)\Phi(z_1,z_2)\cdot\\ \Lambda^T H(\sigma)H^T(\sigma)\Lambda\Lambda^T H(\sigma)\end{array}\right]\\
&\quad-\sigma_W Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\hat{W}\right)\\
&\quad+\sum_{i=1}^{n}L_i^4\varphi^2 Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right)\\
&\quad-\sum_{i=1}^{n}\left(L_i-\delta_{T_i}\right)\Xi_i^T\tilde{D}_i-\frac{1}{4}\left(\tilde{D}_1^T\tilde{D}_1\right)^2\\
&\quad+2\sum_{i=1}^{n}\left(\tilde{D}_i^T\tilde{D}_i\right)^2+\frac{1}{4}\delta_d^2+\sum_{i=1}^{n}\frac{T_i^2}{4\delta_{T_i}}\\
&\quad+\tilde{\Upsilon}\delta_\Upsilon\Lambda^T z_2-\sigma_\Upsilon\tilde{\Upsilon}\hat{\Upsilon}
\end{aligned}\tag{48}$$

Since $a^T b = Tr\left(ba^T\right)$, we can obtain from (48)

$$\begin{aligned}
&\dot{V}(t)\\
&\leq -\left(k_1-\frac{1}{2}\right)z_1^T z_1-\left(k_2-\frac{1}{8\varepsilon_z}-\left(1+\frac{\delta_J^4}{32}\right)\right)\left(z_2^T z_2\right)^2\\
&\quad+\frac{1}{2}\delta_z+\frac{1}{4}\varepsilon^4+\frac{\Upsilon}{4\delta_\Upsilon}-\sigma_W Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\hat{W}\right)\\
&\quad+\sum_{i=1}^{n}L_i^4\varphi^2 Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right)-\sum_{i=1}^{n}\left(L_i-\delta_{T_i}\right)\Xi_i^T\tilde{D}_i\\
&\quad+2\sum_{i=1}^{n}\left(\tilde{D}_i^T\tilde{D}_i\right)^2+\frac{1}{4}\delta_d^2+\sum_{i=1}^{n}\frac{T_i^2}{4\delta_{T_i}}-\sigma_\Upsilon\tilde{\Upsilon}\hat{\Upsilon}\\
&\leq -\left(k_1-\frac{1}{2}\right)z_1^T z_1-\left(k_2-\frac{1}{8\varepsilon_z}-\left(1+\frac{\delta_J^4}{32}\right)\right)\left(z_2^T z_2\right)^2\\
&\quad-\sum_{i=1}^{n}\left(L_i-\delta_{T_i}-2\right)\left(\tilde{D}_i^T\tilde{D}_i\right)^2\\
&\quad-\sigma_W Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\hat{W}\right)\\
&\quad+\sum_{i=1}^{n}L_i^4\varphi^2 Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right)\\
&\quad+\frac{1}{2}\delta_z+\frac{1}{4}\varepsilon^4+\frac{\Upsilon}{4\delta_\Upsilon}+\frac{1}{4}\delta_d^2+\sum_{i=1}^{n}\frac{T_i^2}{4\delta_{T_i}}-\sigma_\Upsilon\tilde{\Upsilon}\hat{\Upsilon}
\end{aligned}\tag{49}$$

It is obvious that

$$\begin{aligned}
-4Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\hat{W}\right)&\leq -Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right)\\
&\quad+Tr\left(W^T W W^T W\right)\\
-2\tilde{\Upsilon}\hat{\Upsilon}&\leq -\tilde{\Upsilon}^2+\Upsilon^2
\end{aligned}\tag{50}$$

According to (50), (49) can be represented as

$$\begin{aligned}
\dot{V}(t)\leq&-\left(k_1-\frac{1}{2}\right)z_1^T z_1\\
&-\left(k_2-\frac{1}{8\varepsilon_z}-\left(1+\frac{\delta_J^4}{32}\right)\right)\left(z_2^T z_2\right)^2\\
&-\sum_{i=1}^{n}\left(L_i-\delta_{T_i}-2\right)\left(\tilde{D}_i^T\tilde{D}_i\right)^2\\
&-\frac{\sigma_W}{4}Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right)+\frac{\sigma_W}{4}Tr\left(W^T W W^T W\right)\\
&+\sum_{i=1}^{n}L_i^4\varphi^2 Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right)\\
&+\frac{1}{2}\delta_z+\frac{1}{4}\varepsilon^4+\frac{\Upsilon}{4\delta_\Upsilon}+\frac{1}{4}\delta_d^2\\
&+\sum_{i=1}^{n}\frac{T_i^2}{4\delta_{T_i}}-\frac{\sigma_\Upsilon}{2}\tilde{\Upsilon}^2+\frac{\sigma_\Upsilon}{2}\Upsilon^2
\end{aligned}\tag{51}$$

Accordingly, we know that

$$\begin{aligned}
\dot{V}(t)\leq&-\left(k_1-\frac{1}{2}\right)z_1^T z_1\\
&-\left(k_2-\frac{1}{8\varepsilon_z}-\left(1+\frac{\delta_J^4}{32}\right)\right)\left(z_2^T z_2\right)^2\\
&-\sum_{i=1}^{n}\left(L_i-\delta_{T_i}-2\right)\left(\tilde{D}_i^T\tilde{D}_i\right)^2\\
&-\left(\frac{\sigma_W}{4}-\sum_{i=1}^{n}L_i^4\varphi^2\right)Tr\left(\tilde{W}^T\tilde{W}\tilde{W}^T\tilde{W}\right)\\
&-\frac{\sigma_\Upsilon}{2}\tilde{\Upsilon}^2+\frac{\sigma_W}{4}Tr\left(W^T W W^T W\right)\\
&+\frac{1}{2}\delta_z+\frac{1}{4}\varepsilon^4+\frac{\Upsilon}{4\delta_\Upsilon}+\frac{1}{4}\delta_d^2+\sum_{i=1}^{n}\frac{T_i^2}{4\delta_{T_i}}+\frac{\sigma_\Upsilon}{2}\Upsilon^2
\end{aligned}\tag{52}$$

Further, we can rewrite (52) as

$$\dot{V}(t)\leq -\lambda V+\beta \tag{53}$$

where

$$\begin{aligned}
\lambda&=\min\left\{\begin{array}{l}2k_1-1,4\left(k_2-\frac{1}{8\varepsilon_z}-\left(1+\frac{\delta_J^4}{32}\right)\right),\\ min_{i=1,\cdots,n}4\left(L_i-\delta_{T_i}-2\right),\\ \left(\sigma_W-4\sum_{i=1}^{n}L_i^4\varphi^2\right),\sigma_\Upsilon\end{array}\right\}\\
\beta&=\frac{\sigma_W}{4}Tr\left(W^T W W^T W\right)+\frac{\sigma_\Upsilon}{2}\Upsilon^2\\
&\quad+\frac{\Upsilon}{4\delta_\Upsilon}+\frac{1}{4}\delta_d^2+\sum_{i=1}^{n}\frac{T_i^2}{4\delta_{T_i}}+\frac{1}{4}\varepsilon^4
\end{aligned}\tag{54}$$

In order to guarantee the stability of closed-loop, the parameters of controller and high-order disturbance observer are limited as

$$k_1>\frac{1}{2},k_2>\frac{1}{8\varepsilon_z}+\left(1+\frac{\delta_J^4}{32}\right)$$

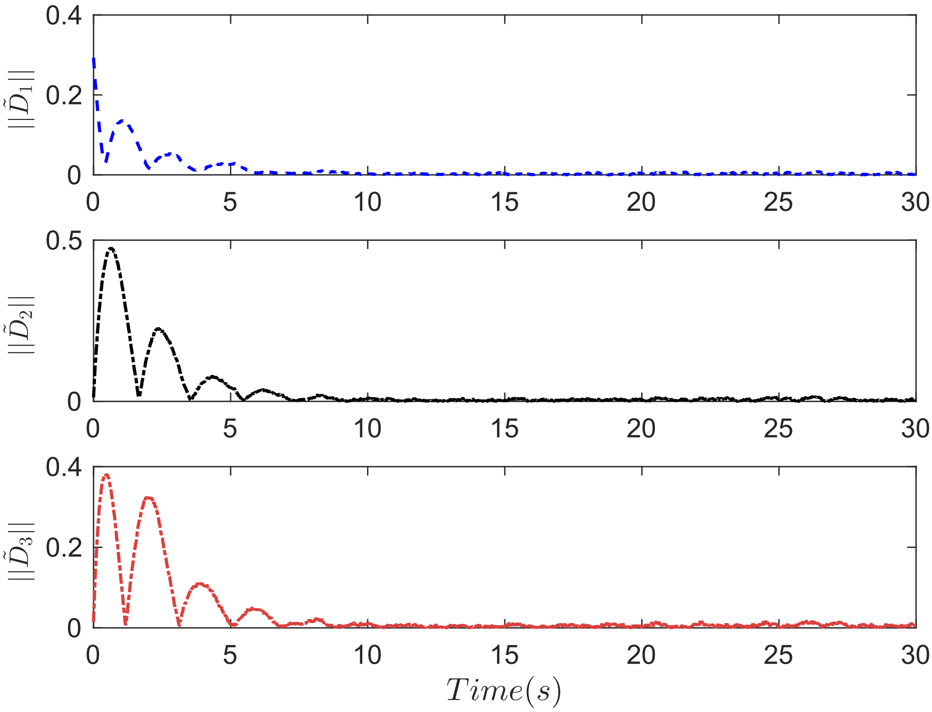

FIGURE 3. The estimation errors of constant disturbances.

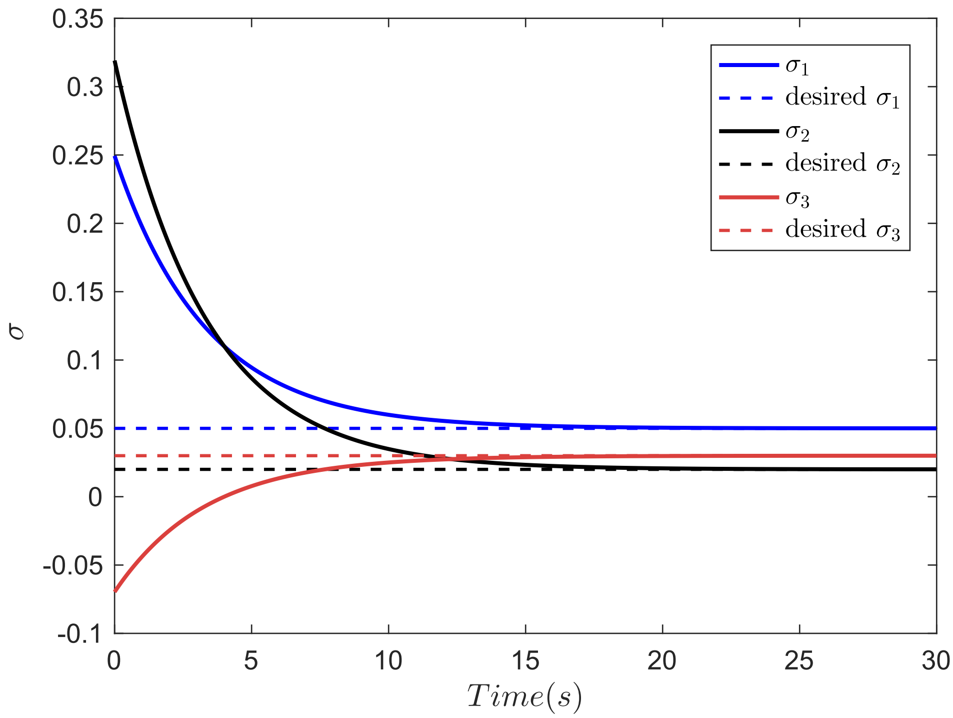

FIGURE 4. The tracking performance for the expected MRPs of the SUS with constant disturbances.

$$L_i > \delta_{T_i} + 2, \quad \sigma_W > 4\sum_{i=1}^{n} L_i^4 \varphi^2, \ \sigma_\Upsilon > 0 \tag{55}$$

Obviously, if the parameters are chosen properly, the closed-loop system signals $z_1, z_2, D_i\,(i = 1, \cdots, n)$, $\tilde{W}, \tilde{\Upsilon}$ in Lyapunov function (29) can ultimately converge to an enough small neighborhood. Therefore, the high-order disturbance observer can realize the estimation of $d_\tau, \dot{d}_\tau, \cdots, d^{(n-1)}$ and compensate the effect of external disturbance in spacecraft attitude control. And the

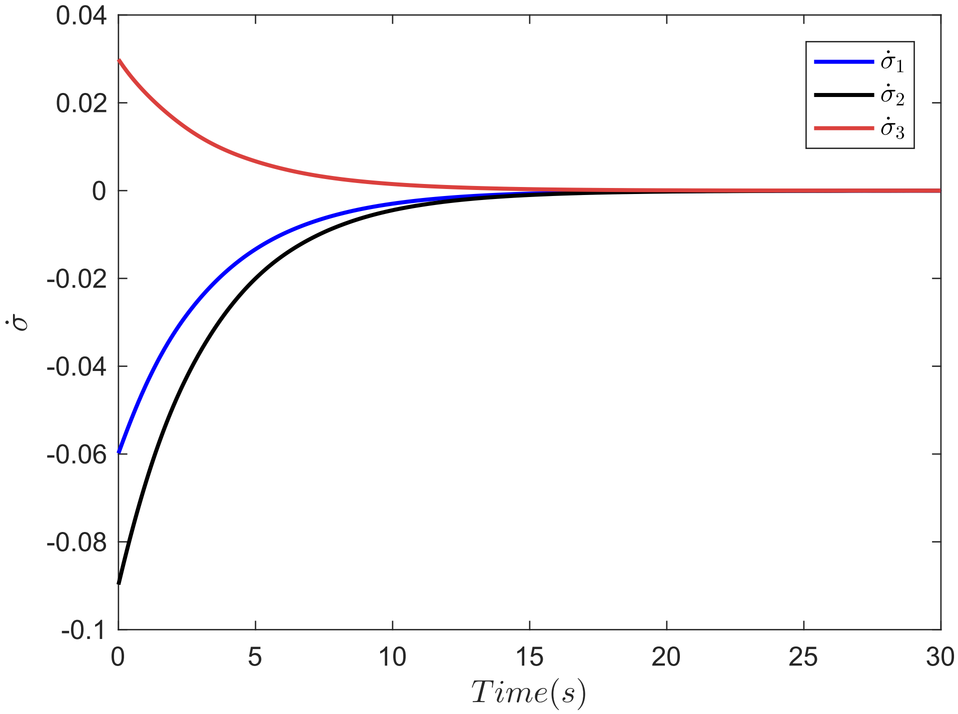

FIGURE 5. The derivatives of MRPs of the SUS with constant disturbances.

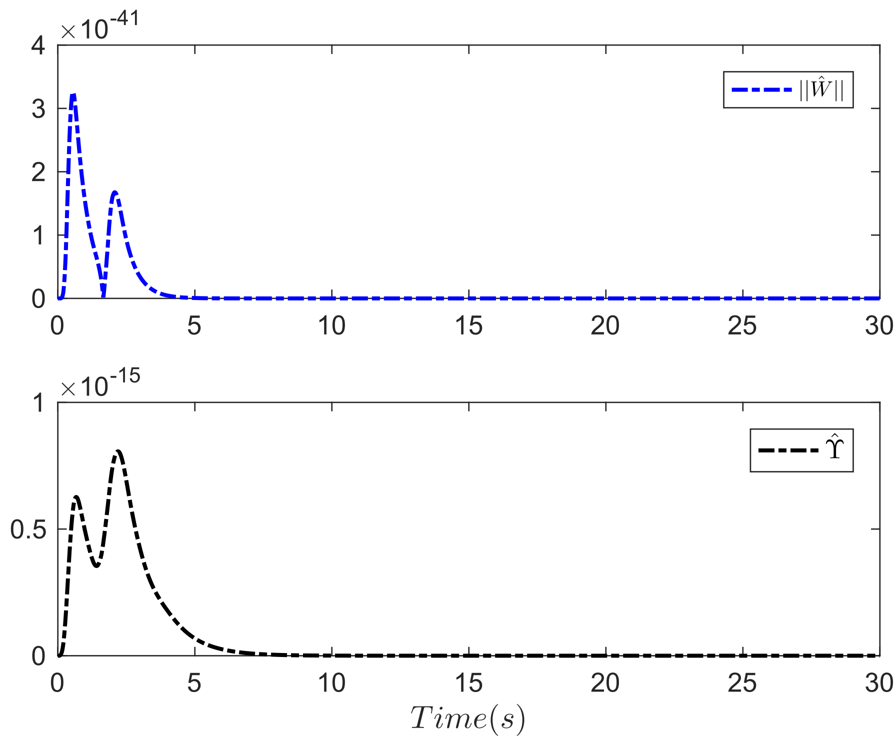

FIGURE 6. The trajectories of the adaptive parameters with constant disturbances.

attitude of the spacecraft can be actuated to the desired value by the designed controller. Therefore, it can be proved that the closed-loop SUS system (1) with the controller (23) and high-order disturbance observer (18) $\sim$ (20) is uniformly ultimately bounded, which completes the proof.□

Remark 3: Compared with the classical disturbance observer, the advantage of the high order disturbance observer

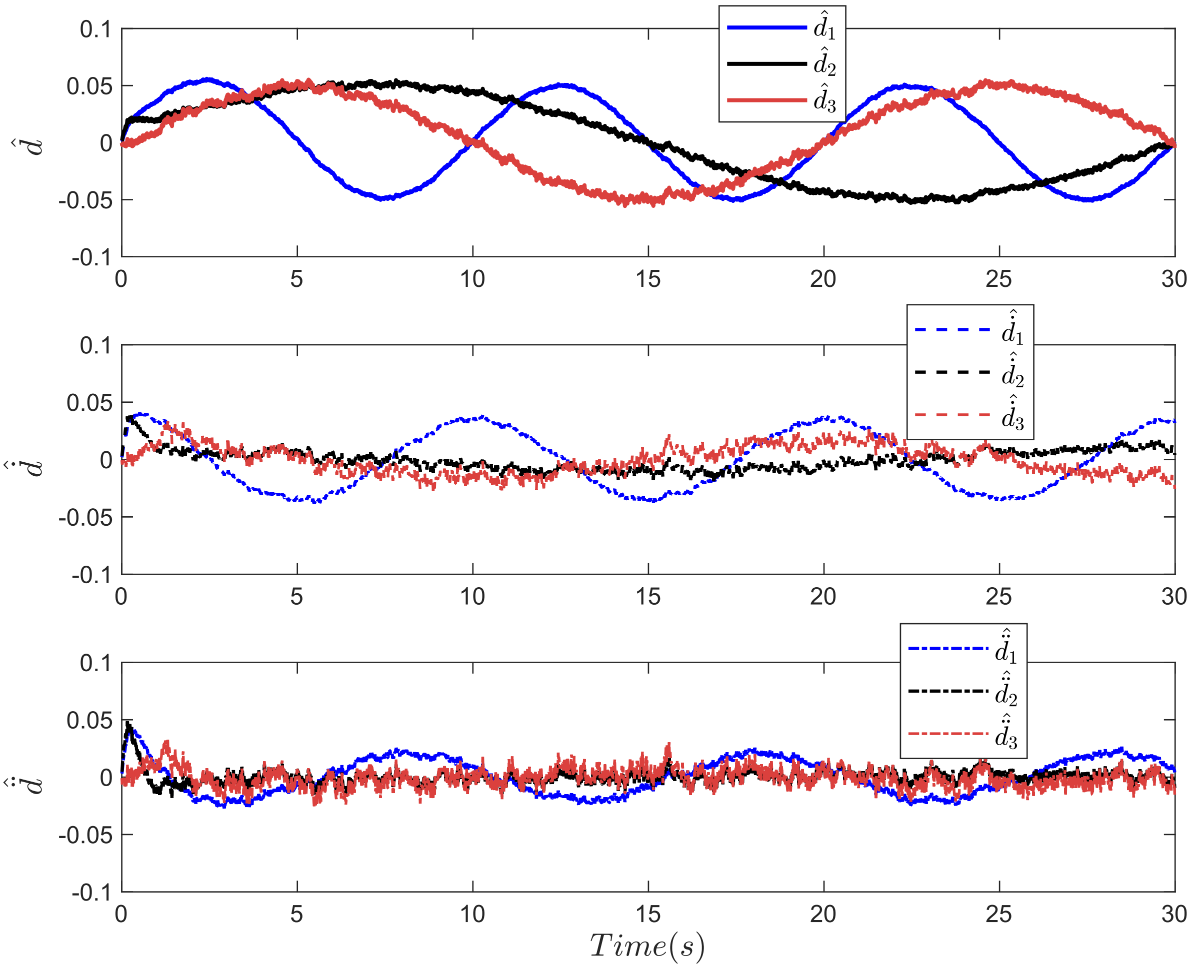

FIGURE 7. The estimation effects for time-varying disturbances.

is remarkable. In fact, by using the high-order disturbance observer, the high dynamic disturbances can be estimated and finally handled, while the classical disturbance observer cannot ensure the estimation performance. In details, to apply the classical disturbance observer, the assumption $\dot{d} = 0$ is required to guarantee the estimation error equation $\dot{\tilde{d}} = -L\tilde{d}$. For the high dynamic disturbances, $\dot{d} = 0$ is not satisfied and the estimation performance of the classical disturbance observer may largely degrade. By using high-order disturbance observer, the estimation error equation

$$
\begin{aligned}
d\tilde{D}_1 &= \left(-L_1\tilde{D}_1 + \tilde{D}_2 - L_1\tilde{W}^T\Phi + L_1\varepsilon\right)dt - L_1\Delta d\zeta \\
d\tilde{D}_2 &= \left(-L_1\tilde{D}_2 + \tilde{D}_3 - L_2\tilde{W}^T\Phi + L_2\varepsilon\right)dt - L_2\Delta d\zeta \\
&\vdots \\
d\tilde{D}_n &= \left(-L_n\tilde{D}_n - L_n\tilde{W}^T\Phi + L_n\varepsilon + d^{(n-1)}\right)dt - L_n\Delta d\zeta
\end{aligned}
$$

can be obtained, the convergence can be proved and the estimation performance can be guaranteed.

Remark 4: There exist several limitations of the proposed method, those are: (1) The tracking errors using the proposed method cannot be reduced to zero accurately. (2) To apply the proposed method, the inertia parameters of the SUS are required in advance. By introducing the integral action limiter into the proposed method, the tracking errors can be reduced. By fusing the inertia free adaptive design algorithm into the proposed controller, the requirement for the inertia parameters can be relaxed.

IV. SIMULATION STUDY

In this section, a numerical example is provided to verify the effectiveness of the proposed method. The desired attitude of the SUS is $\sigma_d = \begin{bmatrix} 0.05 \ 0.02 \ 0.03 \end{bmatrix}^T$. The physical parameters of the SUS are as follows:

$$
J = \begin{bmatrix} 245.3 & -100 & -85 \\ -100 & 45.3 & -120 \\ -85 & -120 & 245.3 \end{bmatrix} kg \cdot m^2
$$

and the unknown nonlinear moment $f(z_1, z_2)$ and the amplitude of uncertainty Δ are

$$
\begin{aligned}
f(z_1, z_2) &= 0.1z_1 + 0.2z_2 \\
\Delta &= [0.01, 0.02, 0.03]^T
\end{aligned}
$$

The order of the high-order disturbance observer is chosen as 3. The initial simulation values of SUS are shown in **Table 1**.

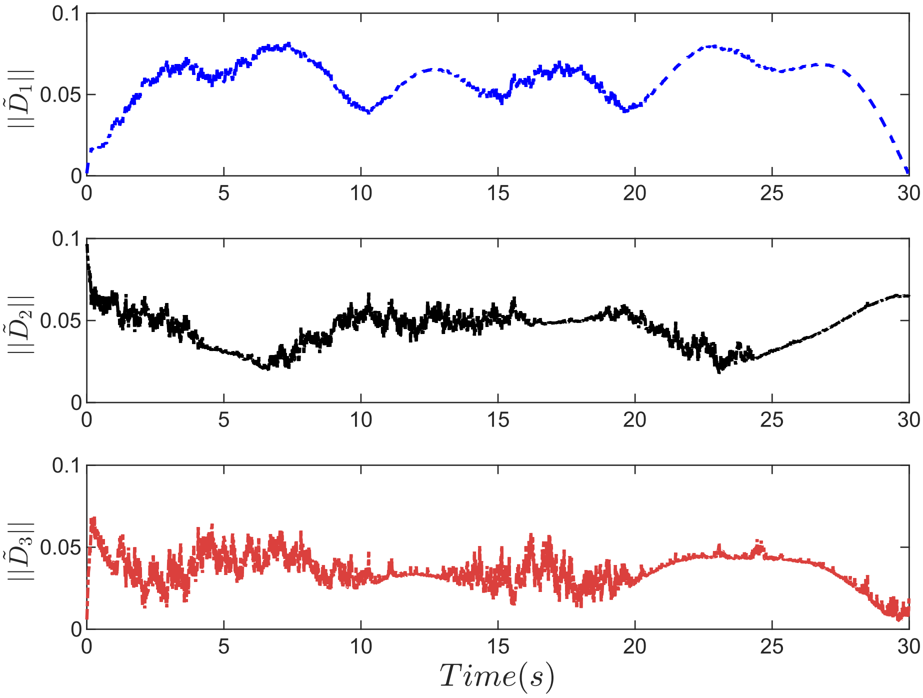

FIGURE 8. The estimation error of time-varying disturbances.

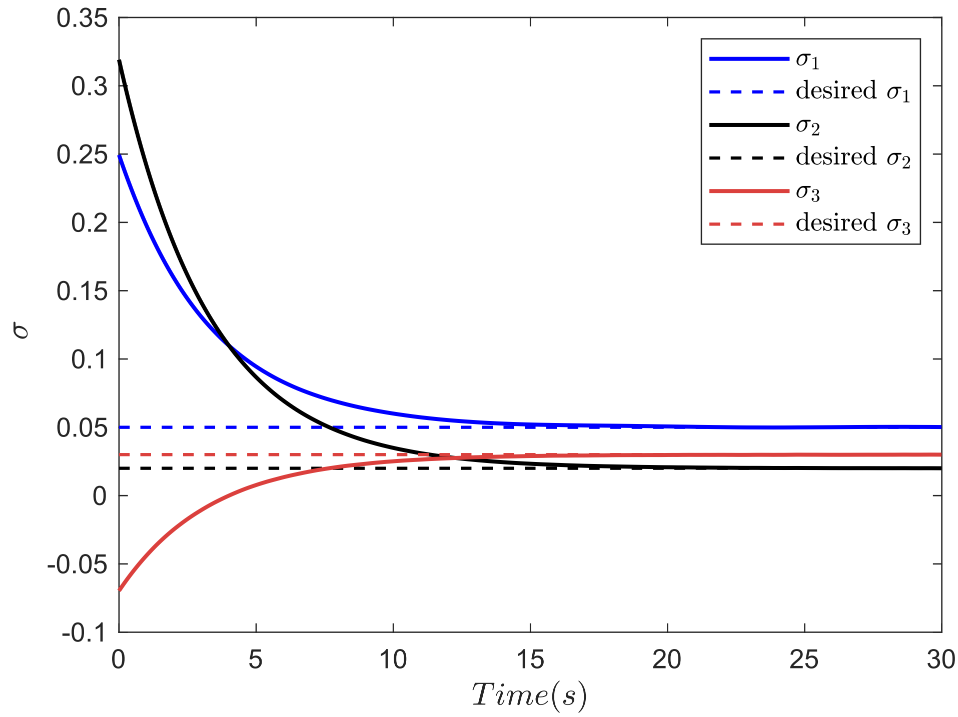

FIGURE 9. The tracking of expected MRPs attitude of the SUS with time-varying disturbances.

The orbital radius r_0 is $7.078 \times 10^8 m$, and the gravitational constant of the Earth is $\mu_g = 3.986 \times 10^{14} m^3/s^2$. The external disturbance d_τ is set as two types. For constant disturbance, d_τ is $d_\tau(t) = [0.2, 0.1, 0.2]^T$. For time-varying case, $d_\tau(t) = \left[0.1 sin\left(\frac{\pi}{5}t\right), 0.1 sin\left(\frac{\pi}{15}t\right), 0.1 sin\left(\frac{\pi}{10}t\right)\right]^T$. The gains of the high-order disturbance observer are $L_1 = 5, L_2 = 10, L_3 = 15$. The controller gains are designed as $k_1 = 0.3, k_2 = 0.9$.

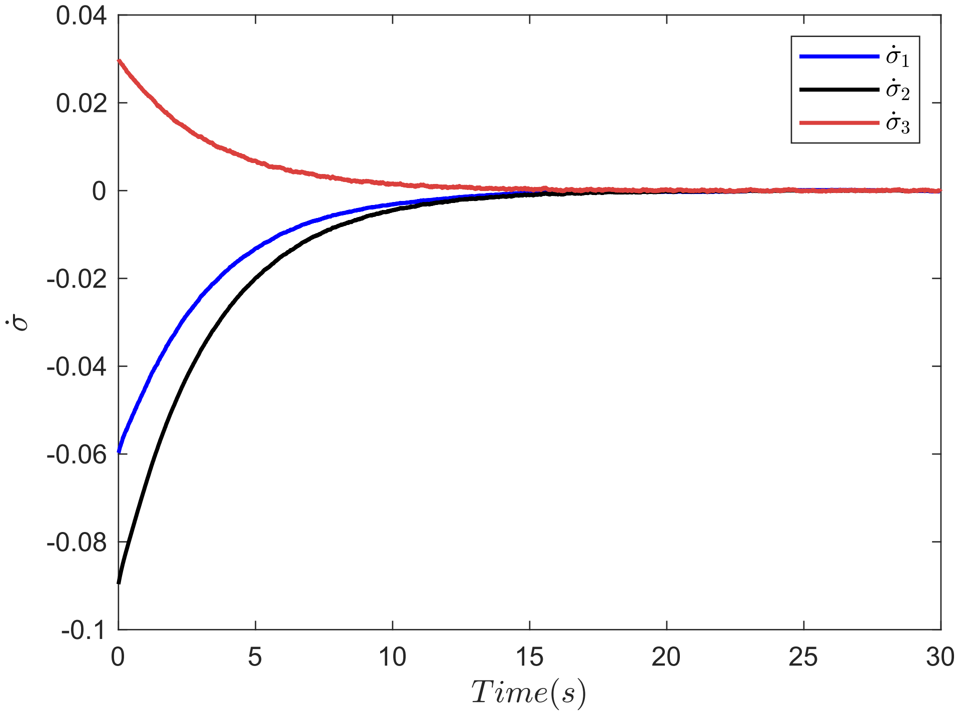

FIGURE 10. The derivatives of MRPs of SUS with time-varying disturbances.

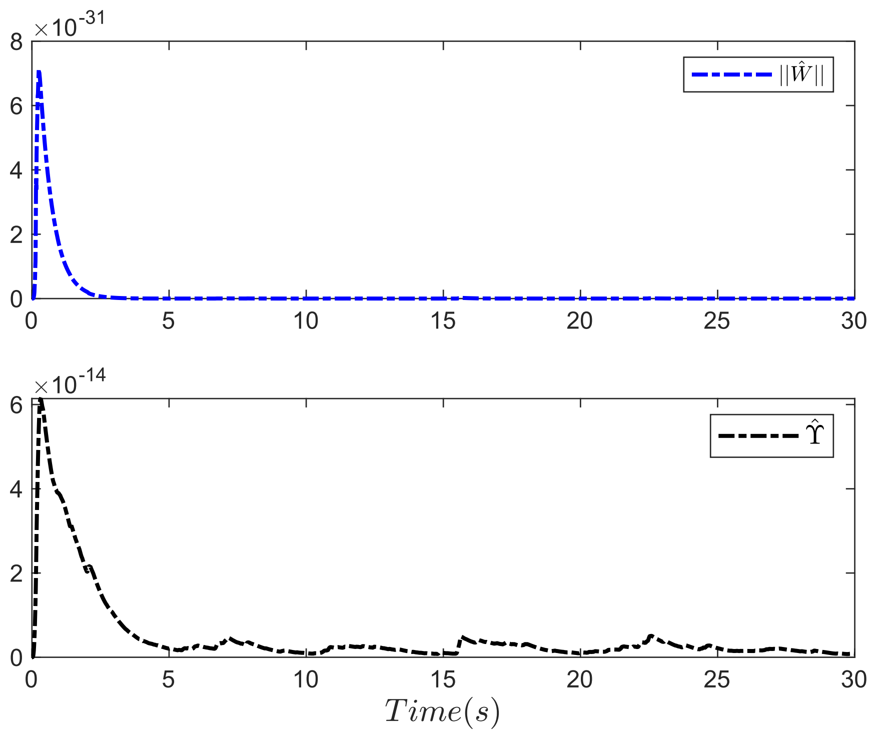

FIGURE 11. The trajectories of the adaptive parameters with time-varying disturbances.

The simulation results are given in **Fig. 2** $\sim$ **Fig. 11**. The estimation effects for the constant and time-varying disturbances by using the high-order disturbance observer are shown in **Fig. 2** $\sim$ **Fig. 3** and **Fig. 7** $\sim$ **Fig. 8**, respectively. Apparently in **Fig. 3** and **Fig. 8**, the constant or high dynamic disturbances can be estimated, the derivative of the disturbances can be estimated by using the high-order disturbance observer, which can enhance the observation precision and

TABLE 1. The initial values in simulation.

Variable	Value
σ	$[0.25, 0.32, -0.07]^T$
$\dot{\sigma}$	$[-0.12, -0.18, 0.06]^T rad/s$
$\hat{D}_1$	$\begin{bmatrix} 0 & 0 & 0 \end{bmatrix}^T$
$\hat{D}_2$	$\begin{bmatrix} 0 & 0 & 0 \end{bmatrix}^T$
$\hat{D}_3$	$\begin{bmatrix} 0 & 0 & 0 \end{bmatrix}^T$
$\hat{W}$	$0_{7\times 3}$
$\hat{\Upsilon}$	0

shorten convergence time. Then the simulation results for SUS with constant disturbance and time-varying disturbance are provided in **Fig. 4** $\sim$ **Fig. 5** and **Fig. 9** $\sim$ **Fig. 10** respectively. It is obvious that the attitudes can converge to the expected value. In summary, the satisfactory control performance can be achieved. **Fig. 6** and **Fig. 11** displays the trajectories of the adaptive parameters under constant or time-varying disturbances, exhibiting the boundedness of the adaptive parameters.

V. CONCLUSION

The problem of the stochastic adaptive anti-disturbance control has been addressed for the SUSs with high dynamic disturbances and stochastic uncertainties in this paper. By designing the high order disturbance observer for the SUSs, the adverse influence of the high dynamic disturbances can be suppressed. By defining a novel variable and designing the corresponding adaptive law, the infaust effects of the stochastic uncertainties can be overcome. Based on the stochastic control theory and the fourth-order Lyapunov function, the closed-loop attitude control system was proved to be stochastically stable. Finally, the simulation experiments have been conducted and the effectiveness and advantages of the proposed stochastic adaptive attitude control strategy have been demonstrated. In the future, we will investigate the cooperate stochastic adaptive control problem for the SUSs with nonlinear multiple disturbances.

REFERENCES

[1] S. Sui, S. Tong, and C. L. P. Chen, "Finite-time filter decentralized control for nonstrict-feedback nonlinear large-scale systems," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 6, pp. 3289–3300, Dec. 2018.
[2] S. Sui, C. L. P. Chen, and S. Tong, "Neural network filtering control design for nontriangular structure switched nonlinear systems in finite time," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 7, pp. 2153–2162, Jul. 2019.
[3] S. Sui, C. L. P. Chen, and S. Tong, "A novel adaptive NN prescribed performance control for stochastic nonlinear systems," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Aug. 13, 2020, doi: 10.1109/TNNLS.2020.3010333.
[4] C. L. P. Chen and Z. Liu, "Broad learning system: An effective and efficient incremental learning system without the need for deep architecture," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 1, pp. 10–24, Jan. 2018.
[5] C. Jia, H. Liu, X. Xu, and F. Sun, "Multi-modal information fusion based on broad learning method," *CAAI Trans. Intell. Syst.*, vol. 14, no. 1, pp. 154–161, 2019.
[6] S. Feng and C. L. P. Chen, "Fuzzy broad learning system: A novel neuro-fuzzy model for regression and classification," *IEEE Trans. Cybern.*, vol. 50, no. 2, pp. 414–424, Feb. 2020.
[7] D. Yu, C. L. P. Chen, and H. Xu, "Fuzzy swarm control based on sliding-mode strategy with self-organized omnidirectional mobile robots system," *IEEE Trans. Syst., Man, Cybern. Syst.*, early access, Jan. 20, 2021, doi: 10.1109/TSMC.2020.3048733.
[8] J. Lin, Z. Liu, C. L. P. Chen, and Y. Zhang, "Quaternion broad learning system: A novel multi-dimensional filter for estimation and elimination tremor in teleoperation," *Neurocomputing*, vol. 380, pp. 78–86, Mar. 2020.
[9] C. L. P. Chen and B. Wang, "Random-positioned license plate recognition using hybrid broad learning system and convolutional networks," *IEEE Trans. Intell. Transp. Syst.*, early access, Aug. 4, 2020, doi: 10.1109/TITS.2020.3011937.
[10] D. Yu and C. L. P. Chen, "Smooth transition in communication for swarm control with formation change," *IEEE Trans. Ind. Informat.*, vol. 16, no. 11, pp. 6962–6971, Nov. 2020.
[11] Y. Zheng and B. Chen, "Least p-norm based broad learning system," *Pattern Recognit. Artif. Intell.*, vol. 32, no. 1, pp. 1–6, 2019.
[12] Y. Kong, "Hyperspectral image analysis based on broad learning," Ph.D. dissertation, China Univ. Mining Technol., Xuzhou, China, 2019.
[13] Z. Yin, J. Tu, and Y. Xu, "Based on board learning system for the capacity configuration of wind and photovoltaic power," *Elect. Meas. Instrum.*, vol. 56, no. 13, pp. 45–50, 2019.
[14] X. Yao, J. H. Park, L. Wu, and L. Guo, "Disturbance-observer-based composite hierarchical antidisturbance control for singular Markovian jump systems," *IEEE Trans. Autom. Control*, vol. 64, no. 7, pp. 2875–2882, Jul. 2019.
[15] N. Koksal, H. An, and B. Fidan, "Backstepping-based adaptive control of a quadrotor UAV with guaranteed tracking performance," *ISA Trans.*, vol. 105, pp. 98–110, Oct. 2020.
[16] T. Espinoza, A. E. Dzul, R. Lozano, and P. Parada, "Backstepping-sliding mode controllers applied to a fixed-wing UAV," *J. Intell. Robotic Syst., Theory Appl.*, vol. 73, nos. 1–4, pp. 67–79, 2014.
[17] Z. Wang, J. Yuan, Y. Pan, and D. Che, "Adaptive neural control for high order Markovian jump nonlinear systems with unmodeled dynamics and dead zone inputs," *Neurocomputing*, vol. 247, pp. 62–72, Jul. 2017.
[18] J. Yu, M. Chen, and C. S. Jiang, "Adaptive sliding mode control for nonlinear uncertain systems based on disturbance observer," *Control Theory Appl.*, vol. 31, no. 8, pp. 993–999, 2014.
[19] T. Zhang, Y. Zong, W. Zheng, C. L. P. Chen, X. Hong, C. Tang, Z. Cui, and G. Zhao, "Cross-database micro-expression recognition: A benchmark," *IEEE Trans. Knowl. Data Eng.*, early access, Apr. 6, 2020, doi: 10.1109/TKDE.2020.2985365.
[20] H. Huang, T. Zhang, C. Yang, and C. L. P. Chen, "Motor learning and generalization using broad learning adaptive neural control," *IEEE Trans. Ind. Electron.*, vol. 67, no. 10, pp. 8608–8617, Oct. 2020.
[21] W.-H. Chen, J. Yang, L. Guo, and S. Li, "Disturbance-observer-based control and related methods—An overview," *IEEE Trans. Ind. Electron.*, vol. 63, no. 2, pp. 1083–1095, Feb. 2016.
[22] X. B. Yu, W. He, C. Q. Xue, Y. K. Sun, and C. Y. Sun, "Disturbance observer-based adaptive neural network tracking control for robots," *Acta Automatica Sinica*, vol. 45, no. 7, pp. 1307–1324, 2019.
[23] E. Sariyildiz, R. Oboe, and K. Ohnishi, "Disturbance observer-based robust control and its applications: 35th anniversary overview," *IEEE Trans. Ind. Electron.*, vol. 67, no. 3, pp. 2042–2053, Mar. 2020.
[24] J. Huang, M. Zhang, S. Ri, C. Xiong, Z. Li, and Y. Kang, "High-order disturbance-observer-based sliding mode control for mobile wheeled inverted pendulum systems," *IEEE Trans. Ind. Electron.*, vol. 67, no. 3, pp. 2030–2041, Mar. 2020.
[25] J. Li, S. Chen, C. Li, C. Gao, and W. Jing, "Adaptive control of underactuated flight vehicles with moving mass," *Aerosp. Sci. Technol.*, vol. 85, pp. 75–84, Feb. 2019.
[26] G. Zong, H. Sun, and S. K. Nguang, "Decentralized adaptive neuro-output feedback saturated control for INS and its application to AUV," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Jan. 26, 2021, doi: 10.1109/TNNLS.2021.3050992.
[27] H. Sun, Y. Li, G. Zong, and L. Hou, "Disturbance attenuation and rejection for stochastic Markovian jump system with partially known transition probabilities," *Automatica*, vol. 89, pp. 349–357, Mar. 2018.
[28] Y. Li, H. Sun, G. Zong, and L. Hou, "Disturbance-observer-based-control and L_2-L_∞ resilient control for Markovian jump non-linear systems with multiple disturbances and its application to single robot arm system," *IET Control Theory Appl.*, vol. 10, no. 2, pp. 226–233, Jan. 2016.

[29] D. Yang, G. Zong, and H. R. Karimi, "H_∞ refined antidisturbance control of switched LPV systems with application to aero-engine," *IEEE Trans. Ind. Electron.*, vol. 67, no. 4, pp. 3180–3190, 2020, doi: 10.1109/TIE.2019.2912780.

[30] D. Shi, J. Xue, L. Zhao, J. Wang, and Y. Huang, "Event-triggered active disturbance rejection control of DC torque motors," *IEEE/ASME Trans. Mechatronics*, vol. 22, no. 5, pp. 2277–2287, Oct. 2017.

[31] H. Tang and Y. Li, "Development and active disturbance rejection control of a compliant micro-/nanopositioning piezostage with dual mode," *IEEE Trans. Ind. Electron.*, vol. 61, no. 3, pp. 1475–1492, Mar. 2014.

[32] H. Yang, L. Cheng, Y. Xia, and Y. Yuan, "Active disturbance rejection attitude control for a dual closed-loop quadrotor under gust wind," *IEEE Trans. Control Syst. Technol.*, vol. 26, no. 4, pp. 1400–1405, Jul. 2018.

[33] C. Linqi and L. Tinghui, "UAV control system based on back-stepping and active disturbance rejection control," in *Proc. 3rd Joint Int. Inf. Technol.-Mech. Electron. Eng. Conf. (JIMEC)*, 2018, pp. 133–137.

[34] L. Dong and J. Edwards, "Active disturbance rejection control for an electrostatically actuated MEMS device," *Int. J. Intell. Control Syst.*, vol. 16, no. 3, pp. 160–169, 2011.

[35] W. Deng, J. Yao, Y. Wang, X. Yang, and J. Chen, "Output feedback backstepping control of hydraulic actuators with valve dynamics compensation," *Mech. Syst. Signal Process.*, vol. 158, Sep. 2021, Art. no. 107769.

[36] W. Deng and J. Yao, "Extended-state-observer-based adaptive control of electrohydraulic servomechanisms without velocity measurement," *IEEE/ASME Trans. Mechatronics*, vol. 25, no. 3, pp. 1151–1161, Jun. 2020.

[37] W. Deng, J. Yao, and D. Ma, "Time-varying input delay compensation for nonlinear systems with additive disturbance: An output feedback approach," *Int. J. Robust Nonlinear Control*, vol. 28, no. 1, pp. 31–52, Jan. 2018.

[38] C. Wei, J. Luo, H. Dai, Z. Bian, and J. Yuan, "Learning-based adaptive prescribed performance control of postcapture space robot-target combination without inertia identifications," *Acta Astronautica*, vol. 146, pp. 228–242, May 2018.

[39] D. Ginoya, P. D. Shendge, and S. B. Phadke, "Sliding mode control for mismatched uncertain systems using an extended disturbance observer," *IEEE Trans. Ind. Electron.*, vol. 61, no. 4, pp. 1983–1992, Apr. 2014.

[40] Z. Wang and J. Yuan, "Full state constrained adaptive fuzzy control for stochastic nonlinear switched systems with input quantization," *IEEE Trans. Fuzzy Syst.*, vol. 28, no. 4, pp. 645–657, Apr. 2020.

[41] C. Qian and W. Lin, "Non-lipschitz continuous stabilizers for nonlinear systems with uncontrollable unstable linearization," *Syst. Control Lett.*, vol. 42, no. 3, pp. 185–200, Mar. 2001.

[42] Q.-Y. Fan and G.-H. Yang, "Nearly optimal sliding mode fault-tolerant control for affine nonlinear systems with state constraints," *Neurocomputing*, vol. 216, pp. 78–88, Dec. 2016.

[43] B. Xu, Z. Shi, F. Sun, and W. He, "Barrier Lyapunov function based learning control of hypersonic flight vehicle with AOA constraint and actuator faults," *IEEE Trans. Cybern.*, vol. 49, no. 3, pp. 1047–1057, Mar. 2019.

[44] H. Lee and M. Tomizuka, "Robust adaptive control using a universal approximator for SISO nonlinear systems," *IEEE Trans. Fuzzy Syst.*, vol. 8, no. 1, pp. 95–106, Feb. 2000.

[45] Z. Wang and J. Yuan, "Dissipativity-based composite antidisturbance control for T–S fuzzy switched stochastic nonlinear systems subjected to multisource disturbances," *IEEE Trans. Fuzzy Syst.*, vol. 29, no. 5, pp. 1226–1237, May 2021.

YAO ZHANG received the B.E. degree from the North University of China, Taiyuan, China, in 2012, and the M.E. degree from the Lanzhou University of Technology, Lanzhou, China, in 2017. He is currently pursuing the Ph.D. degree with Northwestern Polytechnical University. His current research interests include complex space system design and dynamic modeling and control.

XIN NING received the B.E., M.E., and Ph.D. degrees from Northwestern Polytechnical University, Xi'an, China, in 2004, 2007, and 2011, respectively. He is currently a Professor and the Doctoral Supervisor with the School of Astronautics, Northwestern Polytechnical University. His current research interests include complex space system design and dynamic modeling and control.

ZHENG WANG received the B.E., M.E., and Ph.D. degrees from Northwestern Polytechnical University, Xi'an, China, in 2013, 2016, and 2020, respectively. He is currently an Associate Professor and the Master's Supervisor with the Research Center for Unmanned System Strategy Development, Northwestern Polytechnical University. His current research interests include flight dynamics and control, intelligent decision, and autonomous control of the unmanned systems.

DENGXIU YU (Member, IEEE) received the bachelor's degree in mechanical design manufacture and automation and the M.S. degree in mechatronic engineering from Northwestern Polytechnical University, Xi'an, China, in 2013 and 2016, respectively, and the Ph.D. degree in computer science from the University of Macau, Macau, China, in 2019. Since 2019, he has been an Associate Professor with the Unmanned System Research Institute, Northwestern Polytechnical University. His current research interests include swarm intelligent and swarm control.