Observer-based adaptive fuzzy prescribed performance control for intelligent ship autopilot

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ABSTRACT
In this paper, the algorithm design problem of intelligent ship autopilot with an unmeasured yaw rate is investigated based on adaptive fuzzy control. The fuzzy logic system (FLS) is employed to approximate the unknown function, and a fuzzy state observer is designed to estimate the unmeasured state. To achieve the specified performance constraints, the error transformed method is introduced. Based on adaptive backstepping method, an observer-based adaptive fuzzy output-feedback control scheme is developed. The proposed control scheme can reduce the conservativeness and the complexity of controller. It is proved that all the signals in the closed-loop system are bounded via Lyapunov theory. The efficacy of theoretical results is demonstrated by the simulations.

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1. Introduction
Autopilot is one of the most paramount navigation systems for intelligent ship, which has been played an important role in navigation safety, energy cost and intensity of crew, and so on. Since then, the intelligent ship autopilot problems have received considerable attention, such as, model reference control (Yang, 2003), optimal constrained control (Johansen et al., 2008), and active disturbance rejection control (R. Li et al., 2018). Ship heading control, i.e. the design of autopilot algorithm, becomes the first problem to be solved. A study on an active disturbance rejection controller was developed for a ship heading control by R. Li et al. (2018). It should be noted that these studies were developed by using the state-feedback approaches and all states were assumed to be measurable. Unfortunately, in the real-world engineering problems, such as intelligent ship heading control, it is not easy to obtain complete state knowledge.

In fact, the practical applications often desire that the control is able to deal with unknown state information of the system. A major concern about output feedback today is to lessen the assumption that all states are measurable. In ship autopilot, the ultimate goal of the output feedback is to allow utilizing the existing unique output information to design the autopilot controller. Many results have been reported recently in related fields. In Y. Zheng et al. (2010), a full-state observer was designed to estimate system state without the variance information of wave disturbance, and the parameters of the observer were obtained by LMI. In Peng and Hu (2013), an adaptive nonlinear output feedback control scheme was developed for ship autopilot under various sea conditions. In Z. Zheng et al. (2017), a path following control scheme was presented for surface vessel, and the actuator input saturation was considered. The control approaches did not require any restrictive assumptions that all the system states must be measurable. It should be mentioned that all the above schemes have not paid more attention to the transient and steady state tracking performance.

For navigation manoeuvring control design, the tracking error is only required to converge to a small residual set, while practical applications often require a certain specified performance. In Si and Dong (2017), the problem of the tracking control with predefined performance for marine surface vessels was solved. In Dai et al. (2016), based on an error transformation function, the constrained tracking control of marine surface vessel was transformed into the stabilization of an unconstrained system. However, in the marine field, when intelligent ship execute task with unmeasurable yaw rate state, how to achieve a appreciate prescribed performance needs further thinking.

In this study, adaptive fuzzy output feedback prescribed performance control scheme is developed for
intelligent ship autopilot with the unmeasured yaw rate. Compared with the previous intelligent ship autopilot control methods, the contributions of this study are in two ways: (1) Based on a state observer, the designed adaptive fuzzy control scheme can solve the yaw rate unmeasurable problem. (2) The designed fuzzy adaptive control scheme for intelligent ship autopilot can ensure the ship heading converge to the specified region with prescribed performance. Hence, there is a variety of obstacles and challenges in this paper.

2. Problems description and preliminaries

2.1. Mathematical model of ship heading control

Consider the mathematical model of ship heading control as T. Li et al. (2010)

\[
\dot{\phi} + \frac{1}{T}H(\phi) = \frac{K}{T}\delta
\]

(1)

where \(\phi\) is the ship heading angle, \(\delta\) is the rudder angle, i.e. it is the control input, \(K\) is the rudder gain, \(T\) is the time constant, \(H(\phi)\) is an unknown nonlinear function of \(\phi\). Since \(H(\phi)\) can be obtained from the experiment called ‘apiral test’ with the form of \(H(\phi) = a_1\phi + a_2\phi^3 + a_3\phi^5 + \cdots\), \(a_i\) \((i = 1, 2, 3, \ldots)\) are real valued constants.

By defining \(x_1 = \phi, x_2 = \dot{\phi}\) and \(u = KS/T\), the ship heading control model (1) can be transformed into the state space form

\[
\begin{align*}
\dot{x}_1 &= x_2 \\
\dot{x}_2 &= f(x_2) + u \\
y &= x_1
\end{align*}
\]

(2)

where \(x_1, x_2\) are state variables of the system, \(u\) and \(y\) are control input and output, respectively. Obviously, \(f(x_2) = (−1/T)H(x_2)\) is also an unknown smooth nonlinear function, it satisfies Lipschitz condition, and there is a known constant \(l\) such that \(|f(x_2) − f(\hat{x}_2)| \leq |x_2 − \hat{x}_2|\), where \(\hat{x}_2\) is the estimation of \(x_2\). In the real-world engineering problems, ship heading angle is available, and yaw rate is formidable to measure, consequently, \(x_2\) is assumed to be unmeasurable in this paper.

Assumption 2.1 (Wang, 1993): For any \(t \geq 0\), reference ship heading signal \(y_r\) and its time derivatives \(\dot{y}_r\) and \(\ddot{y}_r\) are known and bounded.

Control objective: For the ship heading system (1) with an unmeasured yaw rate, design a prescribed performance controller such that all the signals involved in the closed-loop system are bounded, and the ship heading can track the reference signal \(y_r\) as desired.

2.2. Prescribed performance

The prescribed performance can be described by the following inequality (Bechlioulis & Rovithakis, 2009, 2014):

\[-\delta_{\text{min}}\mu(t) < s(t) < \delta_{\text{max}}\mu(t), \quad \forall t > 0\]

(3)

where \(\mu(t) = (\mu_0 - \mu_{\infty})e^{-\alpha t} + \mu_{\infty}\), \(\delta_{\text{min}}, \delta_{\text{max}}, a, \mu_{\infty}\) are positive design parameters, \(\mu_0 = \mu(0), \mu_0\) is selected such that \(\mu_0 > \mu_{\infty}, \delta_{\text{min}}\mu(0) < s(0) < \delta_{\text{max}}\mu(0)\). It follows from (3) that \(s(t)\) is guaranteed to be less than \(\max(\delta_{\text{min}}\mu(0), \delta_{\text{max}}\mu(0))\), the performance bounds of the error \(s(t)\) can be determined by appropriately choosing the performance function \(\mu(t)\) and the parameters \(\delta_{\text{min}}, \delta_{\text{max}}\).

2.3. Fuzzy logic systems

Lemma 2.1 (Wang, 1993): Let \(f(x)\) be a continuous function defined over a compact set \(\Omega\). Then for any constant \(\epsilon > 0\), there exists an FLS \(\theta^T\psi(x)\) such that

\[
\left\{\sup_{x \in \Omega} |f(x) - \theta^T \psi(x)| \right\} \leq \epsilon
\]

(4)

where \(\theta^* = [\theta_1, \theta_2, \ldots, \theta_N]^T\) is the ideal weight vector. Assume that \(\theta^*\) is unknown but bounded and satisfies \(\|\theta^*\| \leq \tilde{\theta}\) with \(\tilde{\theta} > 0\) being an unknown constant, \(\epsilon\) is the fuzzy minimum approximation error, and there is a positive constant \(\tilde{\epsilon}\) such that \(|\epsilon| \leq \tilde{\epsilon}\). \(N > 1\) is the number of fuzzy rules, fuzzy basic function vector is \(\psi(x) = [\psi_1(x), \psi_2(x), \ldots, \psi_N(x)]^T / \sum_{i=1}^{N} \psi_i(x)\) with the property

\[0 < \psi^T(x)\psi(x) \leq 1, \psi_i(x)\]

is selected as Gaussian function such that

\[
\psi_i(x) = \exp \left[ -\frac{(x - \mu_i)^T(x - \mu_i)}{\eta_i^2} \right]
\]

where \(\mu_i\) and \(\eta_i\) are the centres vector and width of Gaussian function, respectively.

3. Fuzzy state observer-based adaptive controller design

3.1. Fuzzy state observer design

In practice, the yaw rate signal in the intelligent ship may not be available in many cases, and the state observer is introduced to estimate the yaw rate information. In this section, the only available signal of plant (2) is \(y = x_1\), and state observer is served to estimate the unknown yaw rate.


Design the adaptive fuzzy observer as
\[
\begin{align*}
\dot{x}_1 &= \dot{x}_2 + m_1(y - \dot{x}_1) \\
\dot{x}_2 &= u + \theta^T \varphi(x_2) + m_2(y - \dot{x}_1)
\end{align*}
\]  
where \( m_1 > 0 \) and \( m_2 > 0 \) are design parameters, \( \dot{x}_1 \) is the estimation of \( x_1 \), \( \dot{x}_2 \) is the estimation of \( x_2 \), \( \dot{\theta} \) is the estimation of \( \dot{\theta} \).

Rewritten (5) as
\[
\begin{align*}
\dot{\hat{x}} &= A\hat{x} + My + B\dot{\theta}^T \varphi(\hat{x}_2) + Bu \\
\dot{y} &= C^T \hat{x}
\end{align*}
\]  
where \( \hat{x} = [\hat{x}_1, \hat{x}_2]^T \), \( A = \begin{bmatrix} -m_1 & 1 \\ -m_2 & 0 \end{bmatrix} \), \( M = [m_1, m_2]^T \), \( C = [1, 0]^T \), \( B = [0, 1]^T \).

Choose a vector \( M \) to make \( A \) be strict Hurwitz. Thus, given a matrix \( Q = Q^T > 0 \) there exists a matrix \( P = P^T > 0 \) such that
\[
A^T P + PA = -Q
\]

Now, by adding and subtracting \( f(x_2) \) on the right side of the second subsystem in (2), system (2) can be transformed as
\[
\begin{align*}
\dot{x}_1 &= x_2 \\
\dot{x}_2 &= f(\hat{x}_2) + \Delta f + u \\
\dot{y} &= x_1
\end{align*}
\]  
where \( \Delta f = f(x_2) - f(\hat{x}_2) \).

Since \( f(\hat{x}_2) \) is an unknown function, by Lemma 2.1, \( f(\hat{x}_2) \) in (8) can be estimated by the FLS. Let
\[
f(\hat{x}_2) = \theta^T \varphi(\hat{x}_2) + \varepsilon
\]
where \( \varepsilon \) is the estimation error.

Define the observer errors vector as \( e = [e_1, e_2]^T = x - \hat{x} \). According to (5) and (8), the dynamics of the observer errors can be obtained
\[
\dot{e} = Ae + \varepsilon + \Delta F + B\dot{\theta}^T \varphi(\hat{x}_2)
\]
where \( \varepsilon = [0, \varepsilon]^T \), \( \Delta F = [0, \Delta F]^T \), \( \dot{\theta} = \dot{\theta}^* - \dot{\theta} \).

Choose the Lyapunov function candidate \( V_0 = e^T Pe \), the time derivative of \( V_0 \) is
\[
\dot{V}_0 = -e^T Qe + 2e^T P[e + \Delta F + B\dot{\theta}^T \varphi(\hat{x}_2)]
\]
Applying Young’s inequality yields
\[
\begin{align*}
2e^T Pe &\leq ||e||^2 + ||P||^2 ||e||^2 \\
2e^T P \Delta F &\leq ||e||^2 + ||P||^2 ||e||^2 \\
2e^T PB\dot{\theta}^T \varphi(\hat{x}_2) &\leq ||e||^2 + ||P||^2 ||\dot{\theta}||^2
\end{align*}
\]  
Substituting (12)–(14) into (11) results in
\[
\dot{V}_0 \leq -\lambda_0 ||e||^2 + ||P||^2 ||\dot{\theta}||^2 + D_0
\]
where \( \lambda_0 = \lambda_{\min}(Q) - 3 - ||P||^2 \rho^2, D_0 = ||P||^2 \rho^2 \).

### 3.2. Adaptive controller design and stability analysis

In this section, the prescribed performance controller will be designed based on the following change of coordinates
\[
\begin{align*}
s &= y - y_r \\
z_2 &= \dot{x}_2 - r \\
\chi &= r - \alpha_1
\end{align*}
\]  
where \( z_2 \) is the virtual error surface, \( r \) is a state variable, \( \alpha_1 \) is the intermediate control function, \( \chi \) is the error between \( r \) and \( \alpha_1 \). To achieve (3), one can transform the constrained tracking error behaviour into an equivalent unconstrained state. Define the following equation
\[
s(t) = \mu(t) H(\zeta(t)), \quad \forall t > 0
\]
where \( \zeta \) is the transformed error and \( H(\zeta) = (\delta_{\max}e^\zeta - \delta_{\min}e^{-\zeta})/(e^\zeta + e^{-\zeta}) \) is a smooth, strictly increasing function, then one can obtain \( \partial H/\partial \zeta = 2(\delta_{\max} + \delta_{\min})/(e^\zeta + e^{-\zeta})^2 > 0 \), from the definition of \( H(\zeta(t)) \) and (17) one can get
\[
\zeta(t) = H^{-1}\left(\frac{s(t)}{\mu(t)}\right) = \frac{1}{2} \ln \frac{H + \delta_{\min}}{H - \delta_{\max}}
\]
\[
\dot{\zeta}(t) = \frac{1}{2} \left[ \frac{1}{H + \delta_{\min}} - \frac{1}{H - \delta_{\max}} \right] \dot{H}
\]
\[
= \frac{1}{2} \left[ \frac{1}{H + \delta_{\min}} - \frac{1}{H - \delta_{\max}} \right] \left( \frac{\dot{s} \mu - s \dot{\mu}}{\mu^2} \right)
\]
where \( h = \frac{1}{2} \left[ \frac{1}{H + \delta_{\min}} - \frac{1}{H - \delta_{\max}} \right] \), define the following state transformation
\[
z_1(t) = \zeta(t) - \frac{1}{2} \ln \frac{\delta_{\min}}{\delta_{\max}}
\]
Then one can get
\[
\dot{z}_1(t) = h \left( \dot{s}(t) - \frac{s(t) \dot{\mu}}{\mu} \right)
\]
According to the reference Bechlioulis and Rovithakis (2009), one can obtain that if \( z_1(t) \) is bounded, then the prescribed performance as shown in (16) of \( s(t) \) is satisfied. Design the backstepping controller of ship autopilot as follows.
Step 1: It follows from (5), (16) and \( x_2 = \dot{x}_2 + e_2 \), the time derivative of \( z_1 \) is

\[
\dot{z}_1 = h \left( x_2 - \dot{y}_r - \frac{s_j}{\mu} \right) \\
= h \left( z_2 + \dot{\chi} + \alpha_1 + e_2 - \dot{y}_r - \frac{s_j}{\mu} \right) \tag{22}
\]

Choose the candidate Lyapunov function \( V_1 \) as

\[
V_1 = V_0 + \frac{1}{2} z_2^2 \tag{23}
\]

It follows from (8), (15), (16), (22) and (23), the time derivative of \( V_1 \) satisfies

\[
\dot{V}_1 \leq -\lambda_0 \| e \|^2 + \| P \|^2 \hat{\theta}^T \hat{\theta} + D_0 \\
+ z_1 h \left( \frac{3}{2} \| h \frac{1}{2} h^T + \frac{1}{2} X^2 + \frac{1}{2} \| e \|^2 \right) \tag{24}
\]

Applying Young’s inequality yields

\[
z_1 h z_2 + z_1 h \dot{\chi} + z_1 h e_2 \leq \frac{3}{2} z_1^2 h^2 + \frac{1}{2} z_2^2 + \frac{1}{2} X^2 + \frac{1}{2} \| e \|^2 \tag{25}
\]

Substituting (25) into (24) yields

\[
\dot{V}_1 \leq -\lambda_1 \| e \|^2 + \| P \|^2 \hat{\theta}^T \hat{\theta} + D_0 \\
+ z_1 h \left( \frac{3}{2} z_1 + \dot{\alpha}_1 - \dot{y}_r - \frac{s_j}{\mu} \right) + \frac{1}{2} z_2^2 + \frac{1}{2} X^2 \tag{26}
\]

where \( \lambda_1 = \lambda_0 - \frac{1}{2} \).

Design the intermediate control function \( \alpha_1 \) as

\[
\alpha_1 = -\frac{c_1 z_1}{h} - \frac{3}{2} z_1 h + \dot{y}_r + \frac{s_j}{\mu} \tag{27}
\]

where \( c_1 > 0 \) is a design parameter.

Substituting (27) into (26) yields

\[
\dot{V}_1 \leq -\lambda_1 \| e \|^2 + \| P \|^2 \hat{\theta}^T \hat{\theta} \\
- c_1 z_1^2 + \frac{1}{2} z_2^2 + \frac{1}{2} X^2 + D_0 \tag{28}
\]

Define the following first-order filter to avoid repeatedly differentiating \( \alpha_1 \)

\[
\begin{align*}
\tau \dot{r} + r &= \alpha_1 \\
\tau (0) &= \alpha_1 (0) \tag{29}
\end{align*}
\]

where \( \tau > 0 \) is a design parameter.

It follows from (16) that

\[
\begin{align*}
\dot{r} &= -\frac{X}{\tau} \\
\dot{\chi} &= \dot{r} - \alpha_1 = -\frac{X}{\tau} + Y (\cdot) \tag{30}
\end{align*}
\]

where \( Y (\cdot) = \frac{d(\alpha_1)}{dr} + \frac{3}{2} \dot{z}_1 h + \frac{3}{2} X - \frac{\mu}{\mu} \)

Step 2: From (5) and (16), one has

\[
\dot{z}_2 = \dot{x}_2 - \dot{r} \\
= m_2 e_1 + \hat{\theta}^T \varphi (\dot{x}_2) + u - \dot{r} \tag{31}
\]

Choose the Lyapunov function \( V \) as

\[
V = V_1 + \frac{1}{2} z_2^2 + \frac{1}{2} X^2 + \frac{1}{2} \hat{\theta}^T \hat{\theta} \tag{32}
\]

Along the solution of (16), (22), (28), (31) and (32), the derivative of \( V \) can be expressed as

\[
\dot{V} = \dot{V}_1 + z_2 \dot{z}_2 + \chi \dot{\chi} + \frac{1}{2} \hat{\theta}^T \dot{\hat{\theta}} \\
= \dot{V}_1 + z_2 [m_2 e_1 + \hat{\theta}^T \varphi (\dot{x}_2) + \hat{\theta}^T \varphi (\dot{x}_2)] \\
- \hat{\theta}^T \varphi (\dot{x}_2) + u - \dot{r} + \chi \left[ -\frac{X}{\tau} + Y (\cdot) \right] + \frac{1}{2} \hat{\theta}^T \dot{\hat{\theta}} \\
\leq -\lambda_1 \| e \|^2 + \| P \|^2 \hat{\theta}^T \hat{\theta} - c_1 z_2^2 + \frac{1}{2} X^2 + \frac{1}{2} \hat{\theta}^T \hat{\theta} \\
+ z_2 [m_2 e_1 + \hat{\theta}^T \varphi (\dot{x}_2) + \hat{\theta}^T \varphi (\dot{x}_2)] - \hat{\theta}^T \varphi (\dot{x}_2) \\
+ u - \dot{r} + \chi \left[ -\frac{X}{\tau} + Y (\cdot) \right] + \frac{1}{2} \hat{\theta}^T \dot{\hat{\theta}} + D_0 \tag{33}
\]

Applying Young’s inequality again yields

\[
- z_2 \hat{\theta}^T \varphi (\dot{x}_2) \leq \frac{1}{2} z_2^2 + \frac{1}{2} \hat{\theta}^T \hat{\theta} \tag{34}
\]

By substituting (34) into (33) yields

\[
\dot{V} \leq -\lambda_1 \| e \|^2 + \| P \|^2 \hat{\theta}^T \hat{\theta} - c_1 z_2^2 + \frac{1}{2} X^2 \\
+ \frac{1}{2} \hat{\theta}^T \hat{\theta} + z_2 [m_2 e_1 + \frac{1}{4} z_2] \\
+ \hat{\theta}^T \varphi (\dot{x}_2) + \hat{\theta}^T \varphi (\dot{x}_2) + u - \dot{r} \\
+ \chi \left[ -\frac{X}{\tau} + Y (\cdot) \right] + \frac{1}{2} \hat{\theta}^T \dot{\hat{\theta}} + D_0 \tag{35}
\]

Design the actual controller \( u \) and the parameter adaptive law of \( \dot{\hat{\theta}} \) as

\[
u = -m_2 e_1 - \left( c_2 + \frac{1}{4} \right) z_2 - \hat{\theta}^T \varphi (\dot{x}_2) + \dot{r} \tag{36}
\]

\[
\dot{\hat{\theta}} = \gamma z_2 \varphi (\dot{x}_2) - \sigma \dot{\theta} \tag{37}
\]

where \( c_2 > 0 \), \( \gamma > 0 \), \( \sigma > 0 \) are design parameters.
From (15), (32) and (33), by substituting (36)–(37) into (35) yields
\[ \dot{V} \leq -\lambda_1 \| e \|^2 + \| P \|^2 \dot{\theta}^T \dot{\theta} - c_1 z_1^2 - c_2 z_2^2 + \frac{1}{\tau} - \frac{\bar{Y}^2}{2\pi} \chi^2 + \left(1 - \frac{\sigma}{2\gamma} + \| P \|^2 \right) \dot{\theta}^T \dot{\theta} + D _0 \] (38)
Using Young’s inequality, one has
\[ \chi Y (\cdot) \leq \frac{\chi^2 Y^2 (\cdot)}{2\pi} + 2\pi \] (39)
\[ \frac{\sigma}{\gamma} \dot{\theta}^T \dot{\theta} = \frac{\sigma}{\gamma} \dot{\theta}^T (\dot{\theta}^T - \ddot{\theta}) \leq -\frac{\sigma}{2\gamma} \dot{\theta}^T \dot{\theta} + \frac{\sigma}{2\gamma} \dot{\theta}^2 \] (40)
Substituting (39) and (40) into (38) yields
\[ \dot{V} \leq -\lambda_1 \| e \|^2 + \| P \|^2 \dot{\theta}^T \dot{\theta} - c_1 z_1^2 - c_2 z_2^2 + \frac{1}{\tau} - \frac{\bar{Y}^2}{2\pi} \chi^2 + \left(1 - \frac{\sigma}{2\gamma} + \| P \|^2 \right) \dot{\theta}^T \dot{\theta} + D \] (41)
where \( \pi > 0, D = D_0 + \frac{\sigma}{2\gamma} \dot{\theta}^2 + 2\pi \).
Assume that \( A(t) = 2e^T Pe + z_1^2 + z_2^2 + \ddot{\theta}^2 + \chi^2 \), and for a given \( d > 0 \), all initial conditions satisfy \( A(t) < d \). For any \( W_0 \) and \( d \), the sets \( Y_0 := \{ (y, \dot{y}, \ddot{y}) : y^2 + \dot{y}^2 + \ddot{y}^2 \leq W_0 \} \) and \( \Pi := \{ A(t) \leq d \} \) are compacts in \( R^3 \) and \( R \), respectively, and thus, set \( Y \times Y_0 \) is also compact in \( R^4 \).
Since \( Y (\cdot) \) is a continuous function, there exists a positive constant \( \bar{Y} \) such that \( | Y(\cdot) | \leq \bar{Y} \) on \( Y_0 \times Y_0 \). Then (41) can be rewritten as
\[ \dot{V} \leq -\lambda_1 \| e \|^2 - c_1 z_1^2 - c_2 z_2^2 \]
From (42), it can be shown that \( x_1, \dot{x}_1, x_2, \dot{x}_2, e, z_1, z_2 \) and \( \dot{\theta} \) are bounded. From (3), one can obtain that \( | s(t) | \leq \max(\delta_{\min} \mu_0, \delta_{\max} \mu_0) \), where \( \delta_{\min} \) and \( \delta_{\max} \) are design parameters. Moreover, according to reference Tong et al. (2018, 2020), one can make the observer, tracking and estimation errors to be small by suitable design parameters \( m_1, m_2, c_1, c_2, \tau, \pi \) and \( y \). Therefore, the design parameters should be selected properly for achieving the desired transient performance and control objective.
The above-mentioned analysis and control design can be summarized in Theorem 3.1.

**Theorem 3.1:** For ship heading model (1) with unmeasured yaw rate, under Assumption 2.1 and Lemma 2.1, based on a state observer (5), the adaptive fuzzy output feedback controller and the parameter adaptive law are designed as (36) and (37), respectively. Then, all the signals in the closed-loop system are bounded, and the tracking and observer errors converge to a small neighborhood of zero by selecting appropriate design parameters.

Therefore, the diagram of the above observer-based adaptive fuzzy prescribed performance control scheme is shown in Figure 1.

**4. Simulation study**
In this section, simulations are conducted to explain the validity of the designed control algorithm and theorem. The ship autopilot parameters used in the simulation are adopted from T. Li et al. (2010) with the following...
ship particulars: size between vertical lines $L_{pp} = 126$ m, moulded breadth $B = 20.8$ m, draft 8.0 m, block coefficient 0.681, forward speed 7.72 m/s. According to above ship particulars, the autopilot model parameters can be given as $a_1 = 1$, $a_2 = 30$, $K = 0.478$, $T = 216$.

The desired heading signal is given by a representative practical mode as

$$\ddot{\phi}_m(t) + 0.1\dot{\phi}_m(t) + 0.0025\phi_m(t) = 0.0025\phi_l(t) \tag{45}$$

where $\phi_m$ is the desired autopilot performance for ship heading $\phi(t)$ during the ship heading control; $\phi_l$ is an order input signal.

In the simulation investigation, fuzzy if-then rules are chosen as:

- $R_1$: If $\dot{x}_2$ is $F_2^1$, then $y$ is $G^1$,
- $R_2$: If $\dot{x}_2$ is $F_2^2$, then $y$ is $G^2$,
- $R_3$: If $\dot{x}_2$ is $F_2^3$, then $y$ is $G^3$,
- $R_4$: If $\dot{x}_2$ is $F_2^4$, then $y$ is $G^4$,
- $R_5$: If $\dot{x}_2$ is $F_2^5$, then $y$ is $G^5$.

where fuzzy sets are chosen as $F_2^1 = (NL), F_2^2 = (NS), F_2^3 = (ZE), F_2^4 = (PS), F_2^5 = (PL)$, which are defined over the interval $[-2, 2]$ for $\dot{x}_2$. PL, PS, ZE, NS and NL represent positive large, positive small, zero, negative small, negative large, respectively. Their centre points are selected as $-2, -1, 0, 1, 2$, respectively. $G^1, G^2, G^3, G^4, G^5$ are fuzzy sets. The corresponding fuzzy membership functions are shown in Figure 2.

Design parameters in the intermediate control function $\alpha_1$, controller $\nu$ and adaptive law of $\dot{\theta}$ are chosen as $c_1 = 5$, $c_2 = 20$, $\sigma = 0.1$, $\tau = 0.01$, $\pi = 0.02$, $\gamma = 0.1$, $\mu_0 = 0.2$, $\mu_\infty = 0.15$, $\alpha = 0.5$, $\delta_{\min} = 0.2$, $\delta_{\max} = 0.3$.

Choose initial conditions as $x_1(0) = 0$, $x_2(0) = -0.1$, $\dot{x}_1(0) = 0.1$, and the other initial values are chosen as zeros.

Choose observer gain vector $M = [m_1, m_2]^T = [60, 2]^T$, so that $A$ is a strict Hurwitz matrix.

Define $Q = \text{diag}[8, 8]$, by solving Lyapunov equation (7), one has the following matrix $P = \begin{bmatrix} 0.1 & 2 \\ 2 & 120.2 \end{bmatrix}$.

Then one has the simulation results shown by Figures 3–6. Figure 3 shows the trajectories of ship’s heading and its desired heading angle trajectory; Figure 4 is the ship’s heading and its estimated curve of ship’s heading; Figure 5 is the tracking error between ship’s heading and its desired trajectory, the blue lines are the predefined bounds, the red line is the tracking error without prescribed performance control scheme, the black line is the ship heading tracking error under the control algorithm designed in this paper, it can be seen that the tracking error obtained in this paper remains in a neighbourhood of the origin within the prescribed performance bounds for all the time; Figure 6 is the trajectory of rudder angle.

As can be seen from Figures 3–6, all the signals of the closed-loop intelligent ship autopilot system are bounded. Meanwhile, the output ship heading $y$ can track the given angle signal $y_l$ as desired.

In addition, define the ship autopilot performance index of $z_1$ is defined as $l = \sum_{k=1}^{n} |z_1(k)|$, where $n$ is the number of sampling data. $l$ is calculated from 0 to 1200 s.
with a sampling interval 1 s. The comparison results are listed in Table 1. Especially, $z_p$ is the tracking error of $z_1$ in prescribed performance control, and $z_n$ is the tracking error without prescribed performance bounds limitation.

### 5. Conclusion

In this paper, the prescribed performance control scheme is designed for intelligent ship autopilot with unmeasured ship heading rate state. Based on the fuzzy logic system, an adaptive fuzzy state observer is constructed to estimate the unknown yaw rate state. Finally, an adaptive fuzzy output feedback controller is designed. All the signals in the closed-loop system are proved to be bounded, and the ship heading can track the reference signal as desired. Future research will focus on adaptive fuzzy output feedback fault-tolerant control for the intelligent ship autopilot system.

Although some progress has been achieved, there are still some other challenges in the field, for instance, periodic event-triggered synchronization (Ding et al., 2021), reinforcement learning (Bai, Li, et al., 2020), neural network (Bai, Zhou, et al., 2020), leader–follower (Shao et al., 2020), TS fuzzy systems (Wu & Dong, 2018), disturbance rejection (Hu, Wei, et al., 2020), adaptive disturbance estimation (Hu, Wei, et al., 2020), robust synchronization (Hu, Wei, et al., 2021) etc., which will be our future research direction.

### Disclosure statement

No potential conflict of interest was reported by the author(s).

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