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DESIGN OF ROBUST ADAPTIVE COURSE CONTROLLER FOR UNMANNED SURFACE VEHICLE WITH INPUT SATURATION

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Abstract. *On the basis of considering the saturation of the actuator, a robust adaptive course controller of unmanned surface vehicle is presented by introducing an auxiliary function. During the voyage, due to the change of working conditions and the interference of the external environment, the mathematical model of unmanned surface vehicle presents nonlinear characteristics and uncertainty. In view of the model nonlinearity and uncertainty, the RBF neural network is used to approximate the unknown function, and then based on the backstepping method and Lyapunov stability theory, a robust adaptive course controller with input saturation is proposed by means of a saturation aided design system. Finally, the results of numerical simulation show that the proposed control strategy can effectively track the target value and has strong robustness.*

Keywords: Unmanned surface vehicle, Input saturation, Course control, RBF, Robust

1. **Introduction.** Unmanned surface vehicle (USV) is an unmanned ocean platform which can achieve a long time and a large range of marine scientific research tasks. Therefore, USV has a very broad application prospect in civilian and military areas, such as marine environmental monitoring, marine resources exploration and territorial sea surveillance [1]. As an intelligent platform for autonomous navigation, course control is not only the basis for the realization of autonomous driving, but also direct determination of the economy and safety of navigation. Therefore, the design of course controller is very important.

Due to the continuous change of operating conditions, the model of USV is nonlinear and uncertain. On the basis of the above problems, many scholars at home and abroad have done the corresponding research. In [2], backstepping method and parameter adaptation method are used to solve the problems of nonlinearity and uncertainty of the ship model. [3] uses backstepping method to design course controller, and particle swarm intelligence algorithm is employed to optimize the control parameters. In the process of using backstepping method to design the controller, dynamic surface method is used to solve the problem of "computation explosion" [4]. In [5], RBF neural network is employed to approximate the unknown function of the system and Lyapunov function is used to prove the stability of the system. In the case of external interference, two order sliding mode observer is used to estimate the ship yawing angular velocity and backstepping method is used to design course controller, which guarantees the global asymptotic stability of the closed loop system [6]. Despite that the above papers in the numerical simulation have achieved good results, the input saturation problem of actuator is not considered. The problem of input saturation should be considered when designing the controller, rather than limiting the control input through the rudder characteristics forcibly. In [7], on the basis of considering the input saturation, backstepping adaptive and auxiliary function are used to design course controller. In [8], an adaptive fuzzy method is employed to design course controller with input saturation. In [9], based on the Lyapunov stability theory and the backstepping technique, a direct adaptive neural network controller is proposed for ship course-keeping control in the presence of input saturation.

The main contribution of this paper is to design a novel RBF adaptive USV course controller with considering the input saturation. Considering the nonlinearity and uncertainty of the model, BRF neural network approximation theory is used to deal with the uncertainty of the model, and the backstepping method is applied to designing controller which can guarantee that all the state variables of the closed-loop system meet ultimate boundedness. To handle the actuator saturation, the auxiliary design system is introduced to analyze the effect of input saturation.

The rest of the paper is organized as follows. Section 2 introduces the problem formulation of USV. In Section 3, the control design and its stability analysis are given. In Section 4, numerical simulations are carried out to show the effectiveness and practicability of our design. Finally, some conclusions are made and future research directions are introduced in Section 5.

2. Problem Statement and Preliminaries.

Norrbin model [10] is often used to design the course controller.

$$T\ddot{r} + r + \alpha r^3 = K\delta + d(t) \tag{1}$$

where r is yaw rate, K and T are system parameters, α is nonlinear parameter, $d(t)$ is a bounded external disturbance, and δ is rudder angle. $r = \dot{\psi}$ and ψ is course. Selecting state variable $x_1 = \psi$, $x_2 = r$, $u = \delta$, then Formula (1) can be changed as

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f(x) + b(x)u + d(t) \\ y = x_1 \end{cases} \tag{2}$$

where $f(x) = -\frac{1}{T}x_2 - \frac{\alpha}{T}x_2^3$, $b(x) = \frac{K}{T}$. $f(x)$ and $b(x)$ are uncertain and $\|d(t)\| < l_d$, $l_d > 0$. In this paper, considering the presence of input saturation constraints on rudder u as follows: $u_{\min} \le u \le u_{\max}$, where $u_{\max}$ and $u_{\min}$ are the known upper limit and lower limit of the rudder. Define U as the ultimate control input and it satisfies

$$U = sat(u) = \begin{cases} u_{\max} & \text{if } u > u_{\max} \\ u & \text{if } u_{\min} \le u \le u_{\max} \\ u_{\min} & \text{if } u < u_{\min} \end{cases} \tag{3}$$

It is worth noting that the u in Formula (3) is the designed control input of the system and U is the ultimate control law. Generally speaking, $u_{\max} = 35$ and $u_{\min} = -35$.

Assumption 2.1. *The reference course x_d is a sufficiently smooth function of time, and x_d, $\dot{x}_d$, $\ddot{x}_d$ are bounded.*

Lemma 2.1. *For bounded constant $k_1 \ge 0$, $k_2 \ge 0$, when $V(t,x)$ is a positive defined function and satisfies $\dot{V} \le -k_1 V + k_2$, then $V(t,x) \le k_2/k_1 + (V(0) - k_2/k_1)e^{-k_1 t}$.*

Lemma 2.2. *If the $f(t)$ is ultimately continuous function and there exists bounded $\lim_{t\to\infty} \int_0^t f(\tau)d\tau$, then $f(t) \to 0$ when $t \to \infty$.*

3. **Controller Design.** In this section, a robust adaptive course controller considering input saturation will be designed. Define error variable $z_1 = x_1 - x_d$ and $z_2 = x_2 - \alpha_1$. The time derivative of z_1 is $\dot{z}_1 = z_2 + \alpha_1 - \dot{x}_d$. The virtual control law of α_1 is chosen as $\alpha_1 = -c_1 z_1 + \dot{x}_d$, where c_1 is a constant and $c_1 > 0$, so we can obtain $\dot{z}_1 = -c_1 z_1 + z_2$.

Define the first Lyapunov function $V_1 = \frac{1}{2}z_1^2$ and the time derivative of V_1 is $\dot{V}_1 = -c_1 z_1^2 + z_1 z_2$. The time derivative of z_2 is $\dot{z}_2 = \dot{x}_2 - \dot{\alpha}_1$. For convenience of constraint effect analysis of the input saturation, the following auxiliary design system [11] is given as follows

$$\dot{e} = \begin{cases} -\mathrm{H}e - \dfrac{f(\bar{x})}{\|e\|}e + U - u & \|e\| \geq \varepsilon \\ 0 & \|e\| \leq \varepsilon \end{cases} \tag{4}$$

where ε is a small positive design parameter and e is a variable of the auxiliary design system introduced to ease the analysis of the effect of the input saturation, $f(\bar{x}) = |z_2 \cdot b \cdot \Delta u| + \frac{1}{2}\Delta u^2$, $\mathrm{H} > 0$, $\Delta u = U - u$, $b = K/T$. RBF neural network is used to approximate smooth function $f(x)$ and $b(x)$ [12]. Define $\hat{f}(x) = \hat{W}_f^T \phi_f(x)$, $\hat{b}(x) = \hat{W}_b^T \phi_b(x)$, $\widetilde{f}(x) = f(x) - \hat{f}(x)$, $\widetilde{b}(x) = b(x) - \hat{b}(x)$, $\widetilde{W}_f = W_f - \hat{W}_f$ and $\widetilde{W}_b = W_b - \hat{W}_b$. Here ω is the sum of all approximation errors and $|\omega| \leq \omega_{\max}$, $\omega_{\max} > 0$.

Define the second Lyapunov function $V_2 = V_1 + \frac{1}{2}z_2^2 + \frac{1}{2r_1}\widetilde{W}_f^T\widetilde{W}_f + \frac{1}{2r_2}\widetilde{W}_b^T\widetilde{W}_b + \frac{1}{2}e^2$.

The time derivative of V_2 is

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + z_2\dot{z}_2 - \frac{1}{r_1}\widetilde{W}_f^T\dot{\hat{W}}_f - \frac{1}{r_2}\widetilde{W}_b^T\dot{\hat{W}}_b + e\dot{e} \\ &= \dot{V}_1 + z_2\left[\left(\hat{W}_f + \widetilde{W}_f\right)^T \phi_f(x) + \omega + W_b^T\phi_b(x)u + \hat{W}_b^T\phi_b(x)u - \hat{W}_b^T\phi_b(x)u \right. \\ &\quad \left. + d(t) - \dot{\alpha}_1\right] - \frac{1}{r_1}\widetilde{W}_f^T\dot{\hat{W}}_f - \frac{1}{r_2}\widetilde{W}_b^T\dot{\hat{W}}_b + e\dot{e} \\ &= -c_1z_1^2 + z_2\left[z_1 + \hat{W}_f^T\phi_f(x) + \omega + \hat{W}_b\phi_b(x)u + d(t) - \dot{\alpha}_1\right] \\ &\quad - \frac{1}{r_1}\widetilde{W}_f^T\left(\dot{\hat{W}}_f - r_1z_2\phi_f(x)\right) - \frac{1}{r_2}\widetilde{W}_b^T\left(\dot{\hat{W}}_b - r_2z_2\phi_b(x)u\right) + e\dot{e} \end{aligned}$$

It is clear that

$$e \cdot \dot{e} = -\mathrm{H}e^2 - \frac{|z_2 \cdot b \cdot \Delta u| + \frac{1}{2}\Delta u^2}{\|e\|^2} \cdot e^2 + \Delta u \cdot e \tag{5}$$

$$\Delta u \cdot e \leq \frac{1}{2}\Delta u^2 + \frac{1}{2}e^2 \tag{6}$$

We can choose control law

$$u = \frac{1}{\hat{W}_b^T\phi_b(x)}\left(-\left(c_2 + \frac{1}{\gamma^2}\right)(z_2 - e) - z_1 - k_1\mathrm{sgn}(z_2) - \hat{W}_f^T\phi_f(x) + \dot{\alpha}_1\right) \tag{7}$$

where k_1, c_2 and γ are constants that are greater than zero and $k_1 > \omega$. Substituting (5), (6) and (7) into $\dot{V}_2$, then

$$\begin{aligned} \dot{V}_2 \leq &-c_1z_1^2 + z_2\left[-\left(c_2 + \frac{1}{\lambda^2}\right)(z_2 - e) + \omega - k_1\mathrm{sgn}(z_2) + d(t)\right] \\ &- \frac{1}{r_1}\widetilde{W}_f^T\left(\dot{\hat{W}}_f - r_1z_2\phi_f(x)\right) - \frac{1}{r_2}\widetilde{W}_b^T\left(\dot{\hat{W}}_b - r_2z_2\phi_b(x)u\right) - (\mathrm{H} - 0.5)e^2 \end{aligned}$$

$$\begin{aligned}&\leq -c_1z_1^2-\left(c_2+\frac{1}{\lambda^2}\right)z_2^2+z_2\left(c_2+\frac{1}{\lambda^2}\right)e+z_2d(t)-\frac{1}{r_1}\widetilde{W}_f^T\left(\dot{\hat{W}}_f-r_1z_2\phi_f(x)\right)\\&\quad-\frac{1}{r_2}\widetilde{W}_b^T\left(\dot{\hat{W}}_b-r_2z_2\phi_b(x)u\right)-(\mathrm{H}-0.5)e^2\end{aligned} \tag{8}$$

In order to weaken the chattering of the control law, symbolic function $\mathrm{sgn}(z_2)$ is replaced by saturation function $sat(z_2)$.

$$sat(z_2)=\begin{cases}1 & z_2>\Delta\\ k_2z_2 & |z_2|\leq\Delta\\ -1 & z_2<-\Delta\end{cases} \tag{9}$$

where $k_2=1/\Delta$ and Δ is boundary layer. Then Formula (7) can be changed as

$$u=\frac{1}{\hat{W}_b^T\phi_b(x)}\left(-\left(c_2+\frac{1}{\gamma^2}\right)(z_2-e)-z_1-k_1sat(z_2)-\hat{W}_b^T\phi_f(x)+\dot{\alpha}_1\right) \tag{10}$$

Define $d(t)=D$

$$\dot{\hat{W}}_f=r_1\left[z_2\phi(x)-\sigma_0\left(\hat{W}_f-W_{f0}\right)\right] \tag{11}$$

$$\dot{\hat{W}}_b=r_2\left[z_2\phi(x)u-\sigma_1\left(\hat{W}_b-W_{b0}\right)\right] \tag{12}$$

where r_1, r_2, σ_0 and σ_1 are positive constants, and W_{f0} and W_{b0} are the initial values of W_f and W_b.

It is clear that

$$|z_2D|\leq\frac{1}{\gamma^2}\|z_2\|^2+\frac{1}{4}\gamma^2D^2 \tag{13}$$

$$\widetilde{W}_f^T\left(\hat{W}_f-W_{f0}\right)=-\frac{1}{2}\left|\widetilde{W}_f\right|^2-\frac{1}{2}\left|\hat{W}_f-W_{f0}\right|^2+\frac{1}{2}|W_f-W_{f0}|^2 \tag{14}$$

$$\widetilde{W}_b^T\left(\hat{W}_b-W_{b0}\right)=-\frac{1}{2}\left|\widetilde{W}_b\right|^2-\frac{1}{2}\left|\hat{W}_b-W_{b0}\right|^2+\frac{1}{2}|W_b-W_{b0}|^2 \tag{15}$$

$$z_2e\leq\frac{1}{2}z_2^2+\frac{1}{2}e^2 \tag{16}$$

Substituting (11), (12), (13), (14), (15) and (16) into (8)

$$\begin{aligned}\dot{V}_2\leq&-c_1z_1^2-c_2z_2^2+\left(c_2+\frac{1}{\lambda^2}\right)\frac{1}{2}\left(z_2^2+e^2\right)+\frac{1}{4}\gamma^2D^2-\sigma_0\frac{1}{2}\left|\widetilde{W}_f^T\right|^2\\&+\sigma_0\frac{1}{2}|W_f-W_{f0}|^2-\sigma_1\frac{1}{2}\left|\widetilde{W}_b^T\right|^2+\sigma_1\frac{1}{2}|W_b-W_{b0}|^2-(\mathrm{H}-0.5)e^2\\\leq&-c_1z_1^2-\left(c_2-\frac{1}{\lambda^2}\right)\frac{1}{2}z_2^2-\sigma_0\frac{1}{2}\left|\widetilde{W}_f^T\right|^2-\sigma_1\frac{1}{2}\left|\widetilde{W}_b^T\right|^2-\left(\mathrm{H}-0.5-\frac{1}{2}c_2-\frac{1}{2\lambda^2}\right)e^2\\&+\frac{1}{4}\gamma^2D^2+\sigma_0\frac{1}{2}|W_f-W_{f0}|^2+\sigma_1\frac{1}{2}|W_b-W_{b0}|^2\end{aligned}$$

We can choose the appropriate parameters to make $c_2>1/\lambda^2$ and $\mathrm{H}>0.5+0.5c_2+1/2\lambda^2$.

Theorem 3.1. *Considering the system (2) with input constraint effect under Assumption 2.1, auxiliary analysis system (4), robust control law (7), tuning functions (11) and (12), input saturation constraint (3), for bounded initial conditions, the closed-loop system signals z_1, z_2 and e are uniformly ultimately bounded. Besides, we can make it by selecting the appropriate parameters.*

Proof: Define

$$\mu = \min\left[c_1, \left(c_2 - \frac{1}{\lambda^2}\right)\frac{1}{2}, \frac{\sigma_0}{2r_1}, \frac{\sigma_1}{2r_2}, \left(\mathrm{H} - 0.5 - \frac{1}{2}c_2 - \frac{1}{2\lambda^2}\right)\right]$$

$$M = \frac{1}{4}\gamma^2 D^2 + \sigma_0 \frac{1}{2}\left|W_f - W_{f0}\right|^2 + \sigma_1 \frac{1}{2}\left|W_b - W_{b0}\right|^2$$

Then $\dot{V}_2 \le -2\mu V_2 + M$. According to Lemma 2.1, $0 \le V_2 \le \frac{M}{2\mu} + \left[V_2(0) - \frac{M}{2\mu}\right]e^{-2\mu t}$.

Thus it can be obtained that $V_2 - M/2\mu$ is exponential attenuation. This is to say, $\lim_{t\to\infty} \int V_2 - M/2\mu$ is bounded; V_2 and $\dot{V}_2$ are bounded, so V_2 is ultimately continuous. According to Lemma 2.2, it can be further obtained that

$$\lim_{t\to\infty} V_2 = M/2\mu$$

It can be easily concluded that the closed-loop system is uniformly ultimately bounded.

4. **Numerical Simulation.** In this section, the numerical simulation is presented to prove the effectiveness and the performance of the proposed course controller. The considered vehicle is called "Lanxin" USV which belongs to Dalian Maritime University [13,14] and $K = 0.707$, $T = 0.332$ and $\alpha = 0.001$.

The parameters of control law (10) are $c_1 = 0.425$, $c_2 = 1.1$, $\gamma = 1$, $\varepsilon = 1$, $\mathrm{H} = 2$, $k_1 = 0.1$, $k_2 = 0.6$, $r_1 = 0.06$, $r_2 = 0.01$, $\sigma_0 = 0.001$, $\sigma_1 = 0.001$, $W_{f0} = 0.001$, $W_{b0} = 0.001$. The initial conditions of $\hat{f}(x)$ and $\hat{b}(x)$ are 0 and 0.5 respectively. It is worth noting that in order to prevent $\hat{b}(x) = 0$, we can choose a larger initial value.

Due to the fact that the application of the most widely used in the actual ship course control is the PID automatic rudder, the PID controller is compared with the proposed course controller. The control law of PID is

$$\delta = K_p e + K_i \int_0^t e d\tau + K_d \dot{e}$$

where K_p, K_i and K_d are the parameters of PID and $K_p = 0.64$, $K_i = 0.001$ and $K_d = 0.21$. When state of the sea is at level 5, external disturbance can be expressed as a transfer function $L(s)$ driven by white noise with zero mean [13].

$$L(s) = \frac{0.42s}{s^2 + 0.36s + 0.37}$$

In the case of no external disturbance, course control simulation results are shown in Figure 1.

The course comparison result is shown in Figure 1(a) from which it is clearly observed that the controller presented in this paper can make the course fast to reach the target value, and it has a better control effect than PID.

The rudder angle comparison result is shown in Figure 1(b) from which it is clearly observed that in the initial stage, the control input is saturated. When the course reaches the target value, the rudder angle converges to zero quickly.

The estimated values of $f(x)$ and $b(x)$ are shown in Figures 1(c) and 1(d) respectively. It can be seen from Figures 1(c) and 1(d) that the estimated value of $f(x)$ converges to zero, but the estimated value of $b(x)$ does not converge to the actual value. For all that, the controller proposed in this paper still has a good control effect.

Without changing the control parameters and in the presence of external disturbance, the results are shown in Figure 2.

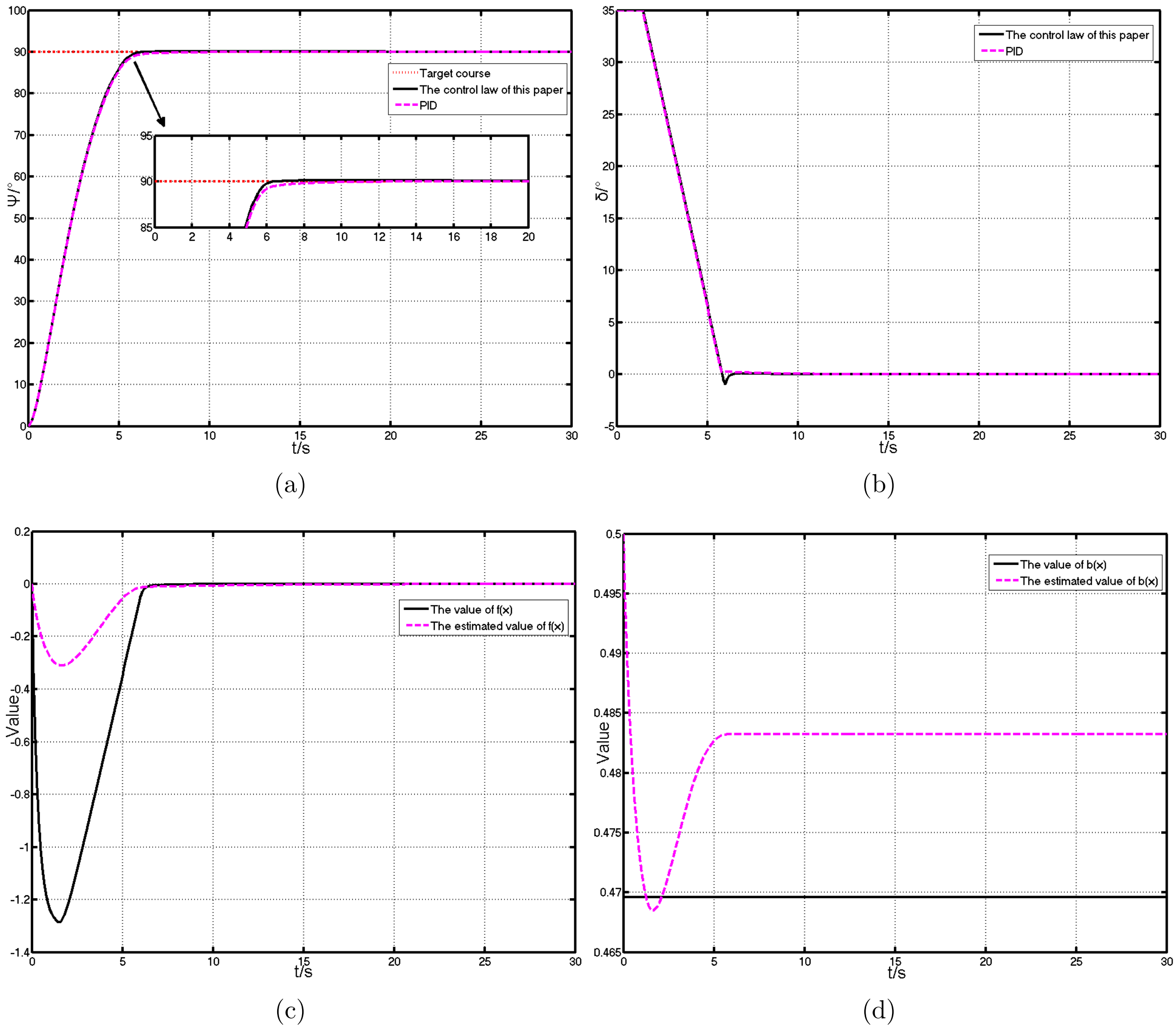

FIGURE 1. The simulation results of no external disturbance

In the case of external disturbance, the course comparison result is shown in Figure 2(a) from which it is clearly observed that the controller presented in this paper can still keep course stable at the target value, and its fluctuation range is less than PID. From Figures 2(b), 2(c) and 2(d) it can be seen that the remaining variables are still within a reasonable range. At this point, it is proved that the controller presented in this paper is effective and positive.

5. **Conclusions.** On the basis of considering the model uncertainty and input saturation, the course controller of USV is designed. Based on backstepping method, the approximation ability of RBF neural network is used to solve the model uncertainty problem firstly. Then the input saturation problem is considered by introducing the auxiliary function. Finally, the stability of the system is proved by Lyapunov function. The numerical simulation results show that the control strategy proposed in this paper can stabilize the course to the target value and the control effect is better than PID. In future research, the control strategy proposed in this paper will be used in real ship experiment.

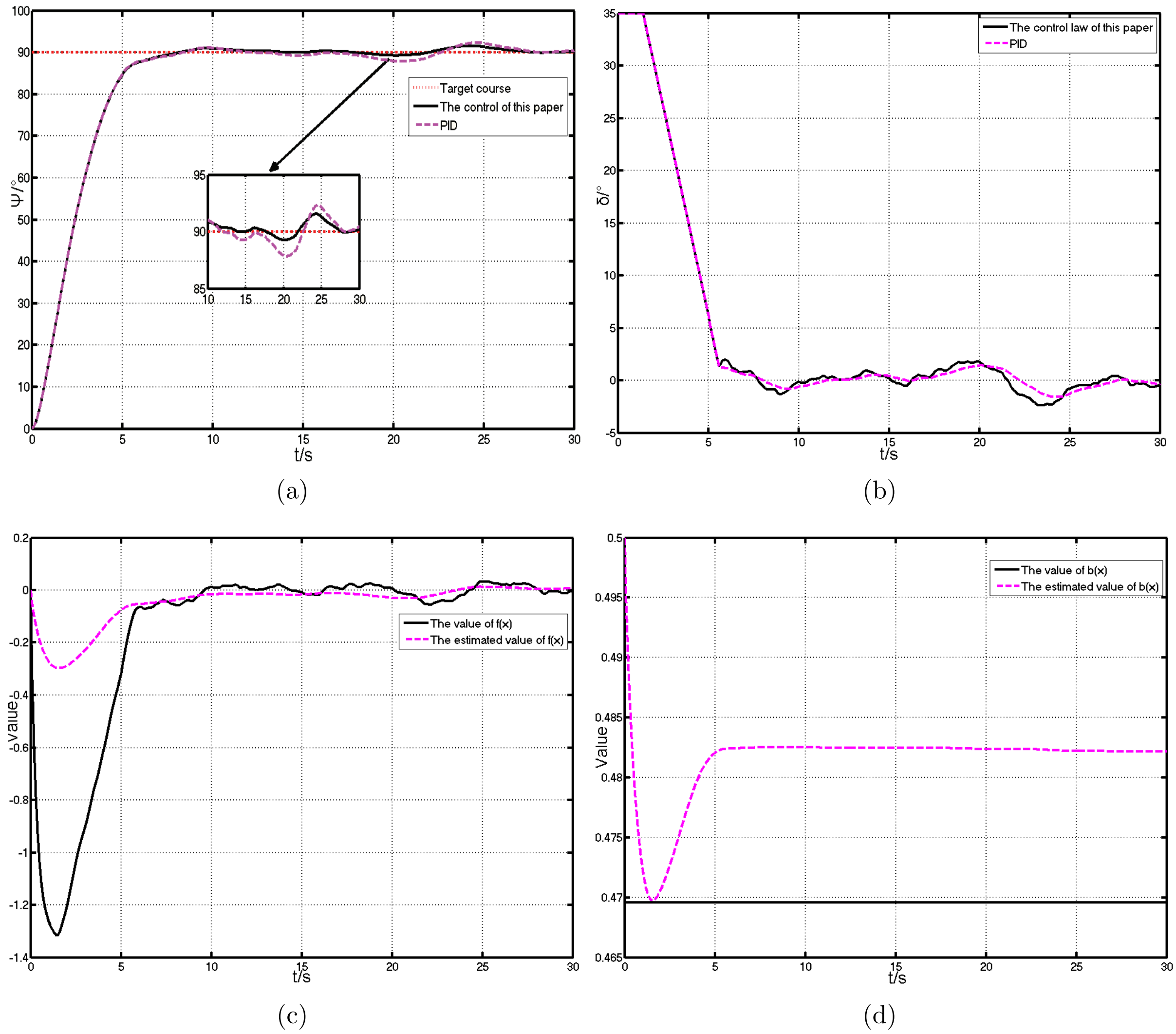

FIGURE 2. The simulation results of under external disturbance

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