11th International Workshop on Ship and Marine Hydrodynamics
Hamburg, Germany, September 22-25, 2019

An Energy-Efficient Adaptive Course Control System for Ocean Surface Ships

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ABSTRACT

In order to improve the performance and the energy efficiency (rudder actions) of the ship control system in presence of changing environmental conditions and system uncertainty, this paper develops a novel adaptive fuzzy-PID course controller with a dynamic compensator and a nonlinear feedback for the autonomous surface ship. Firstly, an adaptive PID control strategy, whose control parameters are real-time adjusted by the fuzzy system, is designed to achieve the optimal control effect and the robust performance. Then, considering the uncertainty and unpredictable external disturbances, the Least Square Support Vector Machines (LSSVM) approach is employed to online identify and suppress the disturbances for the purpose of compensating the Fuzzy-PID controller. Furthermore, the nonlinear feedback is added in the control law to deal with the control inputs, and then the whole control system is named as "NFPL". The effectiveness and quality of the designed controller are investigated in the numerical simulations. Results demonstrate good adaptability and robust performance of the designed control system in spite of the existence of the time-varying environmental disturbance, and the advantages in the reduction of the settling time and rudder energy consumption as well as fast response are also verified.

1 INTRODUCTION

The research of Autonomous Surface Vessels (ASV) has attracted wide attentions due to its application in maritime investigation, ocean environment monitoring and surface rescue, etc. [1]. Ship course control is the foundation and core of autonomous navigation, and the ship navigation safety and manoeuvreability are directly affected by the performance of the ship controller (autopilot) [2]. Thus, a high-quality course controller is then deemed necessary so as to understand better the ship behaviour and improve the performance of ASV.

Since Minorsky undertook the pioneering work to design the Proportional Integral Derivative (PID) controller for an automatic steering system [3], numerous advanced controllers have been developed, such as backstepping control [4], model predictive control (MPC) [5], sliding mode control [6], fuzzy logic control [7], neural network control [8], etc. Nevertheless, the traditional or modified PID autopilot is still one of the most popular controllers in maritime industry applications [9]. The main reasons of widely using the PID controller in the nautical application are subdivided into two parts. On one hand, the high requirements for the control plant and the presented complex algorithms in other control models are difficult to be applied in real project. On the other hand, the PID controller has the characteristics of a simple structure, high reliability, and ease of design, etc [10]. However, the conventional PID control law cannot provide satisfactory performance in the presence of high-order and nonlinear systems [11]. Additionally, the parameters of traditional PID controllers need to be manually tuned by the operator corresponding to the changing navigation conditions. Therefore, its adaptability is very poor, and it cannot achieve satisfactory control effects [12].

To overcome these difficulties and improve the control effects, an adaptive PID autopilot is proposed in this paper. Firstly, the controller is designed based on a basic PID controller, whose gains are online tuned by fuzzy logic algorithm. Furthermore, a disturbance observer, the Least Square Support Vector Machines (LSSVM) model, is introduced to compensate for the Fuzzy-PID controller in the existence of environmental disturbance and system uncertainty. Moreover, the nonlinear feedback approach is added in the control law to regulate the control inputs and improve the energy-efficiency. Finally, taking the KRISO Container Ship (KCS) model as an example for course-keeping and course-following control simulations [13], the results show that the designed controller presents the advantages of good robustness, less rudder energy consumption and faster response compared to conventional PID and fuzzy controllers.

2 CONTROL MODEL

Aiming at designing an intelligent ship autopilot, it is essential to choose a ship mathematical model with simple structure in which the ship dynamic behaviour can be accurately described. The ship response model, as a wildly-used model to design a controller, is adopted to study the performance of the proposed course control system. Although the ship model is simple, it can effectively reflect the characteristics of the ship dynamics from rudder angles to heading angles. In this study, the first-order nonlinear ship response model is selected as control object [14], which is described as:

$$\begin{cases}\dot{\psi}=r \\ T\dot{r}+r+ar^{3}=K\delta\end{cases} \tag{1}$$

where ψ is the heading angle, r is the yaw rate, T is the time constant, K is the gain, a is the nonlinear coefficient, and δ is the rudder angle.

3 CONTROLLER DESIGN

3.1 NPFL control system

The NPFL control system is composed of three parts, the Fuzzy-PID controller, the nonlinear feedback and the LSSVM compensator, and the structure of the designed controller is displayed in Figure 1. In proposed system, Fuzzy-PID control is the main controller, which is used to fast follow desired heading angles. The LSSVM subsystem is utilized to online compensate the Fuzzy-PID controller for changing navigation conditions. Moreover, the nonlinear feedback is employed to regulate the control inputs (heading angle errors) for the purpose of reducing rudder energy cost. The NPFL control system is in more detail described as following subsections.

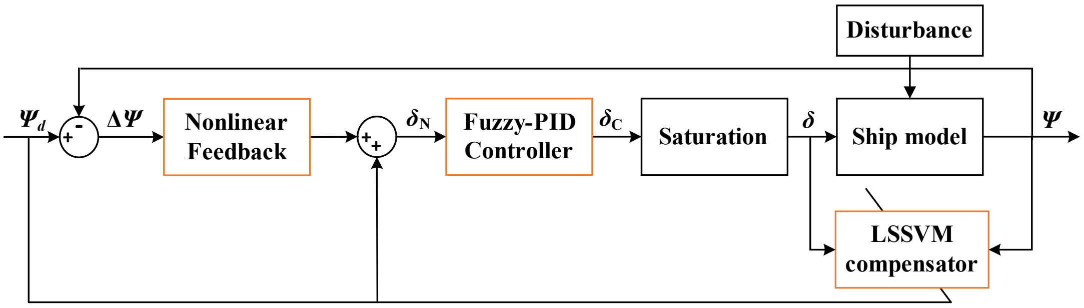

Figure 1: The structure of NPFL control system.

3.2 Fuzzy-PID controller

In present research, the Fuzzy-PID controller is adopted to improve the system adaptability and robustness. The controller structure is depicted in Figure 2, where the fuzzy logic controller is used to online tune the gains of the PID control law. The procedures of tuning the PID controller gains by the fuzzy logic method are in more detail described as four modules.

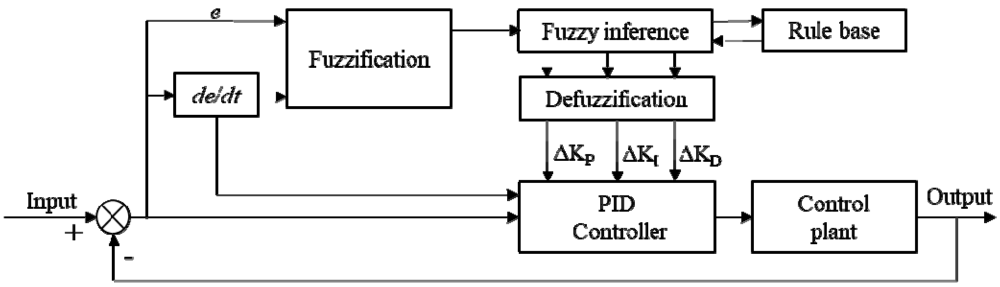

Figure 2: The structure of Fuzzy-PID controller.

Fuzzification. The heading angle error (e) and the error derivative (de/dt) are chosen as the fuzzy system inputs, the tuning gains ΔK_P, ΔK_I and ΔK_D are assigned as the three outputs. Each inputs and outputs are defined as seven fuzzy sets: Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (ZO), Positive Small (PS), Positive Medium (PM), Positive Big (PB). For input and output variables, their membership degrees for every fuzzy set are calculated by the Gaussian membership function [1], the fuzzification results are presented in Figure 3.

Fuzzy rules. The fuzzy rules are defined based on the nautical practice [15]. In the present study, the If-then rules are utilized to describe the relationships between the antecedents and consequents. For example:

If e *is* NB *and* de/dt *is* NB, *then* ΔK_P *is* PB, ΔK_I *is* NB *and* ΔK_D *is* PS

Fuzzy Inference. In this process, the Mamdani reasoning method is selected to map the given inputs to the fuzzy outputs [16]. The fuzzy inference results are displayed in Figure 3.

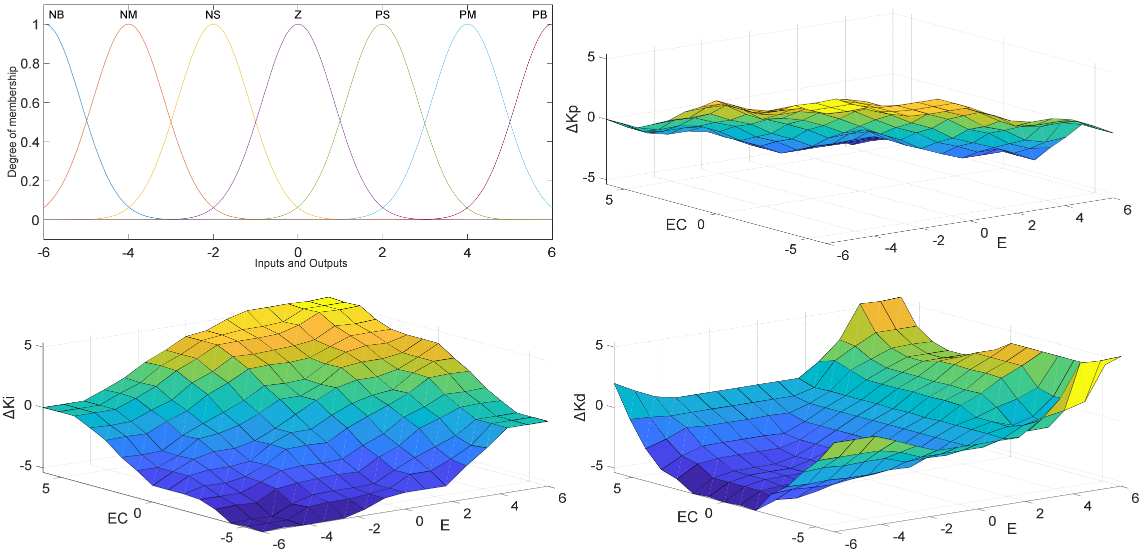

Figure 3: The fuzzy results for inputs and outputs.

Defuzzification. The fuzzy outputs are converted into crisp values ΔK_P, ΔK_I and ΔK_D by defuzzification process [9]. Then, the tuned gains ΔK_P, ΔK_I and ΔK_D are added in the PID controller.

3.3 Dynamic compensator

The dynamic compensator in the proposed control system is assigned as a LSSVM regression model, which is trained by sample data and then generate feed-forward signal for compensating the Fuzzy-PID controller.

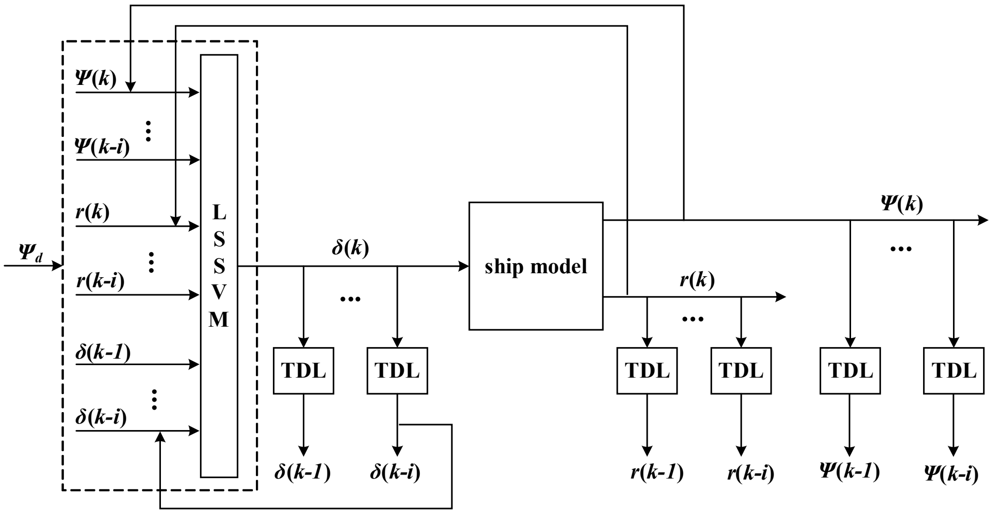

Figure 4: The structure of LSSVM compensator.

The training sample is assumed as:

$$S=\left\{\left(x_k,\delta_k\right),k=1,2,\cdots l\right\}\in\left(\Re^n\times\Re\right) \tag{2}$$

where $x_k\in\Re^n$ is the k^{th} training input, $\delta_k\in\Re$ is the k^{th} training output, l is the number of sample data, $\Re$ is the set of real numbers.

The k^{th} training input and output are defined as:

Input sample:

$$x_k=\left[\psi(k);\psi(k-1);\cdots\psi(k-n);r(k);r(k-1);\cdots r(k-n);\delta(k-1);\delta(k-2);\cdots\delta(k-m)\right] \tag{3}$$

Output sample: $\delta(k)$

where $\psi(k)$, $r(k)$, $\delta(k)$ are the k^{th} heading angle, yaw rate and rudder angle separately. $\psi(k-n),r(k-n),\delta(k-m)$ denotes the n^{th} and m^{th} delay signals.

After obtaining training sample, the goal is then changed to find a feature function, which is used to describe the relationship between the training input x and the output δ:

$$\delta(x)=\omega^T\varphi(x)+b \tag{4}$$

where $\varphi(x)$ is the nonlinear function, which maps input data x to the Euclidean space, ω is the weight coefficient, b is the bias.

According to the structural risk minimum theory [17], the regression problem of obtaining the feature function is shifted to solve a quadratic optimisation problem, which is given as:

$$\begin{gathered}\min_{w,e} J(w,e)=\frac{1}{2}w^T w+\frac{1}{2}\gamma\sum\nolimits_{i=1}^{l}e_i^2\\ s.t.\,\delta_i=w^T\varphi_i(x_i)+b+e_i,i=1,2\cdots n\end{gathered} \tag{5}$$

where δ_i is the i^{th} actual rudder angle, e_i is the i^{th} error between actual and regressed rudder angle, γ is the penalty factor.

The Lagrangian function is then introduced to solve the dual issue:

$$L\left(w,b,e,a\right) = J\left(w,e\right) - \sum\nolimits_{i=1}^{N} a_i \left(w^T \varphi\left(x_i + b + e_i - y_i\right)\right) \tag{6}$$

where a_i is the i^{th} Lagrange multipliers.

The partial derivatives of Eq. (6) with respect to w, b, e, a , and their derivatives are set as zeros:

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \rightarrow w = \sum\nolimits_{i=1}^{N} a_i \varphi\left(x_i\right) \\ \dfrac{\partial L}{\partial b} = 0 \rightarrow \sum\nolimits_{i=1}^{N} a_i = 0 \\ \dfrac{\partial L}{\partial e_i} = 0 \rightarrow a_i = \gamma e_i \\ \dfrac{\partial L}{\partial a_i} = 0 \rightarrow w^T \varphi\left(x_i\right) + b + e_i - \delta_i = 0 \end{cases} \tag{7}$$

The variables w and e_i are eliminated from Eq. (7), which is rewritten as:

$$\begin{bmatrix} 0 & \vec{1}^T \\ \vec{1} & K\left(\cdot\right) + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ \vec{a} \end{bmatrix} = \begin{bmatrix} 0 \\ \vec{\delta} \end{bmatrix} \tag{8}$$

where $\vec{1} = \left[1, \cdots, 1\right]^T$, I is the identity matrix, $\vec{a} = \left[a_1, \cdots, a_n\right]^T$, $\vec{\delta} = \left[\delta_1, \cdots, \delta_n\right]^T$, $K\left(\cdot\right)$ is the kernel function, and expressed as the inner product of the two input in the feature space [18], i.e., $K\left(x_k, x_i\right) = \varphi\left(x_k\right)^T \varphi\left(x_i\right)$.

Solve Eq.(8), and the LSSVM regression model yields:

$$\delta\left(k\right) = \sum\nolimits_{i=1}^{l} a_i K\left(x_k, x_i\right) + b \tag{9}$$

3.4 Nonlinear feedback

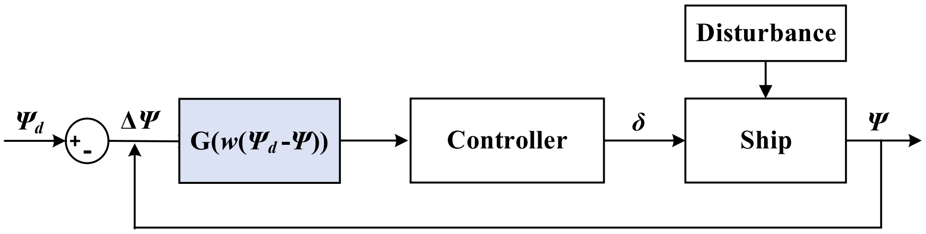

Figure 5: The structure of nonlinear feedback.

The structure of the nonlinear feedback model is depicted in Figure 5, the heading error $\Delta\psi = \psi_d - \psi$ in the nominal control system is regulated by a nonlinear function $G\left(\Delta\psi\right) = G\left(w\left(\psi_d - \psi\right)\right)$, where w is the design parameter. In present research, the $\sin\left(w\left(\psi_d - \psi\right)\right)$ is introduced to regulate the heading error $\psi_d - \psi$.

4 SIMULATION RESULTS

In this section, the effectiveness and quality of the designed controller are investigated with numerical simulations. The KRISO Container Ship (KCS) model is selected as the control object, and its parameters are T= 62.38 s, K= 0.114 s^{-1}, and a = 0.725 s^2/deg^2. These parameters are obtained by system identification technique based on the 20-20 zig-zag tests on the 1/37.89 scale model of the KCS ship conducted at MARIN, more detailed information can found in [19]. A second-order oscillating system driven by a white noise is considered as the disturbances.

$$D_e(s) = \frac{0.42s}{s^2 + 0.36s + 0.37} w_H \tag{10}$$

For a quantitative analysis, three assessment criteria are involved to evaluate their performance: the settling time (t_s), which is defined as the ship courses reach and maintain within a range of 5% reference course. 1-norm of the ship heading error $\|\Delta\psi\|_1$ and 1-norm of the control input $\|\delta\|_1$.

$$\|\Delta\psi\|_1 = \sum_{i=1}^{n} |\Delta\psi_i| \tag{11}$$

$$\|\delta\|_1 = \sum_{i=1}^{n} |\delta_i| \tag{12}$$

4.1 Comparison of course-keeping performance

In the first case, the traditional PID controller and the adaptive Fuzzy-PID controller are chosen as the examples to compare the course-keeping control effect with the proposed NFPL controller. The desired heading angle is defined as: 60 deg, and the gains of the PID controller are assigned as: K_P = 5.9, K_I = 0, K_D = 182.4 [20], these values are also regarded as the gains for the Fuzzy-PID and the NFPL controllers. The results of numerical simulations are depicted in Table 1, Figure 6 and Figure 7.

Compared with the conventional controllers, it can be observed in Figure 6 that the NFPL controller (pink line) can achieve the satisfactory performance with the fastest response, and its settling time t_s is reduced to 86s from 109s and 88s for the PID and the Fuzzy-PID control strategies respectively. Meanwhile, In Table 1 and Figure 7, the NFPL controller presents the smallest mean rudder angle (5.8 deg), and the rudder energy index $\|\delta\|_1$ is around 2902.9 deg for the proposed NFPL controller, which is decreased by 8.6% from 3177.0 deg for the PID controller and by 18.1% from 3545.1 deg for the Fuzzy-PID controller respectively. Therefore, the simulation results demonstrate the good adaptability and robust performance of the designed control system in spite of the existence of the time-varying environmental interferences, and the advantages in the reduction of the settling time and rudder energy consumption as well as fast response are also reported.

Table 1: Comparisons of course-keeping performance among the PID, Fuzzy-PID and NFPL controllers

	t_s (s)	$\|\Delta\psi\|_1$ (deg)	$\|\delta\|_1$ (deg)	$\bar{\delta}$ (deg)
PID	109.0	2888.3	3177.0	6.4
Fuzzy-PID	88.0	2634.5	3545.1	7.1
NPFL	86.0	2601.8	2902.9	5.8

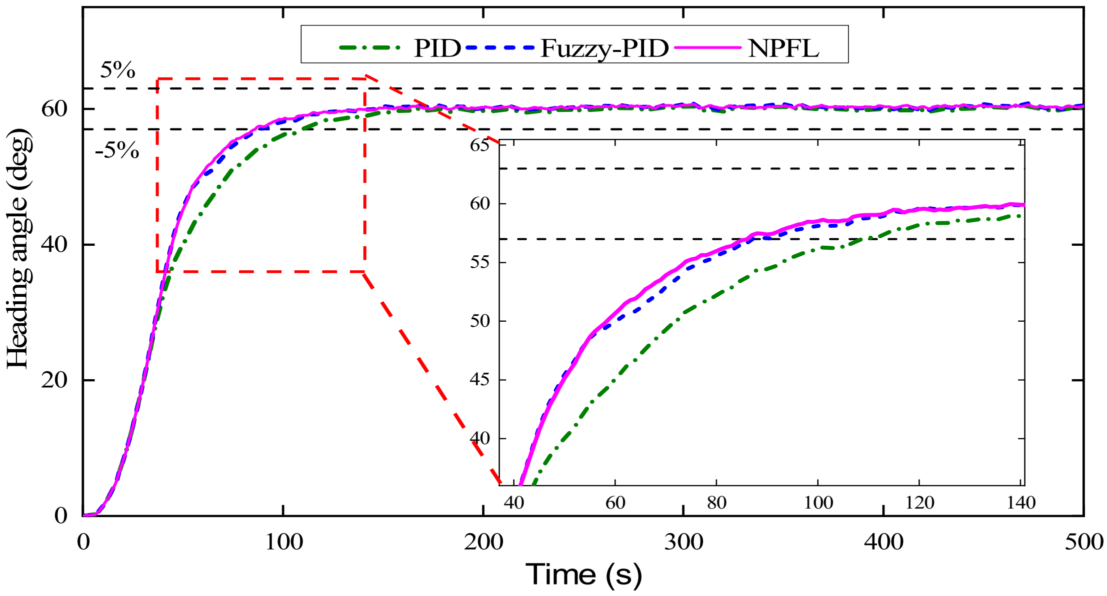

Figure 6: Comparisons of control effect for course-keeping control with different controllers.

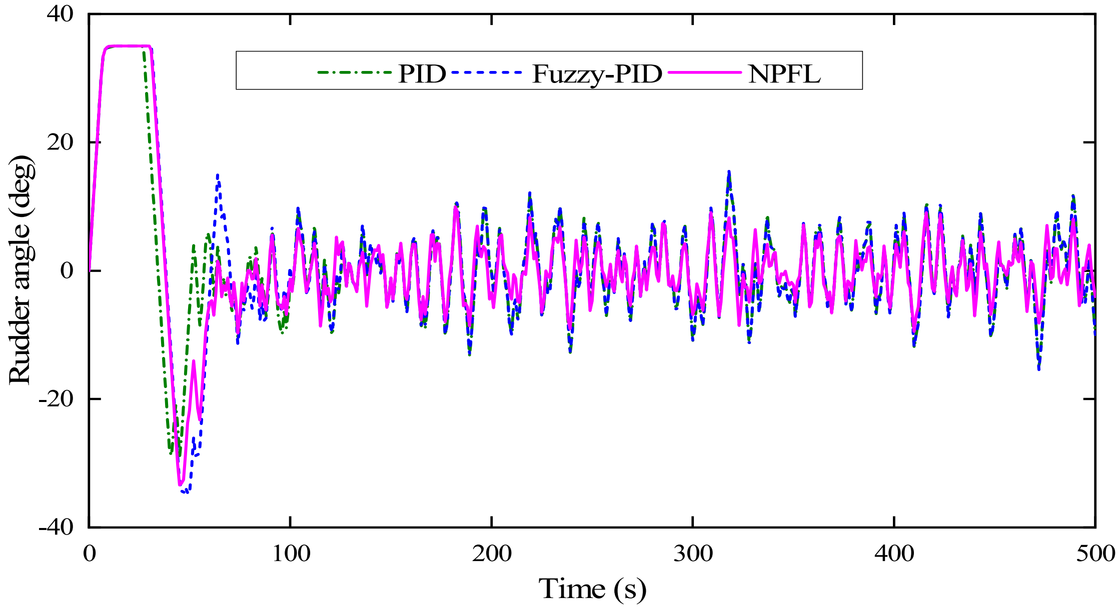

Figure 7: Comparisons of control inputs for course-keeping control with different controllers.

4.2 Comparison of course-following performance

In this subsection, numerical simulations are presented to study the course-following ability for the PID, Fuzzy-PID and the designed NFPL autopilots. Under the same control conditions (the gains and the disturbances), the reference heading angles are changed into a square signal ($\frac{180}{\pi}\left[\operatorname{sign}\left(\sin\left(2\pi t/600\right)\right)\right]$) to conduct the course tracking simulations. The control effects and rudders are depicted in Figure 8-10.

It is shown from Figure 8 that the three control laws are able to quickly track the desired heading angles and obtain satisfactory control effect, but the heading angle trajectory of the proposed NFPL autopilot is closer to the reference track compared to the other two controllers, and the NFPL has the fastest response when there are big changes for heading angles. In Figure 9, the smallest heading tracking errors are presented in the NFPL control law, which illustrates that the course-following accuracy is improved by the designed controllers. In addition, compared with traditional PID and Fuzzy-PID controllers, Figure 10 shows that the rudder angles for the NFPL controller are obviously reduced, which means that the rudder energy consumption is also decreased, in other words, improve the energy efficiency.

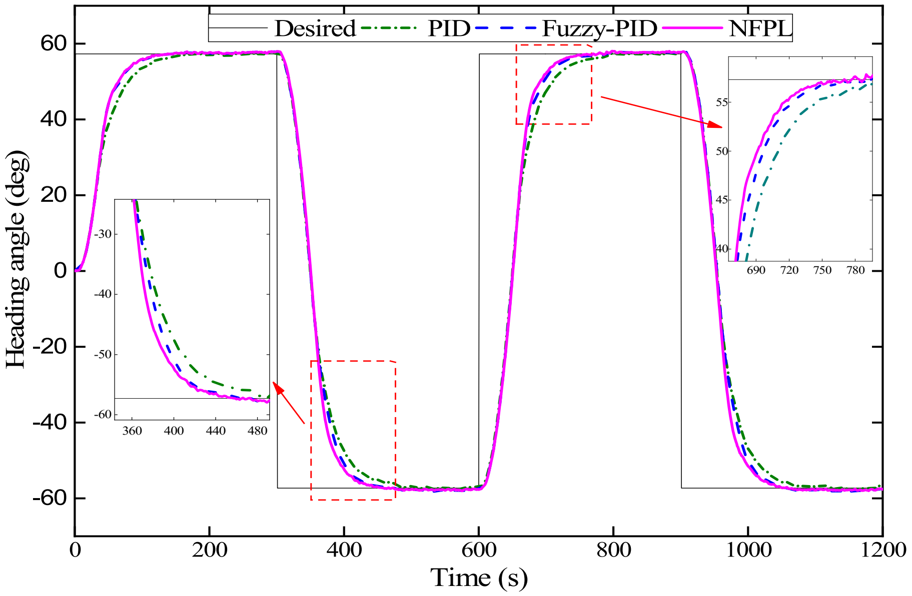

Figure 8: Comparisons of control effect for course-following control with different controllers.

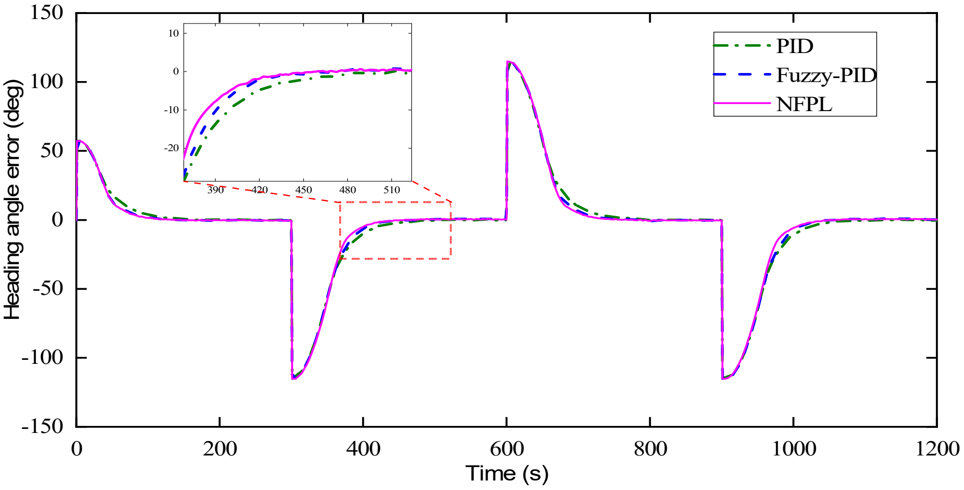

Figure 9: Comparisons of heading angle errors for course-following control with different controllers.

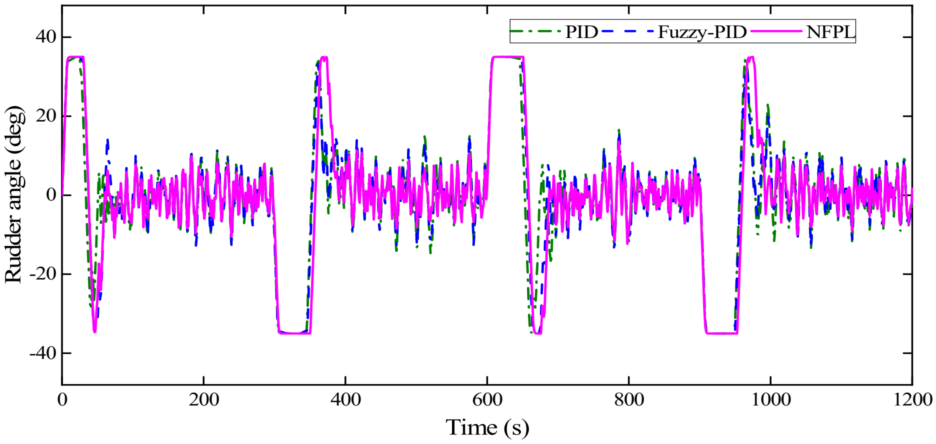

Figure 10: Comparisons of control inputs for course-following control with different controllers.

For quantitative analysis, Table 2 displays that the heading tracking error index $\|\Delta\psi\|_1$ of the NPFL autopilot is 20530 deg with 6.6% and 2.6% drops from the PID and Fuzzy-PID autopilots respectively, while the rudder energy index $\|\delta\|_1$ of the NPFL is reduced by 6.0% from the PID and 9.2% from the Fuzzy-PID. Moreover, the smallest average rudder angle is presented in the NPFL. In the nautical practice, steering small rudders can not only decrease ship roll and improve the ship safety, but the energy is also saved.

Table 2: Comparisons of course-following performance among the PID, Fuzzy-PID and NFPL controllers

	$\|\Delta\psi\|_1$ (deg)	$\|\delta\|_1$ (deg)	$\bar{\delta}$ (deg)
PID	21997	11655	9.7
Fuzzy-PID	21085	12078	10.1
NPFL	20530	10960	9.1

To sum, the course-following performance is enhanced by the proposed NPFL controller compared to the traditional controllers PID and Fuzzy-PID controllers, the faster response, smaller heading tracking error and less control energy cost also are demonstrated based on the above analysis.

5 CONCLUSION

In this article, an energy-efficient adaptive autopilot is designed to tackle the problem of course control for ocean surface ships. By combining adaptive Fuzzy-PID technique, LSSVM compensation algorithm with nonlinear feedback approach, the proposed controller can effectively keep and follow desired courses in presence of external environmental disturbance and system uncertainty. In terms of course-keeping control, compared with traditional PID and Fuzzy-PID controllers, the designed controller can achieve satisfactory robustness performance, and the settling time is reduced while the energy-efficiency and the response performance are improved. In the aspect of course following, compared with other two autopilots, the proposed NPFL can quickly track desired heading angles with smallest errors, the fastest responses are presented in the NPFL controller when there are big heading angles changes, and the rudder energy consumption is obvious decreased. Simulation results indicate that the proposed controller presents the advantages of robustness, fast response, and energy saving.

ACKNOWLEDGEMENTS

This work was supported by the program of China Scholarships Council (No.201706570007) and Special Research Fund - Cofunding for Chinese candidates holding a CSC-grant in Ghent University (01SC8418).

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