

Advances in Observer-Based Line-of-Sight Guidance for Autonomous Vehicles: A Survey

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Abstract. Autonomous vehicles (AVs) face numerous challenges when performing path-following tasks in complex environments such as oceans, rivers, and lakes. In recent years, Line-of-Sight (LOS) guidance has gained widespread attention as an efficient guidance method. This paper reviews the latest advancements in observer-based LOS guidance technology for AVs. First, the main LOS guidance method and its three variants are thoroughly analyzed. Next, the applications of four traditional observers and neural network-based observers in LOS guidance are discussed. These observers enhance the system's robustness and path-following accuracy by enabling real-time estimation of external disturbances and system uncertainties. Finally, four key areas for future research are proposed, including multi-observer fusion, distributed cooperative observation, hybrid observers combining online and offline learning, and the optimization of lightweight neural network-based observers.

Keywords: Autonomous vehicles, Observer, Line-of-Sight guidance, Path following, Neural networks.

1. Introduction

Autonomous vehicles (AVs) face significant challenges in executing path-following tasks in complex environments such as oceans, rivers, and lakes. The unpredictability of these marine environments, coupled with external disturbances like wind and currents, can adversely affect the vehicle's heading and path-following accuracy. In such conditions, designing efficient and robust control algorithms is critical. Line-of-Sight (LOS) guidance, a typical path-following method, adjusts the vehicle's heading to ensure movement toward the target path, and has been widely applied in the control systems of Unmanned Surface Vehicles (USVs) and Autonomous Underwater Vehicles (AUVs).

However, traditional LOS methods exhibit limitations in dynamic and complex environments. For instance, significant external disturbances often lead to cumulative errors, causing vehicles to deviate from their intended path. To address this, researchers have progressively introduced observer technologies, which improve the robustness and tracking accuracy of LOS guidance by estimating external disturbances and system state uncertainties in real time. These observers compensate for environmental disturbances, ensuring high path-following accuracy even in harsh marine environments.

This review focuses on the advancements in observer-based LOS guidance. It first discusses traditional LOS methods and their various improvements, followed by the integration of observers into LOS guidance. Finally, the advantages and limitations of different observers are analyzed, and future

research directions are proposed. This review aims to provide a comprehensive overview of observer-based LOS guidance technologies and offer new insights for future research.

2. Line-of-Sight Guidance and its Variants

In AV guidance, three reference frames are commonly used to describe motion in a two-dimensional plane. The reference frame $\xi E \zeta$ is defined as the tangent plane on the Earth's surface, with the ξ -axis pointing north and the ζ -axis pointing east. The frame xOy is fixed on the AV, where the x -axis directs towards the bow and the y -axis towards the starboard side. The reference frame XPY is attached to a virtual leader moving along the parameterized path, with the X -axis pointing in the tangent direction and the Y -axis in the normal direction. The desired path is denoted as p_d , U represents the AV's velocity vector, β is the AV's sideslip angle, ψ_d is the heading angle of the virtual target point, and ψ is the AV's current heading angle. The lateral and longitudinal errors in the AV's path coordinate system are represented by (x_e, y_e) , as illustrated in Figure. 1.

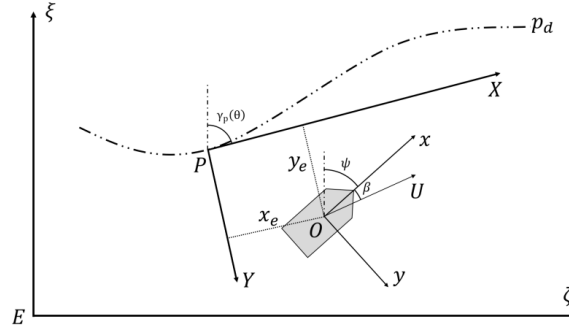


Figure 1. 2-D reference frames for AV guidance.

The core idea behind LOS guidance is to adjust the vessel's heading to gradually approach the desired trajectory. This section focuses on traditional LOS guidance and its three variants.

The traditional LOS guidance method calculates the heading angle between the current position of the vehicle and the target point, ensuring the vehicle is directed toward the target. This method was first applied to Autonomous Underwater Vehicles by Anthony J. Healey and David Lienard [1], and the formula is expressed as follows:

$$\psi_d = \tan^{-1} \left(\frac{Y_k(\theta) - Y(t)}{X_k(\theta) - X(t)} \right) \quad (1)$$

where ψ_d represents the desired heading angle, $P(X_k(\theta), Y_k(\theta))$ denotes the coordinates of the target point, $O(X(t), Y(t))$ indicates the current position of the AV, and $\tan^{-1}$ is the arctangent function used to calculate the direction angle between two points. This formula facilitates path tracking by determining the vehicle's bearing toward the target point. While traditional LOS is simple to implement, computationally efficient, and suitable for basic path-following tasks, it has two significant limitations in practical applications. First, when subject to environmental disturbances such as currents, the vehicle tends to deviate from the planned path; second, in cases of sharp turns or short distances, system response delays can reduce accuracy. To address these issues, proportional LOS (PLOS), integral LOS (ILOS), and adaptive LOS (ALOS) methods have been developed, as summarized in Table 1.

Table 1. Variants of LOS Guidance and their Corresponding Formulas

Guidance Methods	Formula	References
PLOS Guidance	$\psi_d = \gamma_p(\theta) + \tan^{-1} \left(-\frac{y_e}{\Delta} \right)$	[2][3] [4]
ILOS Guidance	$\psi_d = \gamma_p(\theta) + \tan^{-1} \left(-\frac{y_e + \sigma y_{int}}{\Delta} \right)$ $\dot{y}_{int} = \frac{y_e \Delta}{(y_e + \sigma y_{int})^2 + \Delta^2}$	[5] [6] [7]
ALOS Guidance	$\psi_d = \gamma_p(\theta) + \tan^{-1} \left(-\frac{1}{\Delta} (y_e - \hat{\beta}) \right)$ $\hat{\beta} = \frac{kUy_e \Delta}{\sqrt{\Delta^2 + (y_e + \Delta \hat{\beta})^2}}$	[8] [9] [10]

In Table 1, ψ_d is the desired heading angle, $\gamma_p(\theta)$ is the path tangential direction, y_e is the cross-track error, y_{int} represents the integral of the cross-track error, Δ is the look-ahead distance, $\hat{\beta}$ is the estimated sideslip angle, U is the total vehicle speed, σ is the integral gain, and k is the speed gain.

2.1. Observer-Based LOS Guidance

Although traditional LOS and its variants have improved the system's disturbance resistance and path-following accuracy to some extent, they still exhibit limitations in both aspects. Consequently, researchers have increasingly focused on incorporating observers to enhance the performance of LOS guidance.

2.1.1. High-Gain Observer. The High-Gain Observer (HGO) rapidly estimates system states through high-gain feedback, making it particularly suitable for underactuated systems. The general HGO equations are as follows:

$$\epsilon \dot{\xi}_1 = \xi_2, \quad \epsilon \dot{\xi}_2 = -b_1 \xi_2 - \xi_1 + \eta(t) \quad (2)$$

where ξ_1 and ξ_2 are the internal state variables of the observer, $\eta(t)$ is the known input, and ϵ is the gain adjustment parameter. Utilizing these internal states allows the HGO to estimate unmeasurable variables, such as system velocity, from measurable position signals. A study by Wang et al. [11] proposed an LOS guidance law based on the High-Gain Observer, significantly enhancing path-following accuracy and reducing lateral errors in complex marine environments by estimating and compensating for time-varying sideslip angles.

2.1.2. Disturbance Observer. While the HGO can quickly converge to error-free states and is well-suited for high-dynamic environments, it is sensitive to noise. To address this, researchers proposed the Disturbance Observer (DO).

In LOS guidance control, DOs are used to estimate and compensate for external disturbances (e.g., wind, currents) in real time, thereby mitigating their impact on path-following. In [12], lateral error and

heading angle measurements were used to estimate the sideslip angle caused by external disturbances, enabling the system to maintain high path-following accuracy in dynamic disturbance environments:

$$\dot{p} = -k_3 p - k_3^2 y_e - k_3 U \sin(\phi - \gamma_p) \quad (3-1)$$

$$\hat{g} = p + k_3 y_e \quad (3-2)$$

$$\hat{\beta} = \frac{\hat{g}}{U \cos(\phi - \gamma_p)} \quad (3-3)$$

where p is the internal state of the observer, k_3 is the observer gain, $\hat{g}$ is the estimated disturbance effect, y_e is the lateral error, U is the vessel's speed, ϕ is the heading angle, and γ_p is the tangent direction of the path. A fixed-time disturbance observer was designed in [13] to estimate and compensate for sideslip caused by disturbances, ensuring the error converges within a fixed time. A finite-time convergent disturbance observer was proposed in [14], capable of quickly estimating disturbances within a finite time, ensuring stability and accuracy in path-following. An improved indirect adaptive disturbance observer was designed in [15] to precisely estimate large-scale, time-varying ocean currents, providing accurate path-following for curved paths and sharp turns.

2.1.3. Adaptive Observer. While DOs perform well in compensating for external disturbances, they rely on fixed gains, which limits their performance in the presence of time-varying disturbances or highly nonlinear systems. To overcome this limitation, researchers have developed Adaptive Observers (AOs) with dynamic adjustment capabilities. For instance, an observer based on an adaptive Kalman filter was proposed in [16]:

$$\dot{\hat{z}} = A(t)\hat{z} + \phi(t) + \Phi(t)\hat{\beta} + [p_\beta^{-1}\Lambda\Lambda^T + P_z^{-1}]\Sigma(z - \{\hat{z}\}) \quad (4-1)$$

$$\dot{\hat{\beta}} = -p_\beta^{-1}\Lambda^T\Sigma(z - \{\hat{z}\}) \quad (4-2)$$

where $\hat{z} = [\hat{x}_e, \hat{y}_e]^T$ is the estimated path error, $\hat{\beta}$ is the estimated sideslip angle, $\phi(t)$ and $\Phi(t)$ are system input signals, p_β is the adaptive gain, P_z is the gain matrix for path-following error, and Σ is a positive definite matrix used to adjust the system's convergence speed. The following equations dynamically update the adaptive gains Λ , P_z , and p_β , ensuring that the observer's convergence speed adjusts according to real-time system dynamics:

$$\dot{\Lambda} = [A(t) - P_z^{-1}\Sigma]\Lambda + \Phi(t) \quad (5-1)$$

$$\dot{P}_z = -\rho_z P_z - A(t)^T P_z - P_z A(t) + \Sigma \quad (5-2)$$

$$\dot{p}_\beta = -\rho_\beta p_\beta + \Lambda^T \Sigma \quad (5-3)$$

In [17], a LOS guidance law based on a Bounded-Gain-Forgetting adaptive observer was proposed, where sideslip angle estimation is independent of tracking errors. This method effectively mitigates oscillations or peak phenomena resulting from significant initial lateral errors, thereby improving the system's transient performance.

2.1.4. Extended State Observer. While AOs can dynamically adjust gains to manage certain disturbances, their performance is limited when faced with rapidly changing nonlinear disturbances. Since AOs rely on known models, they struggle to handle unmodeled dynamics or strong disturbances. To address this, researchers developed the Extended State Observer (ESO), which simultaneously

estimates both system states and external disturbances, treating uncertainties as extended states. This approach enhances adaptability and significantly improves the robustness and path-following accuracy of systems in complex environments.

In [18], an ESO was proposed to estimate the sideslip angle β , compensating for external disturbances and ensuring accurate path-following. The core equations are:

$$\dot{p} = -kp - k_2 y_e - k \left[U \sin(\psi_d - \alpha_k) - \dot{\alpha}_k x_e \right] \quad (6-1)$$

$$\hat{g} = p + k y_e \quad (6-2)$$

where g represents the unmeasurable disturbances in the system, including the sideslip angle β ; $\hat{g}$ is the estimated value of the disturbance, U is the vessel's speed, ψ_d is the desired heading angle, α_k is the path tangent angle, p is the observer's internal auxiliary state, y_e is the lateral error, and k and k_2 are the observer gains. The sideslip angle β can be estimated using the following equation:

$$\hat{\beta} = \frac{\hat{g}}{U \cos(\psi_d - \alpha_k)} \quad (6-3)$$

Subsequent studies introduced various forms of ESO to estimate system states and external disturbances. In [19], a Finite-Time Extended State Observer (FTESO) was proposed, estimating unmeasurable synthetic disturbances and compensating for them. A Nonlinear Extended State Observer (NESO) was designed in [20] to handle nonlinear time-varying uncertainties. In [21], a Fast Extended State Observer (FESO) was introduced, using finite-time convergence algorithms to estimate sideslip angles. Additionally, a Prescribed-Time Extended State Observer (PTESO) was proposed in [22] to accurately estimate sideslip angles under curved paths or time-varying ocean disturbances, further improving LOS accuracy.

2.2. Neural Network-Based Observers

Traditional observers typically rely on the known structure and characteristics of the system, using feedback mechanisms for state estimation and disturbance compensation. While they offer simplicity and ease of implementation, they exhibit limitations when dealing with complex environments, uncertainties, and nonlinear disturbances. To address these issues, neural network-based observers have emerged as a promising solution.

In [23], a Back Propagation Neural Network-based observer was designed (see Fig. 2). This observer uses measurable physical quantities, such as relative speed U_r , roll rate p , yaw rate r , roll angle φ , and rudder angle δ , to approximate the nonlinear function $H(U_r, p, r, \varphi, \delta)$. The estimated values are then integrated into the controller design to improve the accuracy of LOS guidance in path-following by assisting in controlling the vehicle's heading and speed.

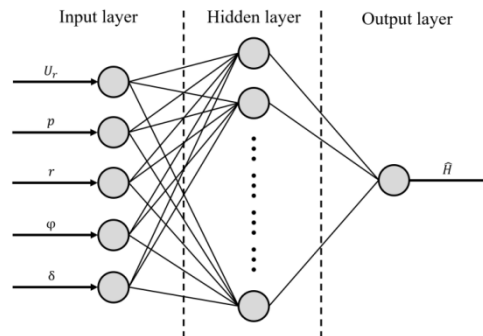


Figure 2. Structure of BP neutral network-based observer.

In [24], an observer based on Echo State Networks (ESN), a special type of recurrent neural network, was proposed (see Fig. 3). Using its dynamic reservoir, the ESN processes and learns complex nonlinear systems. The authors used the ESN to estimate unobservable variables, such as the crab angle, and combined it with a dual reduced-order Extended State Observer (RESO) and adaptive controller to improve the accuracy and stability of LOS guidance.

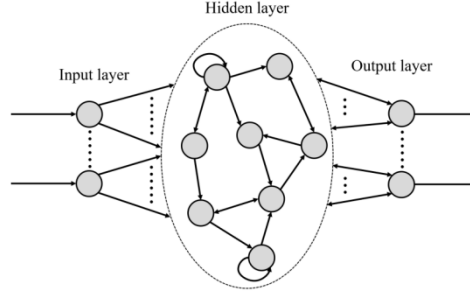


Figure 3. Structure of ESN-based observer.

In [25], a Radial Basis Function Neural Network (RBFNN) was employed as an estimator to handle system dynamics and uncertainties. By incorporating state feedback, the RBFNN estimates disturbances within the system, and in conjunction with reinforcement learning algorithms, facilitates more precise path-following with LOS guidance. The RBFNN estimation process is typically expressed as:

$$f(X) = W^T G(X) + \varsigma(X) \quad (7-1)$$

where X represents the input vector (e.g., observable quantities like vessel speed and angular velocity), W is the weight vector, and $G(X)$ is the radial basis function, usually represented as a Gaussian function:

$$g_i(x) = \exp\left(-\frac{|X - c_i|^2}{2b_i^2}\right) \quad (7-2)$$

where c_i and b_i represent the center and width of the basis functions, respectively. This enables the RBFNN to approximate the system's dynamic equations and estimate external disturbances. The strength of RBFNN lies in its local approximation capabilities, making it effective in estimating uncertainties in complex nonlinear systems.

In [26], a simpler minimal parameter learning method for neural networks was adopted to identify uncertainties and time-varying external disturbances. This method reduces the number of learning parameters in the network, thereby lowering computational complexity and improving real-time performance, which significantly improves the effectiveness of LOS guidance in practical applications.

2.3. Comparison of Observers

Although HGO can quickly estimate system states, they are sensitive to noise, which may lead to instability in the presence of strong marine disturbances. HGOs are better suited for applications requiring fast response. In dynamic disturbance environments, DO improve path-following accuracy by estimating external disturbances, making them suitable for scenarios with significant external interference. The strength of AOs lies in their ability to dynamically adjust gains, enabling them to handle time-varying disturbances, thus enhancing system convergence speed and robustness. ESOs estimate both system states and external disturbances simultaneously, making them well-suited for complex disturbance environments, improving path-following accuracy. Neural network-based observers excel at nonlinear approximation, significantly enhancing the accuracy and stability of LOS guidance in complex and dynamic environments. A comparison of HGO, DO, AO, ESO, and neural network-based observers is summarized in Table 2.

Table 2. Comparison of Observers

Observer Type	Estimation Accuracy	Convergence Speed	Robustness	Noise Resistance ⁰	Dynamic Adaptability	Computational Complexity
High-Gain Observer	Enhanced	Optimal	Moderate	Minimal	Limited	Limited
Disturbance Observer	Moderate	Moderate	Enhanced	Moderate	Limited	Moderate
Adaptive Observer	Enhanced	Enhanced	Optimal	Enhanced	Optimal	Enhanced
Extended State Observer	Optimal	Moderate	Optimal	Enhanced	Optimal	Optimal
Neural Network Observer	Optimal	Limited	Optimal	Optimal	Optimal	Optimal

In summary, selecting the appropriate observer is crucial for improving the accuracy and robustness of LOS guidance, especially in complex marine environments. Different types of observers can be combined and optimized according to the specific requirements of the application.

3. Future Research Directions

Despite significant progress in integrating observers LOS guidance systems, limitations remain, presenting opportunities for further improvements. This section identifies four important but challenging research directions for future studies.

1) Multi-Observer Fusion: Recent years have seen the proposal of various types of Extended State Observers (e.g., FTESO, NESO, RESO, PTESO, FESO) [19-22, 27] to handle external disturbances and system uncertainties. However, most of these methods are applied in isolation. Since each observer has its own advantages and limitations, future research could explore the fusion of multiple observer technologies. For example, combining the fast convergence of FESO [21] with the robustness of NESO [20] could leverage the strengths of different observers in handling various types of disturbances, thereby enhancing the overall observation capacity of the system.

2) Multi-Platform Collaboration and Distributed Observers: A network-based control architecture discussed in [28] highlights an event-triggered LOS guidance method for path-following in a network environment, which reduces network load and communication frequency. Future research could consider applying observer-based LOS guidance technology in multi-platform collaborative scenarios. Through distributed observer technology, multiple platforms could share environmental information and disturbance data, improving the overall observation accuracy and control efficiency of the system.

3) Hybrid Estimators Combining Online and Offline Learning: While neural network-based observer technology has seen progress in recent years, researchers have often relied on either online or offline learning methods to design observers. For example, [24, 25] depend on real-time data for adjustment, categorizing them as online learning, whereas [23] adopts an offline learning approach. Online learning can handle real-time data, while offline learning can optimize the model using historical data. Future studies could explore hybrid models that combine both online and offline learning. In the early stages of system operation, results from offline learning could serve as the foundational model, which can then be continuously updated through online learning, enhancing system adaptability and stability.

4) Lightweight Neural Network Observers: Although [26] employed a minimal parameter learning method for neural networks to replace traditional multi-layer neural networks, reducing the number of parameters and computational burden, research in this area is still sparse. Future research could focus on developing more lightweight neural network architectures. These technologies could reduce the number of parameters and computational complexity without significantly sacrificing accuracy, thus achieving efficient path-following and state estimation with low computational costs.

4. Conclusion

This review summarizes the advancements in observer-based LOS guidance technologies for autonomous vehicles, focusing on various types of observers, including High-Gain Observers (HGO), Disturbance Observers (DO), Adaptive Observers (AO), Extended State Observers (ESO), and neural network-based observers. Furthermore, the paper identifies four key research directions for future work: multi-observer fusion, multi-platform collaboration with distributed observers, hybrid estimators combining online and offline learning, and the optimization of lightweight neural network observers. These directions offer new research pathways and technological advancements for precise path-following of autonomous vehicles, potentially driving further development in this field.

References

- [1] Healey, A. J., & Lienard, D. (1993). Multivariable sliding mode control for autonomous diving and steering of unmanned underwater vehicles. *IEEE journal of Oceanic Engineering*, 18(3), 327-339.
- [2] Fossen, T. I., & Pettersen, K. Y. (2014). On uniform semiglobal exponential stability (USGES) of proportional line-of-sight guidance laws. *Automatica*, 50(11), 2912-2917.
- [3] Sanders, R. M. W. (2003). Control of a model sized hovercraft.
- [4] Breivik, M., & Fossen, T. I. (2005, December). Principles of guidance-based path following in 2D and 3D. In *Proceedings of the 44th IEEE Conference on Decision and Control* (pp. 627-634). IEEE.
- [5] Borhaug, E., Pavlov, A., & Pettersen, K. Y. (2008, December). Integral LOS control for path following of underactuated marine surface vessels in the presence of constant ocean currents. In *2008 47th IEEE conference on decision and control* (pp. 4984-4991). IEEE.
- [6] Wang, X., Sun, S., Jiyang, E., & Wang, Y. (2023, July). Closed-Loop Integral Line-of-Sight Guidance Law Based Adaptive Fuzzy Path-Following Control of Hovercraft. In *2023 42nd Chinese Control Conference (CCC)* (pp. 402-408). IEEE.
- [7] Rout, R., Cui, R., & Han, Z. (2020). Modified line-of-sight guidance law with adaptive neural network control of underactuated marine vehicles with state and input constraints. *IEEE transactions on control systems technology*, 28(5), 1902-1914.
- [8] Fossen, T. I., Pettersen, K. Y., & Galeazzi, R. (2014). Line-of-sight path following for dubins paths with adaptive sideslip compensation of drift forces. *IEEE Transactions on Control Systems Technology*, 23(2), 820-827.
- [9] Su, Y., Wan, L., Zhang, D., & Huang, F. (2021). An improved adaptive integral line-of-sight guidance law for unmanned surface vehicles with uncertainties. *Applied Ocean Research*, 108, 102488.
- [10] Zheng, Z., & Sun, L. (2016). Path following control for marine surface vessel with uncertainties and input saturation. *Neurocomputing*, 177, 158-167.
- [11] Wang, Y., Tong, H., & Wang, C. (2019). High-gain observer-based line-of-sight guidance for adaptive neural path following control of underactuated marine surface vessels. *IEEE Access*, 7, 26088-26101.
- [12] Wan, L., Su, Y., Zhang, H., Shi, B., & AbouOmar, M. S. (2020). An improved integral light-of-sight guidance law for path following of unmanned surface vehicles. *Ocean engineering*, 205, 107302.
- [13] Wang, S., Sun, M., Xu, Y., Liu, J., & Sun, C. (2023). Predictor-based fixed-time LOS path following control of underactuated USV with unknown disturbances. *IEEE Transactions on Intelligent Vehicles*, 8(3), 2088-2096.
- [14] Fu, M., & Wang, L. (2019, July). Disturbance observer based path following control of unmanned surface vessel with time-varying current. In *2019 Chinese Control Conference (CCC)* (pp. 370-375). IEEE.

- [15] Du, P., Yang, W., Chen, Y., & Huang, S. H. (2023). Improved indirect adaptive line-of-sight guidance law for path following of under-actuated AUV subject to big ocean currents. *Ocean Engineering*, 281, 114729.
- [16] Martinović, L., Zečević, Ž., Bibuli, M., Caccia, M., & Nađ, Đ. (2024). Adaptive Observer-Based Line-of-Sight Guidance Law for Path Following of Underactuated Unmanned Surface Vehicle with Sideslip Compensation. *IEEE Access*.
- [17] Wang, Y., Tong, H., & Fu, M. (2019). Line-of-sight guidance law for path following of amphibious hovercrafts with big and time-varying sideslip compensation. *Ocean Engineering*, 172, 531-540.
- [18] Liu, L., Wang, D., & Peng, Z. (2016). ESO-based line-of-sight guidance law for path following of underactuated marine surface vehicles with exact sideslip compensation. *IEEE Journal of Oceanic Engineering*, 42(2), 477-487.
- [19] Fu, M., & Wang, Q. (2023). Safety-guaranteed, robust, nonlinear, path-following control of the underactuated hovercraft based on FTESO. *Journal of Marine Science and Engineering*, 11(6), 1235.
- [20] Wang, Y., Tong, H., & Ren, H. (2020). Neso-based path following control for underactuated hovercrafts with unknown nonlinear uncertainties and a safety limit constraint. *Applied Sciences*, 10(15), 5287.
- [21] Wang, K., Liu, Y., Huang, C., & Cheng, P. (2022). Water surface and ground control of a small cross-domain robot based on fast line-of-sight algorithm and adaptive sliding mode integral barrier control. *Applied Sciences*, 12(12), 5935.
- [22] Yu, C., Zhu, J., Hu, Y., Zhu, H., Wang, N., Guo, H., ... & Liu, S. (2024). Prescribed-time observer-based sideslip compensation in USV line-of-sight guidance. *Ocean Engineering*, 298, 117177.
- [23] Wang, C., & Ji, M. INTEGRAL SFLOS PATH FOLLOWING CONTROL WITH HEADING BP NEURAL NETWORK BACKSTEPPING SLIDING-MODE CONTROLLER AND SPEED ADRC.
- [24] Deng, Y., Zhang, X., & Zhang, G. (2019). Line-of-sight-based guidance and adaptive neural path-following control for sailboats. *IEEE Journal of Oceanic Engineering*, 45(4), 1177-1189.
- [25] Wang, Y., & Zhou, H. (2024). Data-driven constrained reinforcement learning algorithm for path tracking control of hovercraft. *Ocean Engineering*, 307, 118169.
- [26] Mu, D., Wang, G., Fan, Y., Bai, Y., & Zhao, Y. (2018). Fuzzy-based optimal adaptive line-of-sight path following for underactuated unmanned surface vehicle with uncertainties and time-varying disturbances. *Mathematical Problems in Engineering*, 2018(1), 7512606.
- [27] Deng, Y., Zhang, X., & Zhang, G. (2019). Line-of-sight-based guidance and adaptive neural path-following control for sailboats. *IEEE Journal of Oceanic Engineering*, 45(4), 1177-1189.
- [28] Wu, W., Peng, Z., Wang, D., Liu, L., & Han, Q. L. (2021). Network-based line-of-sight path tracking of underactuated unmanned surface vehicles with experiment results. *IEEE Transactions on Cybernetics*, 52(10), 10937-10947.