

Underactuated Merchant Ship Trajectory Tracking Control with Anti-Interference Capability Based on L1-LOS Guidance and Multi-Parameter PSO-PID Optimization

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Abstract. Aiming at the problems of low response efficiency of large heading deviation and low accuracy of trajectory tracking under complex sea state in trajectory tracking control of underactuated merchant ships, this study proposes an improved L1-LOS(LL) algorithm, which introduces the Line-of-Sight (LOS) guidance algorithm in the curved path scenarios with large heading errors on the basis of traditional L1 algorithm to take advantage of its fast response algorithm to correct the large heading errors quickly. And the multi-parameter particle swarm optimization control(PSO-PID) algorithm is designed to combine the centripetal acceleration of underactuated merchant ships navigation with the lateral error to propose a multi-parameter fitness function optimization scheme to improve the dynamic performance of the control system. Through simulation and real ship experiments, it is confirmed that the LL guidance significantly outperforms the traditional L1 method in terms of average lateral error and range under straight line, Z-type and multi-point paths; under wind and wave interference conditions, the stability of the lateral error of the PSO-PID control is also significantly improved by, which verifies the effectiveness of the algorithm in complex environments. This study provides a high-precision and robust solution for the intelligent control of underactuated merchant ships.

Keywords: L1 guidance control, Line-of-sight, LL guidance control, multiparameter PSO, trajectory tracking control, underactuated merchant ships.

1. Introduction

Recent years have witnessed accelerated intelligence and green transformation in maritime shipping. Advanced sensors and automation technologies have enabled preliminary autonomous navigation and collision avoidance, reducing human intervention and energy consumption[1-5]. Modern merchant ships predominantly employ underactuated systems comprising propeller-driven propulsion and rudders, which lack lateral thrust. Such systems often struggle with large heading deviations during sharp turns and exhibit degraded tracking accuracy under environmental disturbances, compromising safety and efficiency[6-7].

Extensive research has been conducted on trajectory tracking methods for underactuated merchant ships. In 2019, Noshahri et al. proposed a simplified control framework using path smoothing and motion curve optimization to reduce redundant maneuvers and adjustment time, yet its tracking precision and response to large heading deviations remained inadequate[8]. In 2024, Zhang et al. enhanced small-to-medium heading deviation response efficiency via L1-VS guidance and saturation fault-tolerant control[9]. Machine learning approaches have also gained traction. Ye et al. (2024) addressed heading control under unknown dynamics using Adaptive Neural Synergetic Control (ANSC) with Radial Basis Function (RBF) networks[10], while Li et al. (2025) integrated

reinforcement learning and sliding mode control for enhanced disturbance rejection in unmanned boats[11].

To enhance the accuracy of trajectory tracking, numerous studies have been conducted by researchers. In 2022, Li B et al. first integrated the Beetle Antennae Search (BAS) algorithm into the Particle Swarm Optimization (PSO) algorithm, proposing a hybrid BAS-PSO algorithm for PID parameter optimization[12]. By simulating the foraging behavior of beetles, this method overcomes the tendency of PSO to fall into local optima, significantly improving the convergence rate and optimization performance of the algorithm, thereby achieving enhanced precision in trajectory tracking. In 2025, Zhu et al. focused on improving the path-following accuracy of USVs under complex environmental disturbances. They developed an adaptive control method rooted in dynamic modeling[13], demonstrating superior performance in dynamic adaptability and disturbance rejection.

Despite advancements, significant gaps persist in precise trajectory tracking for underactuated merchant ships under complex sea conditions, particularly in rapid correction of large heading deviations. This study proposes an improved L1-LL guidance algorithm that dynamically switches between L1 and LOS guidance based on heading error thresholds. The algorithm achieves synergistic "rapid large-deviation correction" and "fine small-deviation tracking." Furthermore, a multi-parameter PSO-PID control framework is developed, integrating centripetal acceleration and lateral error into a fitness function for adaptive parameter tuning. The resultant system, LLPP (L1-LOS Guided Multi-Parameter PSO-Optimized PID Control), is validated through simulations and real-ship experiments.

2. Ships and Wind-Wave-Current Model

2.1 Ships Model

This study focuses on trajectory tracking control for underactuated merchant ships, which is typically analyzed in the horizontal plane. Vertical motions (heave, roll, pitch) are neglected, simplifying the system to 3-DOF motions (surge, sway, yaw). The six-degree-of-freedom ship dynamics are reduced to 3-DOF as follows:

$$\begin{cases} \dot{u} = \frac{1}{(m + m_x)} (X_H + X_R + X_P + v(m + m_y) + rx_G mr) \\ \dot{v} = \frac{1}{(m + m_y)} (Y_H + Y_R - (m + m_x)ur - mx_G \dot{r}) \\ \dot{r} = \frac{1}{(I_z + J_z + mx_G^2)} (N_H + N_R - x_G mur - mx_G \dot{v}) \end{cases} \quad (1)$$

Where, m_x , m_y indicates the added mass, J_z is the added moment of inertia, and x_G specifies the position of the center of mass relative to the coordinate origin. X_H, Y_H, N_H represents the hydrodynamic forces/moments generated by the ship hull itself, X_R, Y_R, N_R denotes the hydrodynamic forces/moments induced by the rudder, and X_P refers to the propulsive force from the propeller.

2.2 Wind-Wave-Current Model

Wind forces primarily act on the hull through aerodynamic drag, affecting the lateral motion and yaw of the vessel. The wind forces on the ship can generally be decomposed into longitudinal force, lateral force, and yaw moment. The lateral force Y_w and yaw moment N_w acting on the vessel due to wind are calculated as follows:

$$\begin{cases} F_w = \frac{1}{2} \rho_a C_{D,w} A_w V_w^2 \\ Y_w = F_w \sin(\theta_w - \psi) \\ N_w = F_w L_w \sin(\theta_w - \theta) \end{cases} \quad (2)$$

where, ρ_a denotes the air density, $C_{D,w}$ is the aerodynamic drag coefficient, A_w represents the frontal projected area, V_w is the relative wind speed, θ_w indicates the wind direction angle, ψ corresponds to the ship yaw angle, and L_w defines the distance from the ship's center to the point of wind force application.

Waves induce periodic disturbances on ship motion, affecting its lateral movement, longitudinal movement, and yaw angle variation. Wave effects are typically described using regular or irregular waves. Assuming sinusoidal waves, the lateral wave force Y_{wave} and yaw moment N_{wave} can be expressed as:

$$\begin{cases} F_{wave} = A \sin(\omega t + \phi) \\ Y_{wave} = A \sin(\omega t) \\ N_{wave} = A L_{wave} \sin(\omega t) \end{cases} \quad (3)$$

where, A represents the wave amplitude, ω is the angular wave frequency, related to the wave period T by $\omega = \frac{2\pi}{T}$. ϕ denotes the initial phase, and L_{wave} is the wave moment arm, defining the lever length for wave-induced torque.

Ocean currents alter the ship's motion by inducing changes in speed and heading. Their primary effects manifest as variations in longitudinal and lateral $Y_{current}$ velocities. Assuming a current with velocity U_c and direction θ_c , the lateral current force and yaw moment $N_{current}$ are calculated as:

$$\begin{cases} Y_{current} = -\rho_{water} C_{D,c} A_c U_c^2 \sin(\theta_c - \psi) \\ N_{current} = Y_{current} L_{current} \end{cases} \quad (4)$$

Where, ρ_{water} is water density, $C_{D,c}$ is the current drag coefficient, A_c is the submerged lateral area of the hull exposed to the current, and $L_{current}$ is the lever arm of the current force, typically defined as a proportional fraction of the ship's length.

The combined effects of wind, waves, and current on ship motion result in a total lateral force Y_{total} and total yaw moment N_{total} , expressed as:

$$\begin{cases} Y_{total} = Y_w + Y_{wave} + Y_{current} \\ N_{total} = N_w + N_{wave} + N_{current} \end{cases} \quad (5)$$

The ship's lateral acceleration v_{dot} and yaw angular acceleration r_{dot} can be expressed as:

$$v_{dot} = \frac{Y_{total} - (DT + m_x)ur}{DT + m_y}, \quad r_{dot} = \frac{N_{total}}{I_z + J_z} \quad (6)$$

3. LL Guidance Algorithm

The L1 guidance algorithm provides gradual heading rate adjustments during trajectory tracking, ensuring smooth path following, the feature beneficial for maintaining navigation stability under the high inertia and significant hysteresis inherent in ship dynamics. However, in scenarios with large angular deviations, its heading correction becomes relatively sluggish, and the computational load increases. To preserve the stability of the L1 algorithm while enhancing its precision in tracking

sharply curved paths, there is a need to improve its responsiveness to significant heading deviations during such maneuvers.

To address this, this paper proposes an enhanced LL guidance algorithm. The LL algorithm achieves coordinated control through dynamic mode switching based on a heading deviation threshold, enabling "rapid elimination of large deviations and refined tracking of minor deviations." Building upon the conventional L1 framework, the improved LL algorithm integrates the LOS guidance method in curved-path scenarios with substantial heading errors. By leveraging LOS's rapid response capability, it swiftly corrects major heading deviations, enhances tracking accuracy in complex maritime conditions, and addresses diverse path-following challenges.

The core principle of the improved LL guidance algorithm is based on classifying and evaluating the heading angle error θ_e between the vessel's current heading and the target point on the current trajectory segment, then selecting the appropriate guidance algorithm. The overall algorithm workflow is illustrated in Figure 1.

$$\begin{cases} L1, & \theta_e \in [(-a+c, a-c) \cup (-\pi, -b-c) \cup (b+c, \pi)] \\ LOS, & \theta_e \in (-b, -a) \cup (a, b) \\ L1+LOS, & \theta_e \in [(-b-c, -b) \cup (-a, -a+c) \cup (a-c, a) \cup (b, b+c)] \end{cases} \quad (7)$$

Calculate the heading angle error θ_e , where θ is the current heading angle, (x, y) is the ship's current position, and (x_d, y_d) is the position of the current target point P_i .

$$\begin{aligned} \theta_e &= \theta_t - \theta \\ \theta_t &= \arctan\left(\frac{y_d - y}{x_d - x}\right) \end{aligned} \quad (8)$$

Determine the range of θ_e and select the corresponding guidance algorithm, where a 、 b 、 c are the thresholds for algorithm switching, determined by experimental conditions.

When $\theta_e \in ((-a+c, a-c) \cup (-\pi, -b-c) \cup (b+c, \pi))$, use the L1 guidance algorithm. Based on the formula for calculating centripetal acceleration in Equation (12), obtain the target centripetal acceleration a , then calculate the target angular velocity ω_{L1} . The angular velocity deviation ω (calculated from ω_{L1} and the current motion angular velocity r) is input as the control variable.

$$\begin{aligned} \omega_{L1} &= \frac{a}{V} = 2 \frac{V}{L_1} \sin \theta \\ \omega &= \omega_{L1} - r \end{aligned} \quad (9)$$

When $\theta_e \in (-b, -a) \cup (a, b)$, the LOS guidance algorithm is employed. Based on Equation (11), calculate the target heading value and the current heading φ to obtain the heading error $\varphi_d = \varphi_p - \varphi$, then compute the target angular velocity ω_{LOS} . The angular velocity deviation ω (calculated from ω_{LOS} and the current motion angular velocity r) is input as the control variable.

$$\begin{aligned} \omega_{LOS} &= \varphi_d / dt \\ \omega &= \omega_{LOS} - r \end{aligned} \quad (10)$$

When $\theta_e \in ((-b-c, -b) \cup (-a, -a+c) \cup (a-c, a) \cup (b, b+c))$, to smooth the algorithm switching process, blending weights are applied to the outputs of both algorithms for weighted fusion to obtain the adjustment. The final adjustment value $\omega = \omega_{adjust}$, calculated based on Equation (17), is input as the control variable.

$$\omega_{adjust} = W_{L1} * (\omega_{L1} - r) + W_{los} * (\omega_{LOS} - r) \quad (11)$$

where, W_{l1} and W_{los} are the blending weights for the L1 and LOS algorithms, while ω_{L1} and ω_{L1} represent the target angular velocities calculated by the L1 and LOS guidance algorithms, respectively. The blending weight function is defined as follows:

$$\begin{aligned} W_{l1} &= 1 / (1 + e^{-P(\theta_e - \theta_0)}) \\ W_{los} &= 1 - W_{los} \end{aligned} \quad (12)$$

The steepness coefficient P governs the sensitivity of the weight function at the threshold θ_0 , which determines the critical point where the function output approaches 1. The threshold value influences the response of the weights to heading angle error: a smaller threshold makes the function sensitive to minor deviations, while a larger threshold ensures significant changes only when errors are substantial. In practical applications, the threshold is initially set based on typical error ranges and then optimized through iterative adjustments.

In summary, the control input calculated by the LL is given by Equation (13)

$$\begin{cases} \omega = \omega_{L1} - r, & \theta_e \in [(-a+c, a-c) \cup (-\pi, -b-c) \cup (b+c, \pi)] \\ \omega = \omega_{LOS} - r, & \theta_e \in (-b, -a) \cup (a, b) \\ \omega = W_{l1} * (\omega_{L1} - r) + W_{los} * (\omega_{LOS} - r), & \theta_e \in [(-b-c, -b) \cup (-a, -a+c) \cup (a-c, a) \cup (b, b+c)] \end{cases} \quad (13)$$

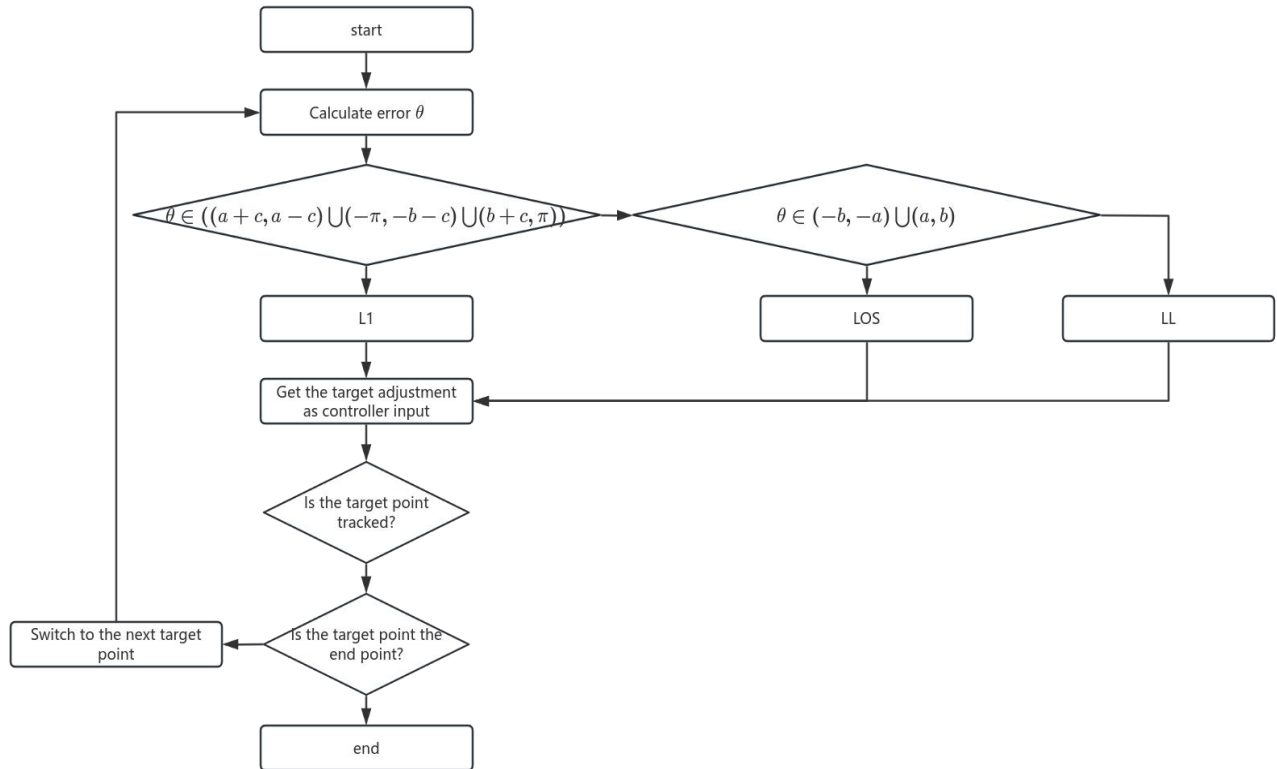


Fig.1 Guidance algorithm flowchart

4. Trajectory Tracking Control System

The target heading angle and lateral acceleration output by the LL guidance algorithm require implementation through rudder control, whose effectiveness is closely related to ship inertia and environmental disturbances. Fixed control parameters tend to cause overshooting during large rudder angle corrections and fail to suppress high-frequency oscillations during steady-state tracking. To address this, this study innovatively integrates lateral error (reflecting trajectory deviation) and centripetal acceleration (characterizing turning dynamics) to construct a multi-parameter fitness function. A dynamic weight allocation strategy is employed to balance tracking accuracy and motion smoothness: accelerating constraints are emphasized during abrupt heading changes to suppress oscillations, while error convergence is prioritized during steady-state

tracking to improve precision. Leveraging the global search capability of Particle Swarm Optimization (PSO), the PID parameters are adaptively tuned, forming a closed-loop architecture where LL guidance generates target commands and PSO-PID dynamically adjusts actuator responses.

The core concept of the PSO algorithm is to iteratively update a group of particles (i.e., candidate solutions) within a search space, gradually approaching the optimal solution. The state of the i -th particle is defined by its position $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$ and velocity $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})$. The particle's position and velocity are updated according to the following equations:

$$v_{id}(t+1) = wv_{id}(t) + c_1r_1(p_{id} - x_{id}(t)) + c_2r_2(g_d - x_{id}(t)), x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (14)$$

where, t represents the current iteration number; w is the inertia weight, controlling the search scope and convergence speed; c_1, c_2 are the individual and social learning factors, respectively; r_1, r_2 are random numbers in the interval $[0, 1]$; p_{id} denotes the historical optimal position of the particle (personal best); and g_d is the global optimal position.

In the trajectory tracking control of underactuated merchant ships, a PID controller is used to compute the rudder angle input to minimize heading deviation and trajectory errors. The parameters of the PID controller significantly affect tracking accuracy, response speed, and system stability. To enhance tracking performance, the Particle Swarm Optimization (PSO) algorithm is applied to optimize the PID parameters. The fitness function for optimization combines lateral error (measuring the deviation between the vessel's trajectory and the target trajectory) and centripetal acceleration (representing the difference between the target and actual accelerations, as defined in Equation (22)). This multi-parameter approach aims to balance trajectory tracking precision with dynamic stability. Simulation experiments validated the effectiveness of the method, demonstrating improved tracking performance under varying weight coefficients for lateral error and centripetal acceleration, as well as stable parameter convergence.

In the trajectory tracking control of underactuated ship models, a PID controller is utilized to calculate the rudder angle input to reduce heading deviation and trajectory errors. Since the parameters K_p, K_i, K_d of the PID controller significantly influence the system's tracking accuracy, response speed, and stability, the PSO algorithm is employed to optimize these PID parameters, thereby improving trajectory tracking performance. Considering that the ship's centripetal acceleration is a critical reference variable in the guidance algorithm and the overarching control objective is to minimize lateral errors, a multi-parameter fitness function is established by combining lateral error and centripetal acceleration as expressed in Equation 15.

$$\begin{cases} MSE_{dis} = \frac{1}{N} \sum_{t=1}^N e^2(t) \\ MSE_a = \frac{1}{N} \sum_{t=1}^N (a_{target}(t) - a_{actual}(t))^2 \end{cases} \quad (15)$$

where, $e(t)$ represents the lateral error at time $a_{target}(t)$ is the target acceleration calculated by the L1 algorithm, $a_{actual}(t)$ denotes the actual centripetal acceleration, and N is the specified number of sampling points. Since MSE_{dis} and MSE_a have different dimensions and exhibit significant disparities in numerical ranges, direct use of these variables would cause metrics with larger numerical ranges to dominate the optimization process. Therefore, normalization is applied to ensure data with distinct dimensions can be optimized within a unified numerical range, thereby enhancing the stability and accuracy of the optimization algorithm. The normalization formula is as follows:

$$\begin{cases} NormalizedMSE_{dis} = \frac{MSE_{dis} - \min(MSE_{dis})}{\max(MSE_{dis}) - \min(MSE_{dis})} \\ NormalizedMSE_a = \frac{MSE_a - \min(MSE_a)}{\max(MSE_a) - \min(MSE_a)} \end{cases} \quad (16)$$

The final fitness function is expressed as Equation (24), where α and β are weight coefficients satisfying $\alpha + \beta = 1$

$$F = \alpha \cdot Normalized_{MSE_{dis}} + \beta \cdot Normalized_{MSE_a} \quad (17)$$

To accommodate varying control requirements during different navigation phases of the ship, a dynamic weight allocation mechanism is adopted: when the heading change rate is large (e.g., during turns or disturbances), the weight coefficient β for dynamic performance is increased to suppress control oscillations; during steady heading change phases, the weight coefficient α for precision is enhanced to improve tracking accuracy, where $\omega_{max} = 30^\circ/s$, $\gamma \in [0.5 \sim 0.8]$.

$$\alpha(t) = 1 - \gamma \frac{|\omega(t)|}{\omega_{max}}, \beta(t) = 1 - \alpha(t) \quad (18)$$

The LLPP trajectory tracking control system for underactuated merchant ships proposed in this paper consists of a guidance system and a control system. The guidance system employs the improved LL guidance algorithm proposed in Section 3, while the control system adopts a multi-parameter PSO-PID optimization control algorithm. The system architecture is illustrated in Figure 2.

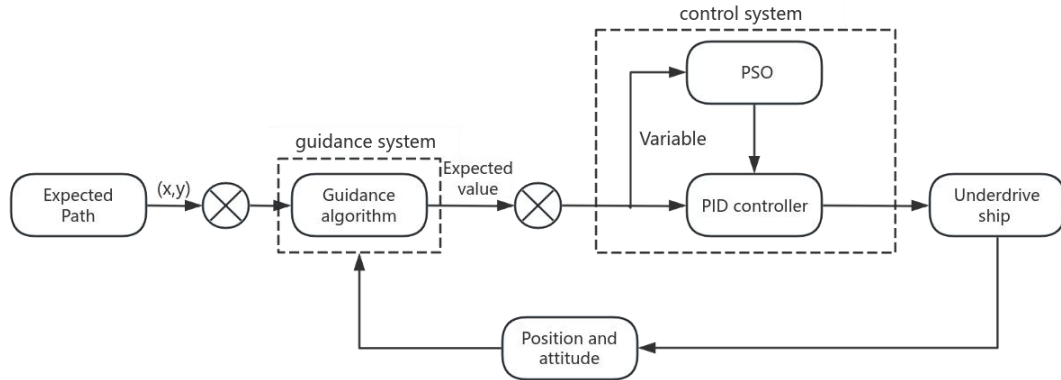


Fig.2 System architecture

5. Simulation and Real Ship Experimental Results

5.1 Simulation Validation of LLPP for Different Paths

In this subsection, simulation experiments of ship trajectory tracking control under the influence of wind and waves will be carried out, and the three methods of L1+PID, LL+PID, and LLPP will be used to carry out comparative simulation experiments of tracking control under the two kinds of paths, straight and curved, respectively. The relevant parameters involved in the particle swarm optimization algorithm are shown in Table 1:

Table 1 Environment termination and reward function design

parameters	numerical value
Number of particles	50
Maximum number of iterations	80
inertial weighting ω	0.9
Inertia weight reduction parameters ω_damp	0.99
Individual learning factor $c1$	2
Group learning factor $c2$	2

5.1.1 Straight-Line Trajectory Tracking Control

The initial position of the ship model(x_0, y_0) is set as(0,0) , the initial speedu is1m/s , the initial heading φ_d is 0° , and the simulation results are shown in Fig. 3. The wind speed is $wind_{speed} = 5$, the wind direction is $wind_{angle} = 90^\circ$, the wave amplitude is $wave_{amp} = 0.2$, and the wave frequency is $wave_{freq} = 2$.

The control algorithm proposed in this paper has the lowest lateral error variance at the shortest sailing distance, indicating that the method reduces the trajectory oscillation and improves the control smoothness while ensuring the trajectory tracking accuracy. The related data are shown in Table 2.

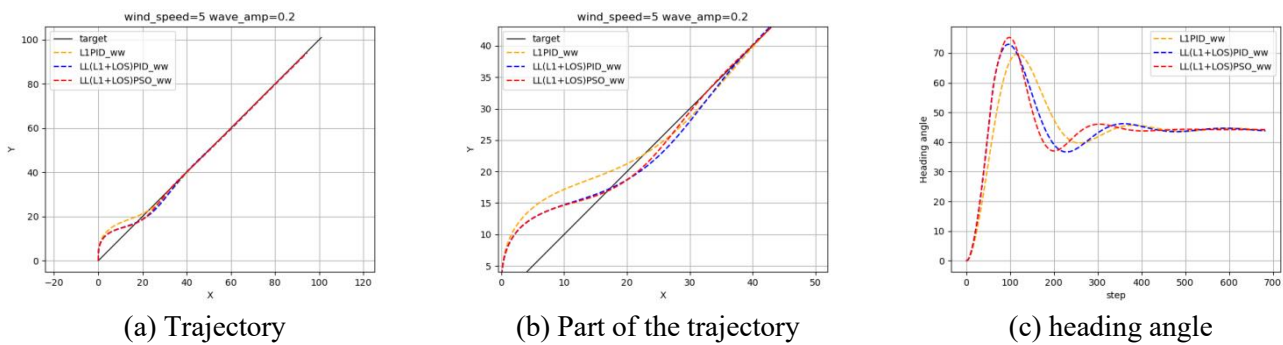


Fig.3 Line path simulate motion trajectory

Table 2 Linear path tracking data

algorithm	Max lateral error	Total distance	Lateral error variance
L1+PID	6.593	136.818	3.636
LL(L1 LOS)+PID	5.739	136.790	2.239
LL(L1 LOS)+PID PSO	5.686	136.741	2.212

5.1.2 Multi-point Trajectory Tracking Control

Set the initial position of the ship model(x_0, y_0) coordinates as(0,0) , the initial speedu as1m/s , the initial heading φ_d as 0° , the wind speed $wind_{speed} = 5$, the wind direction $wind_{angle} = 90^\circ$, the wave amplitude $wave_{amp} = 0.2$, and the wave frequency $wave_{freq} = 2$. The simulation results are shown in Fig. 4.

From the results, it can be seen that the method of this paper still performs best in curved path tracking with the shortest sailing distance and the error variance is lower than that of the traditional L1+PID method, which indicates that the control strategy of PSO optimizing the PID parameters can effectively improve the trajectory tracking accuracy and reduce the deviation. The related data are shown in Table 3.

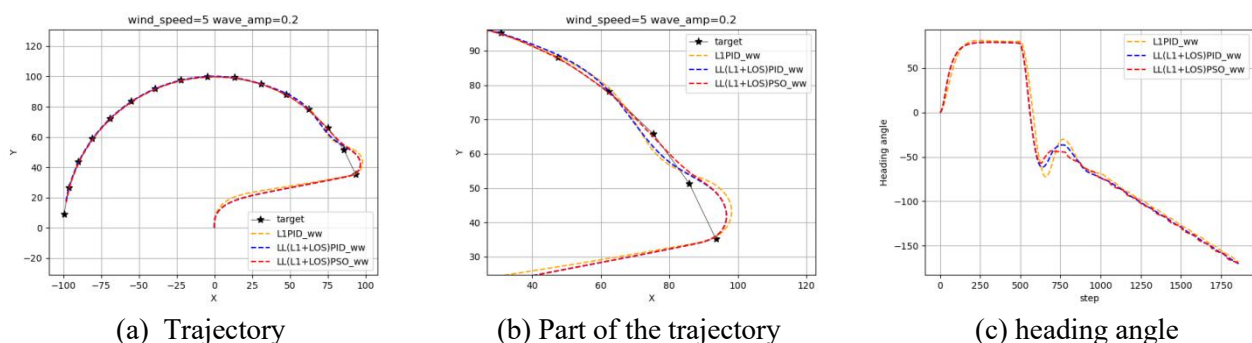


Fig.4 Multi-point path simulate motion trajectory

Table 3 Multi-point path tracking cruise data

algorithm	Max lateral error	Total distance	Lateral error variance
L1+PID	7.959	394.871	2.822
LL(L1 LOS)+PID	6.226	372.269	1.685
LL(L1 LOS)+PID PSO	6.121	371.021	1.440

5.2 Real Ship Tests

The test site is Haiyun Lake of Jiangsu University of Science and Technology (Changshan Campus), which is equipped with a floating dock on the surface of the water, where wind speed and direction meters, monitoring cameras, cabinets and other equipment are placed.

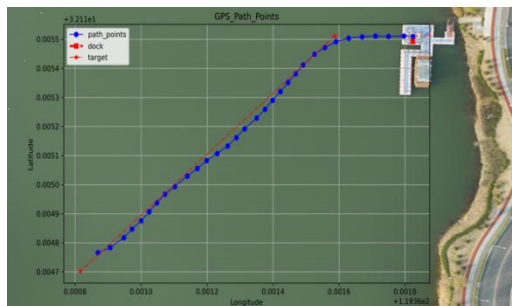
5.2.1 Straight-line real ship verification

On the day of the test, the wind speed was 3-4 from the southeast, the temperature was $12^{\circ}\text{C} \sim 21^{\circ}\text{C}$, the initial heading direction of the ship model was 280° , the given initial speed was 13kn, a total of 2 desired trajectory points were set up, and the setup of the desired trajectory points of the autonomous berthing was as shown in Table 4.

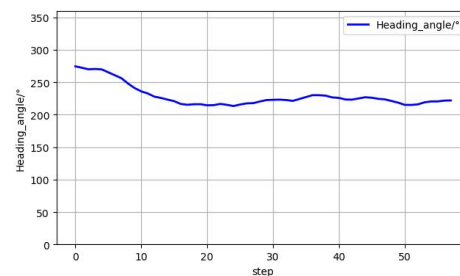
Table 4 Expected track points

Desired path start/end point	Latitude	Longitude
beginning	32.1160347	119.3607404
finishing	32.1153271	119.3617081

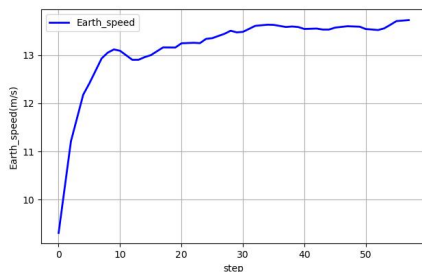
The sailing trajectory of the underdrive ship model, the heading angle, the ground speed, and the lateral error during the sailing process are shown in Fig. 5, and the trajectory deviation analysis is shown in Table 5. The maximum trajectory error is 2.911, the average trajectory error is 1.367, and the variance is 2.593. The above error values are calculated by taking the trajectory information after the ship model reaches the first target point.



(a) Line path



(b) heading angle



(c) Line path earth speed



(d) Line path track error

Fig.5 Line path

Table 5 Analysis of line track error

Max deviation	Mean deviation	Variance deviation
2.911	1.367	2.583

5.2.2 Z-type real ship validation

On the day of the test, the wind speed is from southwest to southeast 3-4, gust 10-12m/s, the temperature is $16^{\circ}\text{C} \sim 28^{\circ}\text{C}$, and the sea current has some influence on the ship's sailing process. The initial heading direction of the ship model is 280° , the initial speed is given as 13kn, 4 desired trajectory points are set in total, and the desired trajectory points for autonomous berthing are set as shown in Table 6.

Table 6 Expected track points

Desired path start/end point	Latitude	Longitude
beginning	32.115499	119.361600
Inflection point 1	32.115079	119.361263
Inflection point 2	32.114707	119.361599
finishing	32.114273	119.361263

The sailing trajectory of the underactuated ship model, the heading angle, the ground speed and the lateral error during the sailing process are shown in Fig. 6, and the analysis of the trajectory deviation is shown in Table 7. From the table, it can be concluded that the maximum trajectory error is 4.222, the average trajectory error is 1.514, and the variance is 3.436. The above error values are calculated by taking the trajectory information of the ship model after it reaches the first target point.

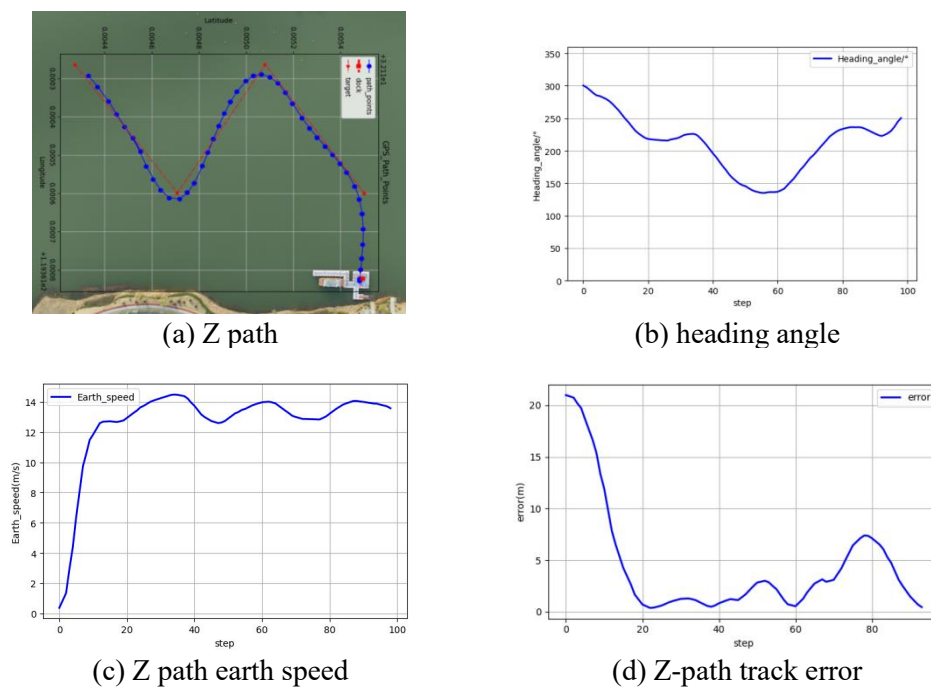


Fig.6 Z path

Table 7 Analysis of Z-track error

Max deviation	Mean deviation	Variance deviation
4.222	1.514	3.436

It can be concluded from the results of the real ship test that the trajectory tracking control method proposed in this paper can realize the trajectory tracking during the sailing of the real ship. The effect is ideal under relatively smooth external environmental conditions, and the ship model will be offset by external interference under the environment of high wind speed and high wave current influence, but the effect of trajectory tracking is still ideal under the compensation of the wind and wave current model.

6. Conclusion

Through the innovation of theory and algorithm, this study provides a solution with both high precision and strong robustness for the intelligent control of underactuated merchant ships, which further promotes the engineering application of marine unmanned systems. Aiming at the problem of trajectory tracking control of underactuated merchant ships, this paper carries out the research on the guidance algorithm and control algorithm, and establishes the trajectory tracking control system for underactuated merchant ships by taking into full consideration of the structural characteristics and navigational features of the underactuated merchant ships, and also the influence of the external environmental disturbances on the ships. The response efficiency of the ship in sailing with large heading deviation is optimized, and the trajectory tracking control accuracy and response speed of the underactuated merchant ship are improved, which will provide support for the control theory research and technology development of intelligent underactuated merchant ships in the future.

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