

Article

An Intelligent Auxiliary Decision-Making Algorithm for Hydrographic Surveying Missions

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Abstract

In view of the problems that the track mode accuracy of the automatic steering gear on survey ships cannot meet the requirements of hydrographic survey accuracy and the workload of manual steering is large, an intelligent auxiliary decision-making algorithm based on LSTM and multiple linear regression is proposed. By learning historical track information, marine environment information, historical steering data, hull state data, etc., it provides the helm with auxiliary operation prompt information, such as the command course and its adjustment timing (time range, area), so as to reduce the number of times the helm steers. The effectiveness of the algorithm is verified through sea trials. The results show that the number of steering times is reduced by 45.5% and the number of effective measuring points is increased by 1.5% through the algorithm in this paper. This result confirms that the algorithm can improve the operational efficiency of offshore survey tasks by optimizing human–computer interaction.

Keywords: hydrographic survey operations; navigation recommended; LSTM; multiple linear regression



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1. Introduction

Marine surveying serves as the fundamental cornerstone for understanding, utilizing, and protecting marine environments. It plays pivotal roles in marine resource exploration, nautical charting, marine climate change research, territorial demarcation, and military defense applications [1–3]. Furthermore, marine surveying data, including bathymetric measurements, gravimetric data, magnetic field readings, and sound velocity profiles, constitute critical components of comprehensive maritime situational awareness. The efficiency and accuracy of marine surveying operations significantly enhance the capability of marine resource development by enabling precise environmental characterization and operational decision-making [4–6].

To ensure measurement accuracy, hydrographic surveying standards stipulate that a valid measurement point must lie within 20% of the line spacing distance from the planned survey line (specific requirements may vary across tasks, with a maximum offset threshold of 10 m commonly adopted). Points exceeding this range are deemed invalid and cannot be used for mapping operations [7]. However, the autopilot systems currently employed on survey vessels—whether in heading control mode or in high-precision track control mode—fail to meet the accuracy requirements [8]. Consequently, during actual hydrographic surveys, operators must manually adjust the vessel's heading throughout the

mission based on their experience to correct deviations from the planned track, ensuring the vessel remains as close as possible to the designated survey line. Given that survey missions typically require several hours of continuous navigation, operators must maintain prolonged high concentration, inevitably leading to instances of overcorrection or delayed response during steering adjustments. These deviations compromise the measurement of data quality to some extent. Therefore, it is imperative to develop an intelligent auxiliary decision-making algorithm that addresses these challenges under existing autopilot conditions. Such an algorithm would significantly reduce the operator workload, transitioning vessel control from human-only to a human-machine collaborative decision-making model, and increase the number of valid measurement points, enhancing the overall quality of hydrographic survey results.

Current marine autopilot systems have evolved into fourth-generation intelligent rudder systems capable of basic ship tracking control, with extensive research conducted by scholars worldwide. Li Shijie et al. [9] investigated active disturbance rejection control (ADRC) and model-free adaptive control (MFAC) technologies, enabling real-time track feature identification and adaptive parameter tuning. However, their tracking performance remains highly dependent on initial parameter selection. Ma Tianheng et al. [10] established a nonlinear ship model and proposed a nonlinear model predictive control (NMPC) algorithm to generate optimal track control signals, though the method suffers from high computational complexity. Van M et al. [11] implemented sliding mode control (SMC) for surface vessel tracking, demonstrating effectiveness in straight-line and circular path tracking through experimental validation. Jinlai Liu [12] introduced a forgetting factor into recursive least squares (RLS) algorithms based on iterative least squares, partially addressing the degradation of update speed during data accumulation. Bowen Sui [13] developed a finite-time convergence control strategy to ensure that tracking errors converge within predefined performance boundaries. Haseltalab et al. [14] applied neural networks to estimate propeller dynamics and handle hydrodynamic uncertainties, proposing a novel NN-based adaptive control algorithm for autonomous vessel motion and path tracking. Zhu et al. [15] constructed radial basis function (RBF) neural networks to compensate for ship model uncertainties, integrating nonlinear transformations and adaptive neural tracking into dynamic surface control (DSC) frameworks. Zhao et al. [16] developed a deep reinforcement learning (DRL)-based path tracking algorithm that reduces control law complexity for 3-DOF ship models while achieving smoother error convergence with strong practical adaptability. Alizadeh et al. [17] proposed an LSTM approach to measure the dynamic distance between target and sample trajectories and achieved excellent predictive results.

Although the latter algorithm has achieved good results in simulation experiments, there is still a certain gap between its application and its actual use in new autopilot products. Therefore, it is extremely urgent to solve the problems with the accuracy of the track mode not meeting the requirements of hydrographic survey accuracy and the heavy workload of manual steering under the existing autopilot conditions.

To this end, this study innovatively develops a recommended command heading model by analyzing historical trajectory data, marine environmental parameters, steering records, and vessel dynamics—effectively encapsulating expertise with optimal heading adjustment operations. By using the track prediction model based on LSTM, the future position of the ship can be predicted during actual navigation. If the predicted deviation exceeds a predefined off-course threshold, the system provides steering personnel with both the optimal timing and angular magnitude for command heading adjustments.

Through model training and learning, the reliance on individual steering experience as the sole decision-making criterion is significantly reduced, thereby minimizing human

factors in heading control and introducing greater scientific rigor and intelligence to the hydrographic survey process. Until next-generation autopilots meeting precise survey accuracy standards become widely available, this algorithm offers an immediate solution to alleviate the workload of current steering operators and contributes to advancing hydrographic surveying practices.

The contents of this paper are arranged as follows: Section 1 presents the research background, literature review, and objectives of this study; Section 2 introduces two primary models underlying the proposed algorithm; Section 3 provides a detailed technical description of the algorithm implementation; Section 4 validates the algorithm's feasibility through simulation experiments and sea trials; Section 5 concludes the paper with critical discussions and future research directions.

2. Introduction of Models

The proposed algorithm fundamentally comprises two core models: the track prediction model and the recommended command heading model. The former is designed to estimate future vessel positions, enabling evaluation of whether the maximum cross-track deviation exceeds predefined thresholds. If the threshold is surpassed, the system triggers subsequent decision-making workflows to initiate corrective actions. The latter is designed to generate optimal rudder angles and timing for course corrections by processing input maximum cross-track deviation values, which provides intelligent auxiliary decision support for helms and enables data-driven heading adjustments while preserving human-in-the-loop oversight.

2.1. Track Prediction Model

Marine vessel trajectory prediction can generally be categorized into model-based prediction algorithms, machine learning-based prediction models, and deep learning-based prediction frameworks [18–22]. Among these, deep learning-based vessel track prediction models represent the current research frontier. These approaches primarily focus on converting vessel track data into dynamic time-series data for network model training. This study employs LSTM networks—a specialized deep learning architecture—to forecast marine vessel tracks. The LSTM's inherent capability to capture long-term temporal dependencies makes it particularly suitable for processing sequential navigation data with complex temporal patterns.

The LSTM network draws inspiration from biological neural mechanisms of selective information retention and forgetting, enabling it to prioritize critical temporal patterns while discarding irrelevant data [23–25]. As a specialized variant of a Recurrent Neural Network (RNN), the LSTM architecture employs three gated mechanisms—an input gate, forget gate, and output gate—alongside a cell state storage unit to dynamically regulate information flow. These components collectively update neuronal states across sequential timesteps, as illustrated in the neural network architecture diagram (Figure 1). The gating mechanisms allow the LSTM to maintain long-term temporal dependencies while minimizing computational redundancy, thereby enhancing model efficiency and reducing the training time [26,27].

In Figure 1, i , f , o , and C denote the input gate, forget gate, output gate, and cell state of the LSTM, respectively; x and y represent the input and output vectors; h indicates the candidate hidden state; and σ denotes the sigmoid activation function. The LSTM network processes sequential information through three key steps:

Gating Mechanisms:

$$\begin{aligned} i_t &= \sigma(W_i \times [h_{t-1}, x_t] + b_i) \\ f_t &= \sigma(W_f \times [h_{t-1}, x_t] + b_f) \\ o_t &= \sigma(W_o \times [h_{t-1}, x_t] + b_o) \end{aligned} \quad (1)$$

Cell State Update:

$$C_t = f_t \times C_{t-1} + i_t \times \tanh(W_c \times [h_{t-1}, x_t] + b_c) \quad (2)$$

Hidden State Generation:

$$h_t = o_t \times \tanh(C_t) \quad (3)$$

In the formulas, W is the weight matrix, b is the bias, $\tanh$ is the activation function, and $\times$ is the Hadamard product.

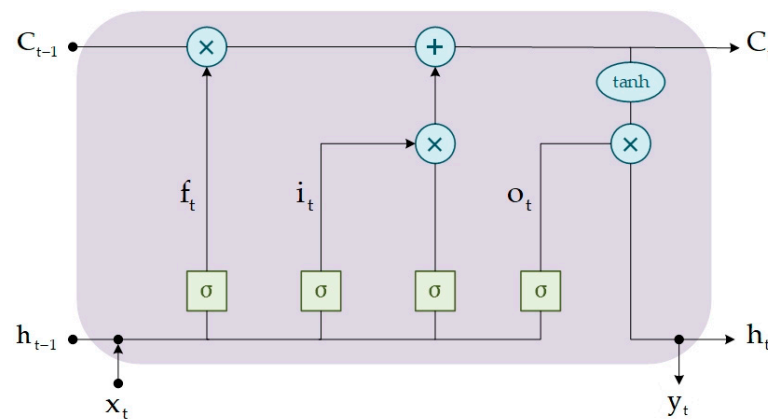


Figure 1. Network architecture of LSTM.

Marine vessel dynamics are conventionally described through 6-DOF motion models [28], encompassing three translational motions (surge, sway, heave) and three rotational motions (roll, pitch, yaw). However, since this study exclusively focuses on positional information, we develop a 3-DOF ship motion model constrained to the horizontal plane, as illustrated in Figure 2.

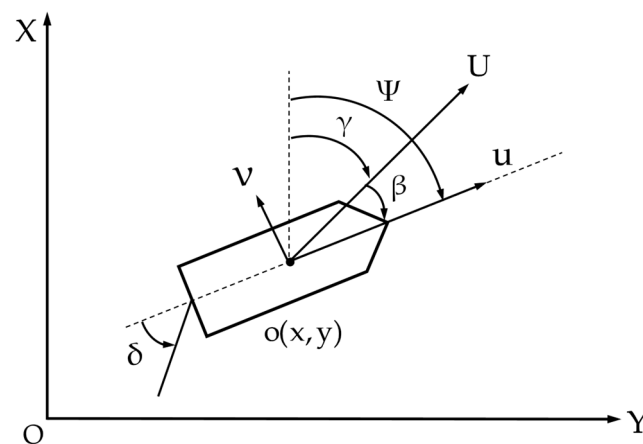


Figure 2. The 3-DOF ship motion model.

In the figure, U is the ground velocity, u is the longitudinal velocity, v is the lateral velocity, Ψ is the heading angle, γ is the track angle, β is the drift angle, δ is the rudder angle, and $o(x, y)$ are the position coordinates of the ship. The 3-DOF ship kin-

matics equations and MMG (Maneuvering Modeling Group) model are formulated as Equations (4) and (5), respectively.

$$\begin{cases} \dot{x} = u \cos \Psi - v \sin \Psi \\ \dot{y} = u \sin \Psi + v \cos \Psi \\ \dot{\Psi} = p \end{cases} \quad (4)$$

$$\begin{cases} (m+m_x) \dot{u} - (m+m_y) vr = X_H + X_P + X_R + X_{Wind} + X_{Wave1} + X_{Wave2} \\ (m+m_y) \dot{v} + (m+m_x) ur = Y_H + Y_P + Y_R + Y_{Wind} + Y_{Wave1} + Y_{Wave2} \\ (I_{xx} + J_{xx}) \dot{p} = K_H + K_P + K_R + K_{Wind} + K_{Wave1} + K_{Wave2} \end{cases} \quad (5)$$

In the formulas, p represents the yaw rate of the vessel; m represents the vessel mass; m_x and m_y represent the added masses in the surge and sway directions; I_{xx} and J_{xx} represent the rotational inertia and additional rotational inertia about the x axis; X , Y , and K represent the moments in the surge, sway, and rolling directions; and subscripts H , P , R , $Wind$, $Wave1$, and $Wave2$ respectively represent the hydrodynamic force, propeller force, rudder force, wind force, first-order wave force, and second-order wave force of the vessel.

Through nonlinear processing and structural simplification, the ship motion model can be transformed into a black-box representation of system input–output relationships (as shown in Equation (6)). This framework integrates with LSTM networks to establish nonlinear mapping relationships among variables in ship motion manipulation, thereby achieving precise ship trajectory prediction.

$$\begin{cases} x(t+1) = f_1[x(t), y(t), u(t), v(t), r(t), p(t), \delta(t)] \\ y(t+1) = f_2[x(t), y(t), u(t), v(t), r(t), p(t), \delta(t)] \end{cases} \quad (6)$$

During training, the ship's position, speed, and heading information are utilized as inputs after normalization processing to enhance the training stability and convergence speed. The subsequent time step's positional coordinates are designated as outputs, requiring inverse normalization post-prediction. Utilizing the Mean Squared Error (MSE) loss function, supervised learning is implemented where the optimization objective minimizes the squared Euclidean distance between the predicted and actual ship positions, ultimately yielding a preliminary trained track prediction model.

In practical applications, the pre-trained model serves as the foundation for real-time track prediction through integration with real-time vessel data, with the complete workflow illustrated in Figure 3.

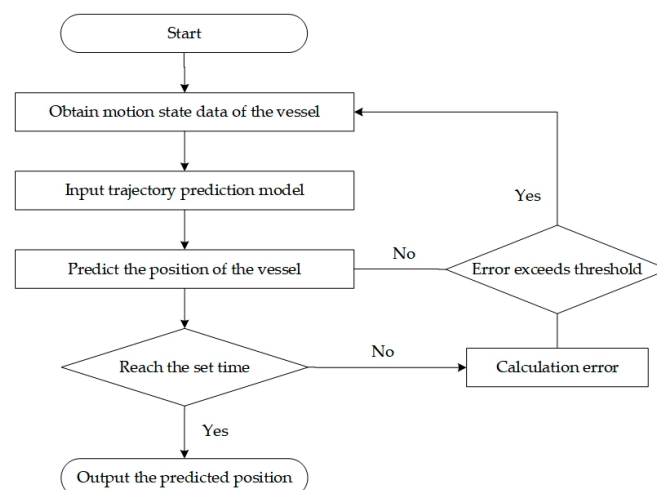


Figure 3. Workflow for vessel track prediction.

2.2. Recommended Command Heading Model

During hydrographic survey missions, helms are required to continuously adjust the autopilot's commanded headings due to environmental disturbances (wind, current, wave forces) [29,30]. The commanded heading refers to the yaw angle set by operators under autopilot heading control mode [31]. Figure 4 shows the changes in the commanded heading over a specific time period and the variations in commanded heading adjustments between adjacent time steps. It can be observed that during actual steering, various states occur, such as single commanded heading adjustments, continuous commanded heading adjustments, and no commanded heading adjustments. To establish algorithm validation criteria, we define an instruction adjustment event as follows: if there is any variation in the numerical value of the commanded heading within a 1 s time window spanning from the past second to the current time instant, this constitutes one commanded heading adjustment event.

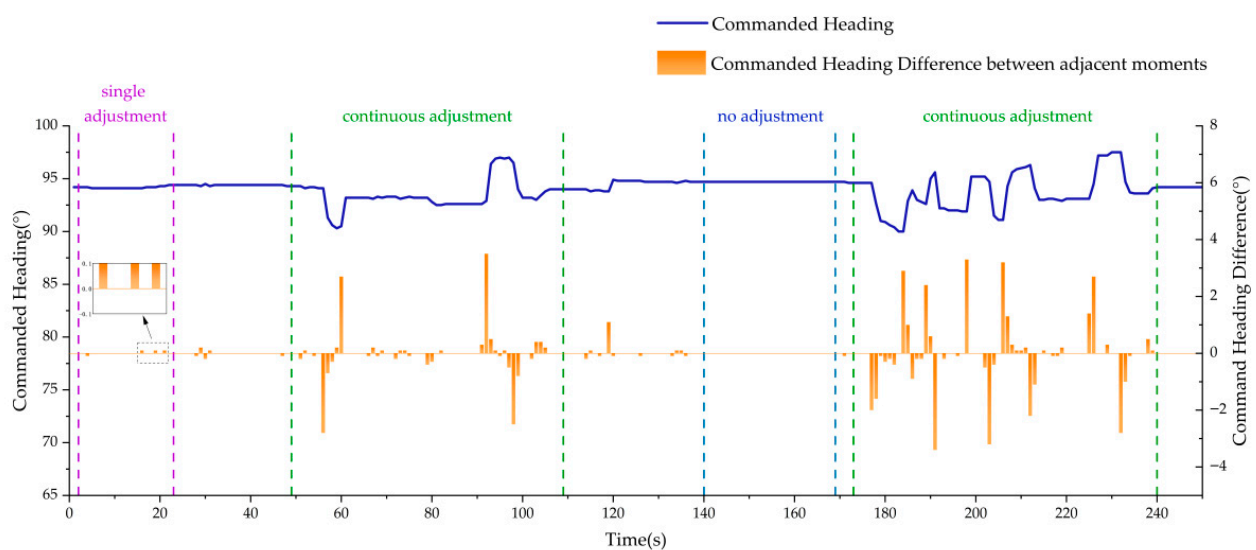


Figure 4. Difference in heading instruction between adjacent moments.

In practical operations, the ship maneuvering process is systematically categorized into two distinct phases: the deviation correction phase and the heading adjustment phase. The relationship between them can be intuitively seen from Figure 5.

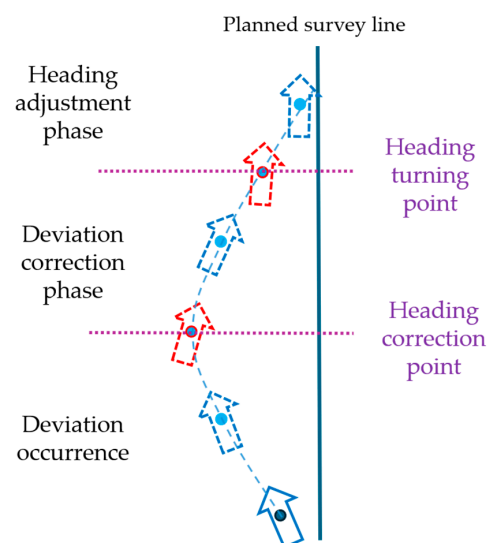


Figure 5. Diagram of deviation correction phase and heading adjustment phase.

The deviation correction phase refers to the process where the vessel adjusts its commanded heading to reduce cross-track deviation when significantly deviating from the planned survey line. The heading adjustment phase involves preemptive heading adjustments before returning to the survey line to prevent over-correction. A single survey line typically contains multiple alternating deviation correction and heading adjustment phases. Therefore, all training data are categorized by maneuvering phase, with features including the yaw distance, yaw direction, yaw rate, yaw direction rate, survey line azimuth, wind speed, wind direction, absolute ship speed, track angle, and recommended commanded heading. The maximum cross-track deviation within each phase is designated as the label value. The related data at the heading correction point and the heading turning point are used to train the deviation correction model and the heading adjustment model, respectively. The model training process can be shown as follows:

(1) Data preprocessing

Calculate the cross-track deviation at each time step. Exclude data where the cross-track deviation exceeds 20 m. The formula for calculating the cross-track deviation is as follows [32]:

$$d_{yaw} = \frac{|-(y_{12} - y_{11}) \times x_t + (x_{12} - x_{11}) \times y_t + (y_{12} - y_{11}) \times x_{11} + (x_{12} - x_{11}) \times y_{11}|}{\sqrt{(y_{12} - y_{11})^2 + (x_{12} - x_{11})^2}} \quad (7)$$

d_{yaw} refers to the cross-track deviation, (x_t, y_t) is the current position of the ship transformed by Mercator coordinates, and (x_{11}, y_{11}) and (x_{12}, y_{12}) are the start point and the end point of the survey line transformed by Mercator coordinates.

(2) Effective deviation correction/heading adjustment operation screening

Traverse the remaining data and sequentially compute differences in cross-track deviation between consecutive time steps. Extract segments with continuous 10 s periods of negative cross-track deviation differences, which indicates a continuous reduction in cross-track error, marking these as valid deviation correction/heading adjustment operations for subsequent learning.

(3) Deviation correction model training data extraction

The command heading corresponding to the maximum cross-track deviation is designated as the command heading adopted during the deviation correction phase. From that moment, search backward to identify the first command heading that differs from this value. The subsequent time step corresponds to the start time of the deviation correction. Assign parameters at the initial time step as features for training the deviation correction model. The maximum cross-track deviation of the phase is designated as the label value.

(4) Heading adjustment model training data extraction

Use the commanded heading at the final time step as the reference commanded heading for the heading adjustment phase. Search forward from the final step to identify the first instance where the commanded heading differs from this value. The subsequent time step corresponds to the start time of the heading adjustment point. Assign parameters of the current step as features for training the heading adjustment model. The maximum cross-track deviation of this phase is designated as the label value. A schematic diagram of the process of acquiring the training sets for the deviation correction model and heading adjustment model is shown in Figure 6.

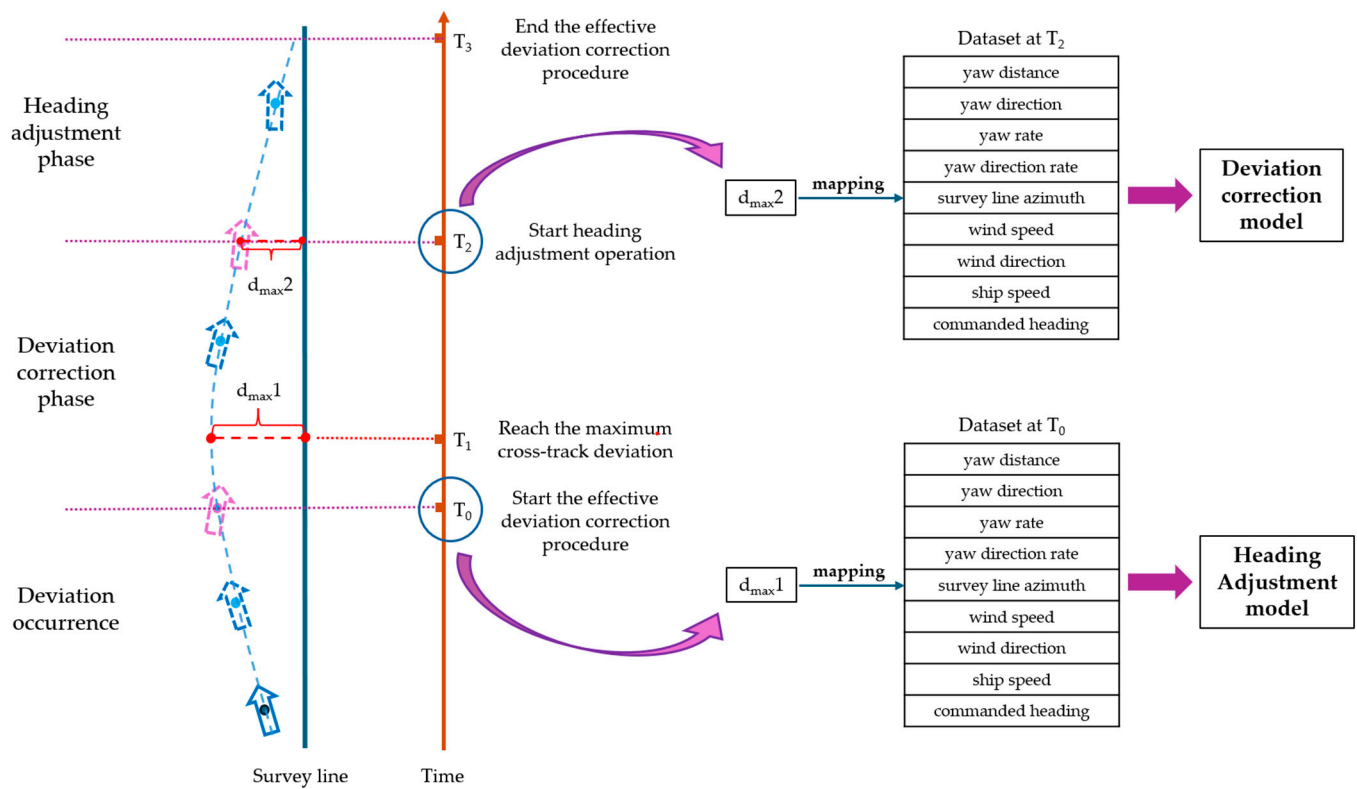


Figure 6. A schematic diagram of the process of acquiring the training sets for the deviation correction model and heading adjustment model.

(5) Model training

This paper employs the multiple linear regression algorithm for model training [33]. Since multiple feature values with different data units are required, normalization operations are performed before training to facilitate rapid model convergence. The recommended command heading regression prediction model is established as follows:

$$d_{\max} = a_1 \times f_{\text{yaw}} + a_2 \times f_{\text{speed}} + a_3 \times f_{\text{wind}} + a_4 \times (f_{\text{yaw-g}}) + a_5 \times (a_{\text{com}} - a_{\text{aim}}) + b \quad (8)$$

In this formula, $d_{\max}$ refers to the maximum cross-track deviation; f_{yaw} refers to the related features of cross-track deviation; f_{speed} refers to ship speed-related features; f_{wind} refers to wind-related features; $f_{\text{yaw-g}}$ refers to the related features of the cross-track deviation change rate; a_{com} refers to the command heading; a_{aim} refers to the course of the planned survey line; and a_1 , a_2 , a_3 , a_4 , a_5 , and b refer to the coefficients and bias characteristic of the multiple linear regression model.

3. The Overall Algorithmic Workflow

Once the trajectory prediction model, deviation correction model, and heading adjustment model are established, the recommended command heading algorithm can be derived based on the following steps to achieve a real-time intelligent auxiliary decision-making function for measurement tasks. Figure 7 illustrates the procedural flow.

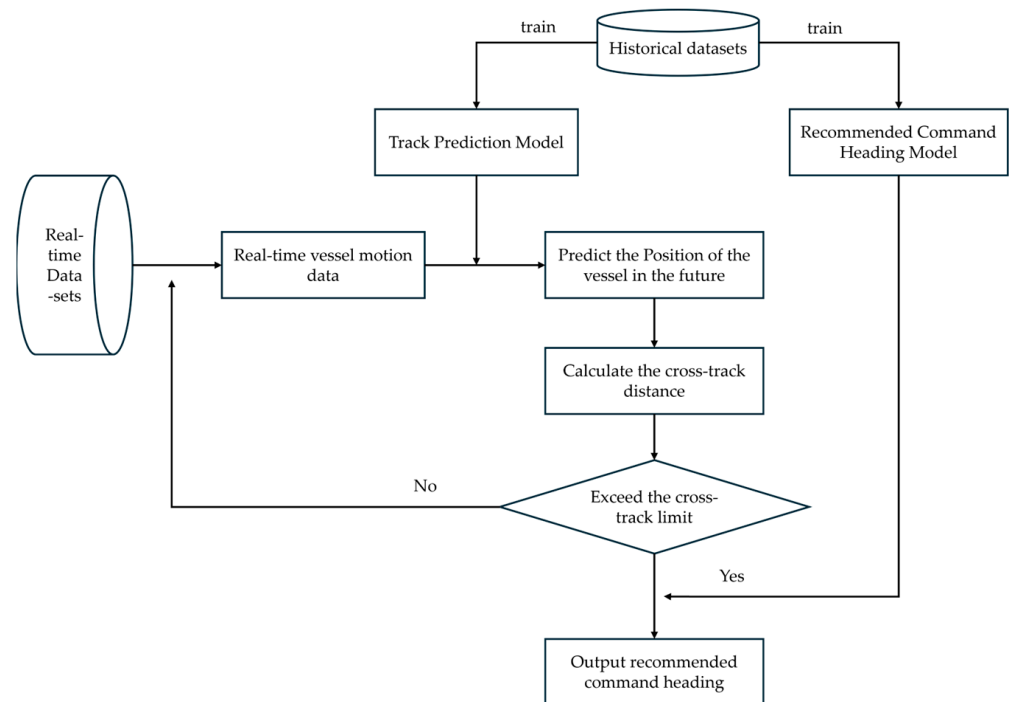


Figure 7. The procedural flow of the algorithm.

1. Feed the current motion state of the vessel into the trajectory prediction model to obtain its predicted position after 15 s. Calculate the deviation distance at this moment and compare it with the predetermined threshold. If the deviation is less than the threshold, the vessel continues its current heading; if the deviation exceeds the threshold, it is determined that a heading adjustment is required, and the process proceeds to the next step.
2. Generate a list of angle ranges $[-5:0.1:5]$ and combine it with the current command heading to obtain a list of recommended command headings. Input each commanded heading into the deviation correction model of the recommended commanded heading model to compute the maximum offset distance for each heading.
3. Filter the maximum offset distances greater than the current offset distance, sort the corresponding recommended commanded headings in ascending order, and select the smallest commanded heading as the recommended value. (Smaller angle adjustments are easier for helms to execute and contribute to smoother vessel navigation.)
4. Adjust the heading magnitude according to the recommended commanded heading and continue navigation, entering the deviation correction phase. During this phase, the deviation distance continuously decreases. When the predicted position after 15 s returns to the survey line (i.e., the deviation distance becomes 0 m), initiate the heading adjustment phase.
5. Like in Step 2, generate a list of angle ranges $[-5:0.1:5]$ and combine it with the current commanded heading. Input each combined heading into the heading adjustment model of the recommended commanded heading model to obtain the maximum offset distance for each heading angle.
6. Filter the maximum offset distance greater than the current offset distance, sort the corresponding recommended commanded headings in ascending order, and select the smallest commanded heading as the recommended turning heading. Execute a commanded heading adjustment accordingly. Continue navigation and repeat Steps 1–6.

Figure 8 shows a schematic diagram of the entire process.

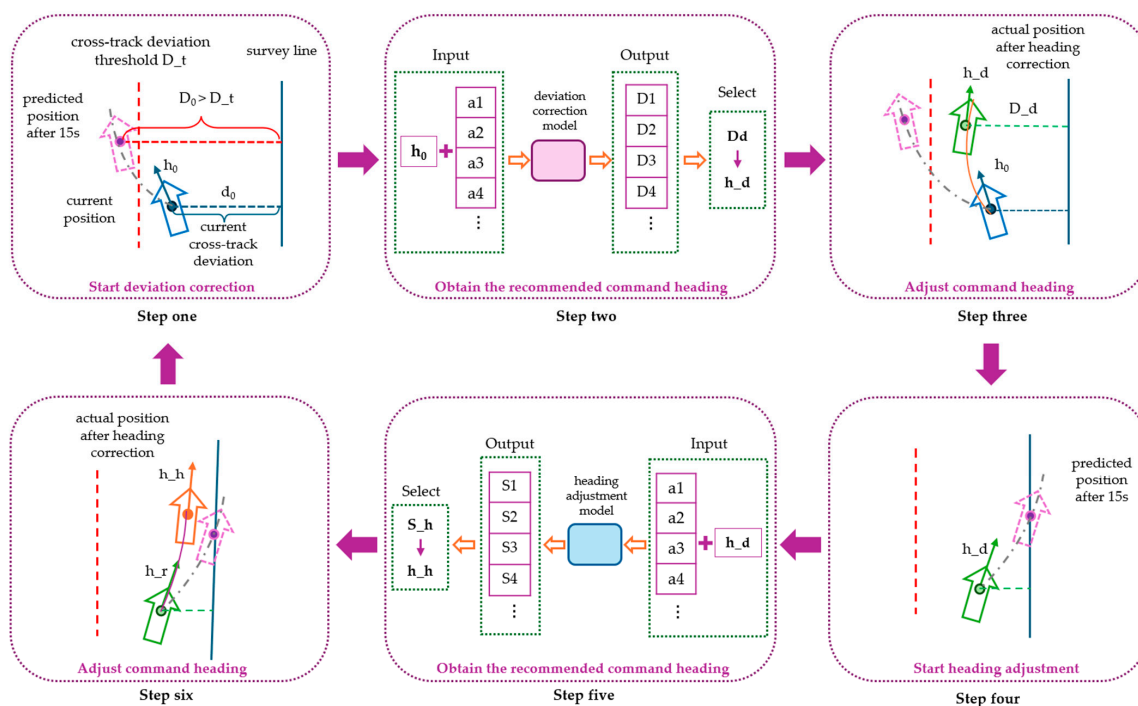


Figure 8. A schematic diagram of the entire process.

4. Experimental Validation

4.1. Data Sources for Experimental Validation

The algorithm models in this study were trained and validated using vessel motion data acquired during a measurement campaign in a specific offshore area. The experimental dataset comprised eight survey lines maneuvered under heading mode, with the spatial distribution of the planned survey lines illustrated in Figure 9.

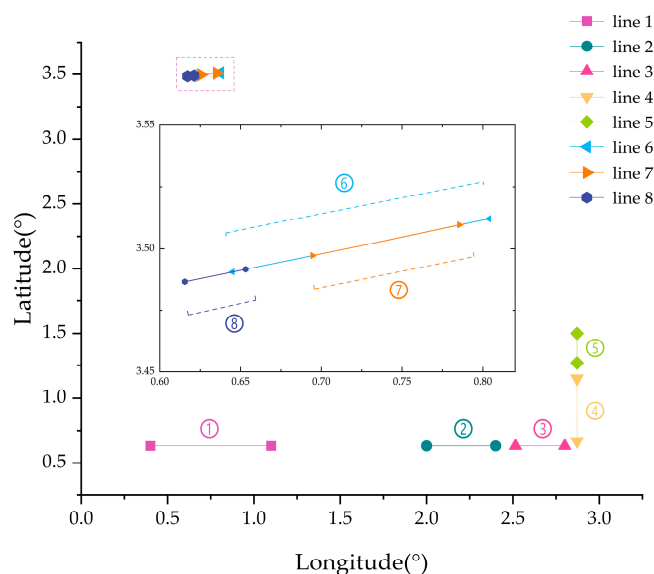


Figure 9. The spatial distribution of survey lines. Planned transects 1–5 were clearly visible. Transects 6–8 represent reciprocal surveys along the same transect. Notably, transects 7–8 were originally designed as a single continuous segment; however, a deviation from the planned trajectory was manually recorded due to the avoidance of an obstruction, resulting in the artificial segmentation of the original path.

The start coordinates, end coordinates, average speed, transect length, measurement duration, and heading angle of each transect are summarized in Table 1.

Table 1. Information on the survey lines.

ID	Start Coordinates (°)	End Coordinates (°)	Speed (kn)	Length (km)	Duration (min)	Heading (°)
1	0.400, 0.633	1.100, 0.633	11.2	77.96	183	90.0
2	2.000, 0.633	2.400, 0.633	11.0	44.50	105	90.0
3	2.515, 0.633	2.800, 0.633	11.5	31.70	72	90.0
4	2.872, 0.670	2.872, 1.150	11.2	64.3	154	0.0
5	2.872, 1.269	2.872, 1.500	10.8	32.1	77	0.0
6	0.645, 3.491	0.804, 3.512	7.9	17.2	57	80.24
7	0.785, 3.510	0.695, 3.497	8.6	9.8	30	260.26
8	0.653, 3.492	0.616, 3.487	8.9	4.8	12	260.26

The onboard instrumentation of the measurement vessel recorded vessel parameters including the position, speed, timestamp, heading angle, meteorological conditions, water depth, commanded heading, actual heading, commanded rudder angle, and actual rudder angle. In this experiment, historical data from the first five transects were utilized for training the ship trajectory prediction and recommended command heading models, while data from the remaining three transects were reserved for algorithm validation. The experimental procedures are detailed in the following.

4.2. Model Training

4.2.1. Trajectory Prediction Model Training

This study employed an LSTM network for ship trajectory prediction, implemented through offline training and online inference phases. The transect dataset was partitioned into training (70%) and testing (30%) subsets following temporal sequence alignment. The input features included the longitude, latitude, absolute speed, track angle, heading angle, commanded heading, wind direction, and wind speed, targeting the prediction of future spatiotemporal coordinates. Experiments were conducted using data from the first five transects. The actual trajectory maps of the survey lines are presented in Figure 10.

The hardware environment for the algorithm was an Intel Core i7 CPU and an NVIDIA RTX 5060Ti GPU. The deep learning framework was Pytorch 2.2.2+ CUDA 12.8. The parameter settings of the LSTM model were as follows: the number of LSTM units was set to 64, the optimizer was “Adam”, the loss function was ‘MSE’, the number of epochs was set to 100, the batch size was set to 32, and the learning rate was set to 1×10^{-3} . Figure 11 displays the predicted trajectory results.

4.2.2. Recommended Command Heading Model Training

According to Section 2.2, training the recommended command heading model requires first identifying trajectory segments with a continuous yaw distance reduction exceeding 10 s, which are considered as phases where heading adjustments effectively corrected the yaw deviation. The effective yaw correction segments for each survey line are illustrated in Figure 12.

Based on Equation (8), the five feature values of each data segment and their corresponding maximum yaw distances were fed into the deviation correction model and the heading adjustment model, respectively, to train the model coefficients. Tables 2 and 3 present training examples for the deviation correction model and the heading adjustment model (20 cases each), while Table 4 shows the final coefficients of both models.

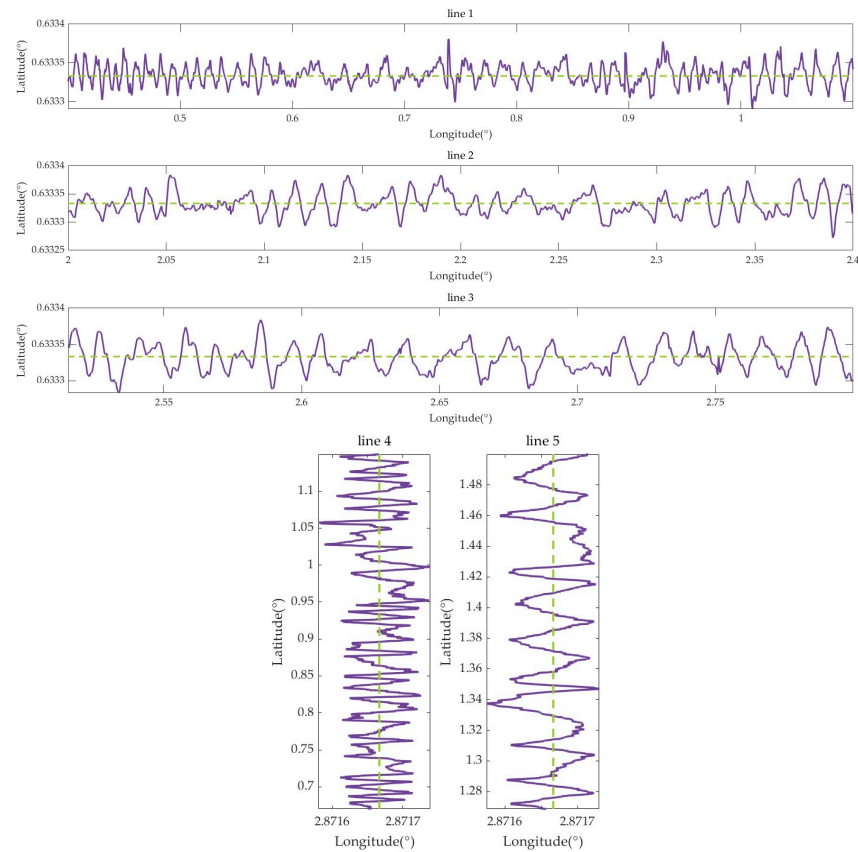


Figure 10. Actual trajectory maps of the survey transects. The green lines represent the planned survey transects, while the purple lines indicate the actual trajectory paths.

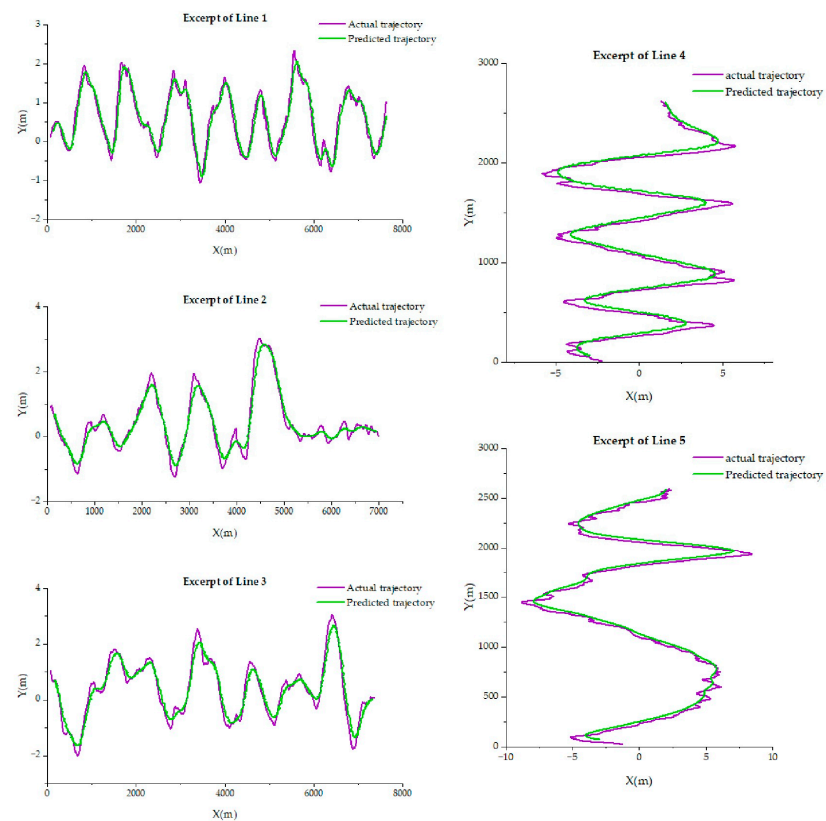


Figure 11. Prediction results for vessel trajectories. For each survey line, a consecutive segment of 1000 trajectory points was selected to perform trajectory prediction using the trained LSTM model.

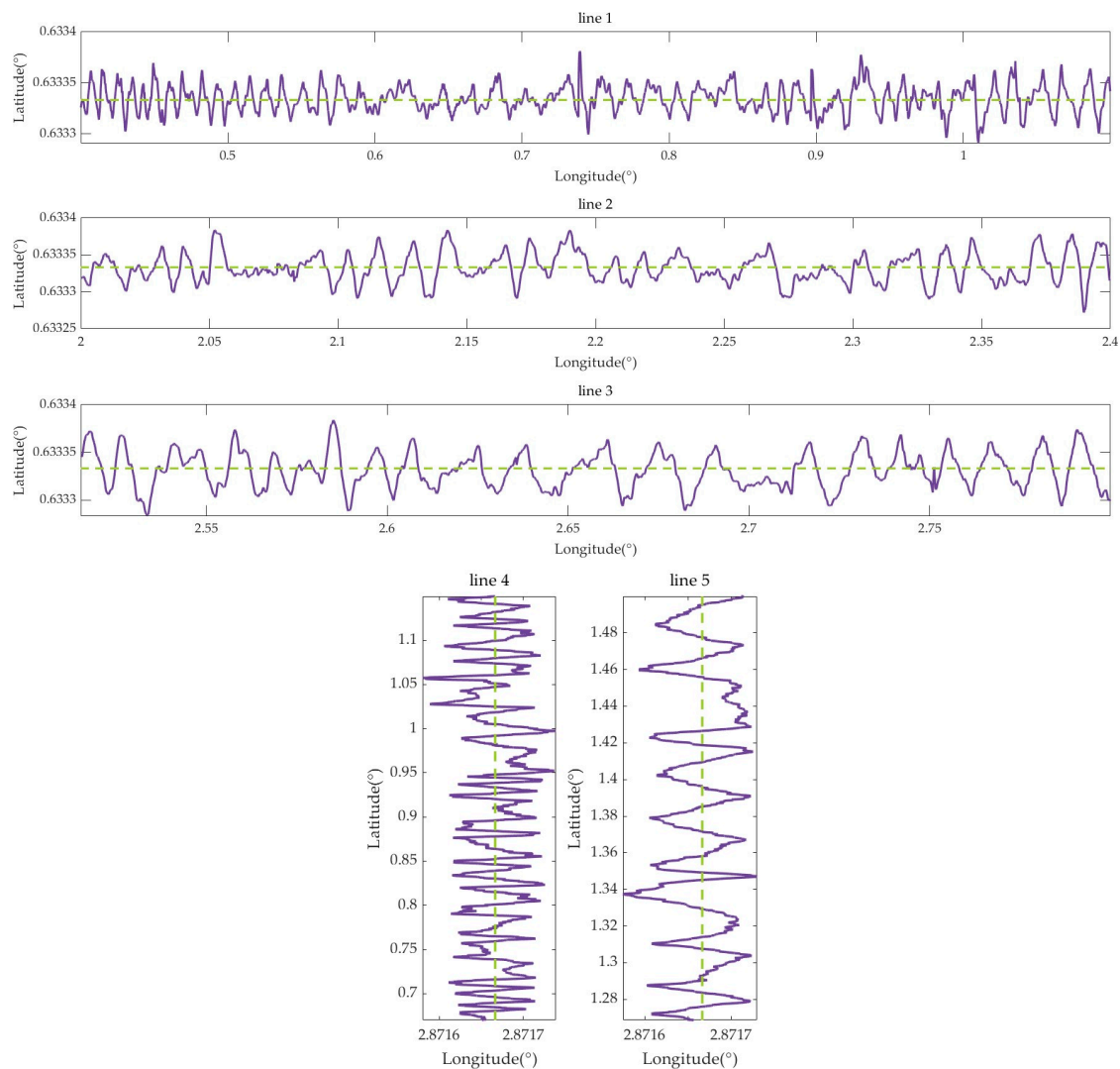


Figure 12. Effective yaw correction segment screening results. The bolded sections represent the extracted valid yaw correction segments.

Table 2. Examples of eigenvalues for deviation correction model.

	f_{yaw}	f_{all}	f_{wind}	f_{yaw_g}	$a_{com} - a_{aim}$	d_{max}
1	8.2207	−4.9497	−8.9170	0.2898	5.4000	8.3380
2	4.3742	−4.2910	−9.1590	0.0400	3.4000	4.3749
3	4.7005	−4.3424	−8.7659	0.0258	1.6000	4.7260
4	6.3473	−4.2731	−8.8779	0.0254	2.6000	6.4253
5	4.0003	−3.6571	−8.8856	0.1186	0.0000	4.1155
6	2.3870	−3.7601	−8.8422	0.0117	1.2000	2.4633
7	0.8062	−3.8116	−8.9049	0.0767	1.6000	0.8697
8	7.0287	−4.6792	−8.7460	0.1051	1.7000	7.0292
9	2.2885	−5.3740	−8.6353	0.0905	1.9000	2.3183
10	7.8471	−5.0912	−8.8522	0.0266	1.7000	7.9728
11	4.8473	−3.5076	−8.6846	0.0243	1.8000	5.6270
12	5.6722	−5.6621	−8.3688	0.0433	2.5000	4.4653
13	4.5712	−3.5932	−8.3572	0.0874	1.2000	6.1255
14	2.3389	−4.2287	−8.2035	0.0137	1.4000	3.4533
15	5.7005	−3.5465	−8.4582	0.0224	1.8000	5.3532
16	4.3573	−5.4633	−8.6647	0.0421	2.6000	5.5831
17	6.2023	−3.5563	−8.5441	0.0845	1.6000	4.3358
18	4.5877	−4.3401	−8.6118	0.0123	1.2000	3.4633
19	1.9043	−4.8316	−8.7852	0.0627	2.2000	1.4537
20	5.2247	−5.3793	−8.8862	0.1103	1.5000	5.2392

Table 3. Examples of eigenvalues for heading adjustment model.

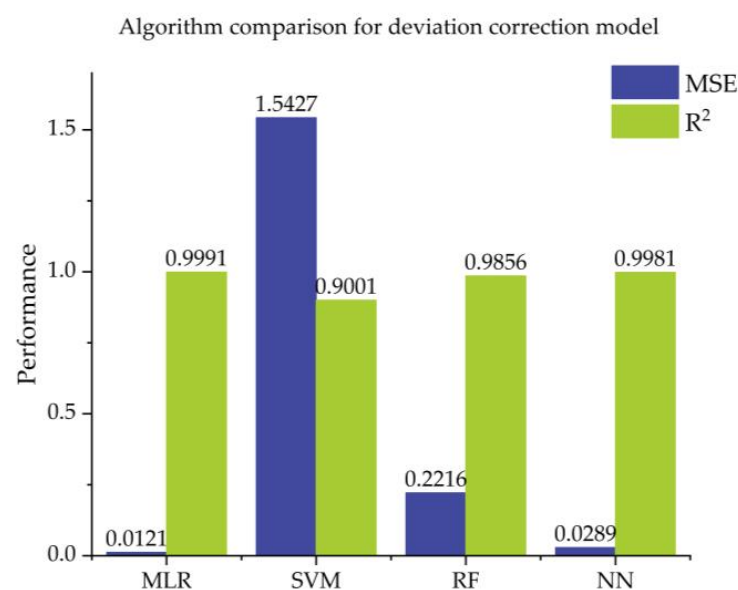
	f_{yaw}	f_{all}	f_{wind}	f_{yaw_g}	$a_{com} - a_{aim}$	d_{max}
1	8.2207	7.0801	9.4016	0.2898	7.2428	8.3380
2	4.3742	8.0126	9.4902	0.0400	6.7428	4.3749
3	4.7005	6.9724	9.6780	0.0258	0.5428	4.7260
4	6.3473	7.7522	9.4037	0.0254	6.4428	6.4253
5	4.0003	7.8581	9.6484	0.1186	4.6428	4.1155
6	2.3870	8.2466	9.4970	0.0117	4.8428	2.4633
7	0.8062	7.9886	9.8891	0.0767	4.8428	0.8697
8	7.0287	8.5346	9.3563	0.1051	4.5428	7.0292
9	2.2885	7.9848	9.3332	0.0905	5.9428	2.3183
10	7.8471	7.9862	9.2044	0.0266	1.6428	7.9728
11	−5.9315	−6.2807	−7.6075	−0.1537	4.3572	−5.9612
12	7.0964	7.1412	8.5358	0.2342	6.5572	−7.2447
13	5.6442	7.8407	8.9500	0.2800	6.2572	−5.7598
14	−4.1254	−6.4596	−7.7251	−0.1638	6.1572	−4.1495
15	−6.8520	−5.7570	−6.7049	−0.0235	4.6572	−6.8956
16	−7.2860	−6.8660	−7.2140	−0.0373	6.3572	−7.3120
17	−6.4028	−7.0703	−7.7792	−0.1312	7.4572	−6.4735
18	−2.5639	−5.9386	−7.4380	−0.0563	7.5572	−2.5794
19	−6.7640	−5.5698	−7.3905	−0.2846	3.0572	−6.8654
20	−7.5701	−6.3697	−6.6611	−0.0708	6.6572	−7.6329

Table 4. Model coefficients.

	b	a_1	a_2	a_3	a_4	a_5
Deviation correction model	3.2144	0.6840	0.1631	1.6587	1.0000	3.5594
Heading adjustment model	0.8627	0.9406	0.1189	0.4898	1.0000	2.3906

In order to verify the rationality and effectiveness of the MLR, the same dataset was analyzed using a support vector machine, random forest model, and neural network, with the MSE and R^2 used as evaluation indicators. The analysis results are shown in Figure 13.

The experimental results showed that the performance of the MLR was the best when compared with the other three algorithms. A possible reason for this is that the number of features extracted in this paper is relatively small, and using a more complex model may have the opposite effect. Therefore, this paper used the multiple linear regression algorithm when training the recommended command heading model.

**Figure 13.** Cont.

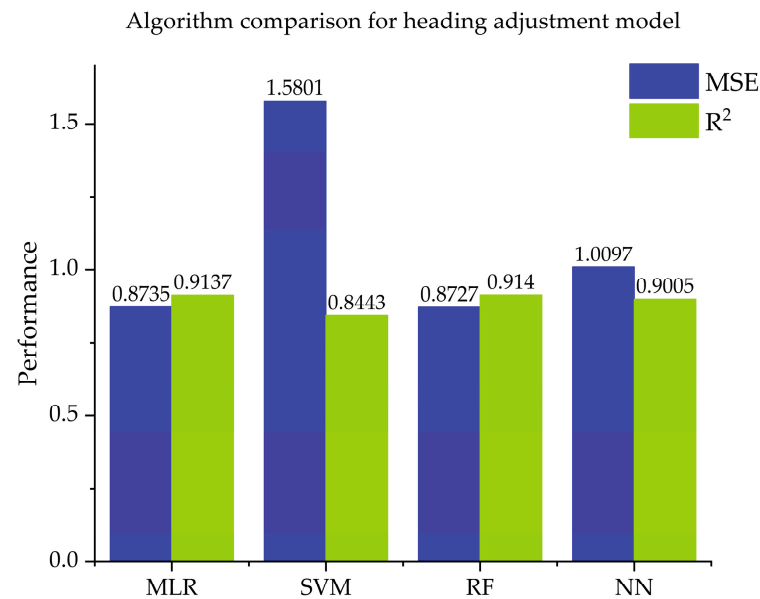


Figure 13. The comparison results of four algorithms. The top picture presents the comparison results for the deviation correction model, while the bottom picture shows those for the heading adjustment model.

4.3. Algorithm Validation

The algorithm was validated using the last three survey lines. Since transects 7 and 8 were artificially segmented due to obstacle avoidance during the same measurement session, they were combined into a single segment for experimental analysis. Transect 6 contained 2275 actual trajectory points with 1140 recorded heading command adjustments, while transects 7 and 8 collectively had 2075 trajectory points and 987 heading command adjustments. Figures 14 and 15 show the information on these three survey lines.

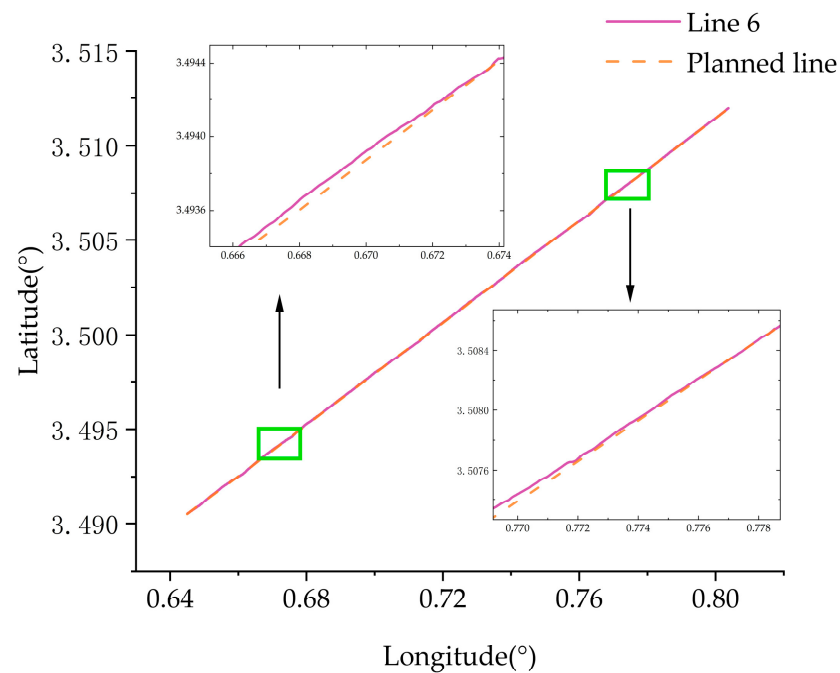


Figure 14. The trajectory of line 6. Since the vessel's trajectory closely aligned with the planned survey lines, two localized zoomed-in views are provided. The enlarged images reveal that the vessel maintained close adherence to the planned survey line while exhibiting irregular deviations.

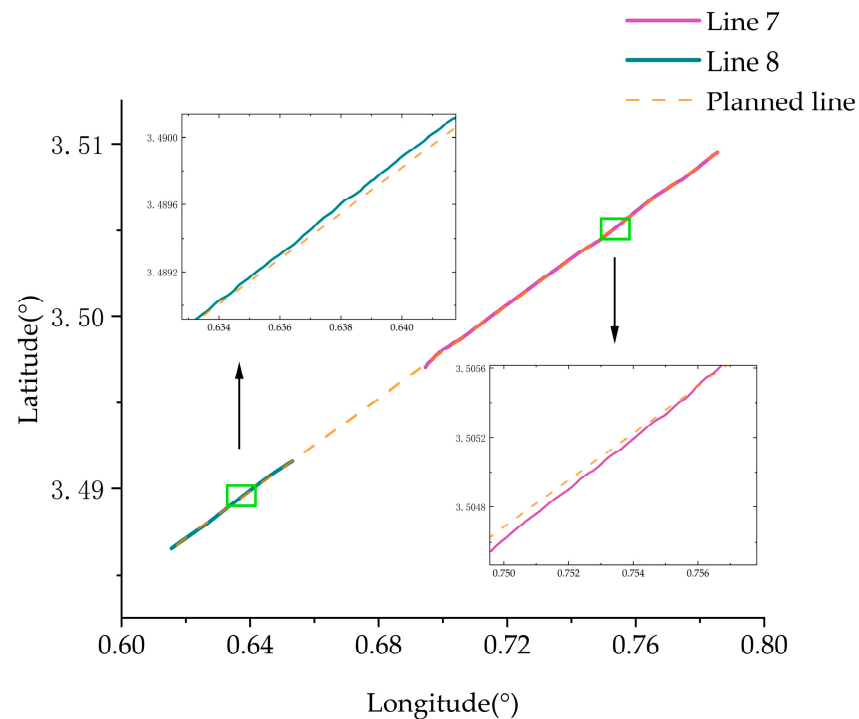


Figure 15. The trajectory of lines 7 and 8. Two localized zoomed-in views are also provided.

Firstly, 10 representative deviation correction processes were selected from each of the three segments. The proposed algorithm was applied to perform local analysis on these segments, generating recommended command headings for each sub-segment, and the effectiveness of these recommendations was validated. Tables 5 and 6 present the selected deviation correction processes in transect 6 and in transects 7 and 8, respectively, along with their corresponding recommended correction angles and heading adjustment angles.

Table 5. The selected processes in line 6.

	Duration (s)	Maximum Deviation (m)	Real Command Heading (°)	Real Adjustment Heading (°)	Numbers of Command Heading Adjustments	Recommended Command Heading (°)	Recommended Adjustment Heading (°)
1	16	8.27	254.10	254.20	10	254.50	254.90
2	8	3.57	252.90	253.00	5	253.40	253.60
3	11	5.55	253.80	253.70	3	254.50	254.80
4	13	5.95	253.70	253.00	10	253.80	254.10
5	14	7.16	257.10	257.60	7	256.10	256.40
6	16	6.52	257.40	257.40	10	256.80	257.20
7	16	6.82	254.80	254.90	15	254.90	255.30
8	26	8.12	254.50	254.50	9	255.10	255.50
9	21	6.38	254.80	254.90	15	256.40	256.10
10	13	5.06	254.70	254.90	6	255.10	255.30

Table 6. The selected processes in lines 7 and 8.

	Duration (s)	Maximum Deviation (m)	Real Command Heading (°)	Real Adjustment Heading (°)	Numbers of Command Heading Adjustments	Recommended Command Heading (°)	Recommended Adjustment Heading (°)
1	33	6.28	85.9	85.5	21	82.10	82.80
2	13	4.47	85.4	85.4	9	85.90	85.40
3	24	10.02	86.7	85.4	10	86.00	86.00
4	11	4.7	86.5	85.9	5	86.40	86.00
5	14	5.52	85.3	84.9	12	84.90	84.40
6	9	4.51	84.6	85.2	4	85.30	84.90
7	14	9.35	85.8	85.4	12	86.50	85.50
8	18	8.07	84	83.9	14	86.00	85.20
9	17	8.22	84.9	83.9	6	85.30	84.50
10	16	3.37	84	84.3	11	83.30	83.70

The two tables reveal that the recommended command headings and turning angles derived from the algorithm closely match the actual adjustment angles chosen during operations. This firstly demonstrates that the proposed algorithm generates practically feasible heading recommendations. Furthermore, validation experiments were conducted under identical marine conditions to evaluate the recommended command headings and turning angles. Taking the first yaw correction process from both tables as an example, the analysis results are presented in Figures 16 and 17.

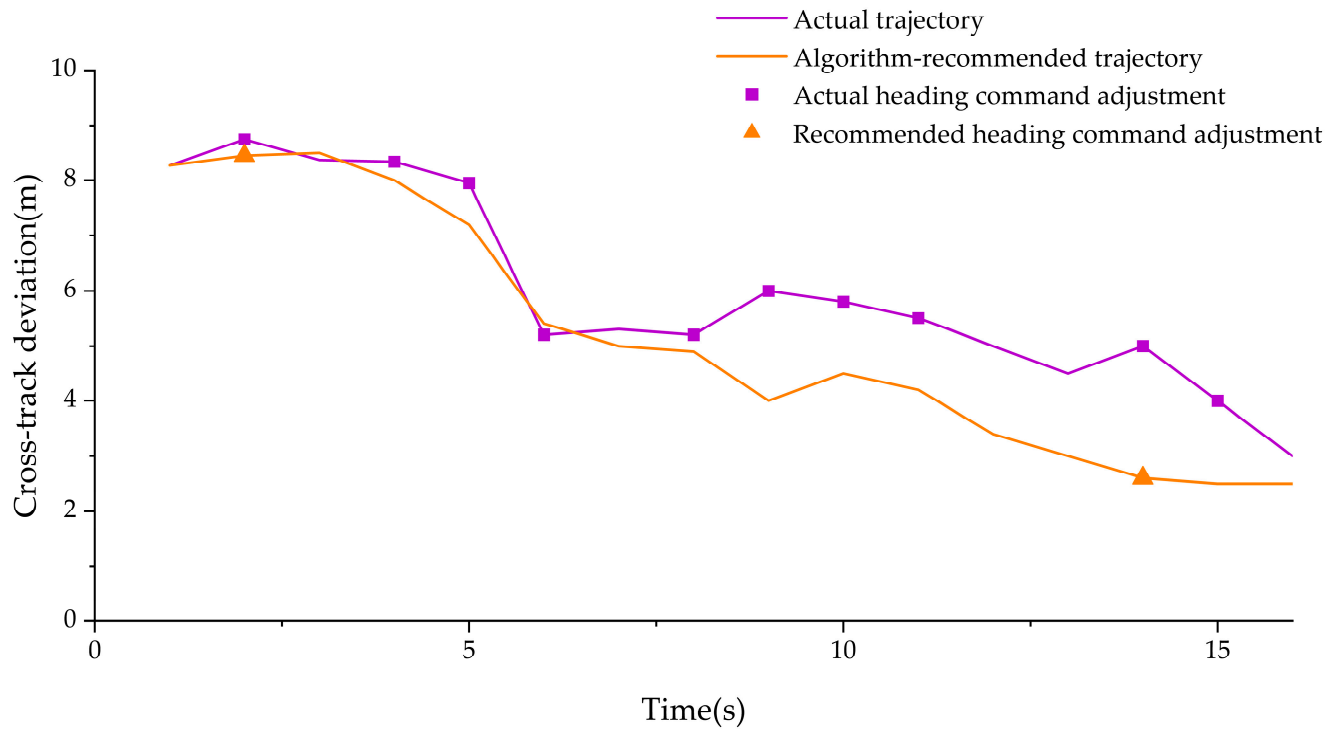


Figure 16. The analysis result for the first process in Table 5.

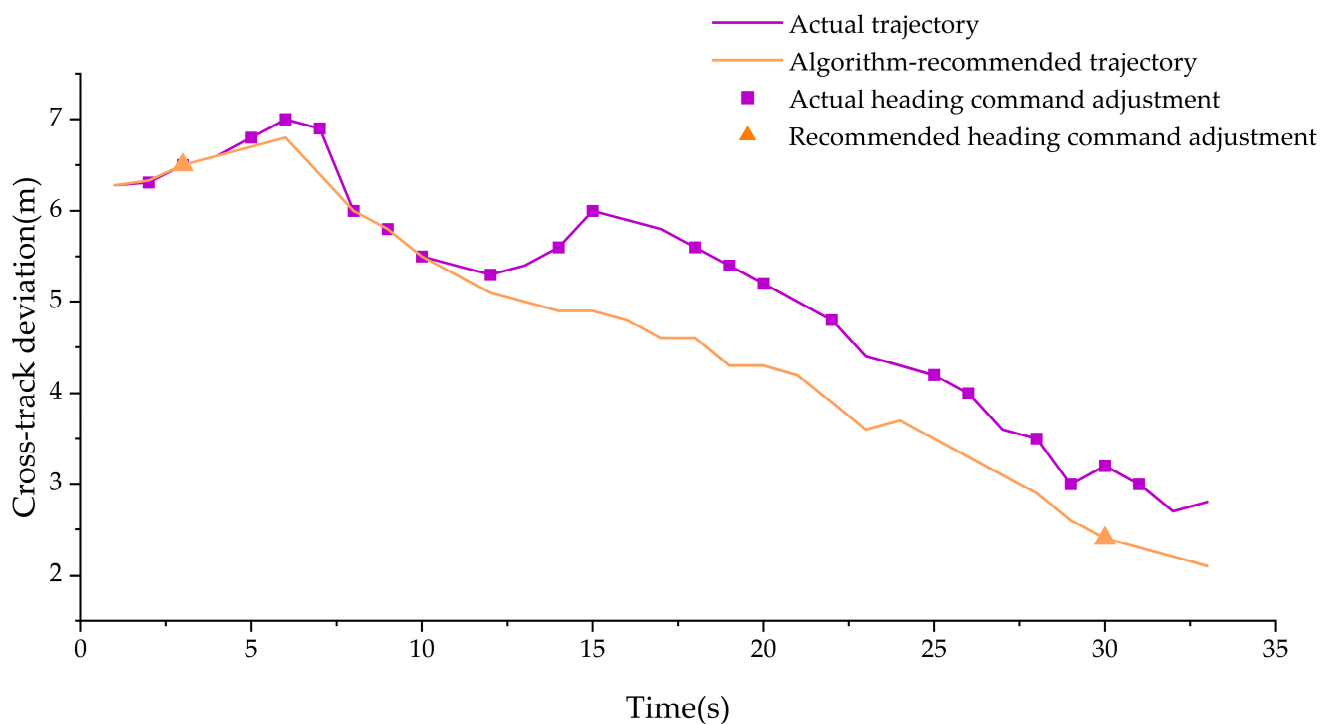


Figure 17. The analysis result for the first process in Table 6.

The original trajectories required 10 and 21 heading command adjustments to correct yaw deviations. When the proposed algorithm was applied, only two heading command adjustments were needed to achieve the same correction, demonstrating its effectiveness. To further validate the algorithm, we modeled real marine environmental conditions (including wind direction, wind speed, current direction, and current speed) and extracted a 30 min segment from the survey line for experimental verification. A control knob prototype with accompanying software was developed to simulate real-world heading command adjustments. By training a ship motion model using historical vessel movement data and constructing a simulation environment based on the proposed algorithm, we conducted tests where the system issued recommended heading commands whenever the predicted trajectory exceeded predefined thresholds. The vessel then adjusted its trajectory based on the updated commands and real-time motion state. The total number of heading command adjustments was recorded and compared with the actual trajectory data. Figure 18 simultaneously presents the raw trajectory and the trajectory optimized by the recommended algorithm. Figure 19 compares cross-track deviation between the two trajectories. Table 7 compares parameters such as the number of heading adjustments and the quantity of valid measurement points between the two trajectories.

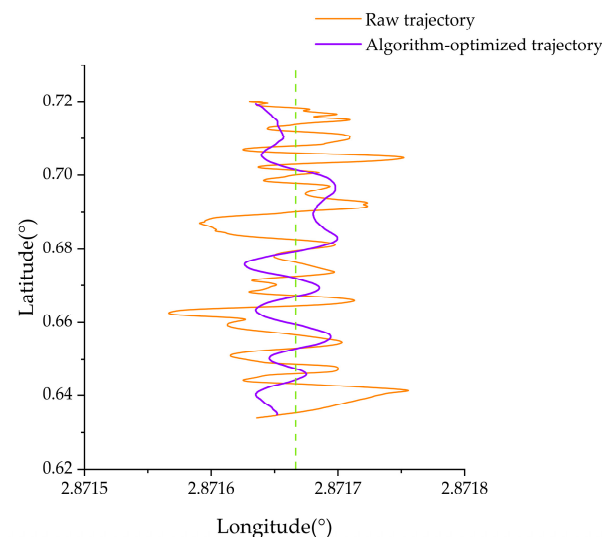


Figure 18. Comparison between the raw trajectory and the algorithm-optimized trajectory. The green dashed line in the figure represents the planned survey line.

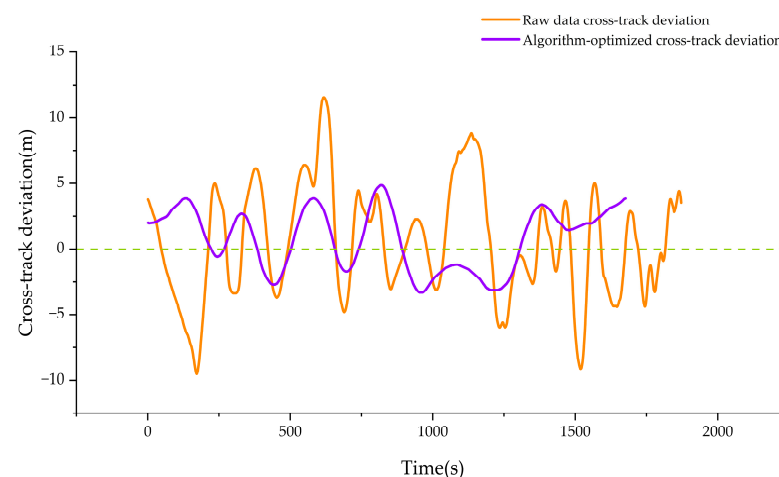


Figure 19. Comparison between the cross-track deviations in the raw data and the algorithm-optimized data. The green dashed line in the figure represents 0 m cross-track deviation.

Table 7. Comparison of experimental results.

	Raw Track	Optimized Track
Navigation duration (s)	1873	1678
Valid measurement points	1845	1678
Ratio of effective measurement points	98.5%	100%
Sailing distance (m)	4364.0	4267.4
Effective navigation distance (m)	4343.1	4266.9
Ratio of effective navigation distance	99.5%	99.9%
Command heading adjustment	714	389
Maximum deviation (m)	11.0	4.9

The effective navigation distance in the table refers to the projected length of the actual trajectory onto the planned survey line, while valid measurement points denotes the number of trajectory points with deviation distances within 10 m (points compliant with hydrographic surveying standards).

As shown in the table, after optimization using the proposed algorithm, the number of command heading adjustments decreased from 714 to 389—a 45.5% reduction—significantly alleviating operator workload. The ratio of effective navigation distance increased from 99.5% to 99.9%, indicating that the algorithm reduces unnecessary voyage losses and achieves measurable energy savings. Meanwhile, the valid measurement point ratio rose from 98.5% to 100% (trajectory points were recorded at a frequency of one per second, with the total number of points proportional to the voyage duration), demonstrating that the algorithm effectively eliminates invalid measurements and provides reliable support for marine survey missions.

5. Conclusions and Discussion

In view of the problems that the accuracy of the current survey vessel autopilot track mode does not meet the requirements of hydrographic surveying and that manual operation in the heading mode has a significant subjective impact, this paper proposed an intelligent auxiliary decision-making algorithm based on LSTM and MLR. By predicting the position of the vessel at future moments, it first determines whether a command heading adjustment is needed. If adjustment is required, the algorithm provides the recommended adjustment timing and adjustment amplitude. Experimental results show that the algorithm in this paper can effectively reduce the workload of steering personnel and build a bridge for human–machine collaboration between full automation and full manual operation.

Although many scholars are committed to research on predictive ship control and next-generation autopilots, due to the unpredictability of the marine environment, most research is still limited to theoretical frameworks or simulation environments. In contrast, this study proposed an intelligent auxiliary algorithm based on the existing autopilot system. Before the popularization of the new generation of autopilots that meet the accuracy requirements of survey tasks, this algorithm can directly reduce the workload of the steering personnel currently performing hydrographic survey tasks and contribute to the cause of hydrographic surveying.

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