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Adaptive Trajectory Tracking Control for Underactuated Unmanned Surface Vehicle Subject to Unknown Dynamics and Time-Varing Disturbances

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Abstract: This paper proposes an adaptive trajectory tracking control strategy for underactuated unmanned surface vehicles subject to unknown dynamics and time-varing external disturbances. In short, the goal of this paper is to provide a control strategy that allows an underactuated unmanned surface vehicle to track a time dependent trajectory. First, a first-order sliding surface is introduced into the design of surge control law to converge to surge tracking error, and then a second-order sliding surface is hired to design yaw control law to deal with sway motion tracking error. Meanwhile, neural network minimum learning parameter method, which has a smaller amount of computation than a multilayer neural network, is employed to preserve the control law robustness against unknown dynamics and time-varing disturbances induced by wind, waves and ocean currents. Furthermore, much effort is made to obtain uniform ultimate bounded stability for the closed-loop control system. Finally, the numerical simulation experiments of straight line and circle trajectory tracking have been given to prove the correctness and feasibility of the proposed control strategy.

Keywords: adaptive; trajectory tracking; underactuated unmanned surface vehicle; sliding mode; neural network minimum learning parameter method

1. Introduction

With the continuous advancement of science and technology, the modern ship system is moving toward a systematic, intelligent and unmanned direction. In recent years, a new type of ship research project has been developed by combining the achievements of small speedboats and advanced control technologies, like the Unmanned Surface Vehicles (USVs) [1,2]. Following the trend of ship systems, USVs has become a unique research field, which attracts more and more institutions and researchers to conduct relevant research [3,4]. Generally, trajectory tracking is an important topic in the field of USV research, and it is the guarantee for many applications in the future, such as formation operations, and so on [5,6]. However, a very realistic and urgent problem to be solved is that the overwhelming majority of USVs with propellers and rudders belong to an underactuated system, while without any actuators for direct control of sway motion [7–9]. Therefore, how to design robust trajectory tracking controllers under the condition of underactuated characteristics for USVs is a very worthwhile problem.

Many researchers have made outstanding contributions to cope with the trajectory tracking problem for underactuated ships [10–13]. In [14], a unified backstepping design methodology is hired to solve the stabilisation and tracking problems for an underactuated ship with only two propellers. Chwa proposes a modular way that cascaded kinematic and dynamic linearizations can be achieved similarly as in the backstepping method. Based on this, under the premise of input and velocity constraints, dynamic surface control (DSC) technology is used to design a trajectory tracking control strategy for an underactuated ship [15]. For an underactuated USV, the experimental implementation of two trajectory tracking control algorithms: a cascade of proportional-derivative controllers and a nonlinear controller are proposed by Sonnenburg et al. through the backstepping control technology [16]. In [17,18], for an underactuated USV, the switching control and modified backstepping methods are used to design the trajectory tracking controller, which can track a straight line track or fixed point. However, in actual navigation, besides the external disturbances caused by wind, waves and currents, the ship's quality, speed and moment of inertia will also change, which will lead to some changes or unknown dynamics in the model of ship. In [19], the backstepping method is hired to design the USV trajectory tracking controller. At the same time, a disturbance observer is employed to compensate for the time-varying external disturbances on line. The sliding mode algorithms have strong robustness, which are often introduced into the motion control of various nonlinear systems. Hierarchical sliding mode-based trajectory tracking controller is designed to allow the underactuated surface vessels to track a pre-specified trajectory [20]. Besides, in [21], the sliding mode control algorithm is introduced into the design of a trajectory tracking controller for underactuated USV, but it does not consider the effects of unknown dynamics and time-varing disturbances. In practical engineering application, when dealing with model structure unknown or unknown dynamics problems, the universal approximation ability of neural network [22,23] or fuzzy logic [24–26] is widely used. Fuzzy logic needs experts' prior knowledge, which often increases the design difficulty of controller. So the multilayer neural network represented by radial basis function (RBF) neural network is the most widely used method to deal with the unknown dynamics problem. Paper [27] proposes a single layer neural network to cope with the completely unknown vehicle dynamics for an autonomous surface vehicle (ASV) to track a predetermined trajectory.

Motivated by the above-mentioned observations, an adaptive trajectory tracking control strategy for engineering implementation, which is performed by using first-order sliding surface, second-order sliding surface and neural network minimum learning parameter method, is designed for an underactuated USV subject to unknown dynamics and time-varing external disturbances. The contributions of this paper can be summarized as follows:

(1) A novel control approach for an underactuated USV to achieve trajectory tracking by stabilizing surge velocity and sway velocity through a first-order sliding surface and a second-order sliding surface, respectively, is proposed.

(2) Compared with the multi-layer neural network, neural network minimum learning parameter method has a small amount of computation. It is used to compensate unknown dynamics and time-varing disturbances, which can not only reduce the calculation burden of the controller, but also reduce the chattering phenomenon of the sliding mode control algorithm.

The rest of this paper is organized as follows. In Section 2, problem formulation and preliminaries are introduced. Trajectory tracking control laws (first-order sliding surface for surge control law and second-order sliding surface for yaw control law) are introduced in Section 3. The stability proof is given in Section 4. In Section 5, numerical simulations are given to prove the correctness of the proposed control scheme. Finally, conclusions of this paper are summarized in Section 6.

2. Problem Formulation and Preliminaries

Throughout this paper, $|\bullet|$ is the absolute operator and $\|\bullet\|$ denotes the euclidean norm. $\hat{(\bullet)}$ is the estimate of $(\bullet)$ and its estimation error $\tilde{(\bullet)} = \hat{(\bullet)} - (\bullet)$.

2.1. Problem Formulation

The corresponding relationship between the body-fixed frame and the earth-fixed inertial frame is shown in Figure 1.

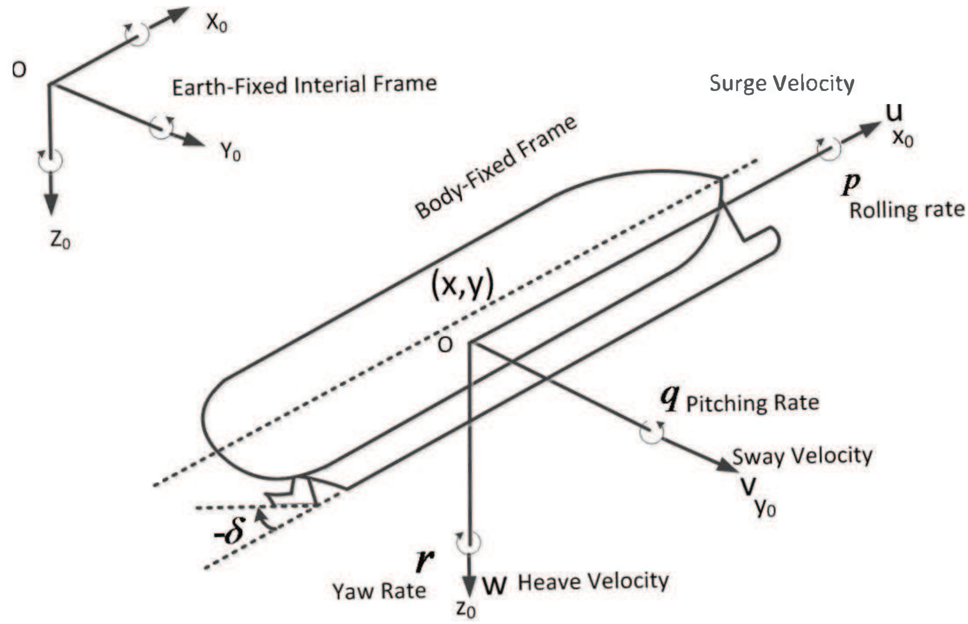

Figure 1. The earth-fixed inertial and body-fixed frame.

$o - x_0y_0z_0$ is the body-fixed frame and $O - X_0Y_0Z_0$ is the earth-fixed inertial frame. As shown in Figure 1, USV has six degrees of freedoms (DOFs): surge velocity u, sway velocity v, yaw rate r, heave velocity w, rolling rate p and pitching rate q. However, in order to reduce the complexity of the model, heave velocity, rolling rate and pitching rate are often ignored in the actual study of its motion control. To be more exact, $w = p = q = 0$. According to [28], the three DOFs kinematic and dynamic models of underactuated USV can be expressed as Equations (1) and (2), respectively.

$$\begin{cases} \dot{x} &= u\cos(\psi) - v\sin(\psi) \\ \dot{y} &= u\sin(\psi) + v\cos(\psi) \\ \dot{\psi} &= r \end{cases} \tag{1}$$

$$\begin{cases} \dot{u} &= f_u - \frac{1}{m_{11}}\Delta_u + \frac{1}{m_{11}}\tau_u + \frac{1}{m_{11}}b_u \\ \dot{v} &= f_v - \frac{1}{m_{22}}\Delta_v + \frac{1}{m_{22}}b_v \\ \dot{r} &= f_r - \frac{1}{m_{33}}\Delta_r + \frac{1}{m_{33}}\tau_r + \frac{1}{m_{33}}b_r \end{cases} \tag{2}$$

with $f_u = \frac{m_{22}}{m_{11}}vr - \frac{d_{11}}{m_{11}}u$, $f_v = -\frac{m_{11}}{m_{22}}ur - \frac{d_{22}}{m_{22}}v$, $f_r = \frac{m_{11} - m_{22}}{m_{33}}uv - \frac{d_{33}}{m_{33}}r$, where (x, y) represents the position of the USV; ψ is the heading angle; m_{11}, m_{22}, m_{33}, d_{11}, d_{22} and d_{33} are the corresponding model parameters; Δ_u, Δ_v and Δ_r represent unknown dynamics in each direction, respectively; τ_u and τ_r are the control inputs: the surge force and yaw moment; b_u, b_v and b_r are used to describe the non measurable and time-varying external disturbances caused by wind, waves, and currents.

Assumption 1. *Assume that the unknown dynamics and external disturbances satisfy* $|\Delta_u| \leq \Delta_{u\max}$, $|\Delta_v| \leq \Delta_{v\max}$, $|\Delta_r| \leq \Delta_{r\max}$, $|b_u| \leq b_{u\max}$, $|b_v| \leq b_{v\max}$, $|b_r| \leq b_{r\max}$, *where* $\Delta_{u\max}$, $\Delta_{v\max}$, $\Delta_{r\max}$, $b_{u\max}$, $b_{v\max}$ *and* $b_{r\max}$ *are unknown positive constants.*

Control objective: Note, the practical conditions considered in this paper include unknown dynamics and time-varing external disturbances. The control objective is to propose a practical adaptive trajectory tracking control strategy (the surge force τ_u and the yaw moment τ_r) to cope with the above considered conditions, so that the underactuated USV can track the reference trajectory (x_d, y_d). All state variables of the underactuated USV are uniform ultimate bounded (UUB).

2.2. Neural Network Minimum Parameter Learning Method

The basic principle of neural network minimum learning parameter method is introduced in this subsection. In control engineering, the multi-layer neural network, represented by back propagation (BP) [29,30] neural network and RBF neural network, are used to approximate nonlinear or unknown functions most widely [31]. Taking RBF neural network as an example, for any given continuous nonlinear function $f(x)$ with $f(0) = 0$, it can be rewritten as

$$f(x) = W^T h(x) + \varepsilon \tag{3}$$

where $W = [w_1, w_2, \ldots, w_p]^T \subset R^p$ is a weight vector; $h(x) = [h_1(x), h_2(x), \ldots, h_p(x)]$ is Gaussian function; ε is the approximation error of the neural network and $|\varepsilon| \leq \bar{\varepsilon}$, $\bar{\varepsilon} > 0$. p is the node number of neural network [32].

However, multilayer neural network needs online estimation of weight vectors of neural network, which inevitably increases the computational load of the control algorithm, that is, the so-called "curse of dimensionality". In order to solve the above problem, in this paper, neural network minimum learning parameter method is used to approximate unknown function instead of RBF neural network. Compared with multi-layer neural network, neural network minimum learning parameter method can significantly reduce the computational burden of the controller. The essence of this method is that the proposed adaptive law does not depend on the number of neural network nodes by online estimation of the weight vector norm of the neural network. Specifically, define $\phi = \|W\|^2$, and ϕ is a normal number. $\hat{\phi}$ is the estimated value of ϕ. Meanwhile, estimation error $\tilde{\phi} = \hat{\phi} - \phi$.

3. Trajectory Tracking Control Design

The sliding mode control (SMC) algorithm is first proposed by Emelyanov in the early 1950s [33], and its advantages are that the algorithm is simple, less computational and has a strong robustness. With the efforts of scientific research all over the world, SMC is gradually applied to the control of robots [34], aircrafts [35], ships [36] and so on. In this section, surge control law and yaw control law are proposed based on a first-order sliding mode and a second-order sliding mode, respectively.

First, define the trajectory tracking error variables:

$$\begin{cases} x_e = x - x_d \\ y_e = y - y_d \end{cases} \tag{4}$$

Taking the time derivative of (4) along (1) produces

$$\begin{bmatrix} \dot{x}_e \\ \dot{y}_e \end{bmatrix} = \begin{bmatrix} \cos\psi & -\sin\psi \\ \sin\psi & \cos\psi \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} - \begin{bmatrix} \dot{x}_d \\ \dot{y}_d \end{bmatrix} \tag{5}$$

Then, define the velocity tracking error variables:

$$\begin{cases} u_e = u - u_d \\ v_e = v - v_d \end{cases} \tag{6}$$

where (u_d, v_d) are the desired surge velocity and sway velocity.

Assumption 2. *The tracked trajectory is required to be smooth enough.* $\dot{u}_d$, $\dot{v}_d$, $\dot{x}_d$, $\ddot{x}_d$, $\dot{y}_d$ *and* $\ddot{y}_d$ *are all bounded.*

Consider the following reference trajectory

$$\begin{cases} x_d = m(t) + D_1 \\ y_d = n(t) + D_2 \end{cases} \tag{7}$$

where $m(t)$ and $n(t)$ are continuous time-varying functions, and D_1 and D_2 are two constants.

Meanwhile, according to [37], the desired surge velocity and sway velocity are related to (x_d, y_d), and they can be represented as

$$\begin{cases} u_d = \cos\psi\dot{x}_d + \sin\psi\dot{y}_d \\ v_d = -\sin\psi\dot{x}_d + \cos\psi\dot{y}_d \end{cases} \tag{8}$$

In this paper, the method to track the reference trajectory is to design the control law to make the (u_e, v_e) converge, and then the convergence of (x_e, y_e) is achieved. Therefore, we assume that (u_d, v_d) is related to (x_d, y_d) and (x_e, y_e), which can be represented as

$$\begin{cases} u_d = \cos\psi\dot{x}_d + \sin\psi\dot{y}_d - k\cos\psi x_e - k\sin\psi y_e \\ v_d = -\sin\psi\dot{x}_d + \cos\psi\dot{y}_d + k\sin\psi x_e - k\cos\psi y_e \end{cases} \tag{9}$$

where k is a positive parameter. By simplifying (1), we can get that

$$\begin{cases} u = \cos\psi\dot{x} + \sin\psi\dot{y} \\ v = -\sin\psi\dot{x} + \cos\psi\dot{y} \end{cases} \tag{10}$$

Based on (9) and (10), (6) can be re-expressed as

$$\begin{bmatrix} u_e \\ v_e \end{bmatrix} = \begin{bmatrix} \cos\psi & \sin\psi \\ -\sin\psi & \cos\psi \end{bmatrix} \begin{bmatrix} \dot{x}_e + kx_e \\ \dot{y}_e + ky_e \end{bmatrix} \tag{11}$$

At the same time, the derivative of u_d and v_d can be represented as

$$\begin{cases} \dot{u}_d = \cos\psi\ddot{x}_d + \sin\psi\ddot{y}_d + v_d r - k\cos\psi\dot{x}_e - k\sin\psi\dot{y}_e \\ \dot{v}_d = -\sin\psi\ddot{x}_d + \cos\psi\ddot{y}_d - u_d r + k\sin\psi\dot{x}_e - k\cos\psi\dot{y}_e \end{cases} \tag{12}$$

Taking the time derivative of (11) along (2) and (12) produces

$$\begin{bmatrix} \dot{u}_e \\ \dot{v}_e \end{bmatrix} = \begin{bmatrix} rv_e \\ -ru_e \end{bmatrix} + \begin{bmatrix} \cos\psi & \sin\psi \\ -\sin\psi & \cos\psi \end{bmatrix} \begin{bmatrix} \ddot{x}_e + k\dot{x}_e \\ \ddot{y}_e + k\dot{y}_e \end{bmatrix} \tag{13}$$

In the following subsection, surge control law τ_u and yaw control law τ_r will be designed to stabilise the velocity tracking errors u_e and v_e, respectively. To facilitate the understanding of the reader, the design block diagram of the trajectory tracking control strategy is shown in Figure 2.

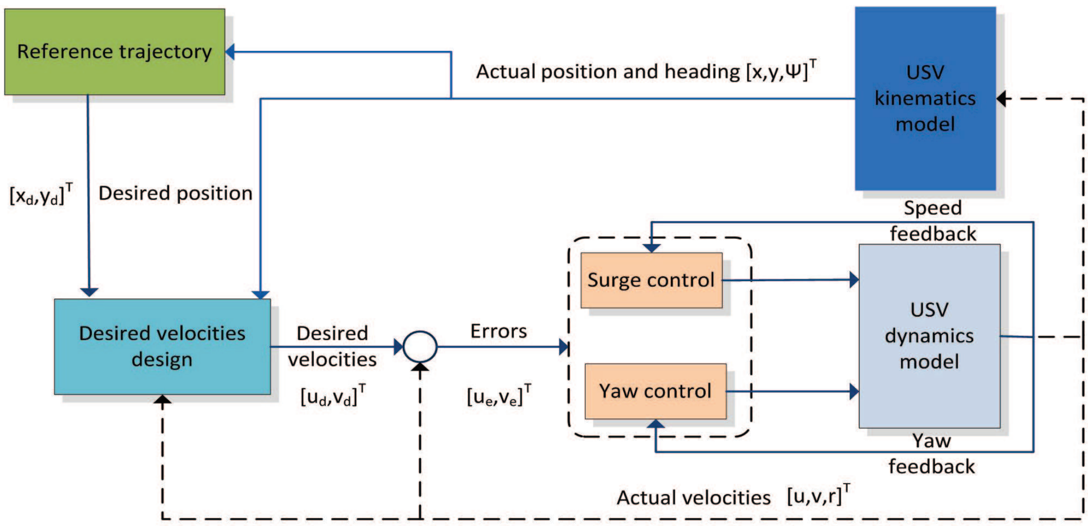

Figure 2. Block diagram of trajectory tracking control strategy.

3.1. Surge Control Law

In this subsection, a first-order sliding mode will be employed to design surge control law τ_u to make make u_e converge. At the same time, neural network minimum learning parameter method is used to compensate unknown dynamics and time-varing disturbances online in real time.

Define the first sliding surface

$$s_u = u_e + \lambda_1 \int_0^t u_e(\mu) d\mu \tag{14}$$

where λ_1 is a positive design parameter. Taking the time derivative of s_u along (13) produces

$$\dot{s}_u = \lambda_1 u_e + \frac{m_{22}}{m_{11}} vr - \frac{d_{11}}{m_{11}} u - \frac{1}{m_{11}} \Delta_u + \frac{1}{m_{11}} \tau_u + \frac{1}{m_{11}} b_u - \dot{u}_d \tag{15}$$

Meanwhile, in order to ensure that the sliding surface can converge to zero within a finite time [38], we define that

$$\dot{s}_u = -k_{ue} s_u - \eta_u \mathrm{sgn}(s_u) \tag{16}$$

where k_{ue} and η_u are two positive design parameters; sgn($\bullet$) represents the symbol function [36].

Therefore, the corresponding surge control law is selected as

$$\tau_u = \tau_{ue} + \tau_{uw} \tag{17}$$

where $\tau_{ue} = m_{11}(-\frac{1}{2} s_u \hat{\phi}_u h^T h - \lambda_1 u_e - \frac{m_{22}}{m_{11}} vr + \frac{d_{11}}{m_{11}} u + \dot{u}_d)$ and $\tau_{uw} = m_{11}(-k_{ue} s_u - \eta_u \mathrm{sgn}(s_u))$.

Finally, the update law for the neural network minimum learning parameter method is taken to be

$$\dot{\hat{\phi}}_u = \frac{\gamma_u}{2} s_u^2 h^T h - \kappa_u \gamma_u \hat{\phi}_u \tag{18}$$

where γ_u and κ_u are positive design parameters.

3.2. Yaw Rate Controller

In this subsection, a second-order sliding mode will be employed to design yaw control law τ_r to make v_e converge.

Define the second sliding surface

$$s_v \;=\; \dot{v}_e(t) + \lambda_2 v_e(t) + \lambda_3 \int_0^t v_e(\mu)d\mu \tag{19}$$

where λ_2 and λ_3 are two positive design parameters. Taking the time derivative of s_v along (13) produces

$$\dot{s}_v \;=\; \ddot{v} - \ddot{v}_d + \lambda_2(\dot{v} - \dot{v}_d) + \lambda_3 v_e \tag{20}$$

where

$$\begin{aligned}
\ddot{v} \;&=\; (-\frac{m_{11}}{m_{22}}ur - \frac{d_{22}}{m_{22}}v - \frac{1}{m_{22}}\Delta_v + \frac{b_v}{m_{22}})' \\
&=\; (-\frac{m_{11}}{m_{22}}\dot{u}r - \frac{m_{11}}{m_{22}}u(\frac{m_{11}-m_{22}}{m_{33}}uv - \frac{d_{33}}{m_{33}}r + \frac{1}{m_{33}}\tau_r - \frac{1}{m_{33}}\Delta_r + \frac{1}{m_{33}}b_r) - \frac{d_{22}}{m_{22}}\dot{v} - \frac{1}{m_{22}}\dot{\Delta}_v + \frac{\dot{b}_v}{m_{22}}) \\
&=\; \frac{1}{m_{22}m_{33}}(-m_{11}m_{33}\dot{u}r - m_{11}(m_{11}-m_{22})u^2v + m_{11}d_{22}ur - m_{11}u\tau_r + m_{11}u(\Delta_r - b_r) \\
&-\; m_{33}d_{22}\dot{v} - m_{33}(\dot{\Delta}_v - \dot{b}_v))
\end{aligned} \tag{21}$$

$$\ddot{v}_d \;=\; v_m - v_n \tag{22}$$

$$\begin{aligned}
v_m \;=\; &-r[\cos(\psi)\ddot{x}_d + \sin(\psi)\ddot{y}_d] - \sin(\psi)_d + \cos(\psi)_d - r[\cos(\psi)\ddot{x}_d + \sin(\psi)\ddot{y}_d + v_d r \\
&- k(\cos(\psi)\dot{x}_e + \sin(\psi)\dot{y}_e)] + k[r\cos(\psi)\dot{x}_e + \sin(\psi)\ddot{x}_e + r\sin(\psi)\dot{y}_e - \cos(\psi)\ddot{y}_e]
\end{aligned} \tag{23}$$

$$v_n \;=\; u_d\frac{\tau_r - d_{33}r + (m_{11}-m_{22})uv}{m_{33}} \tag{24}$$

Based on the above analysis, (20) can be rerepresented as

$$\dot{s}_v \;=\; v_b\tau_r + v_v - v_m + \lambda_2(\dot{v} - \dot{v}_d) + \lambda_3 v_e + v_f \tag{25}$$

where $v_b \;=\; \frac{(m_{22}u_d - m_{11}u)}{m_{22}m_{33}}$, $v_v \;=\; \frac{-m_{11}m_{33}\dot{u}r - m_{11}(m_{11}-m_{22})u^2v + m_{11}d_{22}ur - m_{33}d_{22}\dot{v} - m_{22}d_{33}ru_d + m_{22}(m_{11}-m_{22})u_d uv}{m_{22}m_{33}}$ and $v_f \;=\; \frac{m_{11}u(\Delta_r - b_r) - m_{33}(\dot{\Delta}_v - \dot{b}_v)}{m_{22}m_{33}}$.

Similarly, in order to ensure that the second-order sliding mode surface can converge in a limited time, one can define that

$$\dot{s}_v \;=\; -k_{ve}s_v - \eta_v \mathrm{sgn}(s_v) \tag{26}$$

where k_{ve} and η_v are two positive design parameters.

Therefore, the corresponding yaw control law is selected as

$$\tau_r \;=\; \tau_{re} + \tau_{rw} \tag{27}$$

where $\tau_{re} \;=\; \frac{1}{v_b}(-\frac{1}{2}s_v\hat{\phi}_v h^T h - v_v + v_m - \lambda_2(\dot{v} - \dot{v}_d) - \lambda_3 v_e)$ and $\tau_{rw} \;=\; \frac{1}{v_b}(-k_{ve}s_v - \eta_v \mathrm{sgn}(s_v))$.

The update law for the neural network minimum learning parameter method is taken to be

$$\dot{\hat{\phi}}_v = \frac{\gamma_v}{2} s_v^2 h^T h - \kappa_v \gamma_v \hat{\phi}_v \tag{28}$$

where γ_v and κ_v are positive design parameters.

Remark 1. *The reason that sliding mode control theory has strong robust ability is that the symbol function can resist unknown dynamics and time-varing disturbances better. However, with the increase of unknown dynamics and time-varing disturbances, this undoubtedly increases the degree of chattering of the control signals. If more than a critical value is exceeded, it will lead to the instability and even collapse of the control system. Therefore, neural network minimum learning parameter method is hired to compensate for unknown dynamics and time-varing disturbances, which undoubtedly reduces the chattering of control signals under the premise of ensuring system robustness.*

Remark 2. *Neural network minimum learning parameter method is used instead of the RBF neural network to reduce the computing burden of the controller [22]. At the same time, in the previous literatures [39–41], unknown dynamics and external disturbances are compensated separately. However, in this paper, unknown dynamics and time-varing disturbances are packaged together for compensation, which, to a certain extent, can reduce the computation of controller and make it more convenient for engineering implementation. Of course, through qualitative analysis, this paper concludes that the calculation of the burden is reduced, but how much has it been reduced? In future research, the author will give a quantitative analysis.*

4. Stability Analysis

The following Theorem 1 presents the stability result of the proposed control law.

Theorem 1. *Consider the closed-loop system consisting of the underactuated USV (1) and (2) satisfying Assumptions 1 and 2, the control laws (17) and (27), the adaptive laws (18) and (28). One can adjust control parameters λ_1, λ_2, λ_3, k_{ue}, η_u, γ_u, κ_u, k_{ve}, η_v, γ_v and κ_v, then, all signals in the closed-loop trajectory tracking system for USV are UUB.*

Proof of Theorem 1. Consider the following Lyapunov function candidate:

$$V = \frac{1}{2}(s_u^2 + \frac{1}{\gamma_u}\tilde{\phi}_u^2 + s_v^2 + \frac{1}{\gamma_v}\tilde{\phi}_v^2) \tag{29}$$

Take the time derivative $\dot{V}$ along (14), (25), we have

$$\begin{aligned}
\dot{V} &= s_u \dot{s}_u + \frac{1}{\gamma_u}\tilde{\phi}_u \dot{\hat{\phi}}_u + s_v \dot{s}_v + \frac{1}{\gamma_v}\tilde{\phi}_v \dot{\hat{\phi}}_v \\
&= s_u(\lambda_1 u_e + \frac{m_{22}}{m_{11}} vr - \frac{d_{11}}{m_{11}} u - \frac{1}{m_{11}}\Delta_u + \frac{1}{m_{11}}\tau_u + \frac{1}{m_{11}} b_u - \dot{u}_d) + \frac{1}{\gamma_u}\tilde{\phi}_u \dot{\hat{\phi}}_u \\
&+ s_v(v_b \tau_r + v_v - v_m + \lambda_2(\dot{v} - \dot{v}_d) + \lambda_3 v_e + v_f) + \frac{1}{\gamma_v}\tilde{\phi}_v \dot{\hat{\phi}}_v \\
&\leq \frac{1}{2} s_u^2 \phi_u h^T h + \frac{1}{2} + s_u(\lambda_1 u_e + \frac{m_{22}}{m_{11}} vr - \frac{d_{11}}{m_{11}} u + \varepsilon_u + \frac{1}{m_{11}}\tau_u - \dot{u}_d) + \frac{1}{\gamma_u}\tilde{\phi}_u \dot{\hat{\phi}}_u \\
&+ \frac{1}{2} s_v^2 \phi_v h^T h + \frac{1}{2} + s_v(v_b \tau_r + v_v - v_m + \lambda_2(\dot{v} - \dot{v}_d) + \lambda_3 v_e) + \frac{1}{\gamma_v}\tilde{\phi}_v \dot{\hat{\phi}}_v \\
&\leq s_u(\frac{1}{2} s_u \hat{\phi}_u h^T h + \lambda_1 u_e + \frac{m_{22}}{m_{11}} vr - \frac{d_{11}}{m_{11}} u + \varepsilon_u + \frac{1}{m_{11}}\tau_u - \dot{u}_d) - \tilde{\phi}_u(\frac{1}{2} s_u^2 h^T h - \frac{1}{\gamma_u}\dot{\hat{\phi}}_u) \\
&+ s_v(\frac{1}{2} s_v \hat{\phi}_v h^T h + v_b \tau_r + v_v - v_m + \lambda_2(\dot{v} - \dot{v}_d) + \lambda_3 v_e) - \tilde{\phi}_v(\frac{1}{2} s_v^2 h^T h - \frac{1}{\gamma_v}\dot{\hat{\phi}}_v) + 1
\end{aligned} \tag{30}$$

Submitting the control laws (17), (27) and adaptive laws (18), (28) yields

$$\dot{V} \leq -k_{ue}s_u^2 - \kappa_u\tilde{\phi}_u\hat{\phi}_u - (\eta_u - \varepsilon_u)\,|s_u| - k_{ve}s_v^2 - \kappa_v\tilde{\phi}_v\hat{\phi}_v - (\eta_v - \varepsilon_v)\,|s_v| + 1 \tag{31}$$

Because $(\tilde{\phi}_\iota + \phi_\iota)^2 \geq 0$, then $\tilde{\phi}_\iota^2 + \phi_\iota^2 + 2\tilde{\phi}_\iota(\hat{\phi}_\iota - \tilde{\phi}_\iota) \geq 0$. One can get that $2\tilde{\phi}_\iota\hat{\phi}_\iota \geq \tilde{\phi}_\iota^2 - \phi_\iota^2$, where $\iota = u$ and v.

Moreover, define $\eta_u > \varepsilon_u$ and $\eta_v > \varepsilon_v$, then (32) can be obtained.

$$\dot{V} \leq -k_{ue}s_u^2 - k_{ve}s_v^2 - \frac{1}{2}\kappa_u\tilde{\phi}_u^2 - \frac{1}{2}\kappa_v\tilde{\phi}_v^2 + \frac{1}{2}\kappa_u\phi_u^2 + \frac{1}{2}\kappa_v\phi_v^2 + 1 \tag{32}$$

Define $l_1 = k_{ue}$, $l_2 = k_{ve}$, $l_3 = \frac{1}{2}\kappa_u$, $l_4 = \frac{1}{2}\kappa_v$, $\nabla = \frac{1}{2}\kappa_u\phi_u^2 + \frac{1}{2}\kappa_v\phi_v^2 + 1$, then (32) becomes

$$\dot{V} \leq -l_1s_u^2 - l_2s_v^2 - l_3\tilde{\phi}_u^2 - l_4\tilde{\phi}_v^2 + \nabla \tag{33}$$

Define $l = \min\{l_1, l_2, l_3, l_4\}$, then it follows from (33) that

$$\dot{V} \leq -2lV + \nabla \tag{34}$$

Solving inequality (34) gives

$$V \leq (V(0) - \frac{\nabla}{2l})e^{-2lt} + \frac{\nabla}{2l} \leq V(0)e^{-2lt} + \frac{\nabla}{2l}, \quad \forall t > 0 \tag{35}$$

Through the analysis of inequality (35) we can draw that V is eventually bounded by $\frac{\nabla}{2l}$. Thus, all the error signals in the closed loop system are UUB. In the strict sense, in the case of continuous optimization of the control parameters, $\frac{\nabla}{2l}$ can be made arbitrarily small, thus, more accurate trajectory tracking performance is obtained. □

5. Numerical Simulations

In this section, the numerical simulations of straight line trajectory and circle trajectory tracking are given to prove the correctness and effectiveness of the adaptive trajectory tracking control law. Meanwhile, in order to prove the superiority of the control strategy proposed in this paper, compare it with the [21] (Yu, et al., 2012) that deals with unknown dynamics and disturbances only with the robustness of sliding mode. For this purpose, the underactuated USV (length of 1.255 m, breadth of 0.29 m, mass of 23.8 kg) is selected as the same as that in [42–44].

5.1. Tracking a Straight Line

In the previous approach [45], the straight line trajectory cannot be tracked because of the requirement of zero-yaw velocity. First, a simple straight line is regarded as a reference trajectory, which is described as $x_d = t$, $y_d = t$. According to [42–44], the external disturbances are assumed to be $b_u = 1 + 0.5\sin(0.2t) + 0.3\cos(0.5t)$, $b_v = 1 + 0.5\sin(0.2t) + 0.3\cos(0.4t)$, $b_r = 1 + 0.2\sin(0.1t) + 0.2\cos(0.2t)$, that is a time-varying disturbances. Meanwhile, Δ_u=$0.2f_u$, Δ_v=$0.2f_v$ and Δ_r=$0.2f_r$. The initial state of USV is $[x(0), y(0), \psi(0), u(0), v(0), r(0)] = [15\text{ m}, 0\text{ m}, 0\text{ rad}, 0\text{ m/s}, 0\text{ m/s}, 0\text{ rad/s}]$. The control parameters used in the controller are $k = 0.1$, $\lambda_1 = 1$, $\lambda_2 = 5$, $\lambda_3 = 1$, $k_{ue} = 0.01$, $k_{ve} = 0.015$, $\eta_u = 0.001$, $\eta_v = 0.001$, $\gamma_u = 1$, $\gamma_v = 1$, $\kappa_u = 0.01$ and $\kappa_v = 0.01$. The comparison results of the numerical simulation are provided in Figures 3–6.

Figure 3 depicts the trajectory tracking in two-dimensional plane, where the reference trajectory is a straight line. Despite the presence of unknown dynamics and non measurable external disturbances, the proposed control scheme still has a good performance. Besides, the control strategy of (Yu, et al., 2012) also has a good result. Figure 4 shows the comparison results of tracking errors. It can be observed that the tracking errors of the proposed scheme and (Yu, et al., 2012) both can converge well near the zero point, but it is obvious that the errors range of the proposed scheme have a smaller fluctuation range. Figures 5 and 6 demonstrate the force τ_u and the moment τ_r respectively. Furthermore, one can get that compared with the method proposed in this paper, the control inputs of (Yu, et al., 2012) have a larger chattering phenomenon. For the control system, the chattering is not conducive to the stability of the system. For the actuator, frequent chattering will aggravate the wear of the actuator, which is not conducive to the implementation of the engineering.

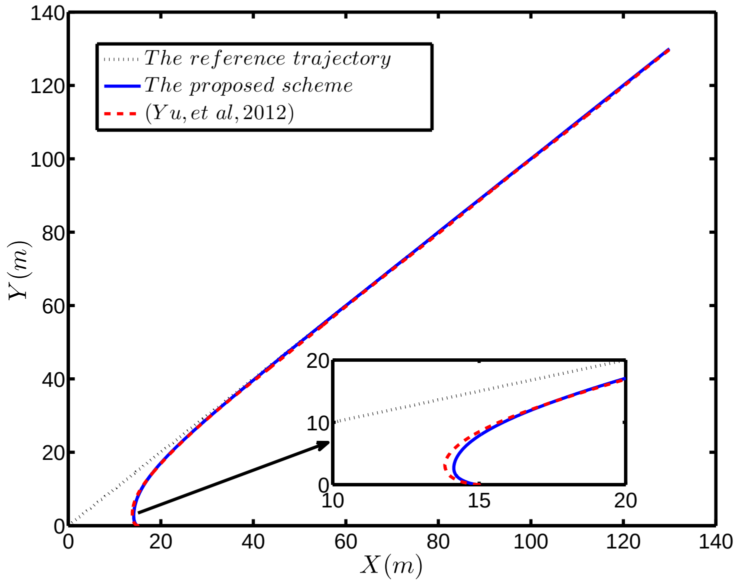

Figure 3. Comparison results of straight line trajectory tracking.

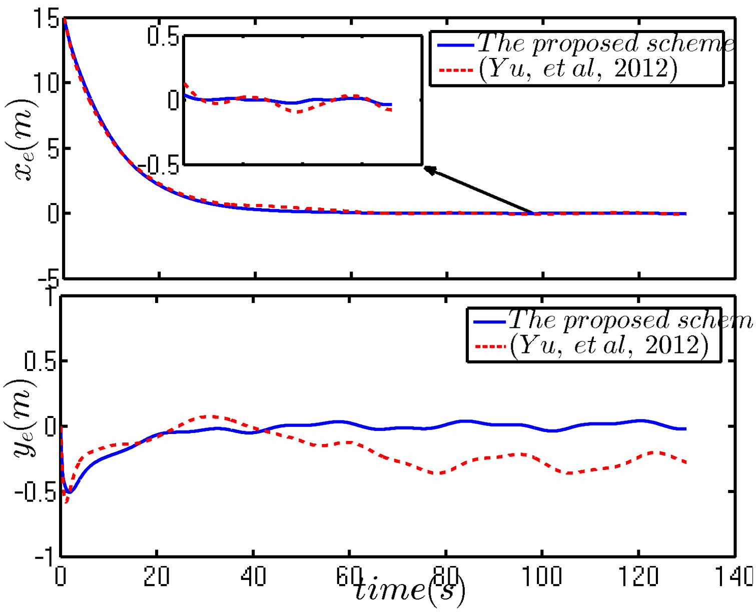

Figure 4. Comparison results of tracking errors.

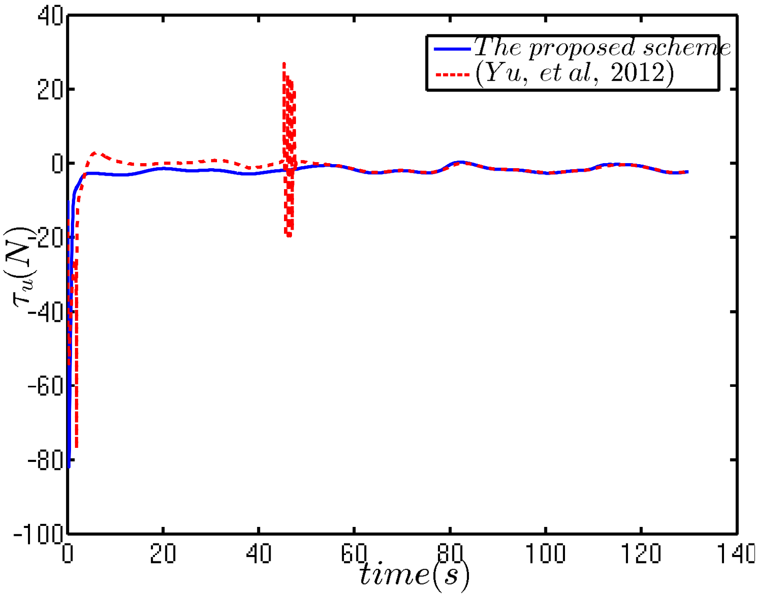

Figure 5. Comparison results of τ_u.

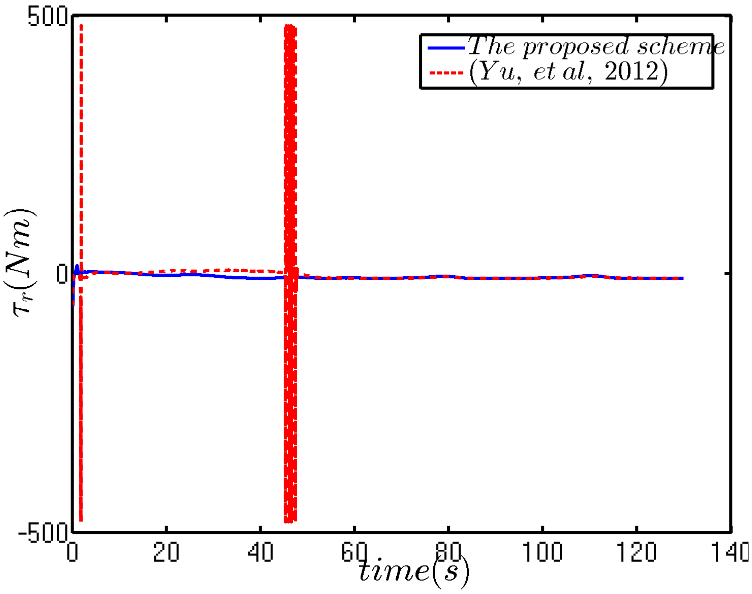

Figure 6. Comparison results of τ_r.

5.2. Tracking a Circle

In the case of USV initial conditions, the control parameters and external disturbances do not make any changes, a circle trajectory tracking simulation experiment with a radius of 20 m is carried out to further verify the correctness of the proposed scheme. The reference trajectory is described as $x_d = 20\cos(0.05t)$, $y_d = 20\sin(0.05t)$. The tracking results are shown in Figures 7–10.

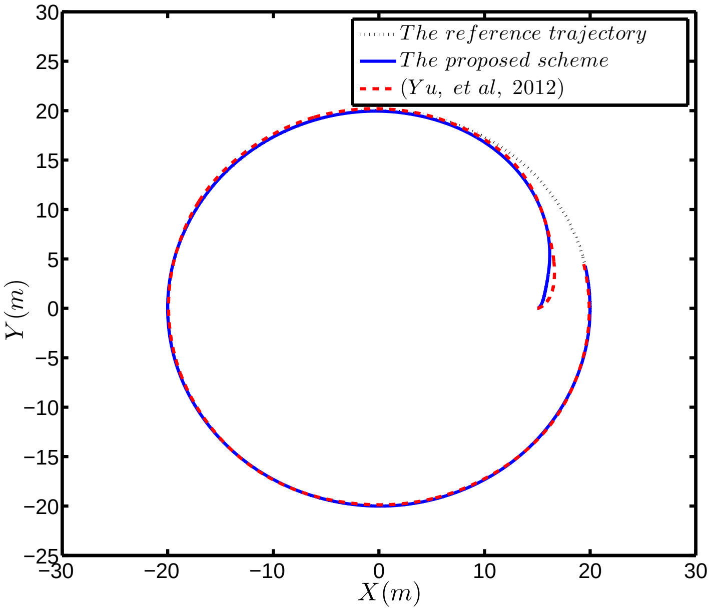

Figure 7. Comparison results of circle trajectory tracking.

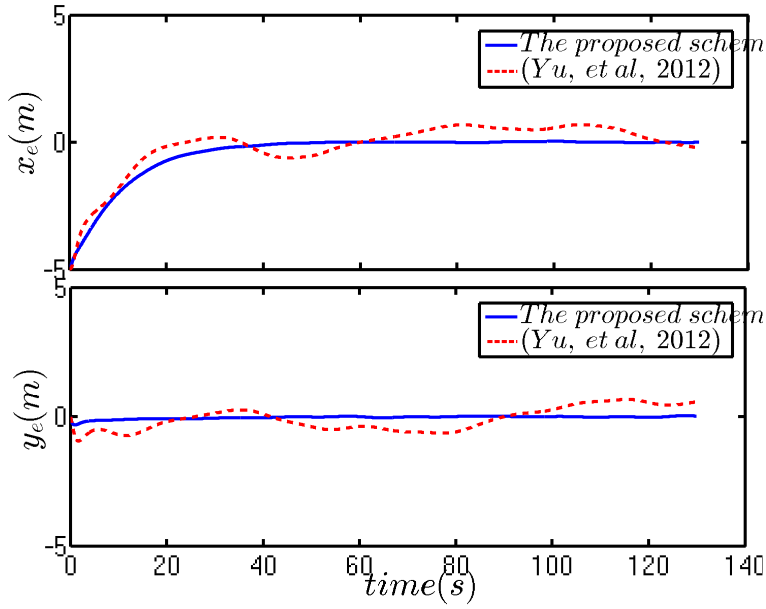

Figure 8. Comparison results of tracking errors.

Although no adjustments have been made to the control parameters, it can be seen from Figure 7 that the proposed scheme and (Yu, et al., 2012) still have satisfactory tracking results, which show that they have good generality. Figure 8 plots the tracking errors of the proposed scheme and (Yu, et al., 2012). It can be observed that the proposed scheme can keep x_e and y_e stable near the equilibrium point and they have very small fluctuations. However, the performance of (Yu, et al., 2012) is not so satisfactory. Figures 9 and 10 depict the comparison results of control inputs. Notice from the simulation results that similar to the straight line tracking, the (Yu, et al., 2012) control inputs τ_u and τ_r generate large chattering phenomena, which are not allowed in actual engineering.

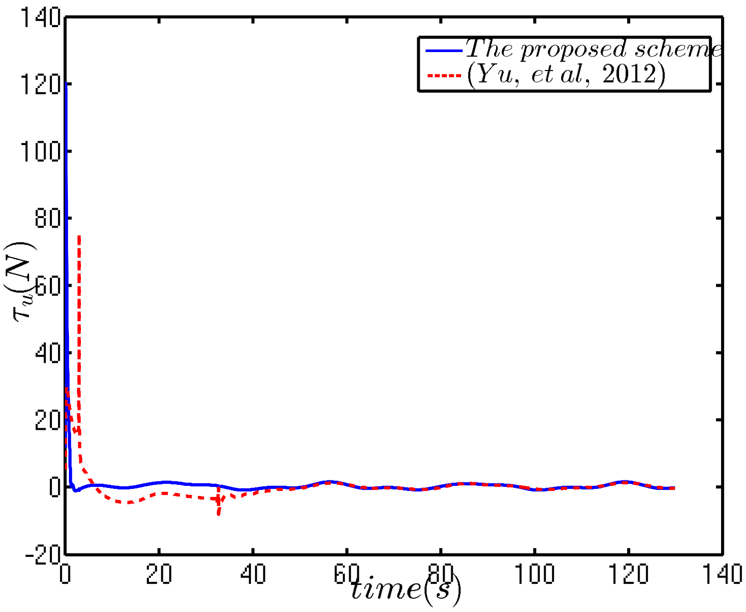

Figure 9. Comparison results of τ_u.

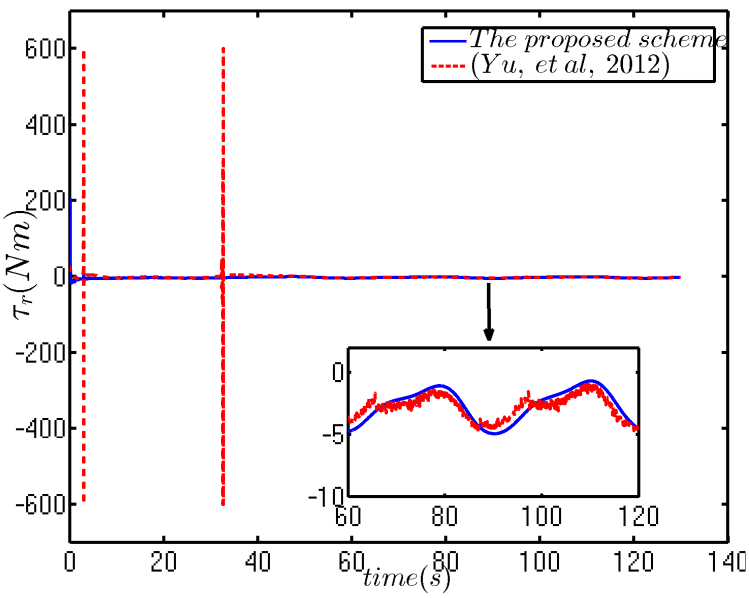

Figure 10. Comparison results of τ_r.

Thus far, the numerical simulations of straight line trajectory tracking and circle trajectory tracking have achieved good results, indicating the superiority and robustness of adaptive trajectory tracking control strategy proposed in this paper.

6. Conclusions

This paper has proposed an adaptive trajectory tracking control strategy for an underactuated USV subject to unknown dynamics and time-varing external disturbances. The scheme is presented by combing first-order sliding mode, second-order sliding mode and neural network minimum learning parameter method, which is obviously different from traditional trajectory tracking control approach. Neural network minimum learning parameter method is introduced into the design of controller. It not only handles the problems of unknown dynamics and external disturbances, but also enhances the robustness of control strategy, and also reduces chattering phenomenon of control signals to some extent. Comparison results of numerical simulation verify the effectiveness and correctness of the proposed method. Although this article has taken more of the actual situation into consideration, there are still a lot of problems that need to be resolved. For example, the reduced amount of the controller's calculation burden is not given quantificationally. This is also one of the future research directions.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

USV	unmanned surface vehicle
DSC	dynamic surface control
RBF	radial basis function
ASV	autonomous surface vehicle
DOF	degree of freedom
UUB	uniformly ultimately bounded
BP	back propagation
SMC	sliding mode control

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