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Research paper

A kinematic model for collaborative icebreaker convoy operations in ice-covered waters

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ABSTRACT

Icebreaker assistance is a common yet intricate operation in ice-covered waters, frequently leading to collisions between ships and icebreakers. This underscores the need for advanced kinematic models to improve safety and coordination in convoy operations. Consequently, this paper introduces a kinematic model for guiding intelligent ships under icebreaker assistance. The model, grounded in the Traffic Factor State Network (TFSN), evaluates the safety state of a fleet in various ice conditions, using data from actual convoy operations. An enhanced Proportional Integral Derivative (PID) algorithm is integrated to formulate a multi-ship following model, which accounts for the kinematic characteristics of ships in ice. The model also incorporates the transmission process of ship maneuvering commands. Its validity is confirmed through application to two ships under icebreaker assistance. The findings show that the model effectively simulates safe speeds and maintains proper inter-ship distances over time, and it generates safe kinematic instructions for the fleet. This model may contribute to navigational safety in ice-covered waters and demonstrates the potential for inclusion in ice navigation support systems.

1. Introduction

The phenomenon of global warming has brought increased attention to ice navigation, leading to reduced navigation time and energy consumption in polar shipping compared to open water routes. Icebreaker assistance has become crucial for facilitating the safe navigation of merchant vessels through ice-covered waters Boström and Österman (2017). However, this assistance introduces the risk of collision between the assisted ship and the icebreaker, posing dangers to both the crew and the ship (Liu et al., 2022a,b; Zhang et al., 2019b; Liu et al., 2022a,b). Therefore, there is an urgent need to develop a kinematic model for collaborative operations of intelligent ships in ice-covered waters, aiming to mitigate navigation risks during icebreaker assistance (Valdez Banda et al., 2015; Fan et al., 2020; Liu et al., 2022, 2022b).

Collaborative operations of intelligent ships are vessels that can be remotely or automatically controlled, relying on advanced technologies such as satellite positioning, sensors, and the Internet of Things to perform designated functions (Xiang et al., 2019). To optimize the design and development of intelligent cargo ships, Yan et al. (2017) introduced the concept of a “navigation brain system” that provides a structured and systematic approach. Effective communication and timely exchange of accurate information can significantly reduce navigation accidents. To address this, Zhang et al. (2020) proposed a multi-ship following model that explores the following behavior of ships under communication conditions while studying the safe distance and maximum speed of vessel navigation in icy regions Franck and Holm (2013). Heading adjustment is an effective approach to avoiding collisions between vessels during navigation. In this regard, Hu et al. (2020) presented an automatic collision avoidance algorithm that considers the steering dynamics of Autonomous Surface Vehicles (ASVs). This algorithm retrieves past similar scenarios and provides solutions for heading adjustment in new collision avoidance scenarios Fujii and Tanaka (1971). Cooperative ship-shore control is another method of controlling the motion state of vessels to ensure safe navigation (Liu and Lv, 2021). Liu and Lv (2021)developed a motion control system for unmanned vessels based on the sliding mode control algorithm, utilizing a DSP and GPRS architecture. Deng et al. (2018) proposed a distributed Kalman filtering cooperative formation model for unmanned ships, simulating single and multiple unmanned ship systems' target tracking to optimize the navigational trajectory. However, problems such as model

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uncertainty, unknown perturbations, and overshooting occur during ship track tracking. To address these issues, Zhang et al. (2022) proposed a self-anti-disturbance control method for ship track tracking based on the Euler method, using a power consumption state observer to resolve internal model uncertainty and external perturbations such as wind, waves, and currents. Zhang et al. (2023) propose a new model for assessing the navigation risk associated with icebreaker convoy operations. This model, based on the Artificial Potential Field (APF) concept, describes the interactions between ships as well as between ships and ice, aiming to quantify the navigation risk for subsequent ships in the fleet Liu and Lv (2021). However, it is worth noting that the current methods may not fully consider the collaborative operations of ships in ice navigation, as they do not account for important factors such as multi-ship following and kinematic features, as well as traffic factor states in ice conditions Liu et al. (2020). This limitation could lead to an underestimation of the navigational safety risks of ships navigating in ice-covered waters during icebreaker assistance.

The safety of ship navigation in ice-covered waters is a crucial issue, which requires careful consideration of various factors. One such factor is the safety distance that ships must maintain, which is negatively correlated with sea ice thickness (Zhang et al., 2017). Furthermore, ship-ship interaction is common during navigation in ice areas, and the distance between ships within a fleet must not be too close (Degrieck et al., 2021). In the past, researchers have proposed several models and methods to address this issue. For example, Fujii and Tanaka (1971) introduced the concept of a safety domain to transform the discrete value of safe distance into a continuous spatial problem. Tsoy (1983) developed a mathematical model for ships in ice-breaking waterways, while Lubbad and Løset (2011) proposed a method based on the PhysX modelling environment to track the ice-ice interaction process of an icebreaker in continuous icebreaking mode. Recently, Zhang et al. (2017) proposed a quantitative model based on ship following theory to calculate the safe distance and collision risk between an icebreaker and assisted vessels in continuous icebreaking conditions. Goerlandt et al. (2017) studied the operational risks associated with assisted navigation based on Automatic Identification System (AIS) data and sea ice data, while Li et al. (2018) studied the safety navigation of ships on the Arctic route and established a ship following model suitable for the Arctic route. Zhang et al. (2019) proposed a ship following model applicable to the Baltic Sea ice area, considering the influence of ice conditions and safety speed constraints. Khan et al. (2019) proposed an improved Nagel-Schrekenberg cellular automation model for maritime convoy traffic based on a Bayesian Network probabilistic approach for predicting safe traffic flow of maximum channel density and the probability of collision between vessels. Besides safe distance, sea ice is another crucial factor affecting ship navigation in ice-covered waters. Liu et al. (2024) indicated that ice concentration and thickness are the factors that have the more significant impact on the need for icebreaker assistance compared to environmental factors (e.g., wind speed and air temperature). Kim et al. (2020) used an artificial neural network-based and data-driven ice resistance estimation method to calculate the resistance of sea ice and investigated the effects of ship width, ice thickness, and ship speed on ice resistance Murray and Perera (2022). All these studies provide theoretical support for the navigational safety of ships in ice-covered waters. Nevertheless, the existing methods may lead to underestimation of ships safety control as they do not account for time-varying kinematics features of multi ships in various ice conditions.

The literature review conducted highlights the research gap in the field of collaborative operations of intelligent ships during icebreaker assistance in ice-covered waters: Current methods for determining safe collaborative speeds and distances in fleet operations under ice conditions are static and tend to underestimate the kinematic characteristics of the fleet during convoy operations.

To address this gap, this study proposes a novel kinematic model for intelligent ships with icebreaker assistance in ice-covered waters. The model is based on the Traffic Factor State Network framework, which determines the safety state of ships. An enhanced Proportional-Integral-Derivative (PID) algorithm is employed to regulate the ship kinematics. This approach is specifically tailored to scenarios where a fleet comprises a human-operated icebreaker and autonomous intelligent ships. The kinematic model is applied to two ships operating under icebreaker assistance in the Baltic Sea. It simulates safe speeds, distances, and kinematic instructions over time. Comparative studies with actual records suggest that the current methodology could aid in the collaborative operation of intelligent ships with icebreaker support in ice-infested waters.

The rest of the paper is organized as follows. Section 2 briefly introduces the algorithms and related conceptual formulations used in this model, Section 3 details the steps in the development of this model, Section 4 presents the simulation results of the model and analyses them, Section 5 provides a discussion of the following model, and Section 6 provides a conclusion.

2. Methods

2.1. General framework of the methodology

The objective of this study is to develop a collaborative model for following and controlling an intelligent fleet based on the safety state of ships in ice conditions. Fig. 1 illustrates the main research framework of the proposed model, which comprises six principal components. The AIS data serves as the starting point, providing a spatial-temporal representation of the sea area where the current ship is sailing, reflecting its current spatial-temporal characteristics, movement state, and external environment. Next, the Traffic Factor State Network (TFSN) model (Zhang et al., 2020) is employed to classify the ship safety states. Subsequently, a kinematic model is constructed to adjust the motion of ships based on the varying safety states. Finally, model validation is conducted, and specific scenarios are introduced to confirm the rationality of the model. Details about the stipulation of the proposed model shown in Fig. 1 are given in the following sections.

2.2. TFSN modeling and ship safety state estimation

2.2.1. The development of TFSN model for fleet navigation in ice areas

Due to the presence of sea ice, ship fleet navigating in ice areas must keep a certain constraint of speed, distance, and speed difference between following ships. Otherwise, collision accidents are likely to occur (Goerlandt et al., 2017). This model studies the scopes of speed and distance for ship fleet and defines the scopes as "states," distinguishing between {"safe," "sub-safe," "over-safe," and "dangerous"}. This is used as a reference for ship navigation control, and ship speed is adjusted by judging whether the ship is in a safe state determined by the combination of ship distance, ship speed and speed difference.

In order to estimate or predict the ship state, the above ideas can be organized into the following assumptions.

Assumption 1. Navigation in ice-covered waters can be thought of as a system. The system comprises factors including ship route segments, ice conditions, the state of nearby ships, weather, and other factors related to navigation. All these factors work together as a system to determine ship state, which reflects system behavior. These factors interact with each other in a complex manner. It is difficult to analyze such behavior with the use of kinetic equations. In fact, the effect of all these factors is inherently included in navigation data on a given ship route segment.

Assumption 2. For a given ship route segment with changing ice conditions, there can be multiple stable states. When ice conditions change, a transition between two stable states happens. In other words, when ice conditions change, the original stable state is broken, and the navigation system will transfer to a new stable state.

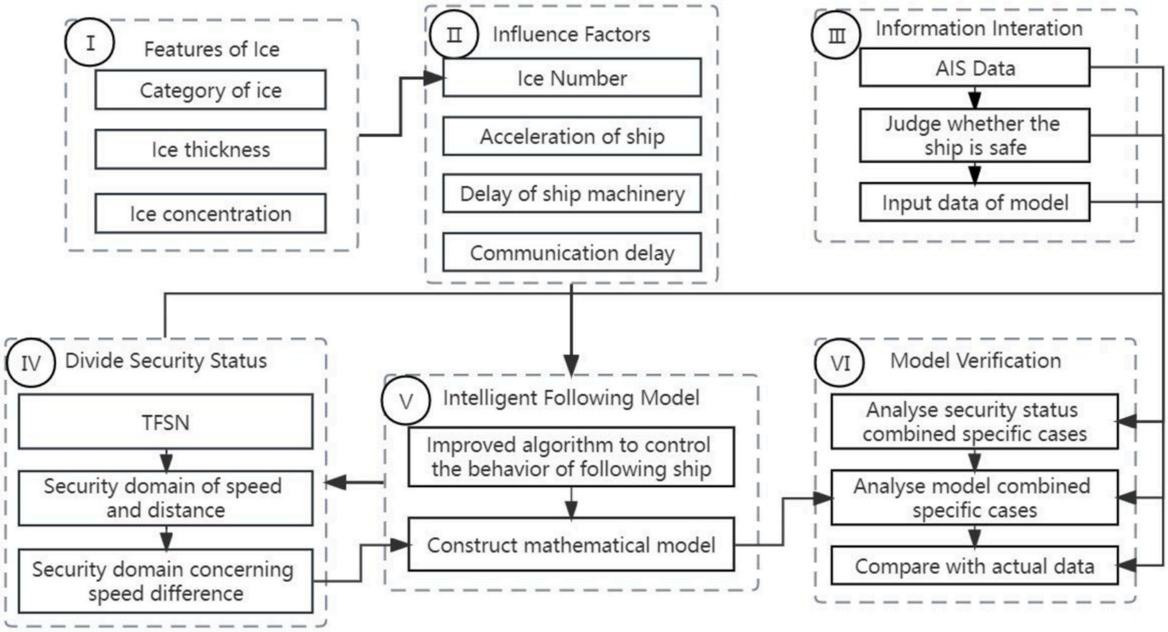


Fig. 1. Flowchart for developing a multi-ship following model for collaborative operations in ice-covered waters.

Assumption 3. A stochastic model can represent the navigation system for a particular ship route segment. The model has nonlinear and stochastic characteristics, which are related to system states and possible behaviors. The system state can be inferred from navigation data. In this way, a random model can be built using transportation principles for how navigation factors, such as volume, speed, distance, ice conditions, etc., influence each other; this model can be trained using historical data, thus establishing a unique model for each ship route segment under specific conditions.

The state of the fleet navigation is related to the parameters of ships and the channel navigation condition, and its classification is carried out through the TFSN model for fleet navigation in ice areas. The TFSN model is an interrelationship model of traffic factors considering environmental influences proposed by Zhang et al. (2020), which considers all traffic factors together to form a system. Traffic factors include traffic parameters such as speed, volume, density, road conditions, weather, etc. The state variables are related to each other by certain transfer probabilities, and the state variables and state transfer probabilities can be used to model the state of the traffic system under study. Previously, the TFSN model was only used for research such as vehicle speed prediction on land. Based on the TFSN model and its properties, the TFSN model for fleet navigation in ice is carried out in this article, as shown in Fig. 2.

Navigation data is an important parameter that reflects the state of a ship in sailing. Factors affecting the current moment of a ship's sailing state include the ship's own parameters, nearby vessel parameters, etc. These are all observable influencing factors. However, environmental factors, such as sea ice properties, currents, sea wind, etc., would also affect the ship's sailing state. These factors together constitute the uniqueness of the ship's sailing state, which is difficult to be measured by a uniform standard. This paper draws on the concept of the TFSN model, defines the observable influencing factors in the process of ship navigation as state factors, and defines the influencing factors that cannot be directly obtained as environmental factors. All the factors can be expressed as discrete or continuous state variables in a time series, and the state variables are related to each other by certain transfer probabilities. Thus, the safety state of a ship can be modeled through state variables and state transfer probabilities.

Fig. 3 shows the correlation between the influencing factors reflecting real fleet operations in ice conditions. The influence factor at time N is $IF_N = \{EF_N, SF_N^K\}$. The environmental factors include ice type, ice thickness, ice concentration and external causes such as ocean currents and wind direction and speed. Its time series is $EF_N = \{ef_{N1}, ef_{N2}, \cdots\}$. The state factors including ship distance, ship speed and speed difference have an effect of each other. It can be expressed as $SF_N^K = \{sf_{N1}^K, sf_{N2}^K, sf_{N3}^K; K = 1, 2, \cdots\}$, K is the state category of the current state

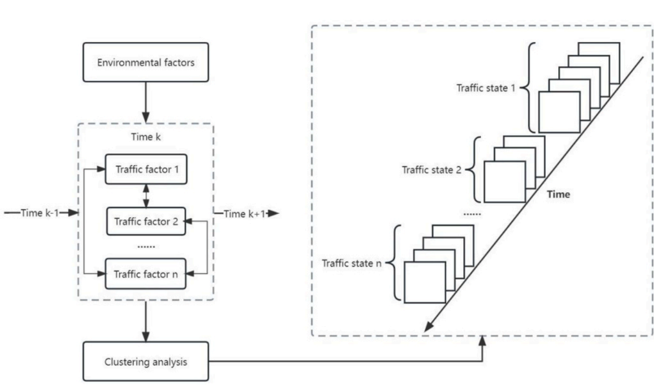


Fig. 2. Traffic Factor State Network model.

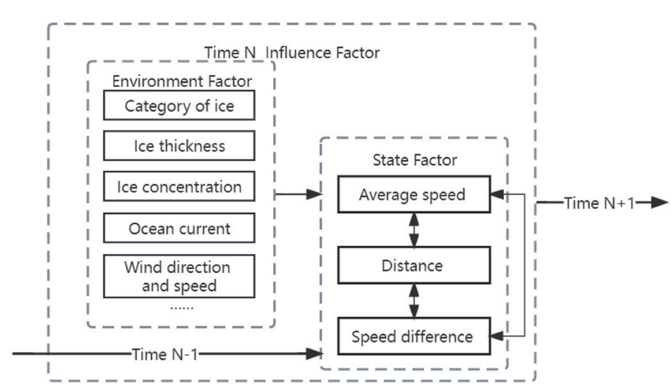


Fig. 3. Schematic diagram of the structure of the safety state influence factors.

factor. The environmental factors of the current moment and the influencing factors of the previous moment together determine the state factor of the current moment, which in turn influences the state factor of the next moment, so that the intelligent fleet can be kept in a safe state to the maximum extent during the navigation. Hence, $SF_N = f(EF_N, IF_{N-1})$.

2.2.2. Ships safety state estimation

A Gaussian distribution is used to describe the speed data of ship following navigation, and then a Gaussian mixture distribution model based on the EM (Expectation-Maximum) algorithm (Murray and Perera, 2022) is used to cluster the ship following navigation data to obtain the safety state of a ship during navigation. The samples of vessel data $x = \{S_1, S_2\}$, which represent the average speed and distance mentioned in Section 4.1. $y = \{1, 2, \cdots \mathrm{N}\}$ means all possible state categories. The maximized posterior probability of the data sample generated by the i th Gaussian mixture component is:

$$f(x) = \underset{j \in y}{argmax}\, p(y = j | S_1, S_2)$$

$$= \underset{j \in y}{argmax} \sum_{i=1}^{N} p(y = j, \theta = i | S_1, S_2)$$

$$= \underset{j \in y}{argmax} \sum_{i=1}^{N} p(y = j | \theta = i, S_1, S_2) p(\theta = i | S_1, S_2) \tag{1}$$

where, $p(\theta = i | S_1, S_2)$ in Equation (2)

$$p(\theta = i | S_1, S_2) = \frac{a_i \bullet p(S_1, S_2 | \mu_i, \sum_i)}{\sum_{i=1}^{N} a_i \bullet p(S_1, S_2 | \mu_i, \sum_i)} \tag{2}$$

is the posterior probability generated by the i $^{\text{th}}$ Gaussian mixture component of the data sample, and $p(y = j | \theta = i, S_1, S_2)$ in Equation (1) is the posterior probability that satisfies both generated by the i th Gaussian mixture component and its class is j.

The probabilistic model of the EM algorithm relies on unobservable hidden variables and operates in two alternating steps. Based on Yue and Wang (2007) and Tian et al. (2011), the probability that the unlabeled data sample $x = \{Q_1, Q_2\}$ belongs to each Gaussian mixture component is calculated according to the current model parameters, and the model parameters are updated. After initializing the model parameters of the Gaussian mixture distribution, the first step is to calculate the expectation (E). The current model parameters are used to calculate the probability that the unlabeled data sample $x = \{S_1, S_2\}$ belongs to each Gaussian mixture component, that is, to calculate the probability that the data sample is generated by the i th Gaussian mixture component and its class is j:

$$\gamma_{ji} = \frac{a_i \bullet p(S_1, S_2 | \mu_i, \sum_i)}{\sum_{i=1}^{N} a_i \bullet p(S_1, S_2 | \mu_i, \sum_i)} \tag{3}$$

The second step is to maximize (M). The model parameters are updated, the number of data samples marked as the Class i Gaussian mixture component is l_i, and its data set is $D_l = \{(x_1, y_1), (x_2, y_2), \ldots, (x_l, y_l)\}$. Marking the unlabeled data set as $D_u = \{x_{l+1}, x_{l+2}, \ldots, x_{l+u}\}$, l and u satisfy $l + u = m$. Then the expressions of a_i , μ_i and $\sum_i$ in Equation (1) are:

$$a_i = \frac{1}{m}\left(\sum_{x_j \in D_u} \gamma_{ji} + l_i\right) \tag{4}$$

$$\mu_i = \frac{1}{\sum_{x_j \in D_u} \gamma_{ji} + l_i}\left(\sum_{x_j \in D_u} \gamma_{ji} x_j + \sum_{(x_j, y_j) \in D_l \cap y_j = i} x_j\right) \tag{5}$$

$$\sum\nolimits_i = \frac{1}{\sum_{x_j \in D_u} \gamma_{ji} + l_i}\left(\sum_{x_j \in D_u} \gamma_{ji} (x_j - \mu_i)(x_j - \mu_i)^T + \sum_{(x_j, y_j) \epsilon D_l \cap y_j = i} (x_j - \mu_i)(x_j - \mu_i)^T\right) \tag{6}$$

The parameter estimates obtained in step M are used in the next step E calculation, which is iterated continuously to obtain the preliminary security domain.

The speed difference between ships in a convoy operation also has a crucial impact on the safety of the convoy (Goerlandt et al., 2017). If the speed difference is too large, it may easily lead to ship-to-ship collision due to untimely braking of ships, or ship-ice collision or even ship besetting in ice due to the gradual increase of the distance between ships (Zhang et al., 2019, 2019b). Therefore, the model limits the absolute value of the speed difference between two adjacent ships, beyond which it is regarded as a non-safe condition. The final combination of the speed difference and the safety domain results in the safety state for a ship.

2.3. Ship speed control method and safe speed determination

In Section 2.2 of this study, the safety state of a ship is determined using state factors, namely ship distance, ship speed, and speed difference, which are all functions of the ship's speed. Consequently, controlling the speed of the vessel is crucial in maintaining its safe state. To this end, an improved PID algorithm, which incorporates various influencing factors into the traditional PID algorithm, is utilized in determining the optimal speed of the vessel.

The PID algorithm is a well-established control method widely utilized in various applications, owing to its ability to make quick and accurate automatic corrections in control systems without requiring an accurate mathematical model of the control object. Its history spans over a century, and it has proven to be a reliable and effective method for controlling a broad range of systems. Hence, an improved PID algorithm is employed in the proposed multi ship following model. The corresponding relationship of a conventional PID control system can be derived as Equation (7):

$$u(t) = k_p e(t) + k_i \int e(t)dt + k_d e_i'(t) \tag{7}$$

in Equation (7), the k_p , k_i and k_d represent the proportional gain, integral gain, and differential gain respectively. $u(t)$ is the controller and $e(t)$ is the error function of the input and output. By comparing the error of the target value to the current value, adjusting these three values can achieve the correction of the system output value, so that the output of the system continuously reaches the target value.

To investigate icebreaker operations, Goerlandt et al. (2017a) developed a procedure to visualize AIS data along with spatio-temporal information about sea ice and atmospheric conditions, and to identify and classify icebreaker operations based on this integrated dataset. Liu et al. (2022b) proposed a data mining method for the automatic identification and analysis of icebreaker assistance operations in ice-covered waters. This method can be used to identify icebreaker assistance operations. To facilitate this classification, videos of icebreaker operations were created. Fig. 4 shows a snapshot of one such video, from which we can derive empirical data on ice thickness, categories, and other information used in this paper..

The safe speed is the maximum speed allowed for a ship during navigation, varies in ice areas mainly depending on the ice conditions (Guinness et al., 2014). According to Arctic Ice Regime Shipping System (AIRSS), the ability of a ship to navigate in an ice area is determined by the Ice Numeral (IN), whose value is influenced by the concentration and thickness of different types of ice and can be expressed as Equation (8) (Zhang et al., 2019).

$$IN = C_a IM_a + C_b IM_b + \cdots + C_n IM_n \tag{8}$$

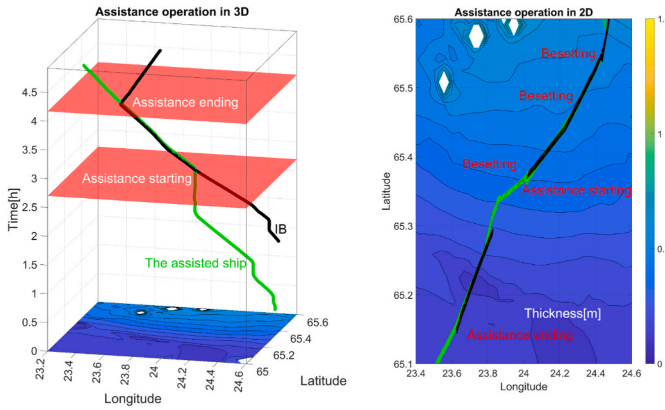


Fig. 4. Snapshot of the video visualizing the icebreaker operations, from Liu et al. (2022b).

where C_a denotes the ice concentration of type a, and IM_a denotes the ice multiplier of type a (Franck and Holm, 2013).

$$IM = \begin{cases} 2, 0 \leq C < 70 \\ 1, 70 \leq C < 120 \\ -1, 120 \leq C < 150 \end{cases} \tag{9}$$

where C denotes the thickness of the ice in centimeters.

The sample data is given by AIS data and a total of 1032 data points were collected, from which it is possible to derive a regression formula for the safe speed determined by the Ice Numeral, which applies to all vessels in the current fleet and is expressed as Equation (10). Accordingly, Fig. 5 shows the regression diagram.

$$V_{max} = 0.0505IN^3 + 0.2879IN^2 + 0.1647IN + 12.1932 \tag{10}$$

3. A kinematic model for intelligent ship fleet

This chapter introduces the division of safety states and the specific methods for establishing a multi-ship following and control model. Firstly, considering the impact of the environment, the EM algorithm is used to perform cluster analysis on the distance and average speed of adjacent ships, and to classify the safety status types of fleet operation; Then, based on expert knowledge, set the speed difference range and determine the time when it is in a safe and unsafe state; Finally, taking into account the safety of the ship's state, corresponding driving strategies should be adopted: navigation behavior remains unchanged when the ship is in a safe state; When the ship is in an unsafe state, use the established following and control model to adjust the ship's navigation behavior.

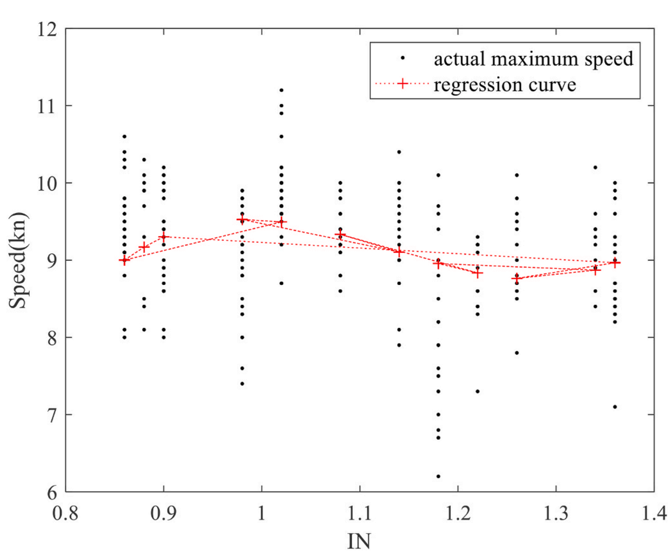


Fig. 5. Polynomial regression analysis of safe speed determined by IN.

3.1. Dividing the safety states for multi ships

The method of dividing the safety states has been briefly described in section 2.2 of this paper. To guarantee the safety of ships during navigation, this section will introduce how to implement the Gaussian mixture model of the EM algorithm to divide the safety domain. The flow chart of the algorithm is shown in Table 1. The algorithm studies the safety states of two adjacent ships and determines the categories of safety states to be four. M is a two-dimensional array including the average speed and distance. Through large amounts of iteration, each data can find out its category.

3.2. Design of the multi ship following and control model

Because of the particularity of the ice-covered waters, the angle of the ship during navigation is very small. The channel can be seen as consisting of several narrow channels that are approximately straight. Ships in the existing ice fleet are crew-driven vessels. Ships in the convoy formation do not need to make decisions by themselves during icebreaker assistance operations, and the icebreaker issues instructions to the assisted ships, specifying their position, speed, and distance from the preceding ships, etc. (Bostrom and Osterman, 2017). There are some differences between the established fleet and the traditional fleet. For the ice region intelligent fleet following and control system studied in this paper, the following reasonable assumptions are made.

1) In the fleet model established in this paper, the pilot ship is an icebreaker driven by the crew, and the following ships are intelligent ships with automatic driving.
2) There is no overtaking and turning in the process of fleet driving, and only includes the navigation behavior of deceleration, uniform speed and acceleration.
3) The ship is regarded as an ideal rigid body, and its mass is fixed during the process of speed change.
4) The following ships calculate their own speed through the established following and control model, instead of the instruction given by the icebreaker captain.

The multi ship following and control model for collaborative operations which has n ships can be simplified to Fig. 6. Assuming that the lead ship in the multi-ship following model established in this paper is a human-piloted icebreaker and the following ships are all intelligent ships with automatic piloting, and there is no overtaking during the course of the fleet, only the motion states of deceleration, uniformity and acceleration are included.

Due to the structural characteristics of the ship herself, there is a mechanical delay in the operation of its power system and control system. Mechanical delay refers to the delay from the input to the mechanical system or equipment to the desired output. In the case of ships, it refers to the time required for the ship's system to transmit the signal to respond. So, there is a deviation between the actual speed of the ship and the desired speed. Assuming that the effect caused by the mechanical delay of the ship is μ, then the relationship between the desired speed and the actual speed of the following ship i can be expressed as (Ploeg et al., 2013):

$$\mu v_i^{'}(t) = u_i(t) - v_i(t) \tag{11}$$

where $u_i(t)$ is the desired velocity of ship i. $v_i(t)$ is the actual speed of ship i. Also, there is a communication delay τ within the convoy system, then

Table 1
The process of EM algorithm for safety states identification.

Algorithm 1: EM algorithm
Input: Dataset $M = \{M_1, M_2\}$, $M_1 = \{v_1, v_2, \cdots, v_n\}$, $M_2 = \{d_1, d_2, \cdots, d_n\}$, where M is vessel data, n is amount of data; Number of safety states k.
Output: Membership of each data sample to each classification r;
1: Initialize model parameters of Gaussian mixture distribution;
2: Select the initial value of the output, start iteration;
3: for i = 1 to k
4: Calculate new mean vector;
5: Calculate new covariance matrix;
6: Calculate new mixing coefficient;
7: end for
8: repeat
9: for i = 1 to n
10: Calculate posterior probability: $Q(r, r^{(i)}) = E_z[logP(M,k\|r)\|M, r^{(i)}] = \sum_k P(k\|M, r^{(i)}) logP(M,k\|r)$;
11: end for
12: for i = 1 to n
13: Maximation $Q(r, r^{(i)})$. $r^{(i)} = arg\max_r Q(r, r^{(i)})$;
14: end for
15: until convergence

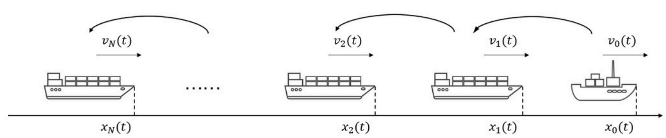


Fig. 6. Schematic diagram of the multi-ship following model.

Equation (11) can be corrected to:

$$\mu v_i'(t) = u_i(t-\tau) - v_i(t) \tag{12}$$

The distance between the current ship i and the preceding ship $i-1$ can be expressed as:

$$\varepsilon_i(t) = x_i(t) - x_{i-1}(t) + L \tag{13}$$

$$e_i(t) = \varepsilon_i(t) + hv_i(t) \tag{14}$$

where, $\varepsilon_i(t)$ is the desired distance of ship at rest, h is the desired time distance in seconds, and $e_i(t)$ is the desired ship distance, and L is the safe distance and is defined as follows:

$$L = \Delta D + \frac{1}{4}(l_i + l_{i-1}) \tag{15}$$

where $\Delta D = \alpha \bullet h_{ave} + \beta$ denotes the additional distance that adjacent vessels in the fleet need to maintain due to ice conditions (Zhang et al., 2018). α and β are coefficients which need to be calibrated on the basis of collected data. h_{ave} is average ice thickness. The value of α decreased with higher ice thickness. l_i is the length of ship i. $\frac{1}{4}(l_i + l_{i-1})$ is the minimum distance that needs to be maintained to avoid ship-ship interaction (Stoddard et al., 2016).

The rear ship in a fleet often needs to adjust its own motion state according to that of the front ship, and it takes a reaction time to complete this process, which is about 84.45s for a traditional fleet (see more in Zhang et al., 2018) and 20s for the crew (see more in Zhang et al., 2017; Wang et al., 2013). So, the intelligent fleet's reaction time is approximately 64.45s. In addition, the model updates the data every 10s. Therefore, this model takes the total reaction time to be 60s. This results in the following correspondence between the speed of the rear vessel and that of the front vessel when the rear vessel is in a safe condition:

$$v_i(t+60) = v_{i-1}(t) \tag{16}$$

When the rear ship is in a non-safe condition, this following model uses an improved PID algorithm to adjust its speed, and the mathematical expression is:

$$u_i(t-\tau) = k_p e_i'(t-\tau) + k_i \int e_i'(t-\tau)dt + k_d e_i''(t-\tau) \tag{17}$$

where $e_i'(t-\tau)$ is determined by Equations (13) and (14), which is also affected by realistic factors, making it conform to the background of intelligent fleet sailing in the ice-covered waters. According to Equations (12), (13) and (17), it is obtained that:

$$v_i'(t) = \frac{1}{\mu}\left(k_p e_i'(t-\tau) + k_i \int e_i'(t-\tau)dt + k_d e_i''(t-\tau) - v_i(t)\right) \tag{18}$$

$$v_{i-1}'(t) = \frac{1}{\mu}\left(k_p e_{i-1}'(t-\tau) + k_i \int e_{i-1}'(t-\tau)dt + k_d e_{i-1}''(t-\tau) - v_{i-1}(t)\right) \tag{19}$$

$$\varepsilon_i''(t) = v_i'(t) - v_{i-1}'(t) \tag{20}$$

Rectifying Equations (18)–(20) to obtain:

$$\begin{aligned} &\mu\varepsilon_i''(t) + v_i(t) - v_{i-1}(t) \\ &= k_p\left(e_i'(t-\tau) - e_{i-1}'(t-\tau)\right) + k_i\left(e_i(t-\tau) - e_{i-1}(t-\tau)\right) \\ &+ k_d\left(e_i''(t-\tau) - e_{i-1}''(t-\tau)\right) \end{aligned} \tag{21}$$

From Equations (14) and (20), we can have:

$$k_p\left(e_i'(t-\tau) - e_{i-1}'(t-\tau)\right) = k_p\left(\varepsilon_i'(t-\tau) - \varepsilon_{i-1}'(t-\tau)\right) + k_p h\varepsilon_i''(t-\tau) \tag{22}$$

Idem:

$$k_i\left(e_i(t-\tau) - e_{i-1}(t-\tau)\right) = k_i\left(\varepsilon_i(t-\tau) - \varepsilon_{i-1}(t-\tau)\right) + k_i h\varepsilon_i'(t-\tau) \tag{23}$$

$$k_d\left(e_i''(t-\tau) - e_{i-1}''(t-\tau)\right) = k_d\left(\varepsilon_i''(t-\tau) - \varepsilon_{i-1}''(t-\tau)\right) + k_d h\varepsilon_i'''(t-\tau) \tag{24}$$

Rectifying Equations (21)–(24) to obtain:

$$\begin{aligned} &k_d h\varepsilon_i'''(t-\tau) + (k_p h + k_d)\varepsilon_i''(t-\tau) + (k_i h + k_p)\varepsilon_i'(t-\tau) + k_i\varepsilon_i(t-\tau) \\ &-\mu\varepsilon_i''(t) - \varepsilon_i'(t) = k_d\varepsilon_{i-1}''(t-\tau) + k_p\varepsilon_{i-1}'(t-\tau) + k_i\varepsilon_{i-1}(t-\tau) \end{aligned} \tag{25}$$

Then, the transfer function of the following and control model is:

$$G(s) = \frac{\varepsilon_i(s)}{\varepsilon_{i-1}(s)} = \frac{\left(k_d s^2 + k_p s + k_i\right)e^{-\tau s}}{-\mu s^2 - s + \left(k_d h s^3 + \left(k_p h + k_d\right)s^2 + \left(k_i h + k_p\right)s + k_i\right)e^{-\tau s}} \tag{26}$$

In view of the ship's own characteristics and the safety of the crew, there exists a limit to the acceleration of the ship, which should be limited to $(a_{min}\ ,\ a_{max})$ (kn/h). For following ship 1, the acceleration range is (−150,180) (kn/h); for following ship 2, the acceleration range is (−80,110) (kn/h). Acceleration ranges were determined by the AIS data collected in the early stage, which is shown in Fig. 4. Considering the ship data is updated every 10s, the maximum value and minimum value of the ship speed are:

$$v_{imax}(t-\tau) = v_i(t-\tau-10) + 10 * a_{max} \tag{27}$$

$$v_{imin}(t-\tau) = v_i(t-\tau-10) - 10 * a_{min} \tag{28}$$

Therefore, the final ship speed is obtained by comparing the PID algorithm control result $u_i(t-\tau)$ with the result after limiting the acceleration to make the ship speed fit the actual situation, then the result of the ship speed is:

$$v_i(t-\tau) = \begin{cases} v_{imax}(t-\tau), u_i(t-\tau) > v_{imax}(t-\tau) \\ u_i(t-\tau), v_{imin}(t) \leq u_i(t-\tau) \leq v_{imax}(t-\tau) \\ v_{imin}(t-\tau), u_i(t-\tau) < v_{imin}(t-\tau) \end{cases} \tag{29}$$

4. Experiments

This section validates the proposed model. The validation data came from the fleet of ships sailing in the Baltic Sea piloted by Icebreaker Fennica in March 2011. The fleet contains two following ships, and about 1500 pieces of pre-processing data, including speed, distance, coordinates of all three ships in the fleet, and type, thickness, concentration of sea ice in the surrounding environment. The ship parameters are shown in Table 2.

4.1. Safety state classification

The proposed model in Section 3 was demonstrated using real operation data from a fleet of ships navigating in the Baltic Sea waters led by the icebreaker Fennica, which consisted of one icebreaker and two following ships. The icebreaker and the first following ship were first clustered based on the average speed and distance, and the safety domain was divided into four categories as shown in Fig. 7, with the horizontal axis indicating the distance between the two ships and the vertical axis indicating the average speed of the two ships.

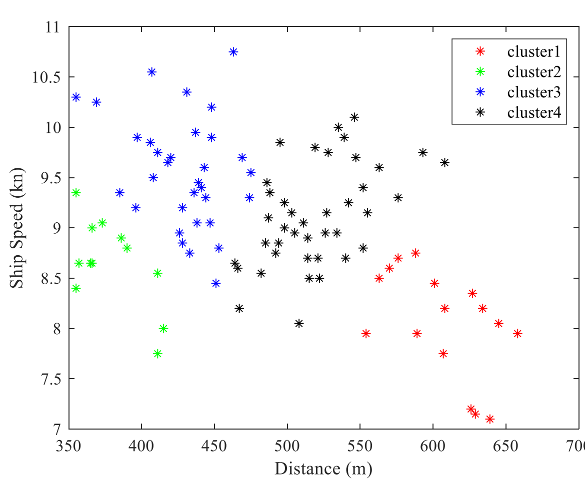


Fig. 7. Classification results of voyage data for icebreaker and following ship 1.

Table 2
Ship parameters.

Name	Length(m)	Width(m)	Draft(m)	Acceleration range (kn/h)
Fennica	116	26	6.7	–
Erik	138	21	6.6	(-150,180)
Reymar	100	14	3.8	(-80,110)

The classification of the results in Fig. 7 is shown in Table 3, which allows the safety domain to be divided into over-safe, sub-safe, dangerous, and safe state.

To make the model more accurate, it is also necessary to consider the range of speed differences between the two vessels, so the four categories of safety domain above are subdivided. This model determined that the reasonable speed difference range is $(-1, 1)$ (kn), beyond which is considered unsafe, see Fig. 8. Further subdivision of the safety domain for the above four states can obtain, see more in Section 2.3.

It follows that only the green part of cluster 4 means the safe state, i. e., the two vessels are in safe when their average speed and distance are moderate, and the speed difference is between −1 and 1 (kn). The same can be derived into Fig. 9 for the roughly classified safety domain of following ship 1 and following ship 2 based on cluster analysis of the speed and distance of vessels.

The classification of the results in Fig. 9 is shown in Table 4, which allows the safety domain to be divided into over-safe, sub-safe, dangerous, and safe state.

A further division of the above four safety domains into the safety states based on speed differences is given as Fig. 10. The examination of cluster 3 reveals that the green component of this cluster is indicative of the safe state, whereas the remaining components require modification to meet the necessary safety criteria.

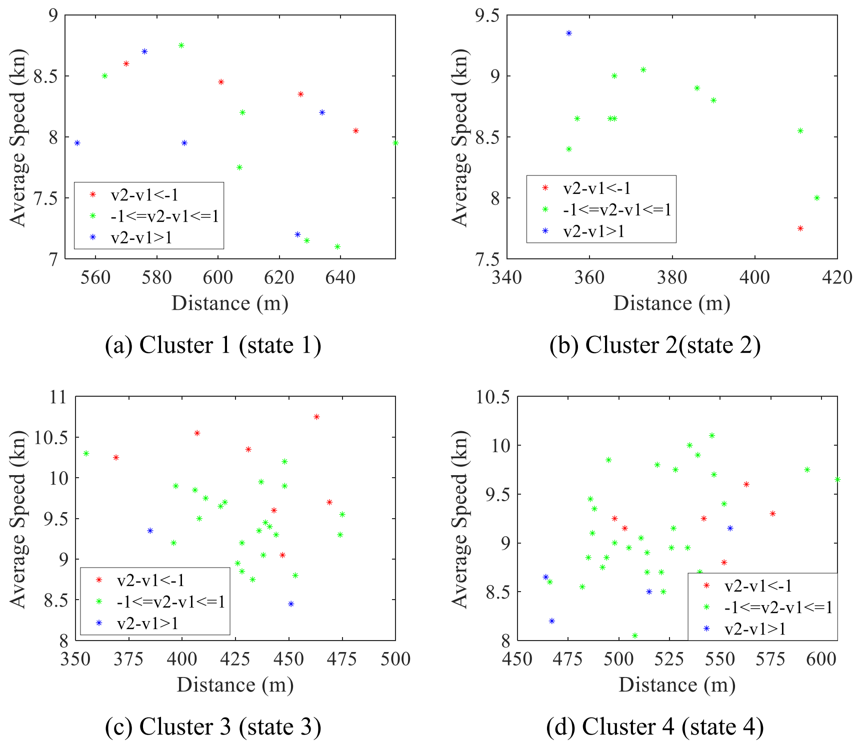
4.2. Model validation

To verify the intelligent fleet following and control model based on the safety state and improved PID algorithm, the data of the fleet led by the icebreaker Fennica sailing in the Baltic Sea will be simulated and verified as follows. The icebreaker is piloted by human and the two following ships are piloted automatically according to the sailing status of the icebreaker, and the feasibility of the fleet following control method is tested by observing the movement status of the following ships.

The motion state of following ship 1 will be simulated using the motion state of the icebreaker as a reference. As shown in Equation (26), the transfer function includes factors such as mechanical delay, communication delay, and expected time interval. In terms of the transfer function has high order and unknown coefficients, MATLAB has been used to identify the transfer function and obtain the proper PID parameters. To get the exact value of transfer function, the System Identification APP has been applied. Then, the PID controller can be built by Simulink. Finally, the PID parameters are adjusted by PID tuner automatically. In this case, the influencing factors affect the values of k_p , k_i and k_d through the transfer function. The total time lag is 60s and the simulation results for following ship 1 are shown as Fig. 11. Fig. 11(a) shows the simulated speed of following ship 1, Fig. 11(b) shows the actual speed of the icebreaker compared to the simulated speed of following ship 1, Fig. 11(c) shows the speed of following ship 1

Table 3
Analysis of classification results for icebreakers and following ships1.

Classification	Features	Status
Cluster 1	Low speed, long distance	Over safe
Cluster 2	Low speed, short distance	Sub-Safe
Cluster 3	High speed and short distance	Dangerous
Cluster 4	Moderate speed and distance	Safe



(a) Cluster 1 (state 1)   (b) Cluster 2(state 2)

(c) Cluster 3 (state 3)   (d) Cluster 4 (state 4)

Fig. 8. Classification results of the four clusters according to acceleration.

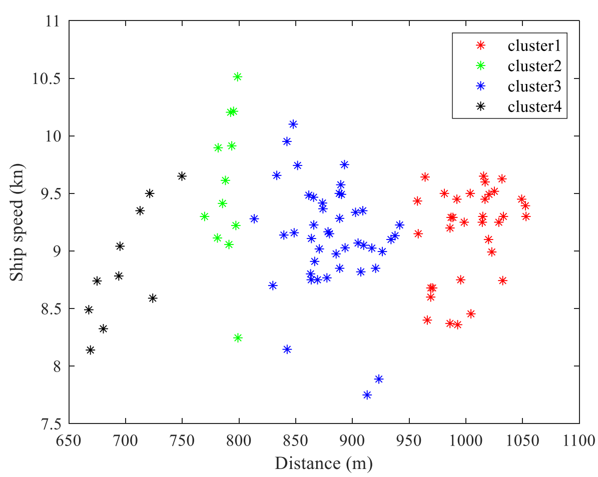


Fig. 9. Classification results of voyage data for following ship 1 and ship 2.

Table 4
Analysis of classification results for following ship 1 and ship 2.

Classification	Features	Status
Cluster 1	Long distance	Over safe
Cluster 2	High speed and short distance	Sub-Safe
Cluster 3	Moderate speed and distance	Safe
Cluster 4	Short distance	Dangerous

simulated only using the improved PID algorithm and then simulated after dividing the safe state and limiting the acceleration, Fig. 11(d) shows the actual distance between following ship 1 and the icebreaker compared to the simulated distance.

The motion state of following ship 2 will be simulated using the motion state of following ship 1 as a reference, with a total time lag of 60s, and the simulation results for following ship 2 are shown as Fig. 12.

It can be clearly observed from Fig. 11(c) that after limiting the acceleration range, the trend of the ship's speed changes slows down, which helps to protect the crew and cargo; after dividing the safety state, the ship reduces unnecessary speed changes, which helps to save ship power resources.

A comparative analysis of Figs. 11 and 12 shows that the simulated distance in Fig. 12(d) is larger compared to the simulated distance in Fig. 11(d). This is because the experimental data was taken from only one section of the fleet's voyage, not the complete data, and that the initial value in Fig. 12(d) is larger, but this does not affect the stability of the spacing range of the vessels.

Although the simulated data have been compared with the input data in Figs. 11(b) and Fig. 12(b), to make the comparison more accurate and intuitive, the performance of the model can be assessed by three metrics: mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE):

$$MAE = \frac{1}{n}\sum\nolimits_{i=1}^{n} \left| v_{model,i} - v_{obs,i} \right| \tag{30}$$

$$MAPE = \frac{1}{n}\sum\nolimits_{i=1}^{n} \frac{\left| v_{model,i} - v_{obs,i} \right|}{v_{obs,i}} \times 100\% \tag{31}$$

$$RMSE = \sqrt{\frac{\sum\nolimits_{i=1}^{n} \left(v_{model,i} - v_{obs,i} \right)^2}{n-1}} \tag{32}$$

where n denotes the number of sample data and $v_{obs,i}$ denotes the actual ship speed of the preceding ship at moment i, i.e., the reference speed, and $v_{model,i}$ denotes the simulation data of the speed of the following ship. Table 5 shows the error between the reference speed and the simulated speed of the two following ships in the ice area.

Upon comparing the simulation results with the actual data, it was observed that the difference between the two was found to be negligible,

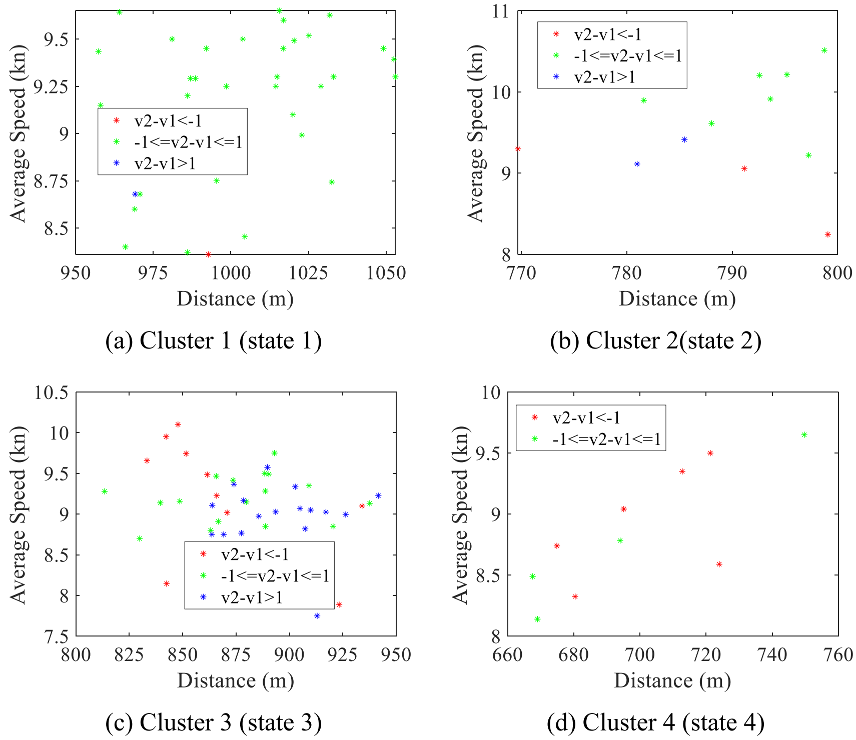


Fig. 10. Classification results of the 4 clusters according to acceleration.

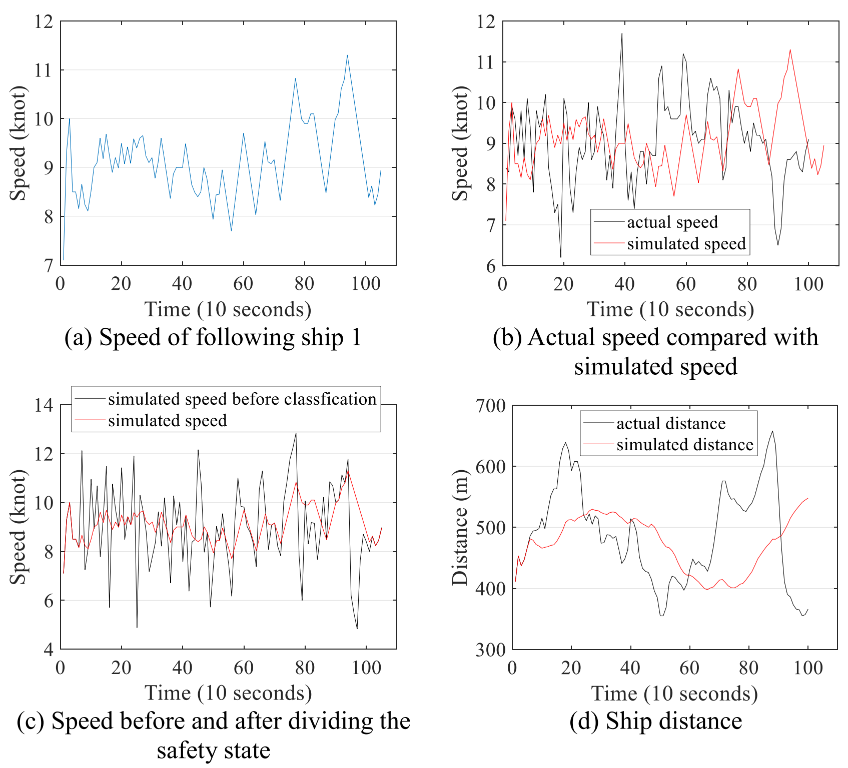


Fig. 11. Comparison of simulation results and empirical historical data of following ship 1.

see Table 5. Moreover, the error was observed to decrease gradually with an increase in the number of simulations performed. Hence, it can be concluded that the proposed model exhibits superior performance in accurately predicting the behavior of the rear ship while ensuring the safety of both ships. This is because the model successfully maintains good following behavior between the two ships.

Based on Equation (10), the safe navigation speed can be determined, and as illustrated in Fig. 13, the simulation results obtained using

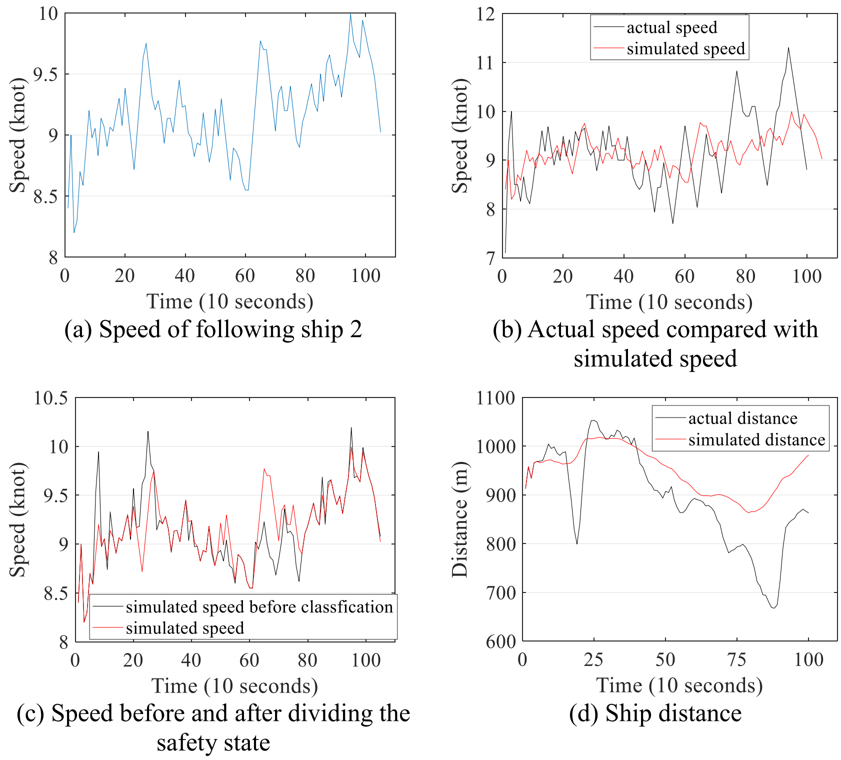


Fig. 12. Comparison of simulation results and empirical historical data of following ship 2.

Table 5
Evaluation of simulated speeds for the two following vessels.

	MAE (kn)	MAPE	RMSE (kn)
Icebreaker and Ship 1	1.0632	0.1223	1.3106
Ship 1 and Ship 2	0.5339	0.0582	0.6921

the proposed model fall within the safe speed range. These findings suggest that the proposed model accurately simulates the multi-ships following behavior, ensuring that both ships maintain a safe distance. Thus, it can be concluded that the simulation results are in alignment with the actual data and the proposed model provides a reliable means of simulating multi ships following kinematics control.

5. Discussion

The proposed kinematic model for intelligent ships presented in this study introduces a novel approach to ship safety state classification, utilizing a TFSN methodology. Furthermore, the model parameters are established by incorporating information from real-world convoy scenarios in ice covered waters, including the fleet's time delay, the ship acceleration restrictions, and the secure distance required under ice conditions. However, it should be noted that solely relying on the clustering results using EM algorithm for the safety domain classification of ship navigation data may present a limited perspective. After processing the data, it becomes evident that the safety domain classification outcomes exhibit certain temporal characteristics. Figs. 14 and 15 depict the chronological analysis of the safety domain classification outcomes for two following ships. As depicted in Fig. 14, following ship 1 undergoes a sequence of state transitions in the order of "dangerous to safe to over-safe to safe too dangerous to safe to over-safe to sub-safe." The ship safety state remains constant for a certain continuous period, with changes in speed and distance gradually contributing to state transitions, which accurately reflects the real-life movement of ships and validates the classification outcomes from a temporal viewpoint.

As can be seen from Fig. 15, following ship 2 goes through a

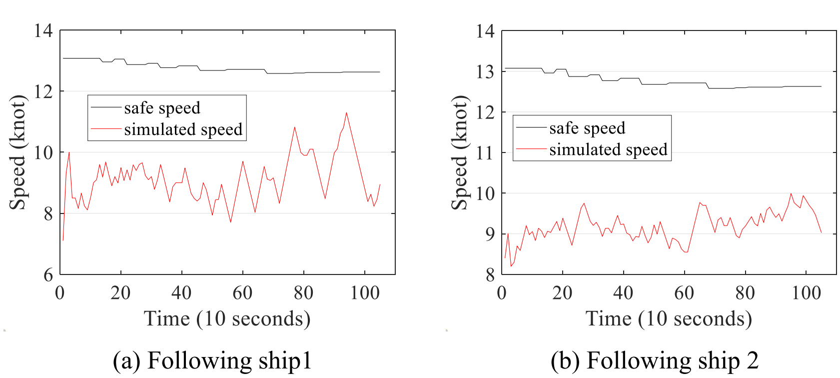


Fig. 13. Comparison of simulation speed and safety speed.

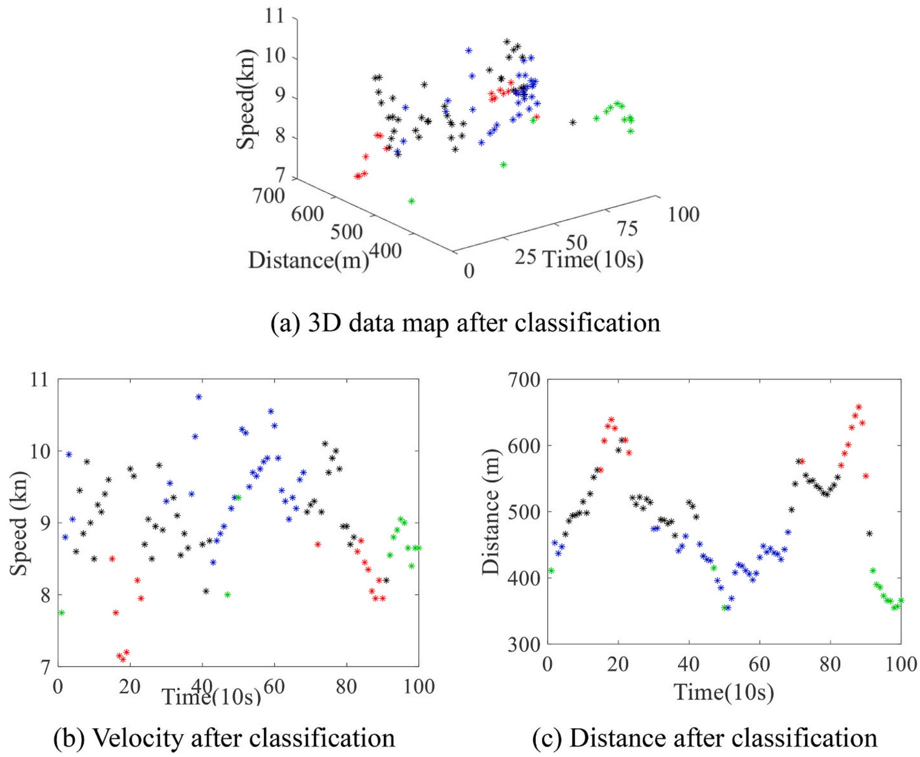


Fig. 14. Temporal analysis of the results of the following ship 1 safety domain classification.

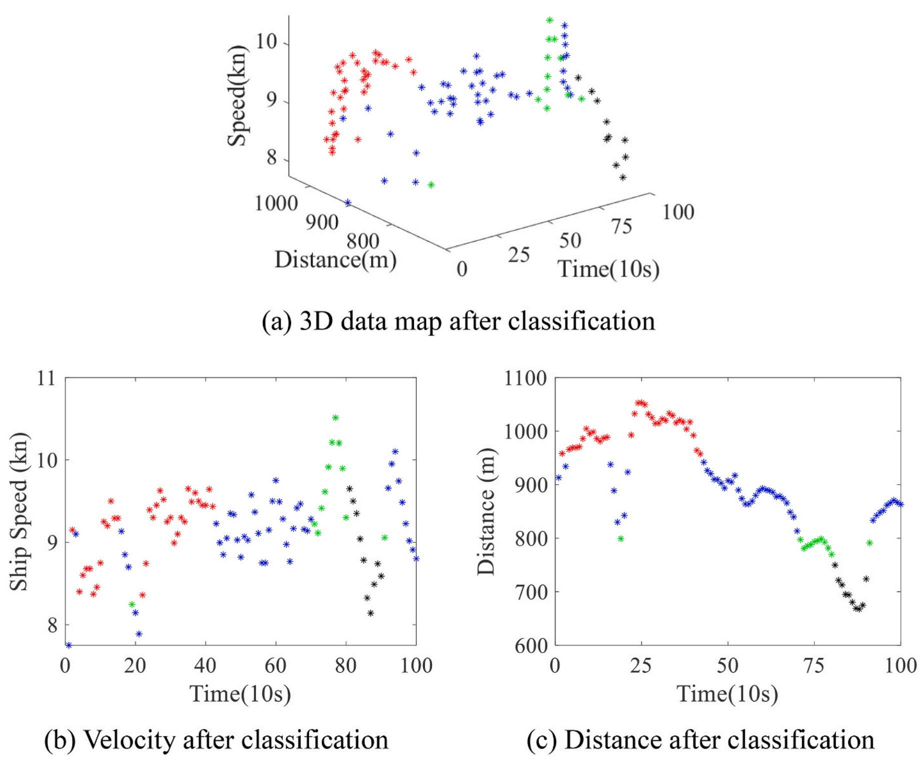


Fig. 15. Temporal analysis of the results of the following ship 2 safety domain classification.

chronological transition of "safe to over-safe to safe to over-safe to safe to sub-safe too dangerous to safe". Also, in line with the actual situation of ship movement and validating the classification results from a temporal perspective. This shows that it is feasible to use the EM algorithm to classify the safety domain of a ship, and that although there is the phenomenon of individual different state points occasionally occurring over a continuous period, the overall state of the ship is consistent over the time series.

6. Conclusion

This paper introduces a kinematic model for the collaborative operations of intelligent ships navigating in ice-covered waters with icebreaker assistance, utilizing TFSN approach. The novelty of the model is the categorization of ship safety states, centered around an advanced PID control algorithm that considers various factors, including mechanical delay, communication delay, ship transmission delay, and ice resistance. This model enables simulation of safe speeds, distances, and kinematic instructions over time for intelligent ships collaboratively operating with icebreaker support in ice covered waters. To assess the model, two ships operating under icebreaker assistance in the Baltic Sea are studied in ice conditions. The results show that the model effectively simulates safe speeds and maintains proper distances between ships over time. It generates reliable kinematic instructions for the fleet, aligning well with actual records. The findings suggest that this model could enhance navigational safety in ice-covered waters and has potential for integration into ice navigation decision support systems. However, certain factors such as ice type, icebreaker drift, icebreaker capabilities, and the sensitivity of following ships can affect the model's stability, owing to the intricate ice conditions and ship characteristics. Future research could include more variables, like ice and wind resistance, as well as current velocity, to improve the model's realism and accuracy.

CRediT authorship contribution statement

Weibin Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ye Xiao:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Cong Liu:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Mingyang Zhang:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Long Wang:** Validation, Writing – review & editing. **Luqi Feng:** Software, Visualization, Writing – review & editing.

Declaration of competing interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled, '*A Kinematic Model for Collaborative Icebreaker Convoy Operations in Ice-Covered Waters*.

Data availability

Data will be made available on request.

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