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Ship Steering Adaptive CGS Control Based on EKF Identification Method

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Abstract: In recent years, marine autonomous surface vessels (MASS) have grown into a ship research issue to increase the level of autonomy of ship behavior decision-making and control while sailing at sea. This paper focuses on the MASS motion control module design that aims to improve the accuracy and reliability of ship steering control systems. Nevertheless, the stochastic sea and wind environment have led to the extensive use of filters and state observers for estimating the ship-motion-related parameters, which are important for ship steering control systems. In particular, the ship maneuverability Nomoto index, which primarily determines the designed ship steering controller's performance, cannot be observed directly due to the model errors and the external environment disturbance in the process of sailing. Hence, an adaptive robust ship steering controller based on a closed-loop gain shaping (CGS) scheme and an extended Kalman filter (EKF) on-line identification method is explored in this paper. To verify the effectiveness of the proposed steering controller design scheme, the motor vessel ***YUKUN*** was taken as the control plant and a series of simulation experiments were carried out. The results show the advantages of the dynamic response performance of the proposed steering controller compared with the classical PD and traditional CGS controllers. Therefore, the proposed adaptive CGS steering controller would be a good solution for MASS motion control module design.

Keywords: ship steering control; marine autonomous surface vessel (MASS); extend Kalman filter (EKF) identification; adaptive closed-loop gain shaping (CGS) controller

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1. Introduction

Marine surface vessels autonomously sailing at sea had been in the dreams of ship designers for several decades. With the development of artificial intelligent decision-making technology, satellite communication systems, high-tech sensors, and advanced actuators, their dreams might turn into a possible reality. Therefore, the concept of marine autonomous surface vessels (MASS) had been introduced by the International Maritime Organization (IMO) for fueling present ship navigation and control technologies [1]. To unify the MASS theoretical research and project practice, a typical MASS hierarchical decision-making and control (HDMC) model was introduced [2]. The MASS HDMC model can be hierarchically decomposed into three components, as shown in Figure 1. At the highest level, a global routing planning module is designed. This is followed by a behavior decision-making (BDM) module, which decides on a local driving task to progress the MASS towards the destination and to keep it collision-free with obstacles and other ships. At the lowest level, a motion control (MC) module is used to control the ship actuator mechanism to execute the BDM module output commands (such as steering rudder and propeller rotation). These modules are in charge of the different tasks. In particular, the MC module is the foundation module which can determine the performance of MASS autonomous navigation and the sailing process [3]. The MASS steering operation to maintain or change ship course is the key function of the MC module. Hence, ship steering controller design is one of the most important tasks of ship motion control.

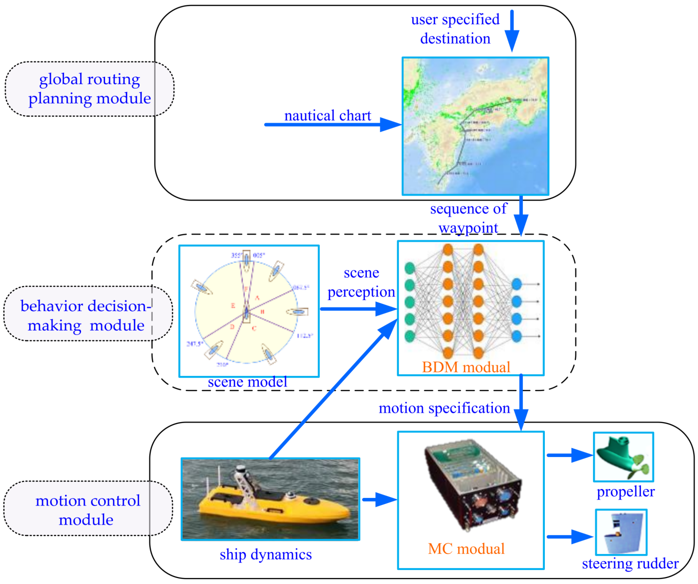

Figure 1. The concept of the MASS HDMC model.

With the last few decades of research, researchers have improved and optimized the ship steering controller consistently. A proportional-integral-derivative (PID) ship steering controller was proposed in 1922, which is the milestone of the modern ship steering control system and is still widely used today [4]. An adaptive steering controller is based on the filter and observer, which was proposed to improve the ship steering controller's dynamic response performance [5]. The ship steering adaptive disturbance rejection control (ADRC) solution is a typical adaptive steering controller which can estimate and compensate for both the internal and external disturbance based on the state observer [6,7]. However, there still exist problems relating to difficult stability analysis and arbitrary tuning parameter settings with this solution.

Optimal control is also a classical ship steering controller design scheme, which can achieve optimum performance in certain control constraints [8]. For instance, the ship steering model predictive control (MPC) is derived from the concept of optimal control [9]. Although there exist limitations relating to poor stability in the open-loop control system, the ship steering MPC is becoming a hot academic issue nowadays.

Furthermore, incorporating the unmodelled uncertainties and external disturbance into the consideration of ship steering controller design, the H_∞ robust controller [10] and the sliding mode controller [11] are both typical robust ship steering controllers and have good practical ship steering control application benefits.

However, linear controllers are widely available in the design of a ship steering controller. The validity of linear controllers is limited to the course-keeping maneuver, since only a small rudder angle action is involved. Once the ship maneuver calls for rapid and large course-changing movements, hydrodynamic nonlinearities need to be taken into consideration in the steering controller design. Hence, the feedback linearization technique was used in ship steering controller design with the cancellation of the system model nonlinear term [12]. The backstepping algorithm is the most successful controller synthesis method in dealing with the nonlinear control problem in the last few decades. Based on the Lyapunov stability theorem, the processes of controller design and controller stability analysis are synthesized. Fossen [13] presented a nonlinear backstepping design for the ship steering controller, and a nonlinear steering controller with "good nonlinearities term" was explored. Furthermore, the novel nonlinear feedback technique [14] and nonlinear decoration technique [15] were used to improve the nonlinear backstepping design methodology and the ship steering steady state performance.

Additionaly, a series of intelligent ship steering controllers, such as the neural network controller [16], quantum neural network controller [2], expert system controller [17], adaptive fuzzy controller [18], adaptive neuro-fuzzy inference controller [19], and the state-of-the-art artificial intelligence (AI) controller based on deep reinforcement learning [20] were proposed to enhance ship steering controllers' adaptability and self-learning ability. However, due to their strong subjectivity and poor theoretical interpretation, the practical applications of the above intelligent ship steering controllers have not been reported.

The above achievements might be a good solution for ship steering control under the concept of the MASS HDMC model, while there are still two limitations which need to be addressed in future studies:

(1) The proposed steering controller might be a hybrid algorithm which has a high-complexity structure and poor real-time control performance. Hence, these steering controllers might not be suitable for the MC module design under the MASS HDMC concept.

(2) The optimization or intelligent algorithm might be used as the steering controller design, but the tuned parameters of the controllers might have indefinite physical meaning, resulting in instability and poor robustness.

Based on the overlook of the ship steering control scheme in previous works, a ship steering adaptive closed-loop gain shaping (CGS) controller, which combined the CGS controller design approach [21] with the extended Kalman filtering (EKF) on-line identification technique [22,23], was proposed to address the ship steering control problem based on the MASS HDMC concept. To ensure the stability and robustness of the proposed controller, the conventional CGS controller design methodology was used as the basic structure of the proposed ship steering controller, since the CGS controller has a concise controller structure and definite controller design procedures. However, the conservative robustness controller design scheme might undermine the dynamic response performance of the CGS controller. Hence, the on-line EKF identification technique was introduced to improve the controller's dynamic response performance. Consequently, the proposed ship steering adaptive CGS controller would have a concise structure, the definite physical meaning of tuning parameters, and better dynamic response performance of the ship course-keeping and course-changing.

This paper is organized as follows. In Section 2, the nonlinear model of the ship steering control system is described. Section 3 is devoted to the proposed ship steering adaptive CGS controller design procedure. In Section 4, analysis of system stability is carried out. In Section 5, numerical simulations are given. Section 6 contains the conclusions and discussions.

2. Mathematical Models

The nonlinear ship motion mathematic model is generally described as

$$\ddot{\psi} = -\frac{1}{T_R}\dot{\psi} - \frac{a}{T_R}\dot{\psi}^3 + \frac{K_R}{T_R}\delta - K_d \tag{1}$$

where ψ is the yaw angle, δ is the rudder angle, K_R and T_R are donated as the ship maneuverability index, a is the coefficient of the nonlinear term function, and K_d is considered as the bounded external interference.

As shown in Figure 2, only the ship lateral drift velocity v and the yaw angular velocity r are considered, and the ship motion mathematic model can be expressed as

$$\begin{bmatrix} \dot{v} \\ \dot{r} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} v \\ r \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \delta \tag{2}$$

where a_{11}, a_{12}, a_{21}, a_{22}, b_1, and b_2 are the ship maneuverability parameters. Ignoring the lateral drift velocity v in Equation (2), the response equation of the ship steering rudder to yaw motion can be written as

$$T_1T_2\ddot{r} + (T_1 + T_2)\dot{r} + r = K_R\delta + K_RT_3\dot{\delta} \tag{3}$$

where T_1, T_2, T_3, and K_R are maneuverability indexes. According to [22], their values can be estimated by $T_1T_2 = 1/(a_{11}a_{22} - a_{12}a_{21})$, $T_1 + T_2 = (a_{11} + a_{22})/(a_{12}a_{21} - a_{11}a_{22})$, $T_3 = b_2/(a_{21}b_1 - a_{11}b_2)$, $K_R = (a_{21}b_1 - a_{11}b_2)/(a_{11}a_{22} - a_{12}a_{21})$. Then, the Laplace transform of Equation (3) can be carried out to obtain the transfer function of the ship steering control system, as shown in Equation (4)

$$G(s) = \frac{\psi(s)}{\delta(s)} = \frac{K_R(1 + T_3s)}{s(1 + T_1s)(1 + T_2s)} \tag{4}$$

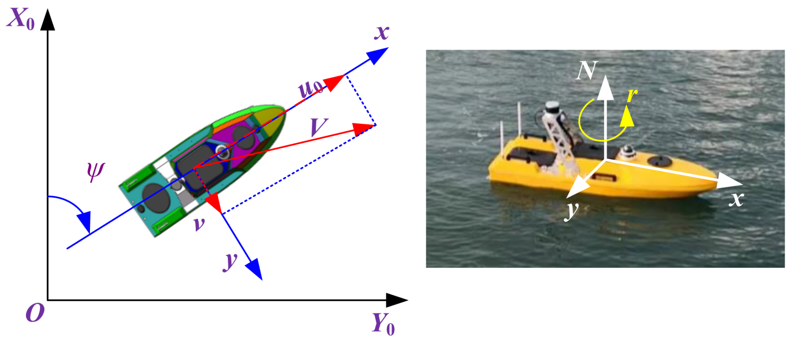

Figure 2. Ship motion and yaw motion coordination.

Since the ship has large inertia characteristics, only the low-frequency part of the ship's dynamic characteristics is considered. Let $s = j\omega \to 0$; the transfer function (4) can be rewritten as Equation (5),

$$G(s) = \frac{K_R}{s(T_Rs + 1)} \tag{5}$$

where $T_R = T_1 + T_2 - T_3$, and the model is a second-order linear Nomoto model [11]. Furthermore, the transfer function Equation (5) can be expressed as Equation (6).

$$T_R\ddot{\psi} + \dot{\psi} = K_R\delta \tag{6}$$

Let the ship yaw velocity term $\dot{\psi}$ be a nonlinear function $H(\dot{\psi}) = \dot{\psi} + a\dot{\psi}^3$. Therefore, Equation (6) can be written as Equation (1). Defining $\alpha = -1/T_R$, $\beta = -a/T_R$ and $\gamma = K_R/T_R$, Equation (1) can be written as Equation (7) for the following ship steering controller design.

$$\ddot{\psi} = \alpha\dot{\psi} + \beta\dot{\psi}^3 + \gamma\delta - K_d \tag{7}$$

3. Ship Steering Adaptive CGS Control Based on EKF

3.1. Ship Steering CGS Controller Design

Considering a typical structure of the ship steering control system as shown in Figure 3, $G(s)$ and $K(s)$ represent the transfer function of the ship mathematical model and steering controller, respectively. y is defined as the steering to yaw motion system output signal, and ψ_r is the demand course reference signal. K_d is the external disturbance of the system. u is defined as the ship steering rudder angle δ. Defining the error of the steering control system as $e = \psi_r - \psi$, the purpose of the steering controller design is to produce the ship steering rudder angle δ to make the output yaw angle y track the input demand course signal ψ_r under the disturbance K_d, which can be expressed as a transfer function as follows:

$$\frac{y(s)}{\psi_r(s)} = \frac{G(s)K(s)}{1 + G(s)K(s)} \tag{8}$$

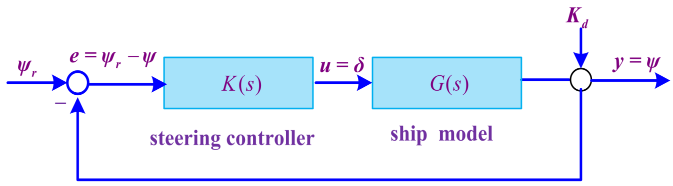

Figure 3. Typical structure of ship steering control system.

To design the ship steering CGS controller, the following hypotheses should be made:

Hypothesis 1. *The spectrum of the ship steering control system works as a low-frequency pass filter. That is, the main work frequency band of the system is in the low-frequency region, and the high-frequency region is regarded as an interference signal.*

Hypothesis 2. *The maximum singular value of the ship steering control system is set to 1. That is, the peak value of the system is 0, thus ensuring the system could track the reference signal without any overshoot.*

Hypothesis 3. *The spectrum slope of the ship steering closed loop control system could be set as* -20 *dB/dec to suppress external disturbance.*

Based on the above hypotheses, the controlling performance of the entire ship steering to the yaw control system will be primarily determined by the system bandwidth $1/\lambda$, which simplifies the controller design procedures, and causes the controller tuning parameters to have definite physical meanings. Therefore, the transfer function of the ship steering control system can be rewritten as

$$\frac{G(s)K(s)}{1 + G(s)K(s)} = \frac{1}{\lambda s + 1} \tag{9}$$

Then, the ship steering controller $K(s)$ can be obtained according to Equation (9), which is

$$K(s) = 1/(\lambda G(s)s) \tag{10}$$

Therefore, according Equation (5), the ship steering CGS controller shown in Figure 3 can be realized by Equation (11),

$$\delta = \lambda_1 \left(\lambda_2 e + \dot{e}\right) \tag{11}$$

where $\lambda_1 = T_R/(\lambda K_R)$, $\lambda_2 = 1/T_R$. Since λ is the only tuning parameter, the estimation of the ship maneuverability index T_R and K_R would be predominant in the process of ship steering CGS controller design. Hence, an extend Kalman filter (EKF) identification method can be used in the ship steering parameter identification technique to complete the ship steering CGS controller design.

3.2. Extend Kalman Filter Identification

For the estimation of the ship maneuverability index T_R and K_R, the least-square method [24], multi-innovation method [25], and support vector machine method [26] are all good solutions. Additionally, the parameters of the ship steering control system can be estimated by the on-line EKF identification technique, and successful results were reported in [22]. Due to the effectiveness of capturing the dynamic behavior of ship steering to yaw motion, the EKF on-line identification technique might be a good solution to improve the ship steering controller's dynamic performance.

The EKF identification technique for adaptive ship steering controller design can be summarized as follows:

(1) The ship steering control system, described in Equation (1), can be rewritten as

$$\dot{\boldsymbol{X}}(t) = \boldsymbol{f}(\boldsymbol{X}(t)) + \boldsymbol{W}(t) \tag{12}$$

where $\boldsymbol{X}^{\mathrm{T}}(t) = \begin{bmatrix} \psi(t) & \dot{\psi}(t) & \alpha(t) & \beta(t) & \gamma(t) & \delta(t) \end{bmatrix}$, $\boldsymbol{W}(t)$ is the noise vector, and $\boldsymbol{f}(\boldsymbol{X}(t))$ is represented as

$$\boldsymbol{f}(\boldsymbol{X}(t)) = \begin{bmatrix} \dot{\psi}(t) \\ \alpha(t)\dot{\psi}(t) + \beta(t)\dot{\psi}(t)^{3} + \gamma(t)\delta(t) \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{13}$$

Then, the Jacobian matrix of Equation (13) can be given by

$$\frac{\partial}{\partial \boldsymbol{X}(t)}(\boldsymbol{f}(\boldsymbol{X}(t))) = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & \alpha(t) + 3\beta(t)\dot{\psi}^{3}(t) & \dot{\psi}(t) & \dot{\psi}^{3}(t) & \delta(t) & \gamma(t) \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{14}$$

(2) Define the measured state matrix as

$$\boldsymbol{z}(k) = \boldsymbol{h}(\boldsymbol{X}(k)) + \boldsymbol{\xi}(k) \tag{15}$$

where $\boldsymbol{z}^{T}(k) = \begin{bmatrix} z_{\psi}(k) & z_{\dot{\psi}}(k) & z_{\delta}(k) \end{bmatrix}$ and $\boldsymbol{\xi}(k)$ is the measured noise, and $\boldsymbol{h}^{T}(\boldsymbol{X}(t)) = \begin{bmatrix} \psi(t) & \dot{\psi}(t) & \delta(t) \end{bmatrix}$. Then, the Jacobian matrix of $\boldsymbol{h}^{T}(\boldsymbol{X}(k))$ can be computed as

$$\frac{\partial}{\partial \boldsymbol{X}(k)}\boldsymbol{h}(\boldsymbol{X}(k)) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{16}$$

(3) Define the extrapolation law of error covariance as

$$\dot{\boldsymbol{P}}(t) = \boldsymbol{F}(\hat{\boldsymbol{X}}(t))\boldsymbol{P}(t) + \boldsymbol{P}(t)\boldsymbol{F}^{T}(\hat{\boldsymbol{X}}(t)) + \boldsymbol{Q}(t) \tag{17}$$

where $\boldsymbol{Q}(t)$ is the covariance of state error, and $\boldsymbol{F}(\hat{\boldsymbol{X}}(k))$ can be achieved by Equation (18).

$$\boldsymbol{F}(\hat{\boldsymbol{X}}(k)) = \left.\frac{\partial}{\partial \boldsymbol{X}(t)}\boldsymbol{f}(\boldsymbol{X}(k))\right|_{\boldsymbol{X}(k)=\hat{\boldsymbol{X}}(k)} \tag{18}$$

(4) Define the update law of estimated states as

$$\hat{\boldsymbol{X}}(k^{+}) = \hat{\boldsymbol{X}}(k^{-}) + \boldsymbol{K}(k)\left[\boldsymbol{z}(k) - \boldsymbol{h}_{\boldsymbol{k}}(\hat{\boldsymbol{X}}(k^{-}))\right] \tag{19}$$

where $\hat{\boldsymbol{X}}(k^+) = \begin{bmatrix} \hat{\psi}(k^+) & \hat{\dot{\psi}}(k^+) & \hat{\alpha}(k^+) & \hat{\beta}(k^+) & \hat{\gamma}(k^+) & \hat{\delta}(k^+) \end{bmatrix}^{\mathrm{T}}$ is the estimated state vector, $\hat{\boldsymbol{X}}(k^-) = \begin{bmatrix} \hat{\psi}(k^-) & \hat{\dot{\psi}}(k^-) & \hat{\alpha}(k^-) & \hat{\beta}(k^-) & \hat{\gamma}(k^-) & \hat{\delta}(k^-) \end{bmatrix}^{\mathrm{T}}$ is the prior state vector, $\boldsymbol{z}(k) = \begin{bmatrix} z_\psi(k) & z_{\dot{\psi}}(k) & z_\delta(k) \end{bmatrix}^{\mathrm{T}}$ is the measured state vector, and $\boldsymbol{h_k}(\hat{\boldsymbol{X}}(k^-)) = \begin{bmatrix} \hat{\psi}(k^-) & \hat{\dot{\psi}}(k^-) & \hat{\delta}(k^-) \end{bmatrix}^{\mathrm{T}}$. Equation (19) can be rewritten as

$$\begin{bmatrix} \hat{\psi}(k^+) \\ \hat{\dot{\psi}}(k^+) \\ \hat{\alpha}(k^+) \\ \hat{\beta}(k^+) \\ \hat{\gamma}(k^+) \\ \hat{\delta}(k^+) \end{bmatrix} = \begin{bmatrix} \hat{\psi}(k^-) \\ \hat{\dot{\psi}}(k^-) \\ \hat{\alpha}(k^-) \\ \hat{\beta}(k^-) \\ \hat{\gamma}(k^-) \\ \hat{\delta}(k^-) \end{bmatrix} + \boldsymbol{K}(k) \begin{bmatrix} z_\psi(k) - \hat{\psi}(k^-) \\ z_{\dot{\psi}}(k) - \hat{\dot{\psi}}(k^-) \\ z_\delta(k) - \hat{\delta}(k^-) \end{bmatrix} \tag{20}$$

Through the above steps, the values of $\hat{\alpha}$, $\hat{\beta}$ and $\hat{\gamma}$ can be estimated, and their estimated values are used to design the adaptive steering controller. However, only the Kalman gain needs to be determined.

(5) Define the update law of error covariance as

$$\boldsymbol{P}(k^+) = \left[1 - \boldsymbol{K}(k)\boldsymbol{H}_k(\hat{\boldsymbol{X}}(k^-))\right]\boldsymbol{P}(k^-) \tag{21}$$

where $\boldsymbol{P}(k^+)$ is the priori error covariance, $\boldsymbol{P}(k^-)$ is the posteriori error covariance, and $\boldsymbol{H}_k(\hat{\boldsymbol{X}}(k^-)$ is defined as

$$\boldsymbol{H}_k(\hat{\boldsymbol{X}}(k^-)) = \left.\frac{\partial h(\boldsymbol{X}(k))}{\boldsymbol{X}(k)}\right|_{\boldsymbol{X}(k)=\hat{\boldsymbol{X}}(k^-)} \tag{22}$$

Then, the Kalman gain can be calculated by

$$\boldsymbol{K}(k) = \frac{\boldsymbol{P}(k^-)\boldsymbol{H}(\hat{\boldsymbol{X}}(k^-))}{\boldsymbol{H}(\hat{\boldsymbol{X}}(k^-))\boldsymbol{P}(k^-)\boldsymbol{H}(\hat{\boldsymbol{X}}(k^-))^T + \boldsymbol{R}(k)} \tag{23}$$

where $\boldsymbol{R}(k)$ is the measured noise covariance.

Remark 1. *To guarantee the convergence of the EKF identification method, the priori and posteriori error covariance $\boldsymbol{P}(k^+)$ and $\boldsymbol{P}(k^-)$ should be positive. The initial value of estimated state $\hat{\boldsymbol{X}}(0)$ and error covariance matrix $\boldsymbol{P}(0)$ should be set suitably.*

Therefore, the adaptive steering controller based on the on-line EKF identification method can be expressed as

$$\delta = \hat{\lambda}_1(\hat{\lambda}_2 e + \dot{e}) \tag{24}$$

where $\hat{\lambda}_1 = \hat{T}_R/(\lambda\hat{K}_R) = 1/\lambda\hat{\gamma}$ and $\hat{\lambda}_2 = 1/\hat{T}_R = -\hat{\alpha}$.

Remark 2. *The ship steering adaptive CGS control concept based on the on-line EKF identification method is described in Figure 4. The final form of the ship steering adaptive CGS controller is described in Equation (24). The significant parameter of the controller $\hat{T}_R$ and $\hat{K}_R$ can be estimated by the EKF on-line identification technique. The whole EKF on-line identification process is an iterative process, which includes the state prediction process (17) and (18), and the measurement state update process (22), (23), (19) and (21). More details of the EKF parameter identification technique can be found in the literature* [22].

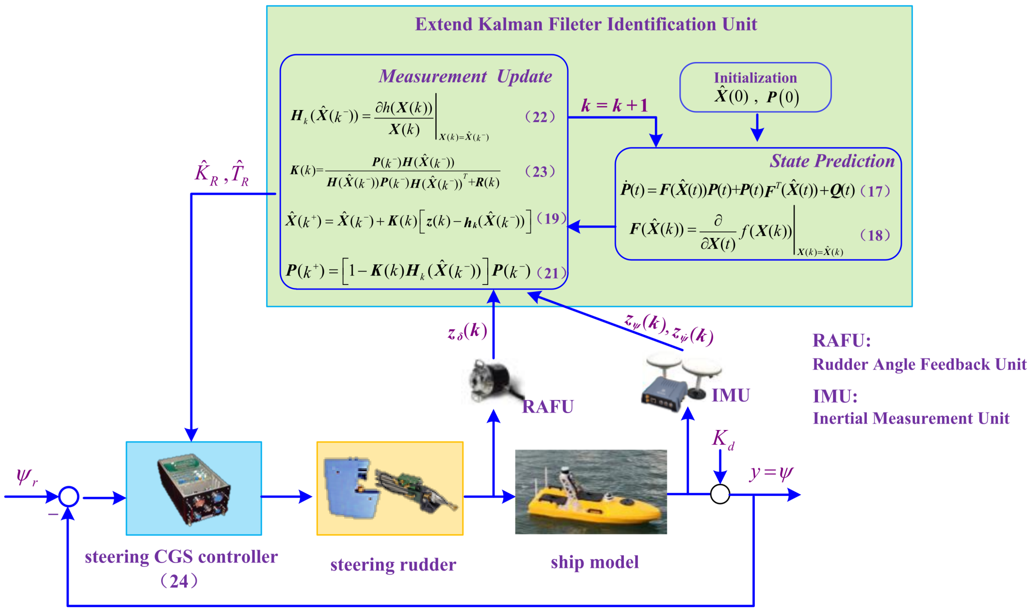

Figure 4. The concept of ship steering adaptive CGS controller based on the EKF identification method.

4. Stability Analysis

To facilitate the analysis of the proposed controller, we need the following assumptions.

Assumption 1. *According to the conclusions given in* [23]*, the inequality (25) should be satisfied to guarantee the convergence of the ship steering system on-line EKF estimated parameters.*

$$\varepsilon^T(k)\varepsilon(k) \le tr\{\text{var}[\varepsilon(k)]\} \tag{25}$$

where $\varepsilon(k) = z(k) - \boldsymbol{H}(\hat{\mathbf{X}}(k^-))$.

Assumption 2 . *The convergence of EKF estimated values is satisfied with* $\left\| inf\left(\frac{K_R}{\hat{K}_R}\right) \right\|_\infty < \theta_K$, $\left\| inf\left(\frac{\hat{T}_R}{T_R}\right) \right\|_\infty < \theta_T$*, where* θ_K*, and* θ_T *are positive constant.*

Assumption 3 . *The interference* K_d *is a slow time-varying signal, bounded with* $\|K_d\|_\infty \le \rho$*, where* $\rho > 0$.

Assumption 4. *The demand course reference signal* ψ_r *is a step signal, so* $\dot{\psi}_r = \ddot{\psi}_r = 0$.

Hence, the mathematic model of the ship steering control system (1) can be described by Equation (26)

$$\ddot{e} = -\frac{1}{T_R}\dot{e} - \frac{a}{T_R}\dot{e}^3 - \frac{K_R}{T_R}\delta + K_d \tag{26}$$

Define the Lyapunov function (27),

$$V = \frac{1}{2}e^2 + \frac{1}{2}\dot{e}^2 \tag{27}$$

Substituting Equations (24) and (26) into the derivative of the Lyapunov function V, we can obtain Equation (28)

$$\begin{aligned} \dot{V} &= e\dot{e} + \dot{e}\ddot{e} \\ &= e\dot{e} + \dot{e}\left(-\tfrac{1}{T_R}\dot{e} - \tfrac{a}{T_R}\dot{e}^3 - \tfrac{K_R}{T_R}\cdot\tfrac{1}{\hat{K}_R}\cdot\tfrac{1}{\lambda}\cdot e - \tfrac{K_R}{T_R}\cdot\tfrac{\hat{T}_R}{\hat{K}_R}\cdot\tfrac{1}{\lambda}\cdot\dot{e} + K_d\right) \\ &\le e\dot{e} - \tfrac{1}{T_R}\dot{e}^2 - \tfrac{K_R}{T_R}\cdot\tfrac{1}{\hat{K}_R}\cdot\tfrac{1}{\lambda}\cdot e\dot{e} - \tfrac{K_R}{T_R}\cdot\tfrac{\hat{T}_R}{\hat{K}_R}\cdot\tfrac{1}{\lambda}\cdot\dot{e}^2 + K_d\cdot\dot{e} \end{aligned} \tag{28}$$

Since the inequality $K_d \cdot \dot{e} \leq \eta\dot{e}^2 + \rho^2/(4\eta)$, where $\eta > 0$, then

$$\dot{V} \leq e\dot{e} - \frac{1}{T_R}\dot{e}^2 - \frac{K_R}{T_R} \cdot \frac{1}{\hat{K}_R} \cdot \frac{1}{\lambda} \cdot e\dot{e} - \frac{K_R}{T_R} \cdot \frac{\hat{T}_R}{\hat{K}_R} \cdot \frac{1}{\lambda} \cdot \dot{e}^2 + \eta\dot{e}^2 + \rho^2/(4\eta) \tag{29}$$

According to Assumption 2, we can obtain

$$\begin{aligned} &\dot{V} \leq e\dot{e} - \tfrac{1}{T_R}\dot{e}^2 - \tfrac{1}{T_R} \cdot \tfrac{1}{\lambda} \cdot \theta_K \cdot e\dot{e} - \tfrac{1}{\lambda} \cdot \theta_T \cdot \theta_K \cdot \dot{e}^2 + \eta\dot{e}^2 + \rho^2/(4\eta) \\ &\leq -\left(\tfrac{1}{T_R} \cdot \tfrac{1}{\lambda} \cdot \theta_K - 1\right)e^2 - \left(\tfrac{1}{\lambda} \cdot \theta_T \cdot \theta_K + \tfrac{1}{T_R} + \tfrac{1}{T_R} \cdot \tfrac{1}{\lambda} \cdot \theta_K - \eta - 1\right)\dot{e}^2 + \rho^2/(4\eta) \end{aligned} \tag{30}$$

Observing the inequality (30), we can define

$$a_0 = \min\left\{ \left(\frac{1}{T_R} \cdot \frac{1}{\lambda} \cdot \theta_K - 1\right), \left(\frac{1}{\lambda} \cdot \theta_T \cdot \theta_K + \frac{1}{T_R} + \frac{1}{T_R} \cdot \frac{1}{\lambda} \cdot \theta_K - \eta - 1\right) \right\},\ \varepsilon_0 = \rho^2/(4\eta),$$

Taking into account the definition of the Lyapunov function (27), the inequality (31) can be obtained:

$$\dot{V} \leq -2a_0 V + \varepsilon_0 \tag{31}$$

By the integration of (31), it follows that

$$V_0(t) \leq \frac{\varepsilon_0}{2a_0} + (V(0) - \frac{\varepsilon_0}{2a_0})\exp(-2a_0 t) \tag{32}$$

Hence, while $a_0 > 0$, we can achieve

$$\lim_{t\to\infty}(V(t) - \frac{\varepsilon_0}{2a_0}) = 0 \tag{33}$$

Therefore, based on the above analysis, we can give the main result of this paper in the theorem.

Theorem. *Consider the system (1), and the control law (24) with the estimated parameters update law (19). If Assumptions 1, 2, 3, and 4 are satisfied, then the proposed steering controller can suppress the external disturbance and make the whole ship steering control system semi-globally uniform and ultimately bounded, and the course tracking error can converge to a compact set* $\Omega = \left\{e : e \leq \sqrt{\varepsilon_0/a_0}\right\}$ *gradually.*

5. Simulations and Analysis

5.1. Ship Model Description

In order to verify the feasibility of the proposed adaptive CGS ship steering controller based on the EKF identification technique, the motor vessel ***YUKUN***, a special teaching and training ship belonging to Dalian Maritime University, was taken as the simulation case The value of K_R was 0.28, T_R was 71.84, the nonlinear coefficient was 0.9. We then obtained the transfer function of the motor vessel ***YUKUN*** steering control system formulated as Equation (34) according to Equation (5).

$$G(s) = \frac{0.28}{s(71.84s + 1)} \tag{34}$$

5.2. Disturbance Description

While the ship is sailing at sea, sea waves are considered as the main disturbance of the ship steering control system. The description of sea waves can be formulated as a second-order transfer function driven by Gaussian white noise. The work frequency is 1.0, and the second-order wave transfer function can be formulated as

$$h(s) = \frac{2\xi\omega_n\sigma_w s}{s^2 + 2\xi\omega_n s + \omega_n^2} \tag{35}$$

where $\sigma_w = \sqrt{0.0185 T_w} \cdot h_{1/3}$ is the wave spectrum intensity, ξ is the damping coefficient, $\omega_n = 4.85/T_w$ is the wave frequency, and T_w is the wave period. Then, the second-order wave transfer function under wind scale 6 can be written as

$$K_d(s) = \frac{0.5927s}{s^2 + 0.4157s + 0.48801} \tag{36}$$

5.3. Course-Keeping Control Comparison and Analysis

The proposed adaptive CGS ship steering controller based on the on-line EKF identification technique can achieve better course-keeping performance and corresponding steering rudder angle actuation signals, as shown in Figure 5 (the orange line). The adaptive CGS controller parameter λ was taken as 100, and the initial values of K_R and T_R were taken as 0.28 and 71.84, respectively. In order to further verify the performance of the proposed controller, the traditional PD controller was used to carry out comparison simulation experiments.

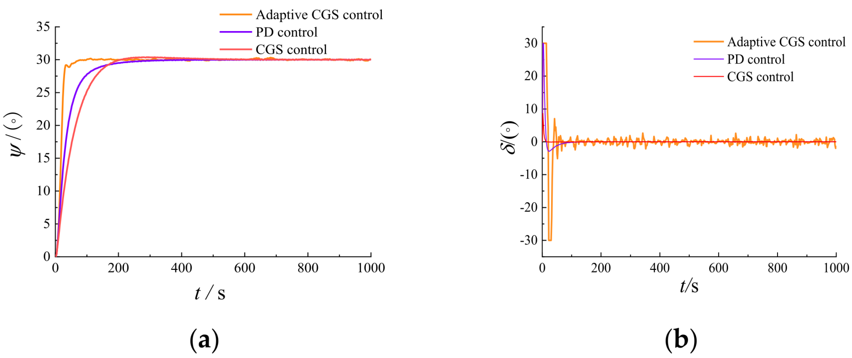

Figure 5. Comparison of different ship steering controllers. (**a**) Yaw angle. (**b**) Steering rudder angle.

(1) PD controller

The control strategy of the PD controller is $\delta_c = K_p e + K_d \dot{e}$. The ***MATLAB*** Simulink Control System Tuner APP was used to automatically tune the PD controller coefficients K_p and K_d from the specified tuning goals, such as rising time and overshoot. Finally, we obtained K_p's value as 0.0984, and K_d's value as 7.5549.

(2) Traditional CGS controller

The traditional CGS controller described in Equation (11) was also used to carry out comparison experiments. The parameters of the traditional CGS controller were taken as $\lambda = 100$, $K_R = 0.28$ and $T_R = 71.84$.

The final simulation results are shown in Figure 5. Compared with the ship steering PD controller (the blue line) and the traditional ship steering CGS controller (the red line), the proposed adaptive CGS ship steering controller (the orange line) based on the on-line EKF identification technique can achieve better course-keeping dynamic response performance. Additionally, from the EKF on-line identification results as presented in Figure 6, it can be concluded that accurate and convergent estimated values of the ship steering control system parameters α, β and γ can be observed. Furthermore, the significant parameters T_R and K_R of the proposed controller were obtained, where α is about -0.014, β is about -0.0129, and γ is about 0.0039. Furthermore, as presented in Figure 7, the measured and estimated ship states of course angle, course turning rate, and steering rudder angle are similar due to the EKF's accurate estimation capabilities. That means that the estimated ship states converge into the measured ship states. This can also be used to monitor the validity of the EKF on-line identification results during the proposed adaptive CGS ship steering controller's working time.

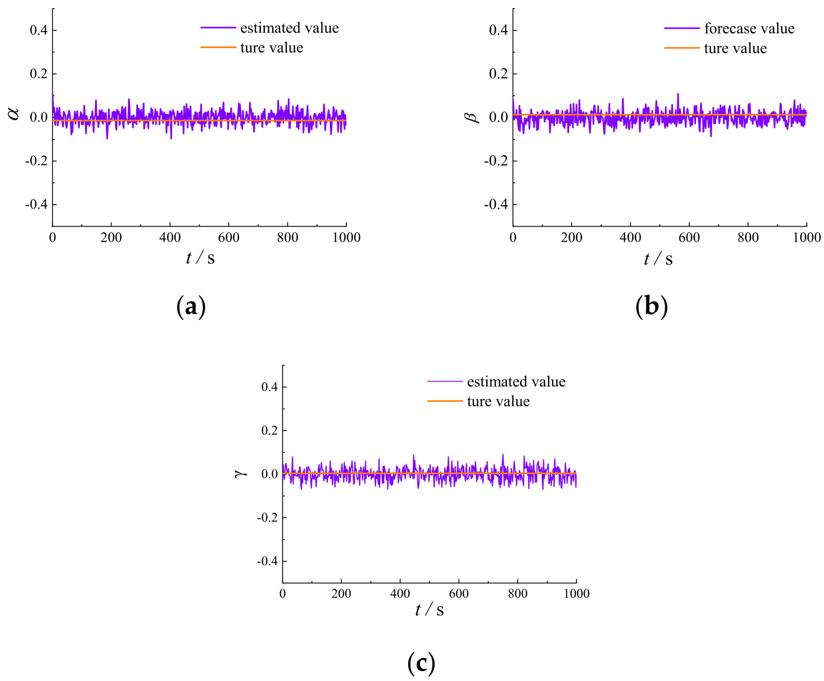

Figure 6. The estimated parameters of the ship steering adaptive CGS controller. (**a**) Estimated ship parameter α. (**b**) Estimated ship parameter β. (**c**) Estimated ship parameter γ.

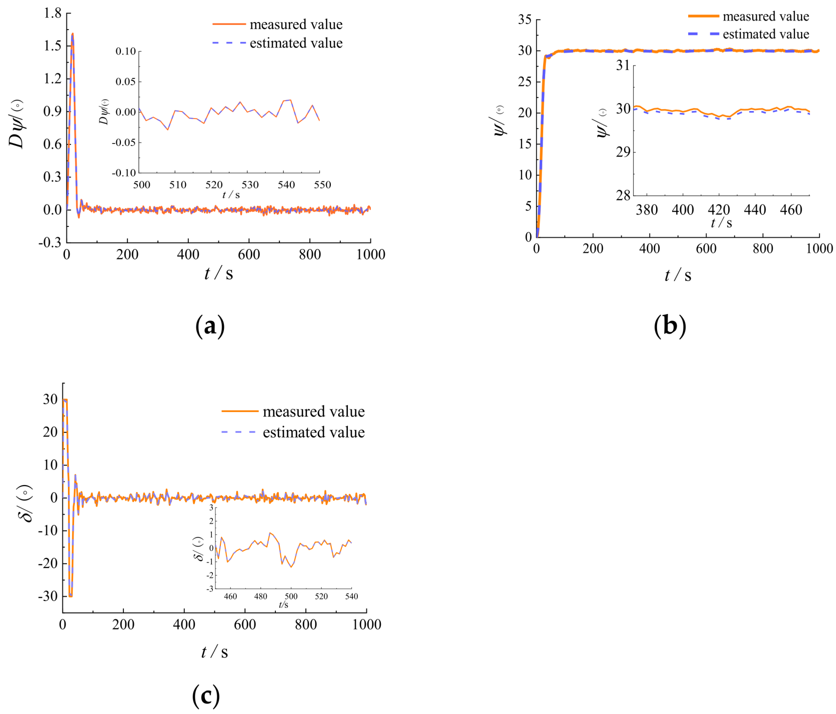

Figure 7. The ship's measured and estimated ship states based on the EKF identification technique. (**a**) Measured and estimated ship state $\dot{\psi}$. (**b**) Measured and estimated ship state ψ. (**c**) Measured and estimated ship state δ.

5.4. Simulation Results Analysis

In order to further evaluate the performance of the controllers, the rising time t_r, the mean absolute error of dynamic (MAED) value, the mean absolute input of dynamic

(MAID) value, the mean absolute error of static (MAES) value, and the mean absolute input of static (MAIS) were defined to evaluate the controller performance accurately.

In the simulations, the first 500 s were defined as the dynamic phase of the ship steering control, where the values of MAED and MAID were used to describe the dynamic performance of the ship steering controller. The next 500 s were defined as the static phase of the ship steering control, where the values of MAES and MAIS were used to describe the static performance of the ship steering control. The value of the MAED and MAES can be calculated by Equations (37) and (38),

$$\mathrm{MAED} = \sum_{i=1}^{n} |\psi_i| / n \tag{37}$$

$$\mathrm{MAES} = \sum_{i=1}^{n} |\psi_i - \psi_r| / n \tag{38}$$

where $|\psi_i|$ is the absolute value of the ship yaw angle in each sampling period. The value of dynamic and static steering input signals can be calculated by Equation (39),

$$\mathrm{MAID} = \mathrm{MAIS} = \sum_{i=1}^{n} |\delta_i| / n \tag{39}$$

where $|\delta_i|$ is the absolute value of the steering control rudder angle in each sampling period.

Therefore, the performance of adaptive CGS, PD, and traditional CGS controllers can be summarized in Table 1, and the advantages and disadvantages of the different controllers can be observed:

Table 1. Performance evaluation of the different controllers.

Controller	t_r	MAED	MAID	MAES	MAIS
Adaptive CGS controller	18.511	28.023	2.351	0.065	0.504
PD controller	70.648	26.766	1.079	0.015	0.017
CGS Controller	110.181	26.771	0.086	0.030	0.004

(1) The proposed adaptive CGS controller has a faster rising time and better dynamic response performance compared with the PD controller and traditional CGS controller.

(2) In the ship steering control steady state phase, compared with the PD controller and traditional CGS controller, the proposed adaptive CGS controller has a similar course-keeping performance. However, the violent maneuver of the proposed adaptive CGS steering controller is obvious, and further improvement is required.

5.5. Trajectory Tracking Analysis and Comparison

The performance of ship trajectory tracking is usually determined by the ship course-changing capability of the ship steering control system. The trajectories shown in Figure 8 were registered during the ship steering trajectory tracking simulation, incorporating set course angles of 10° and 30°. The results show that the proposed adaptive CGS ship steering based on EKF on-line identification method had better trajectory tracking performance compared with the classical PD controller and traditional CGS controller.

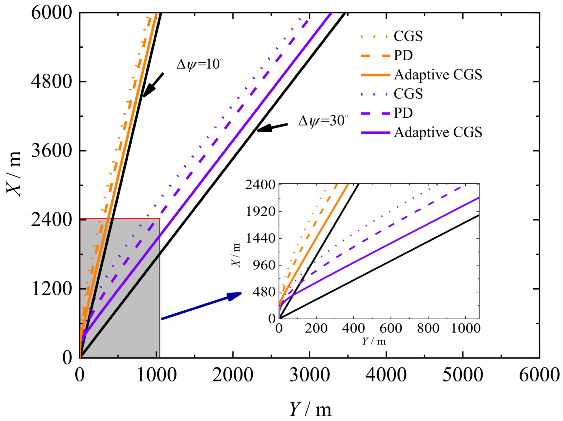

Figure 8. Ship trajectory tracking performance for different ship steering controllers.

6. Conclusions and Discussion

In this paper, the CGS controller design methodology combined with the on-line EKF identification technique was proposed to design a ship steering controller. Through the numeric simulations, it can be concluded that the dynamic response and trajectory tracking performance of the proposed ship steering adaptive CGS controller were significantly improved. This is the main contribution of this study. Furthermore, it can be inferred that the proposed steering controller design methodology might be a good solution for future practical MASS MC module design, especially as MASS call for a rapid course dynamic response maneuver under the MASS HDMC strategy.

However, due to the high sampling frequency of the EKF identification technique, the violent ship steering rudder operation and higher rudder control energy consumption are also prominent. This means that the effectiveness of the proposed ship steering adaptive CGS steering controller has great potential for improvement. Hence, the proposed adaptive CGS steering controller is the first step to applying advanced controllers to the practical MASS MC module design. The event trigger mechanics might be a potential scheme to provide a more reasonable steering operation frequency and remarkable rudder control energy savings.

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