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Robust Adaptive Fuzzy Design for Ship Linear-tracking Control with Input Saturation☆

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Abstract

A robust adaptive control approach is proposed for underactuated surface ship linear path-tracking control system based on the backstepping control method and Lyapunov stability theory. By employing T-S fuzzy system to approximate nonlinear uncertainties of the control system, the proposed scheme is developed by combining “dynamic surface control” (DSC) and “minimal learning parameter” (MLP) techniques. The substantial problems of “explosion of complexity” and “dimension curse” existed in the traditional backstepping technique are circumvented, and it is convenient to implement in applications. In addition, an auxiliary system is developed to deal with the effect of input saturation constraints. The control algorithm avoids the singularity problem of controller and guarantees the stability of the closed-loop system. The tracking error converges to an arbitrarily small neighborhood. Finally, MATLAB simulation results are given from an application case of Dalian Maritime University training ship to demonstrate the effectiveness of the proposed scheme.

Keywords: Underactuated surface ship, Path- tracking control, Fuzzy Control, DSC, MLP, Input Saturation

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1. Introduction

When a ship is travelling via way-points at a constant cruise speed, ship linear-path tracking control is of great importance to saving travelling time, distance and fuel in practice. So the path-following control is very suitable for practical engineering. Actually, ship motion control has always received considerable attention. Sutton et al. (1991, p. 35) applied the fuzzy theory to the field of ship course control. Due to strong approximation ability, the Fuzzy System is mainly used to approximate the unknown nonlinear uncertainties. The application of the Fuzzy system has promoted the development of ship motion control. Yang (2004, p.406) presented novel robust adaptive fuzzy control algorithms based on backstepping and small-gain approach.

However, with the increasing orders of control systems, the repeated derivatives of control laws in the design cause the problem of "computational expansion". Fortunately, Swaroop (1997, p. 3028) and Yip (1998, p.959) proposed the dynamic surface control (DSC) technique. By introducing the first order filter into traditional backstepping method, it simplifies the complexity of the controller. After that, the literatures (Wang, 2005, p. 195) and (Wang, 2009, p.16) applied this technique to nonlinear systems and uncertain nonlinear systems.

In practical application, the controller will inevitably be affected by the control input saturation and uncertain nonlinear characteristics. Aiming at nonlinear system, Hu (2001) proposed a nonlinear saturation compensation design algorithm. And then, the introduction of an auxiliary design in Chen (2009, p. 85), Li (2009) and Chwa (2011, p.1357) compensated the impact of input saturation constraints that existed in the ship's adaptive rudder input control. Li (2014, p.2299) considered input saturation in composite adaptive fuzzy control design for uncertain nonlinear strict-feedback systems. The well-known “dimension curse” is a substantial problem, which imposes that many parameters need to be tuned in the adaptive control schemes based on fuzzy or neural networks system. As we move to high dimensional systems, the learning time tends to become unacceptably large. In order to serve this problem, the paper (Li, 2011, p.2277) utilized MLP approach to reduce learning parameters and computation load, which is convenient to be implemented in applications.

In this paper, the dynamic surface control technique and MLP algorithm are combined to apply to ship's path-tracking control system with unknown nonlinear items. An adaptive fuzzy tracking control algorithm is proposed considering input saturation based on Lyapunov method, and guarantees the stability of the closed loop system.

2. Preliminaries

In this part, we briefly describe the structure of the T-S type fuzzy logic system. Generally, there are N rules in the fuzzy system, and each rule has the following form:

$\mathrm{R_j}$: If x_1 is h_1^j, AND x_2 is h_2^j, AND$\cdots$AND x_n is h_n^j, then y_j is $a^j x$,which is the function of $a_1^j x_1 + a_2^j x_2 + \cdots a_n^j x_n$.

a_i^j , $j = 1, 2, \cdots N$, $i = 1, 2, \cdots n$ are unknown constants, h_i^j is input variable, $a^j x$ is output variable.

The product fuzzy inference is used to evaluate the ANDs of the fuzzy rules. After being defuzzified by a typical center average defuzzifier, the output of the T-S fuzzy system is in the following vector form:

$$\hat{f}(x, A_x) = \xi(x) A_x x \tag{1}$$

where $\xi(x) = \left[\xi_1(x), \xi_2(x) \cdots \xi_N(x),\right]$.

The Fuzzy basis function $\xi_j(x)$ and vector A_x are as follows:

$$\xi(x) = \frac{\prod_{i=1}^{n} \mu_{h_i^j}(x_i)}{\sum_{j=1}^{N} \prod_{i=1}^{n} \mu_{h_i^j}(x_i)}, \quad A_x = \begin{bmatrix} a_{11} a_{12} \cdots a_{1n} \\ a_{21} a_{22} \cdots a_{2n} \\ \vdots \ \vdots \ \vdots \ \vdots \\ a_{N1} a_{N2} \cdots a_{Nn} \end{bmatrix} \tag{2}$$

where $\mu_{h_i^j}(x_i)$ is membership function.

The step steering operation is unable to realize in the actual process of handling the ship, so it is necessary to consider the rudder actuator dynamics, otherwise it will affect the performance of heading control.

The mathematical steering model is added to nonlinear ship mathematical model and can be expressed as follows:

$$T_E \dot{\delta} + \delta = K_E \delta_E \tag{3}$$

where δ_E is the command rudder angle, δ is the actual rudder angle, T_E is the time delay constant, and K_E is the control gain.

The ship course cannot be arbitrarily changed in the actual course control. Rudder angle and steering speed will be restricted. It is necessary to consider the rudder angle input, because the rudder angle has limitation of $|\delta| \le 35^\circ$.

3. Problem Formulation

Now we consider the nonlinear ship straight-line motion mathematical model with the rudder actuator dynamics:

$$\begin{cases} \dot{y} = U\, sin\psi, \\ \dot{\psi} = r, \\ \dot{r} = f(r) + g\delta, \\ \dot{\delta} = -(1/T_E)\delta + (K_E/T_E)\delta_E \end{cases} \tag{4}$$

where y is the sway displacement or cross-track distance, U is the cruise speed of ship, ψ is the heading angle, r is the yaw rate , $f(r)$ is an unknown nonlinear function of r, g is control gain.

In order to simplify the design, we employ the output redefinition by following coordinate transformation:

$$x_1 = \psi + arcsin\left(\frac{ky}{\sqrt{1+(ky)^2}}\right) \tag{5}$$

where $k > 0$ is a designed constant.

Then we can obtain

$$\begin{cases} \dot{x}_1 = f_1(\cdot) + g_1 x_2 + \Delta_1, \\ \dot{x}_2 = f_2(x_2) + g_2 x_3 + \Delta_2, \\ \dot{x}_3 = f_3(x_3) + g_3 u + \Delta_3, \end{cases} \tag{6}$$

where $x_2 = r, x_3 = \delta$, $g_1 = 1$, $g_2 = K/T$, $g_3 = K_E/T_E$,

$u = \delta_E$, $f_1(\cdot) = \dfrac{k}{1+(ky)^2} U\, sin\psi$, $f_2(x_2) = f(r)$,

$f_3(x_3) = -(1/T_E)\bar{x}_3$, $\Delta_i, i = 1,2,3$ denote unknown external disturbances.

Similar to (Li T S, 2005), given U and y, if the subsystem (6) above is stabilized, then the system (4) is also stabilized after the transformation.

Now, the control goal is to design an adaptive fuzzy controller making all signals of the closed-loop system uniformly ultimately bounded. The following assumptions are introduced to simplify the control design.

Assumption1 The reference signal $y_d(t)$ is a sufficiently smooth function of t and $y_d, \dot{y}_d, \ddot{y}_d$ are bounded, and there exists a positive constant B_0, such that $\prod_0 := \{(y_d, \dot{y}_d, \ddot{y}_d) : y_d^2 + \dot{y}_d^2 + \ddot{y}_d^2 \le B_0\}$.

Assumption 2 $f_i, i = 1,2,3$ are assumed to be unknown.

Assumption 3 $g_i(\cdot)$, $i = 1,2,3$ are confined within a certain range such as $g_{i1} \ge g_i(\bar{x}_i) \ge g_{i0} > 0, \forall \bar{x}_n \in \Omega \subset R^n$. g_{i0}, g_{i1} are the lower and upper bound. Without losing generality, we assume that $g_i(\bar{x}_i) \ge g_{i0} > 0$.

4. Controller Design

In this section, the design of adaptive fuzzy control is presented based on the DSC technique and MLP algorithm .Similar to the traditional backstepping method. There are 3 steps in recursive design procedure. At each step, the virtual controller $\alpha_{i+1}, i = 1,2$ shall be developed. Finally, an overall control law considering input saturation is conducted at the last step.

Step1: Define the first error variable $z_1 = x_1 - y_d$, one has

$$\dot{z}_1 = f_1 + x_2 - \dot{y}_d + \Delta_1 \tag{7}$$

The Fuzzy system is proposed to approximate an unknown continuous f_1 as:

$$f_1 = \xi_1(\bar{x}_1) A_1 \bar{x}_1^T + \varepsilon_1 = c_1 \xi_1 \omega_1 + d_1' \tag{8}$$

where $d_1' = \xi_1 A_1 y_d + \varepsilon_1$, let $c_1 = \|A_1\|$,the normalized term $A_1^m = A_1 / c_1$, $A_1^m \le 1$ and $\omega_1 = A_1^m \bar{z}_1$.

Let $\theta_1 = b_{\min}^{-1} \max(\|A_1 y_d\|, \|\varepsilon_1 + \Delta_1\|)$, $\psi_1 = 1 + \|\xi_1\|$, $d_1 = d_1' + \Delta_1$ has a bound such that

$$\|d_1\| \le \|A_1 y_d + \varepsilon_1\| \le b_{\min} \theta_1 \psi_1(x_1) \tag{9}$$

Substituting f_1 into $\dot{z}_1$, one has

$$\dot{z}_1 = c_1 \xi_1 \omega_1 + d_1 + x_2 - \dot{y}_d \tag{10}$$

Now choose a virtual control law α_2 for x_2 in the subsystem above.

$$\begin{aligned} \alpha_2 = &-k_1 z_1 + \dot{y}_d - \frac{\hat{\lambda}_1}{4\gamma_1^2} \xi_1(x_1) \xi_1^T(x_1) z_1 \\ &- \hat{\theta}_1 \psi_1(x_1) \tanh\left(\frac{\hat{\theta}_1 \psi_1(x_1) z_1}{\delta_1}\right) \end{aligned} \tag{11}$$

where $\lambda_1 = b_{\min}^{-1} c_1^2$, k_1 , γ_1 , δ_1 are positive design parameters; $\hat{\lambda}_1, \hat{\theta}_1$ are respectively the estimates of λ_1, θ_1. The update laws $\hat{\lambda}_1$, $\hat{\theta}_1$ will be designed later.

In order to avoid repeatedly differentiating α_2, we introduce the DSC technique firstly proposed in (Swaroop, 1997). Let α_2 pass through a first-order filter of β_2 with time constant τ_2, such that

$$\tau_2 \dot{\beta}_2 + \beta_2 = \alpha_2 \ , \ \beta_2(0) = \alpha_2(0) \tag{12}$$

Define the second error variable $z_2 = x_2 - \beta_2$, then

$$\dot{z}_1 = c_1 \xi_1 \omega_1 + d_1 + z_2 + \beta_2 - \dot{y}_d \tag{13}$$

The output error of the filter above can be defined as

$$\eta_2 = \beta_2 - \alpha_2 \tag{14}$$

Then $\dot{\beta}_2 = -\eta_2 / \tau_2$, then one obtains

$$\begin{aligned}\dot{\eta}_2 = \dot{\beta}_2 - \dot{\alpha}_2 &= -\frac{\eta_2}{\tau_2} + (-\frac{\partial \alpha_2}{\partial z_1}\dot{z}_1 - \frac{\partial \alpha_2}{\partial x_1}\dot{x}_1 - \frac{\partial \alpha_2}{\partial \hat{\lambda}_1}\dot{\hat{\lambda}}_1 - \frac{\partial \alpha_2}{\partial \hat{\theta}_1}\dot{\hat{\theta}}_1 - \frac{\partial \alpha_2}{\partial \dot{y}_d}\ddot{y}_d) \\ &= -\frac{\eta_2}{\tau_2} + B_2(z_1, z_2, \eta_2, \hat{\lambda}_1, \hat{\theta}_1, y_d, \dot{y}_d, \ddot{y}_d)\end{aligned} \tag{15}$$

where $B_2(\cdot)$ is a continuous function having a maximum value of M_2 (Chen, 2009).

Step 2 According to the second subsystem (11), one obtains

$$\dot{z}_2 = f_2 + g_2 x_3 - \dot{\beta}_2 + \Delta_2 \tag{16}$$

Similarly, the unknown function f_2 is approximated as follows:

$$f_2 = \xi_2(\bar{x}_2) A_2 \bar{x}_2^T + \varepsilon_2 = c_2 \xi_2 \omega_2 + d_2' \tag{17}$$

where $d_2' = \xi_2 A_2^1 y_d + \xi_2 A_2^2 \beta_j + \varepsilon_2$, let $c_2 = \|A_2\|$, $A_2^m = A_2 / c_2$, $A_2^m \le 1$, and $\omega_2 = A_2^m \bar{z}_2$.

Let $\theta_2 = b_{\min}^{-1} \max(\|A_2^1 y_d\|, \|A_2^2 \beta_2\|, \|\varepsilon_2 + \Delta_2\|)$, $\psi_2 = 1 + \|\xi_2\|$, then $d_2 = d_2' + \Delta_2$ has a bound such that

$$\|d_2\| \le \|A_2^1 y_d + A_2^2 \beta_2 + \varepsilon_2\| \le b_{\min} \theta_2 \psi_2 \tag{18}$$

Then one has

$$\dot{z}_2 = c_2 \xi_2 \omega_2 + d_2 + g_2 x_3 - \dot{\beta}_2 \tag{19}$$

Choose a virtual control law for x_3 in (19) as

$$\begin{aligned}\alpha_3 = &-k_2 z_2 + \dot{\eta}_2 - \frac{\hat{\lambda}_2}{4\gamma_2^2}\xi_2(\bar{x}_2)\xi_2^T(\bar{x}_2) z_2 \\ &-\hat{\theta}_2 \psi_2(\bar{x}_2)\tanh(\frac{\hat{\theta}_2 \psi_2(\bar{x}_2) z_2}{\delta_2})\end{aligned} \tag{20}$$

where $\lambda_2 = b_{\min}^{-1} c_2^2$, k_2 , γ_2 , δ_2 为are positive design parameter; $\hat{\lambda}_2$, $\hat{\theta}_2$ are the estimates of λ_2 , θ_2 respectively. The update control laws $\hat{\lambda}_2$, $\hat{\theta}_2$ will be designed later.

Following the same way, introduce a variable β_3 and let α_3 pass through a first-order filter of β_3 with time constant τ_3 as

$$\tau_3 \dot{\beta}_3 + \beta_3 = \alpha_3 \ , \ \beta_3(0) = \alpha_3(0) \tag{21}$$

Then defining $\eta_3 = \beta_3 - \alpha_3$, one obtains $\dot{\beta}_3 = -\eta_3 / \tau_3$, then

$$\begin{aligned}\dot{\eta}_3 = \dot{\beta}_3 - \dot{\alpha}_3 &= -\frac{\eta_3}{\tau_3} + (-\frac{\partial \alpha_3}{\partial z_2}\dot{z}_2 - \frac{\partial \alpha_3}{\partial \bar{x}_2}\dot{\bar{x}}_2 - \frac{\partial \alpha_3}{\partial \hat{\lambda}_2}\dot{\hat{\lambda}}_2 - \frac{\partial \alpha_3}{\partial \hat{\theta}_2}\dot{\hat{\theta}}_2 + \ddot{\beta}_2) \\ &= -\frac{\eta_3}{\tau_3} + B_3(\bar{z}_3, \eta_2, \eta_3 \bar{\hat{\lambda}}_2, \bar{\hat{\theta}}_2, y_d, \dot{y}_d, \ddot{y}_d)\end{aligned} \tag{22}$$

where $B_3(\cdot)$ is a continuous function having a maximum value of M_3.

Step 3: In this step, the final control law shall be given.

Define the last error variable $z_3 = x_3 - \beta_3$, then

$$\dot{z}_3 = f_3 + b_3 u - \dot{\beta}_3 + \Delta_3 \tag{23}$$

Similarly, using fuzzy system to approximate f_3, one has

$$f_3 = c_3 \xi_3 \omega_3 + d_3' \tag{24}$$

where $d_3' = \xi_3 A_3^1 y_d + \xi_3 \sum_{j=2}^{3} A_3^j \beta_j + \varepsilon_2$, let $A_3^m = A_3 / c_3$, $c_3 = \|A_3\|$, $A_3^m \le 1$ and $\omega_3 = A_3^m \bar{z}_3$.

Let $\theta_3 = b_{\min}^{-1} \max(\|A_3^1 y_d\|, \left\|\sum_{j=2}^{3} A_3^j \beta_j\right\|, \|\varepsilon_3 + \Delta_3\|)$ and $\psi_3 = 1 + \|\xi_3\|$, then $d_3 = d_3' + \Delta_3$ has a bound such that

$$\|d_3\| \le \left\|A_3^1 y_d + \sum_{j=2}^{3} A_3^j \beta_j + \varepsilon_3\right\| \le b_{\min} \theta_3 \psi_3 \tag{25}$$

Then, the derivation of z_3 is as follows

$$\dot{z}_3 = c_3 \xi_3 \omega_3 + d_3 + g_3 u - \dot{\beta}_3 \tag{26}$$

In order to consider the influence of the input saturation, an auxiliary design system is selected as follows:

$$\dot{e}=\begin{cases}-ke-\dfrac{f(\cdot)}{e^2}\cdot e+(u-v), & |e|\ge\varepsilon \\ 0, & |e|<\varepsilon\end{cases} \tag{27}$$

where $f(\cdot)=f(z_n,\Delta u)=|z_n\cdot\Delta u|+\frac{1}{2}\Delta u^2$, $\Delta u=u-v$, $k>0$, ε is a positive parameter, e is a variable introduced to reduce the input saturation effects in the system.

Then, one gets

$$\dot{z}_3=c_3\xi_3\omega_3+d_3+b_3(\Delta u+v)-\dot{\beta}_3 \tag{28}$$

Choose the final control input as

$$\begin{aligned}v=&-k_3z_3+\dot{\beta}_3-\frac{\hat{\lambda}_3}{4\gamma_3^2}\xi_3(\bar{x}_3)\xi_3^T(\bar{x}_3)z_3-\\&\hat{\theta}_3\psi_3(\bar{x}_3)\tanh\Big(\frac{\hat{\theta}_3\psi_3(\bar{x}_3)z_3}{\delta_3}\Big)+e\end{aligned} \tag{29}$$

where $\lambda_3=b_{\min}^{-1}c_3^2$, k_3 , γ_3 , δ_3 are positive design parameters; $\hat{\lambda}_3$, $\hat{\theta}_3$ are the estimates λ_3 , θ_3 respectively. Now it is time to conduct the update laws for $\hat{\lambda}_i$ and $\hat{\theta}_i$, $i=1,2,3$.

$$\begin{cases}\dot{\hat{\lambda}}_i=\Gamma_{i2}\left[\dfrac{1}{4\gamma_i^2}\xi_i(\bar{x}_i)\xi_i^T(\bar{x}_i)z_i^2-\sigma_{i2}(\hat{\lambda}_i-\lambda_i^0)\right]\\ \dot{\hat{\theta}}_i=\Gamma_{i1}\left[\Psi_i(\bar{x}_i)\|z_i\|-\sigma_{i1}(\hat{\theta}_i-\theta_i^0)\right]\end{cases} \tag{30}$$

where σ_{i1} , σ_{i2} , λ_i^0 , θ_i^0 are design parameters.

5. Stability Analysis

Select the Lyapunov function candidate as follows

$$\begin{aligned}V=&\frac{1}{2}\sum_{i=1}^{3}z_i^2+\frac{1}{2}\sum_{i=1}^{3}\left(\tilde{\theta}_i^{\mathrm{T}}b_{\min}\Gamma_{i2}^{-1}\tilde{\theta}_i+\tilde{\lambda}_i^{\mathrm{T}}b_{\min}\Gamma_{i1}^{-1}\tilde{\lambda}_i\right)\\&+\frac{1}{2}\sum_{i=1}^{2}\eta_{i+1}^2+\frac{1}{2}e^2\end{aligned} \tag{31}$$

where $\tilde{\theta}_i=\theta_i-\hat{\theta}_i$, $\tilde{\lambda}_i=\lambda_i-\hat{\lambda}_i$.

By mentioning $x_{i+1}=z_{i+1}+\beta_{i+1}$ and $x_{i+1}=z_{i+1}+\beta_{i+1}$. The time derivative of V is

$$\begin{aligned}\dot{V}=&\sum_{i=1}^{3}\left(z_i\dot{z}_i-\tilde{\theta}_i^{\mathrm{T}}b_{\min}\Gamma_{i2}^{-1}\dot{\hat{\theta}}_i-\tilde{\lambda}_i^{\mathrm{T}}b_{\min}\Gamma_{i2}^{-1}\dot{\hat{\lambda}}_i\right)+\sum_{i=1}^{2}\eta_{i+1}\dot{\eta}_{i+1}+e\dot{e}\\
\le&\sum_{i=1}^{2}\Bigg(-b_{\min}k_iz_i^2+c_i\xi_i(\bar{x}_i)\omega_iz_i+d_iz_i-b_{\min}\frac{\hat{\lambda}_i}{4\gamma_i^2}\xi_i(x_i)\xi_i^T(x_i)z_i^2\\
&-b_{\min}\tilde{\lambda}_i^{\mathrm{T}}(x_i)\Gamma_{i2}^{-1}\dot{\hat{\lambda}}_i+g_i\eta_{i+1}z_i+g_iz_{i+1}z_i-\tilde{\theta}_i^{\mathrm{T}}b_{\min}\Gamma_{i1}^{-1}\dot{\hat{\theta}}_i\\
&-g_i\hat{\theta}_i\psi_iz_i\tanh\Big(\frac{\hat{\theta}_i\psi_iz_i}{\delta_i}\Big)\Bigg)+\sum_{i=2}^{n}\left(g_i\dot{\beta}_iz_i-\dot{\beta}_iz_i\right)-b_{\min}k_3z_3^2+g_1\dot{y}_dz_1\\
&-\dot{y}_dz_1+b_3\xi_3(x)\omega_3z_3+d_iz_i-b_{\min}\frac{\hat{\lambda}_i}{4\gamma_i^2}\xi_i(x_i)\xi_i^T(x_i)z_i^2\\
&-b_{\min}\tilde{\lambda}_3^{\mathrm{T}}(x_3)\Gamma_{i2}^{-1}\dot{\hat{\lambda}}_3-\tilde{\theta}_3^{\mathrm{T}}b_{\min}\Gamma_{i1}^{-1}\dot{\hat{\theta}}_3-g_3\hat{\theta}_3\psi_3z_3\tanh\Big(\frac{\hat{\theta}_3\psi_3z_3}{\delta_3}\Big)\\
&+\sum_{i=1}^{n-1}\left(-\frac{\eta_{i+1}^2}{\tau_{i+1}}+|\eta_{i+1}B_{i+1}|\right)+z_3(e+\Delta u)+e\dot{e}\end{aligned} \tag{32}$$

It is worth to noting that

$$|AB|\le\frac{A^2}{4\gamma^2}+\gamma^2B^2 \tag{33}$$

$$\begin{aligned}c_i\xi_i\omega_iz_i\le&\frac{c_i^2}{4\gamma_i^2}\xi_i\xi^Tz_i^2+\gamma_i^2\omega_i^{\mathrm{T}}\omega_i\\ \le&\, b_{\min}\frac{\hat{\lambda}_i}{4\gamma_i^2}\xi_i\xi^Tz_i^2+b_{\min}\frac{\tilde{\lambda}_i}{4\gamma_i^2}\xi_i\xi^Tz_i^2+\gamma_i^2\omega_i^{\mathrm{T}}\omega_i\end{aligned} \tag{34}$$

$$\begin{aligned}d_iz_i\le&\, b_{\min}\hat{\theta}_i\psi_i(\bar{x}_i)\|z_i\|+b_{\min}\tilde{\theta}_i\psi_i(\bar{x}_i)\|z_i\|\\ \le&\, g_i\hat{\theta}_i\psi_i(\bar{x}_i)\|z_i\|+b_{\min}\tilde{\theta}_i\psi_i(\bar{x}_i)\|z_i\|\end{aligned} \tag{35}$$

$$\begin{aligned}g_1\dot{y}_dz_1-\dot{y}_dz_1\le&\frac{b_{\max}+1}{4}z_1^2+(b_{\max}+1)\dot{y}_d^2\\ \le&\frac{b_{\max}+1}{4}z_1^2+(b_{\max}+1)B_0^2\end{aligned} \tag{36}$$

$$\begin{aligned}g_i\dot{\beta}_iz_i-\dot{\beta}_iz_i\le&\, g_i\left|\dot{\beta}_iz_i\right|+\left|\dot{\beta}_iz_i\right|=(g_i+1)\left|\frac{\eta_i}{\tau_i}\right||z_i|\\ \le&\frac{b_{\max}+1}{\tau_i}z_i^2+\frac{b_{\max}+1}{4\tau_i}\eta_i^2\end{aligned} \tag{37}$$

According to (20), notice that

$$\begin{aligned}e\cdot\dot{e}=&-ke^2-\frac{|z_n\cdot\Delta u|+\frac{1}{2}\Delta u^2}{e^2}\cdot e^2+\Delta u\cdot e,\quad \Delta u\cdot e\\ \le&\frac{1}{2}\Delta u^2+\frac{1}{2}e^2\end{aligned} \tag{38}$$

$$\begin{aligned}z_3(e+\Delta u)+e\dot{e}\le&\, z_3e+z_3\Delta u+e\dot{e}\\ \le&\frac{1}{2}z_3^2+\frac{1}{2}e^2+z_3\Delta u-ke^2-|z_n\cdot\Delta u|\\ &-\frac{1}{2}\Delta u^2+\frac{1}{2}\Delta u^2+\frac{1}{2}e^2\\ \le&\frac{1}{2}z_3^2-(k-1)e^2\end{aligned} \tag{39}$$

Then $\dot{V}$ becomes

$$\begin{aligned}\dot{V} \le& -(b_{\min}k_1 - \frac{b_{\max}+1}{4})z_1^2 + \sum_{i=2}^{3}\left(-(b_{\min}k_i - \frac{b_{\max}+1}{\tau_i})z_i^2\right) \\ &+\frac{1}{2}z_3^2 - (k-1)e^2 + \sum_{i=1}^{3}\left(\begin{array}{l}\gamma_i^2\omega_i^{\mathrm{T}}\omega_i + b_{\min}\dfrac{\tilde{\lambda}_i}{4\gamma_i^2}\xi_i(x_i)\xi_i^T(x_i)z_i^2 \\ -b_{\min}\tilde{\lambda}_1^{\mathrm{T}}(x_i)\Gamma_{i2}^{-1}\dot{\hat{\lambda}}_i - \tilde{\theta}_i^{\mathrm{T}}b_{\min}\Gamma_{i1}^{-1}\dot{\hat{\theta}}_i\end{array}\right. \\ &\left.+b_{\min}\tilde{\theta}_i\psi_i(\bar{x}_i)\|z_i\| + g_i\hat{\theta}_i\psi_i(\bar{x}_i)\|z_i\| - g_i\hat{\theta}_i\psi_i z_i\tanh(\frac{\hat{\theta}_i\psi_i z_i}{\delta_i})\right) \\ &+\sum_{i=1}^{2}\left(g_i\eta_{i+1}z_i + g_i z_{i+1}z_i\right) + \sum_{i=2}^{3}\left(\frac{b_{\max}+1}{4\tau_i}\eta_i^2\right) \\ &+\sum_{i=1}^{2}\left(-\frac{\eta_{i+1}^2}{\tau_{i+1}} + |\eta_{i+1}B_{i+1}|\right) + (b_{\max}+1)B_0^2\end{aligned} \tag{40}$$

Notice

$g_i\hat{\theta}_i\psi_i(\bar{x}_i)\|z_i\| - g_i\hat{\theta}_i\psi_i z_i\tanh(\frac{\hat{\theta}_i\psi_i z_i}{\delta_i}) \le g_i\delta_i \le b_{\max}\delta_i$,

$g_i\eta_{i+1}z_i \le z_i^2 + (b_{\max}/4)\eta_{i+1}^2$, $g_i z_{i+1}z_i \le z_i^2 + (b_{\max}/4)z_{i+1}$.

Then it has

$$\begin{aligned}\dot{V} \le& -(b_{\min}k_1 - \frac{b_{\max}+1}{4} - 2)z_1^2 - (b_{\min}k_2 - \frac{b_{\max}+1}{\tau_2} - 2)z_2^2 \\ &-(b_{\min}k_3 - \frac{b_{\max}+1}{\tau_3} + \frac{b_{\max}+2}{4})z_3^2 \\ &+\sum_{i=1}^{3}\left(b_{\min}\tilde{\lambda}_i\Gamma_{i2}^{-1}\left(\frac{\Gamma_{i2}}{4\gamma_i^2}\xi_i(x_i)\xi_i^T(x_i)z_i^2 - \dot{\hat{\lambda}}_i\right)\right) \\ &+\sum_{i=1}^{3}\left(\tilde{\theta}_i^{\mathrm{T}}b_{\min}\Gamma_{i1}^{-1}\left(\Gamma_{i1}\psi_i(\bar{x}_i)\|z_i\| - \dot{\hat{\theta}}_i\right)\right) \\ &+\sum_{i=1}^{3}\left(\gamma_i^2\omega_i^{\mathrm{T}}\omega_i + b_{\max}\delta_i\right) + (b_{\max}+1)B_0^2 - (k-1)e^2 \\ &+\sum_{i=1}^{2}\left(\frac{b_{\max}}{4}\eta_{i+1}^2 - \frac{(3-b_{\max})\eta_{i+1}^2}{4\tau_{i+1}} + |\eta_{i+1}B_{i+1}|\right)\end{aligned} \tag{41}$$

Let $1/\tau_{i+1} = (3 - b_{\max}/4)^{-1}\left(b_{\max}/4 + M_{i+1}^2/2\alpha + \alpha_0\right)$, where α_0 and α are positive constants, M_{i+1} denotes the maximum value of B_{i+1} (Chen M, 2009, p.85).

Notice $\tilde{\theta}_i^{\mathrm{T}}(\hat{\theta}_i - \theta_i^0) \ge |\tilde{\theta}_i|^2/2 - (\theta_i^* - \theta_i^0)^2/2$ and $|\eta_{i+1}B_{i+1}| \le \eta_{i+1}^2 B_{i+1}^2/2\alpha + \alpha/2$.

Then

$$\begin{aligned}&\sum_{i=1}^{3}\left(b_{\min}\tilde{\lambda}_i\Gamma_{i2}^{-1}\left(\frac{\Gamma_{i2}}{4\gamma_i^2}\xi_i(x_i)\xi_i^T(x_i)z_i^2 - \dot{\hat{\lambda}}_i\right)\right) \\ &\le -\sum_{i=1}^{3}\left(\frac{\sigma_{i2}}{2\lambda_{\max}b_{\min}\Gamma_{i2}^{-1}}\tilde{\lambda}_i^T\Gamma_{i2}^{-1}\tilde{\lambda}_i - \frac{\sigma_{i2}(\lambda_i^* - \lambda_i^0)^2}{2}\right)\end{aligned} \tag{42}$$

$$\begin{aligned}&\sum_{i=1}^{3}\left(\tilde{\theta}_i^{\mathrm{T}}b_{\min}\Gamma_{i1}^{-1}\left(\Gamma_{i1}\psi_i(\bar{x}_i)\|z_i\| - \dot{\hat{\theta}}_i\right)\right) \\ &\le -\sum_{i=1}^{3}\left(\frac{\sigma_{i1}}{2\lambda_{\max}b_{\min}\Gamma_{i1}^{-1}}\tilde{\theta}_i^{\mathrm{T}}\Gamma_{i1}^{-1}\tilde{\theta}_i - \frac{\sigma_{i1}(\theta_i^* - \theta_i^0)^2}{2}\right)\end{aligned} \tag{43}$$

$$\begin{aligned}&\frac{b_{\max}}{4}\eta_{i+1}^2 - \frac{(3-b_{\max})\eta_{i+1}^2}{4\tau_{i+1}} + |\eta_{i+1}B_{i+1}| \\ &\le -\alpha_0\eta_{i+1}^2 - \left(1 - \frac{B_{i+1}^2}{M_{i+1}^2}\right)\frac{M_{i+1}^2\eta_{i+1}^2}{2\alpha} + \frac{\alpha}{2} \le -\alpha_0\eta_{i+1}^2 + \frac{\alpha}{2}\end{aligned} \tag{44}$$

Set $\sigma_{i1}/2\lambda_{\max}b_{\min}\Gamma_{i1}^{-1} = \sigma_{i2}/2\lambda_{\max}b_{\min}\Gamma_{i2}^{-1} = \alpha_0$, and choose the parameters as

$k_1 = \left(2 + (b_{\max}+1)/4 + \alpha_0\right)/b_{\min}$,

$k_2 = \left(2 + (b_{\max}+1)/\tau_2 + b_{\max}/4 + \alpha_0\right)/b_{\min}$,

$k_3 = \left((b_{\max}+1)/\tau_3 - (b_{\max}+2)/4 + \alpha_0\right)/b_{\min}$, then $\dot{V}$ can be expressed as

$$\begin{aligned}\dot{V} \le& -\alpha_0\sum_{i=1}^{3}z_i^2 - \alpha_0\sum_{i=1}^{3}\left(\tilde{\theta}_i^{\mathrm{T}}b\min\Gamma_{i1}^{-1}\tilde{\theta}_i + \tilde{\lambda}_i^T b\min\Gamma_{i2}^{-1}\tilde{\lambda}_i\right) \\ &-\alpha_0\sum_{i=1}^{2}\eta_{i+1}^2 + \sum_{i=1}^{3}\left(\gamma_i^2\omega_i^{\mathrm{T}}\omega_i\right) + \rho \le -2\alpha_0 V + \gamma^2\|\omega\|^2 + \rho\end{aligned} \tag{45}$$

where, $\gamma = (\gamma_1^2 + \gamma_2^2 + \gamma_3^2)$, $\omega = [\omega_1, \omega_2, \omega_3]^T$,

$$\rho = \sum_{i=1}^{3}\left(\begin{array}{l}(b_{\max}+1)B_0^2 + b_{\max}\delta_i + \dfrac{\sigma_{i2}(\lambda_i^* - \lambda_i^0)^2}{2} \\ +\dfrac{\sigma_{i1}(\theta_i^* - \theta_i^0)^2}{2}\end{array}\right) + \sum_{i=1}^{2}\alpha/2 .$$

Notice $\omega_i = A_i^m\bar{z}_i^T$, $A_i^m \le 1$, $i = 1,2,3$, then

$$\omega = \begin{bmatrix}w_1\\w_2\\w_3\end{bmatrix} = \begin{bmatrix}A_1^m & 0 & 0\\ A_2^{m1} & A_2^{m2} & 0\\ A_3^{m1} & A_3^{m2} & A_3^{m3}\end{bmatrix}\begin{bmatrix}z_1\\z_2\\z_3\end{bmatrix} = Az , \|\omega\| \le \|A\|\|z\| \le \|z\| \tag{46}$$

Choose $\gamma \ge 1$, one finally has

$$\dot{V} \le -2\alpha_0 V + \|\omega\|^2 + \rho \le c_1 V + \rho \tag{47}$$

where $c_1 = 2\alpha_0 - 1$. Then

$$V(t) = \frac{\rho}{c_1} + \left(V(t_0) - \frac{\rho}{c_1}\right)e^{-(t-t_0)}, \forall t \ge t_0 \ge 0 \tag{48}$$

It can be seen that all the solutions of the closed-loop system are bounded. For any $\mu_1 \geq (\rho / c_1)^{1/2}$ and $T \geq 0$, there exists $\|z_1(t) \leq \mu_i\|$ for all $t \geq t_0 + T$. By selecting the appropriate design parameters, ρ / c_1 can be arbitrarily small, thus the tracking error can be made as small as possible.

6. Simulation

In this section, simulation results are given on the base of an ocean-going training ship YULONG. The initial conditions are U=11Kn, $x_0 = 0m$, $y_0 = 500m$, $\psi_0 = -\pi / 18$, $r = 0$. The desired reference signal is $y_d = 0$. The heading rate has a limitation of $|\dot{\psi}(t)|_{\max} \leq 3^\circ /s$.

In simulation, we define five fuzzy sets for each variable with labels $A_{h_1^j}(NL)$, $A_{h_2^j}(NM)$, $A_{h_3^j}(ZE)$, $A_{h_4^j}(PM)$, $A_{h_5^j}(PL)$ which are characterized by the following membership functions

$$\mu_{h_1^j} = \exp\left[-(x+1)^2\right], \quad \mu_{h_5^j} = \exp\left[-(x-1)^2\right],$$

$$\mu_{h_2^j} = \exp\left[-(x+0.5)^2\right], \quad \mu_{h_4^j} = \exp\left[-(x-0.5)^2\right],$$

$$\mu_{h_3^j} = \exp\left[-x^2\right].$$

Choose the design parameters as $k = 0.02$, $k_1 = 0.5$, $k_2 = 2.5$, $k_2 = 2.5$, $\tau_2 = \tau_3 = 0.25$, $\Gamma_{i1}=\Gamma_{i2}=2$, $\sigma_i = 0.05$, $\gamma_i = 3$, $\hat{\theta}_i^0 = 0$, $\hat{\lambda}_i^0 = 0$, the initial value $e = 0.1$. The external disturbance signals are chosen as $\Delta_2 = 0.001*(1+sin(0.1*t))$, $\Delta_1 = \Delta_3 = 0$.

Simulation results are shown as follows:

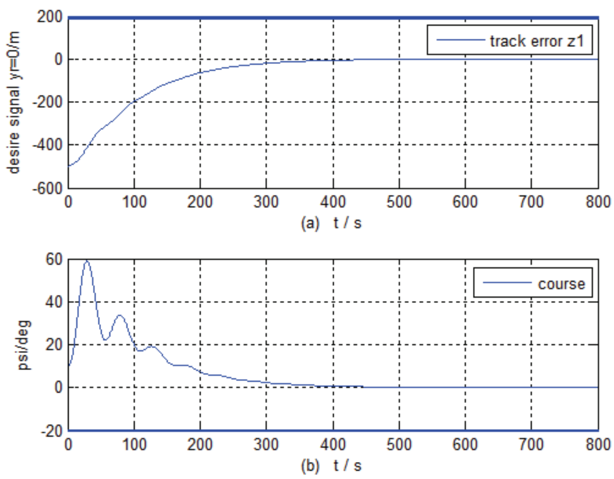

Figure 1 Time curves of tracking distance and course

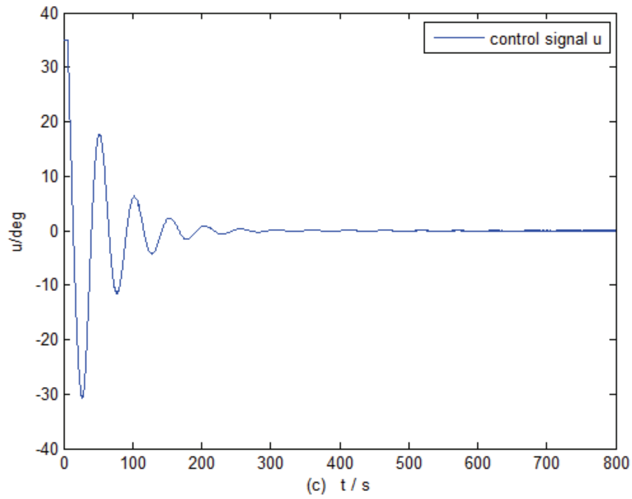

Figure 2 Time curve of command rudder angle

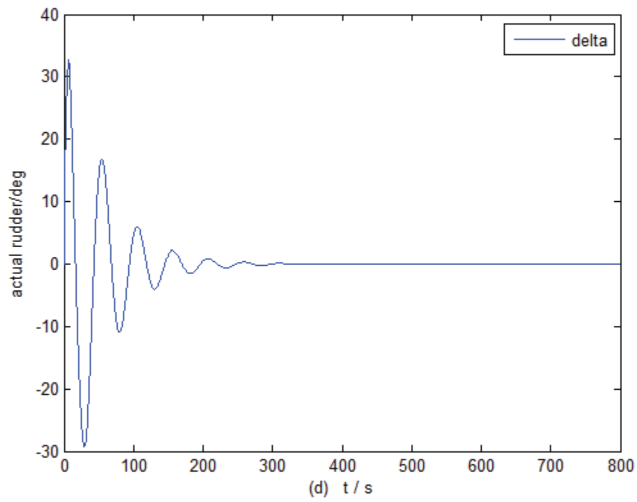

Figure 3 Time curve of actual rudder angle

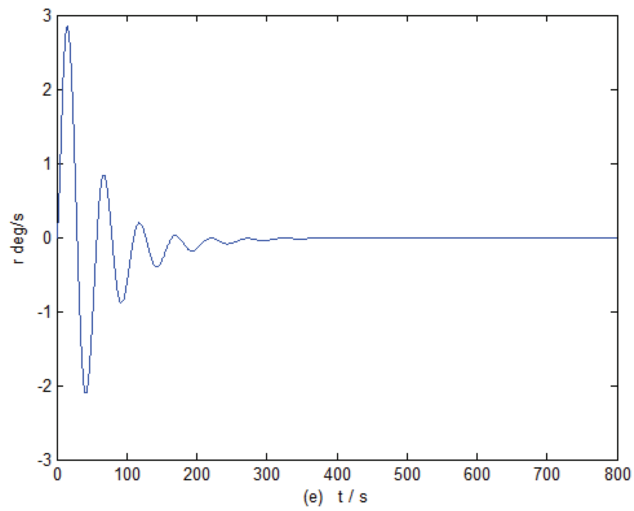

Figure 4 Time curve of course rate (heading rate)

In the simulation figures, Fig(a) is the curve of ship path-tracking distance. It can be seen that the distance error is almost zero at the time of 400s which indicates the effect of the path-tracking control; Fig(b) is the course, Fig(c) is command rudder angle of ship.

We can see from the figure that the controller has fast response speed; Fig(d) is actual rudder angle of ship; Fig(e) is course rate of ship. In fact, course rate is restrained by a maximum of $|\dot{\psi}(t)|_{\max} = 3^{\circ}/\mathrm{s}$ and the autopilot is restrained by the maximum rudder angle $|\delta|_{\max} = 35^{\circ}$. Obviously， all signals are reasonable in tracking a desired trajectory achieved by the scheme proposed in this paper.

7. Conclusion

This paper has discussed the problem of linear path-tracking control for an underactuated surface vessel with rudder actuator dynamics and input saturation. An adaptive fuzzy control algorithm is constructed with the combination of DSC technology and MLP approach, which greatly reduces the complexity of the controller. The fuzzy approximation system improves the robustness for unknown nonlinear functions. This proposed scheme has a good control performance in following a desired path, and guarantees the stability of the closed-loop system. Simulation results validate the effectiveness of this proposed scheme.

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