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Research paper

A framework for ship semantic behavior representation and indexing

Shunqiang Xu [a,b,c], Liang Huang [a,b,c,d], Yamin Huang [a,b,c,*], Yuanqiao Wen [a,b,c], Xiaodong Cheng [a,b,c], P.H.A.J.M. van Gelder [d]

[a] State Key Laboratory of Maritime Technology and Safety, Wuhan University of Technology, Wuhan, 430063, China
[b] National Engineering Research Center for Water Transport Safety, Wuhan University of Technology, Wuhan, 430063, China
[c] Intelligent Transportation System Research Center, Wuhan University of Technology, Wuhan, 430063, China
[d] Safety and Security Science Group, Faculty of Technology, Policy and Management, Delft University of Technology, Delft, 2628 BX, the Netherlands

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ABSTRACT

The advancement of smart shipping and autonomous navigation relies on Automatic Identification System (AIS) data, which provides essential ship trajectory information. However, raw AIS data lacks semantic context, making behavior annotation crucial for understanding navigation tasks and processes. Existing research faces two challenges: (1) a lack of clarity on which semantics should be abstracted for effective behavior annotation, and (2) insufficient consideration of spatial interactions between ship maneuvering and the navigational environment, particularly topological interactions. These issues complicate data extraction and hinder machine learning-based applications such as explainable trajectory prediction. This paper proposes a comprehensive framework for semantic annotation and indexing of ship behavior. The framework deconstructs ship behavior into a unified data structure using a relational database, where three types of behavior semantics are defined, including atomic, topological, and traffic behavior. Atomic behaviors (e.g., move and stop) are extracted to annotate raw trajectories, while topological behaviors, describing interactions between trajectories and the environment, are modelled using an improved Dimensionally Extended 9-Intersection Model (DE-9IM). The combination of these semantics enables the annotation of higher-level traffic behavior. The model is further evaluated via behavior annotation statistics, demonstrating its effectiveness in annotation and indexing high-level ship behavior.

1. Introduction

Smart shipping is transforming the maritime industry by integrating advanced technologies such as artificial intelligence, big data analytics, and the Internet of Things to enhance operational efficiency, safety, and sustainability (Gan et al., 2025; Li et al., 2024a; Liang et al., 2025). One of the cores of this transformation is Automatic Identification System (AIS) data, which provides real-time ship tracking and navigation insights (Li and Yang, 2023). AIS data plays a crucial role in enabling smart shipping by supporting a series of navigation tasks, such as collision avoidance (He et al., 2021; Zhu et al., 2025), route optimization (Huang et al., 2024), autonomous navigation (Li and Yang, 2023), etc. By leveraging AIS data with predictive analytics and machine learning, smart shipping systems can enhance decision-making and ensure compliance with maritime regulations. As a result, AIS data serves as a fundamental pillar in the development and advancement of intelligent and sustainable shipping solutions (Shu et al., 2024).

One of the key contributions of AIS data to smart shipping is its ability to extract ship movement patterns of various navigation tasks and processes in different places, providing valuable insights into ship behavior and maritime traffic flows. Many studies have investigated various ship movement patterns in the AIS data (Gu et al., 2024; Li et al., 2024b; Zhang et al., 2024). Nevertheless, its limitations, such as data sparsity, noise, and lack of semantic information, pose challenges in accurately extracting ship movement patterns. Semantics explicit integrates the navigation environment data, and the dynamic and static data of ships. Understanding the semantics behind the AIS data is of great significance for ship path planning (Li et al., 2024c; Li and Yang, 2023), trajectory predictions (Li et al., 2024a), and maritime traffic monitoring (Xin et al., 2024), etc. Therefore, there is a growing demand

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* Corresponding author. Intelligent Transportation System Research Center, Wuhan University of Technology (WUT), 1178 Heping road, Wuhan, Hubei, China.
E-mail addresses: s.xu-1@utwente.nl (S. Xu), leung.huang@whut.edu.cn (L. Huang), yaminhuang@whut.edu.cn (Y. Huang), wenyuanqwhut@foxmail.com (X. Cheng), P.H.A.J.M.vanGelder@tudelft.nl (P.H.A.J.M. van Gelder).

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for the automated semantic annotation of the AIS data.

Existing methods for semantic annotation mainly achieved by recognizing specific semantic behavior using machine learning and deep learning models, such as stop, U-turn, and self-intersection behavior (Kabir et al., 2022; Yan et al., 2022; Yang et al., 2024; Zhang et al., 2022). The models rely on large volume of AIS data for training, and require large amounts of data annotation and classification information. However, most current learning-based ship behavior studies focus on utilizing raw AIS data, e.g., longitude and latitude, overlooking hidden semantics, to perform tasks of trajectory prediction, etc., leading to poor ability to generalize in another place. Moreover, the behavior understanding and recognition depend on accurate representations of contextual information, while the existing methods cannot establish an effective behavior abstraction. Thus, it is difficult to achieve a common behavior interpretation for ship AIS data. It will also hinder the efficiency of indexing behavior information.

Semantic model offers a powerful tool to organize contextual information for ship behavior interpretation, which is inspired by the way that how people conceive of the world and has arisen as a popular research topic (Cheng et al., 2025; Song et al., 2024a,b). It not only offers a structural perspective to fuse multi-source maritime data (Santipantakis et al., 2020), but also a new way to analyze and interpret ship (traffic) behavior for intelligent machines (Song et al., 2024a,b). However, existing semantic-based ship behavior model is lacking consideration of spatial interaction between ship maneuvering and navigational environment, leading to uncomprehensive interpretation of ship behavior, especially related to space-activities.

To solve the above requirements and problems, it is necessary to describe ship behavior in a unified way and build a centralized framework for the processing, and annotation of AIS-based ship trajectory data. We propose a ship semantic behavior framework, which can facilitate the indexing and extraction of behaviors, thus generating important semantic database for further behavior model and analysis. First, atomic behavior is introduced to exploit spatiotemporal characteristics from the raw trajectory (i.e., stop, turn, etc.), transforming the raw trajectory into a sequence of maneuvering semantics. Secondly, a spatial semantic map model is developed to represent navigation environment information and a computational method to obtain spatial interactions between ship maneuvering and the navigation environment is proposed. Lastly, higher-level semantics of ship behaviors with domain knowledge can be abstracted by combining the semantics mentioned above. The main contributions can be summarized as follows.

1) A framework is proposed, in which semantics related to ship behavior abstraction and interpretation are structurally represented in a relational database, thus, annotation and indexing can be performed to generate interpretable semantic trajectories database for depth ship behavior modeling and analysis.
2) An improved Dimensionally Extended 9-Intersection Model that integrates navigation environment (e.g., nautical infrastructures) into raw trajectory is developed. Thereby, the space-related semantics can be annotated to enhance behavior interpretation.

The remainder of this paper is organized as follows: the related work is overviewed in Section 2; Section 3 presents the proposed model; Experiments, Discussion, and Conclusion are addressed in Sections 4-6, respectively.

2. Related work

2.1. Feature-based analysis of ship behavior

Current feature-based ship behavior modeling and analysis can be broadly conducted based on hand-crafted features and automated feature extraction. Hand-crafted features involve manually designing features from AIS data, such as speed, distance, and trajectory patterns, which are then fed into machine learning and deep learning models for behavior interpretation, such as move-and-stop (Huang et al., 2024; Iphar et al., 2024), maneuvering patterns (Gao and Shi, 2020; Huang et al., 2020), etc. For instance, Zhang et al. (2022) proposed a two-stage strategy for extracting ship loitering behavior. The feature of trajectory redundancy was defined to measure the shape characteristics of loitering patterns. The patterns were then transferred into images for a conventional neural network model to capture the typical trajectory shapes of loitering. To obtain stay behavior, Yan et al. (2022) utilized speed, distance, and time interval between trajectory points to train a random-forest-based classification model for berthing and anchoring behavior extraction. However, this approach relies on domain expertise to select meaningful features but may struggle to capture complex, hidden patterns in ship movements.

Learning-based feature extraction allows deep learning models to automatically learn informative representations directly from raw AIS data, eliminating the need for manual feature engineering. For example, Murray and Perera (2021) proposed a variational recurrent autoencoder model to learn AIS representation for ship behavior cluster extraction. Li et al. (2024b) developed a geohash-coded AIS data representation to enhance the position correlation between trajectory points for further trajectory prediction. However, they are limited by interpretability. Unlike hand-crafted features, which are explicitly designed based on domain knowledge, the features purely learned from AIS data using deep learning models are often abstract and difficult to interpret, making it challenging for maritime experts to validate.

In summary, most existing studies prioritize the feature of AIS trajectory as the main way to discover behavior patterns, in which additional spatial information is not well incorporated. As a result, interpreted behaviors of ship trajectory are inaccurate. For instance, a U-shape trajectory might be identified as a turn-around behavior in the open waters, whereas it also might be interpreted as navigating alongside the waterway in a river with a dramatic shape. Thus, it is essential to integrate environment information, particularly navigational environment, into ship trajectories for comprehensive annotation of ship behavior semantics (Koutroumanis et al., 2021).

2.2. Semantic-based analysis of ship behavior

To obtain a better behavior understanding of ship trajectory, additional information, e.g., geospatial information, has drawn attention. The concept of semantic trajectory was introduced to enrich spatio-temporal trajectory with external information (Parent et al., 2013). Several semantic trajectory models have been proposed, such as MASTER (Mello et al., 2019) and FrameSTEP (Nogueira et al., 2018). However, these models are not widely considered in the maritime domain due to insufficient domain knowledge. Therefore, ship semantic trajectory models were developed.

Ontology-based methods are generally used to organize the semantics around ship behavior. Classes that are strongly connected with ship behavior, such as ship (Song et al., 2024a,b), trajectory (Santipantakis et al., 2020; Van Hage et al., 2012), event (Santipantakis et al., 2020), and place (Brandoli et al., 2022), are abstracted and formalized in the ontology. Knowledge bases written in semantic web rule language (Song et al., 2022) and graph-based (Elayam et al., 2022) are built to infer potential behaviors, such as fishing and docking. Additionally, external information is utilized. For example, a framework named CRISIS was proposed by Soares et al. (2019), in which heterogeneous data, such as ice conditions, was combined to reason and query ship maneuvering information for maritime situation awareness. Wen et al. (2019) developed a semantic network-based method, where nautical infrastructures, e.g., channels, were incorporated to reason ship semantic behaviors.

However, ship semantic behavior models mentioned above lack detailed consideration of space-related semantics, especially in topological interactions between ship and navigation environment, hindering the comprehensive interpretation and annotation of trajectory data.

3. Models

We decompose the traffic behavior into the most basic set of elements and establish a general conceptual model. The universal traffic behavior mainly consists of two categories: ship and infrastructure, as shown in Fig. 1.

For ship, we describe each ship in terms of both static and dynamic properties. Static property, which includes the attributes (e.g., identifier, type, length, etc.) of the ship. The attributes will not change with the temporal progression of the behavior. The dynamic information contains the position (i.e., longitude and latitude) of the ship at each timestamp, as well as the velocity and course that the ship maintains.

For the infrastructure, we refer to the existing nautical chart file description format, with points representing various elements at sea, such as marks, and a series of discrete points constituting the nautical area, such as channel. In addition, related information should also include the following four descriptions: types (e.g., channel, anchorage, pier), configuration (e.g., traffic flow direction, lane width, sea bed, etc.), static traffic facilities (e.g., marks), and dynamic attributes (e.g., depth).

In addition to the data about the ship and infrastructure mentioned above, the description of the traffic behavior should also contain information about the semantic information behind the data, which is also reflected in Fig. 1. Our deconstructed model has three types of semantic information descriptions.

(1) Atomic behavior. The semantic features of ship maneuvering performance.
(2) Spatial semantic map. The topology of the nautical infrastructures, which contains the topological relationships among, including the touching between two channels, the disjoint between channel and pier, etc.
(3) Topological behavior. The topological interaction between the ship maneuvering and the infrastructure.

According to ontology-related studies (Song et al., 2024a,b), we deconstruct ship traffic behavior into basic elements according to inclusion and interaction relationships, which is consistent with the idea of ontology deconstruction. Based on the traffic behavior description

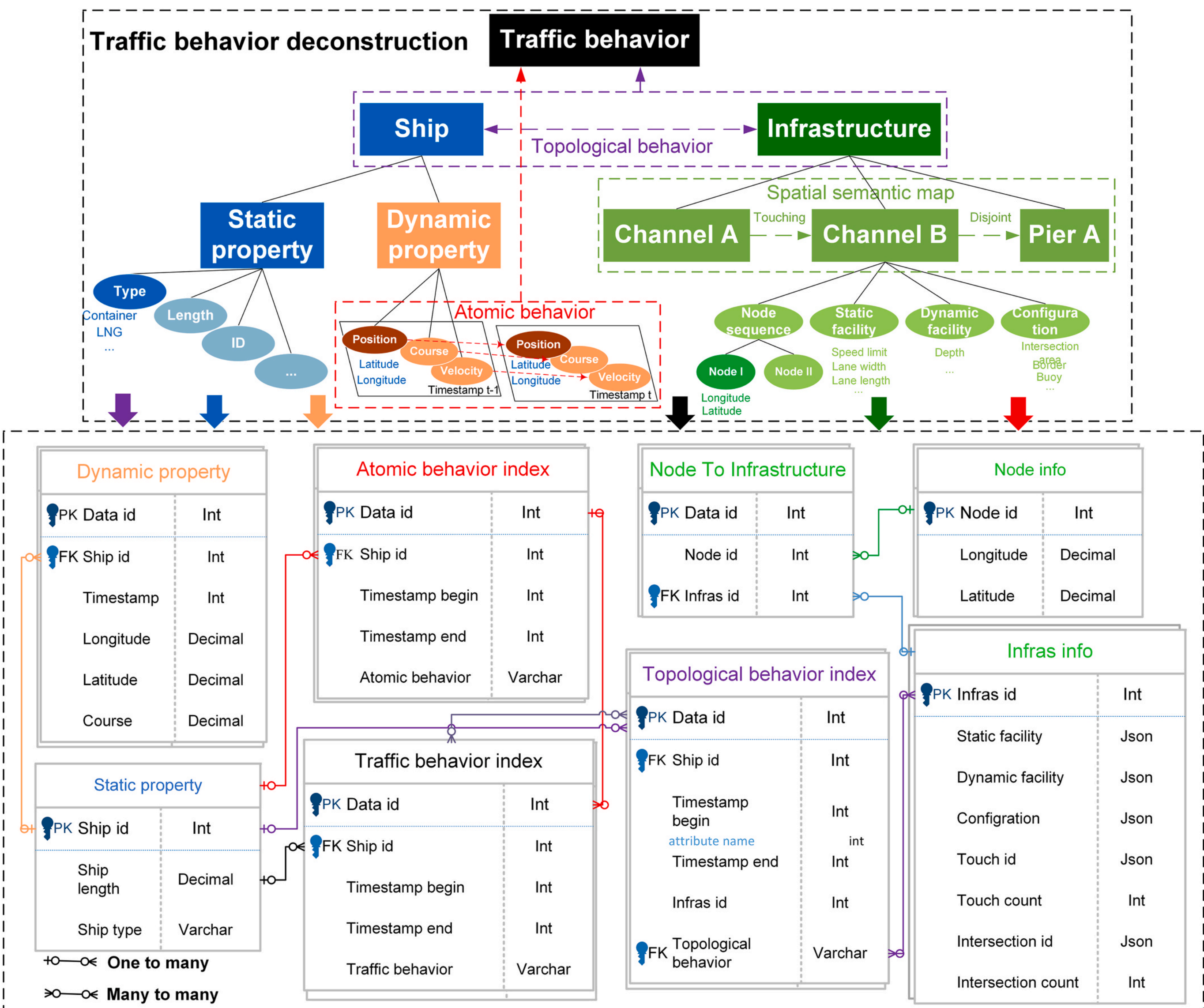


Fig. 1. The unified organization framework for ship traffic behavior data.

conceptual model, we map the traffic behavior deconstructed elements to the relational tables of the database system. As shown in Fig. 1, the parts corresponding to each other are represented with different color distinctions. The database system contains 8 types of relational data tables. The tables are linked to each other through foreign keys to enhance the coupling of ship data and infrastructure data, which can support fast data extraction and indexing.

Node Info: With reference to the mainstream nautical chart description format, the nodes represent critical elements for shaping the infrastructure. The table contains the sampled nodes identifier and location coordinates (i.e., longitude and latitude).

Node To Infras: The primary key is constructed with the data ID. The table stores the ID of the sampled node and infrastructure, playing the role of a transfer table to facilitate the extraction of which infrastructure contains which nodes.

Infras Info: The table contains the infrastructure ID, infrastructure configuration, static facility, dynamic attribute, and other information. It is more appropriate to use JSON fields because the complexity and variety of infrastructure information require more flexible data fields. Not only to include the description of different facilities but also to ensure a certain degree of extendability. The infrastructure information table also records its ID, as well as the topological relationships to others, to facilitate the construction of the spatial semantic map.

Static Property: The table contains ship ID and its static attributes, including ship type, length, and other information, which will not change over time.

Dynamic Property: The table records dynamic information such as timestamp, ship ID, ship position coordinates, course, velocity, etc. The primary key is constructed by data ID. The table can be indexed by foreign keys with the static property table via ship ID. Considering the changes over time, we generate several dynamic timing information tables.

Atomic Behavior Index: The annotation index table of the behavior corresponds to each ship trajectory data segment, describing the maneuvering performance of each ship at each moment. The table is indexed to the static property table foreign keys. The specific description and methods will be detailed in Section 3.1.

Topological Behavior Index: The annotation index table of the behavior corresponds to each ship trajectory data segment, describing the behavior generated by interacting with infrastructures. The table is also indexed to the static property table foreign keys. The specific description and methods will be detailed in Section 3.2.

Traffic Behavior Index: The annotation index table describes the behavior of each ship maneuvering over a period of time and the interaction of infrastructures. The table is indexed to the ship static property table, atomic behavior index, and topological behavior index by foreign keys. The specific description and methods will be detailed in Section 3.3.

Aspecific traffic behavior, such as navigating through a bridge area, involves a series of ship maneuverings, e.g., deceleration and course alteration, and interactions with infrastructures, e.g., channel and bridge area. Thus, one traffic behavior index associates many atomic behavior indexes and topological behavior indexes. Also, one type of atomic or topological behavior may appear in different traffic behaviors. Therefore, the relationship between each other is “many to many”.

3.1. Ship atomic behavior model

Based on our previous work (Wen et al., 2021), atomic behavior is defined as a trajectory segment with unchanged kinematic status (e.g., speed and course) in consecutive trajectory points. It presents the minimum segment of ship AIS trajectory, and any trajectory representing a ship behavior can be intuitively deemed as a time series of segments annotated with atomic behavior. Furthermore, such atomic behavior can be divided into *move* and *stop*. Considering the characteristics of ship steering gear, segments annotated with *move* can be categorized into course and speed change. Furthermore, course change can be classified into turning port, turning starboard, and straightforward. Speed change labels acceleration, deceleration, and keep speed. Therefore, along with stop behavior, by integrating simultaneous course and speed change in a segment, 10 types of behavior can be concluded as atomic behavior, listed in Table 1. The algorithms of atomic behavior extraction are shown in Appendix A.

Here we emphasize the relationships and differences between the concepts of ship traffic behavior and atom behavior. Traffic behavior focuses on a trajectory that indicates a maneuvering process over a temporal and spatial range. While atomic behavior refers to the minimal maneuvering unit (i.e., cannot be further sliced) of the trajectory with no consideration of spatial range.

3.2. Ship topological behavior model

Ship behavior also can be inferred from the interaction with nautical infrastructure. Thus, first of all, the spatial semantic map, used to organize nautical infrastructures, is abstracted from the Electronic Nautical Chart (ENC), which can be used to organize spatial information. Then, a computational model is proposed to represent rich topological interactions between ship atomic behavior and nautical infrastructure, turning out topological semantics (or topological behaviors).

3.2.1. Spatial semantic map model

To comprehensively interpret ship behavior, spatial information from nautical infrastructures should be further integrated. Thus, a spatial semantic map is developed. The spatial semantic map mainly contains the infrastructure and the topological relationships among them, formulated as below:

$$SM = \{I, R\} \tag{1}$$

where I indicates infrastructure and R denotes topological relationships.

From a topology perspective, the infrastructure can be classified into point-based, line-based, and polygon-based. Each one has its attributes, such as nodes, static facility, dynamic facility, and configuration.

Relationships among them mainly contain six types, point-point, point-line, point-polygon, line-line, line-polygon, and polygon-polygon, which are summarized in Table 2.

To get a thorough and transferable description of the layout of nautical infrastructures, detailed semantics need to be contained, which can be defined uniformly to adapt to different places. The semantic graph fits well, which is defined as a structure for representing knowledge in patterns of interconnected nodes and edges. Semantic graphs are able to store information in a rich, contextual, and conceptual construct that represents the real world. In short, we need to establish a semantic graph with a range of information on infrastructure. The nodes in the semantic graph represent map elements, storing information such as attributes. The edges store the relationships between the graph nodes.

Fig. 2 shows an example to illustrate the spatial semantic map in graph manner. For the area of Wuhan Yangtze Bridge in the electronic channel chart, as shown in Fig. 2(a), we visualize key elements in the

Table 1
Ship atomic behavior.

Acceleration while turning starboard (*TS_Acc*)	Acceleration while turning port(*TP_Acc*)
Acceleration while straightforward (*GS_Acc*)	Deceleration while turning starboard (*TS_Dec*)
Deceleration while turning port(*TP_Dec*)	Deceleration while straightforward (*GS_Dec*)
Keep speed while turning starboard (*TS_Ks*)	Keep speed while turning port(*TP_Ks*)
Keep speed while straightforward (*GS_Ks*)	Stop

Table 2
Spatial relationships between infrastructures.

Type	Relationship
Point-point, e.g., mark-mark	*equal, disjoint*
Point-line, e.g., mark-channel border	*On, disjoint*
Point-polygon, e.g., mark-channel	*Inside, onboundary, outside*
Line-line, e.g., two channel borders	*Equal, intersect, overlap, touch, disjoint*
Line-polygon, e.g., channel-channel borders	*Inside, intersect, touch, disjoint*
Polygon-polygon, e.g., pier-channel	*Equal, overlap, touch, Within, disjoint*

semantic map Fig. 2(b), including piers, channel, and bridge area, and extract the attributes, the semantic relationship of among those elements. The relationships are obtained and organized in Fig. 2(c). Green nodes are the coordinates to shape piers, channel, and bridge areas. Red nodes are piers and cyan nodes denote bridge areas. The yellow node indicates the main channel. Examples of nodes in the graph are formulated as follows:

Pier-Node:

$$pier\_djg \xrightarrow{hascoordinate} coordinate(114.2907118, 30.55606528) \tag{2}$$

A pier called "pier_djg" has a coordinate with the value of (114.2907118, 30.55606528).

Bridge area-Channel:

$$main\_channel \xrightarrow{Within} wh\_cj1\_bri\,deg\_area \tag{3}$$

The main channel has the relationships of "Within" with the Wuhan Yangtze bridge area, which means the channel is in the bridge area.

Pier-Pier:

$$pier\_djg \xrightarrow{Touch} pier\_dmt \tag{4}$$

A pier called "pier_djg" touches the pier called "pier_dmt", which means two piers are neighbors.

Channel-Pier:

$$main\_channel \xrightarrow{disjoint} pier\_dmt \tag{5}$$

The main channel in the bridge area and pier "pier_dmt" have relationships of disjoint, indicating there are no intersection of these two areas.

3.2.2. *Ship topological behavior computation*

When topological intersections between segment-based atomic behavior (i.e., a trajectory segment terminated with two consecutive trajectory points) and various nautical infrastructures happen, behavioral meanings might differ. Therefore, the concept of topological behavior is introduced, formally expressed as follows:

$$TB = Seg \cap Infras \tag{6}$$

The Dimensionally Extended 9-Intersection Model (DE-9IM) is a good tool to compute topological intersections between geometries. In DE-9IM, geometry is separated as outside, boundary, and interior, which are formulated as follows:

$$I = \{I^{\circ}, \partial I, I^{-}\} \tag{7}$$

where I denotes infrastructure, including point, line, and polygon. I^{o} indicates the interior of I, ∂I is the boundary of I, and I^{-} refers to the outside. Components of different geometries have respective meanings in terms of the interior, boundary, and outside, see Fig. 3, which are described as follows:

(1) Point

The interior of the point is the point itself. The boundary of the point is an empty set, and the outside is the rest of the plane excluding the point.

(2) Line

Two endpoints define the boundary of a line, while the interior of the line refers to the space between the endpoints. The outside of the line encompasses everything else within the plane.

(3) Polygon

For a polygon, the boundary is a continuous line that encloses the entire polygon, while the inside of that is the region enclosed by the boundary. The outside is the remainder of the plane over the boundary.

However, DE-9IM overlooks the direction of line-shape geometry, which is not applicable to the ship trajectory segment, as it is time-dependent.

To improve the applicability of DE-9IM for representing the topological intersection between the trajectory segment and nautical infrastructure, an improved model is proposed considering the ship trajectory segment as a time series. The computational model is formulated as follows:

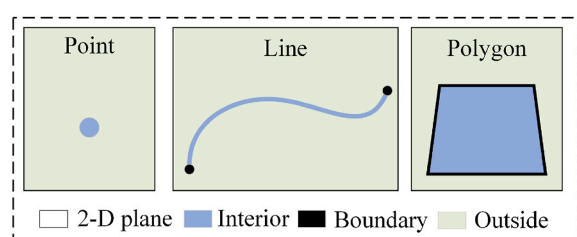


Fig. 3. Geometric semantics of nautical contexts.

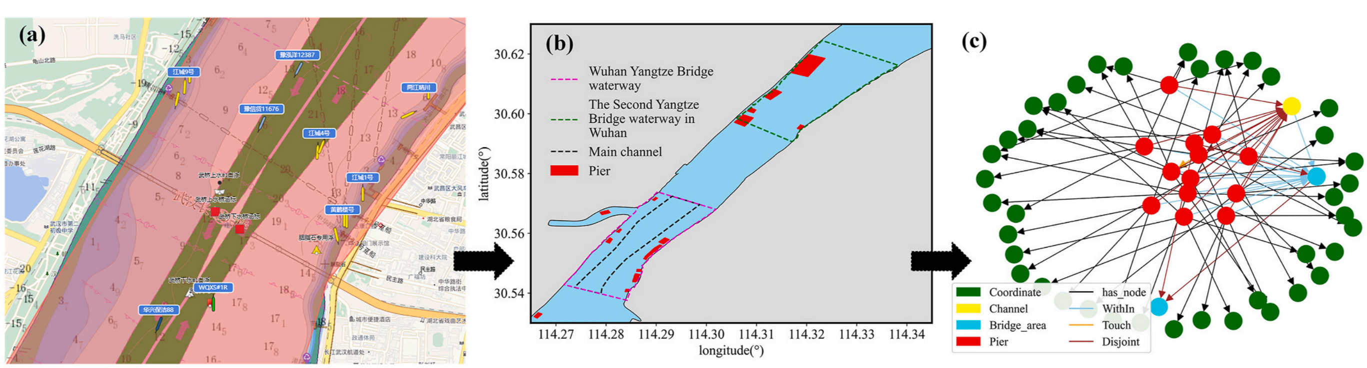


Fig. 2. Spatial semantic map construction. (a) Electronic channel chart; (b) Spatial semantic map; (c) Spatial semantic map representation.

$$TB(Seg, I) = \begin{bmatrix} Seg_s \cap I^\circ & Seg_s \cap \partial I & Seg_s \cap I^- \\ Seg_m \cap I^\circ & Seg_m \cap \partial I & Seg_m \cap I^- \\ Seg_e \cap I^\circ & Seg_e \cap \partial I & Seg_e \cap I^- \end{bmatrix}, \tag{8}$$

where $TB(Seg, I)$ represents the topological intersections between segment Seg and infrastructure I. Seg_s implies the start point of the segment. Seg_e suggests the endpoint of the segment, and Seg_m refers to the interior of the segment in a line shape. For each element in the matrix, the "∩" operator outputs the results of the intersection, described as follows:

- 0 means there is no intersection between segment and infrastructure;
- 1 means that the start point of the segment intersects with infrastructure;
- -1 means that the endpoint of the segment intersects with infrastructure;
- 2 means that the intersection between segment and infrastructure is a line.

The examples in Table 3 are taken to illustrate the method proposed. The segment is in orange color, abbreviated as Seg. Infrastructure is in blue, abbreviated as I. The second row in Table 3 presents an instance of topological intersection. The result is shown in the last column. The start point is out of the area, i.e., no intersection with the boundary and interior of the area, thus, $Seg_s \cap I^\circ = 0$ and $Seg_s \cap \partial I = 0$. It intersects the exterior of the area with a point, thus, $Seg_s \cap I^- = 1$. The endpoint is in the area, indicating point-intersection with the interior of the area (i.e., $Seg_e \cap I^\circ = -1$). The exterior and boundary have no intersection with the end point, thus, $Seg_e \cap \partial I = 0$ and $Seg_e \cap I^- = 0$. The interior of the trajectory (i.e., a line) intersects with both interior and exterior of the area in line, i.e., $Seg_m \cap I^\circ = 2$ and $Seg_m \cap I^- = 2$, and has a public point with boundary of the area, thus, $Seg_m \cap \partial I = 1$.

The results in column DE-9IM are the same, which means DE-9IM cannot handle the line-shape geometry with direction, whereas our method can distinguish that.

Other typical results are presented in Table 4, which represent various topological behaviors computed by the proposed model. The algorithm for topological behavior detection is in Appendix C.

A trajectory case study is presented to compare the performance of the original DE-9IM model and the improved DE-9IM model, shown in Fig. 4. It is obvious that the original model, see Fig. 4(a), can distinguish whether the trajectory intersects with the water or not, while the improved model furtherly provides an explicit recognition of behavior that the ship intersects the water with direction, illustrated in Fig. 4(b), where red arrows denote intersect-in and black arrows represent intersect-out. In this way, ship trajectories can be embedded with spatial information from infrastructures for capturing space-related activities.

3.3. Ship traffic behavior model

The traffic behavior can be defined as the following 5-tuple:

$$TB_T(P^t, AB^t, TB^t, I, R, \omega)_{t \in T} \tag{9}$$

Table 3
Comparison between DE-9IM and our method.

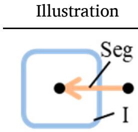
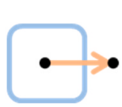
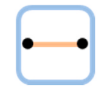
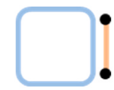
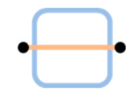
Illustration	Type	DE-9IM	Our method
	Intersect-in	$\begin{array}{cc} & \begin{array}{ccc} I^\circ & \partial I & I^- \end{array} \\ \begin{array}{c} Seg^\circ \\ \partial Seg \\ Seg^- \end{array} & \begin{bmatrix} 1 & 0 & 1 \\ 0 & F & 0 \\ 2 & 1 & 2 \end{bmatrix} \end{array}$	$\begin{array}{cc} & \begin{array}{ccc} I^\circ & \partial I & I^- \end{array} \\ \begin{array}{c} Seg_s \\ Seg_m \\ Seg_e \end{array} & \begin{bmatrix} 0 & 0 & 1 \\ 2 & 1 & 2 \\ -1 & 0 & 0 \end{bmatrix} \end{array}$
	Intersect-out	$\begin{array}{cc} & \begin{array}{ccc} I^\circ & \partial I & I^- \end{array} \\ \begin{array}{c} Seg^\circ \\ \partial Seg \\ Seg^- \end{array} & \begin{bmatrix} 1 & 0 & 1 \\ 0 & F & 0 \\ 2 & 1 & 2 \end{bmatrix} \end{array}$	$\begin{array}{cc} & \begin{array}{ccc} I^\circ & \partial I & I^- \end{array} \\ \begin{array}{c} Seg_s \\ Seg_m \\ Seg_e \end{array} & \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 2 \\ 0 & 0 & -1 \end{bmatrix} \end{array}$

Table 4
Typical topological behaviors.

Intersection	Illustration	Type
$\begin{array}{cc} & \begin{array}{ccc} I^\circ & \partial I & I^- \end{array} \\ \begin{array}{c} Seg_s \\ Seg_m \\ Seg_e \end{array} & \begin{bmatrix} 1 & 0 & 0 \\ 2 & 0 & 0 \\ -1 & 0 & 0 \end{bmatrix} \end{array}$		Inside
$\begin{array}{cc} & \begin{array}{ccc} I^\circ & \partial I & I^- \end{array} \\ \begin{array}{c} Seg_s \\ Seg_m \\ Seg_e \end{array} & \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 2 \\ 0 & 0 & -1 \end{bmatrix} \end{array}$		Outside
$\begin{array}{cc} & \begin{array}{ccc} I^\circ & \partial I & I^- \end{array} \\ \begin{array}{c} Seg_s \\ Seg_m \\ Seg_e \end{array} & \begin{bmatrix} 0 & 0 & 1 \\ 2 & 1 & 2 \\ 0 & 0 & -1 \end{bmatrix} \end{array}$		Cross

where T is the duration of traffic behavior. P^t is the set of properties (i.e., static and dynamic property) at each timestamp t. AB^t is the atomic behavior at timestamp t. TB^t is the topological behavior at timestamp t. I is the set of infrastructures interacted with during the traffic behavior. R is the relationship among the traffic behavior elements, and ω is the set of parameters for traffic behavior extraction. We further define relationships as following:

$$R = \{before, after, withInfrastructure\} \tag{10}$$

We mainly consider *before* and *after* between atomic behaviors. By a sequential combination of atomic behavior, traffic behavior is expressed. *withInfrastracture* is the relationship between topological behavior and infrastructures.

Ship traffic behavior is introduced expressing domain knowledge by combining atomic and topological behavior. The same atomic behavior taking place in different places might indicate completely different traffic behavior. This paper formalizes a set of traffic behaviors that are always not easily captured without appropriate spatial information as follows.

(1) Enter

$$\exists AB = \{AB^i, AB^j, AB^k\}, TB = \{TB^i, TB^j, TB^k\}$$
$$s.t. \begin{cases} AB^{i:k} = \neg stop \\ TB^i = outside \\ TB^j = intersect - in \\ TB^k = inside \\ I.type = Channel/anchorage/Pier \end{cases} \tag{11}$$

(2) Leave

$$\exists AB = \{AB^i, AB^j, AB^k\}, TB = \{TB^i, TB^j, TB^k\}$$
$$s.t. \begin{cases} AB^{i:k} = \neg stop \\ TB^i = inside \\ TB^j = intersect - out \\ TB^k = outside \\ I.type = Channel/anchorage/Pier \end{cases} \tag{12}$$

(3) Berthing/anchoring

The behavior of stop in the maritime domain often includes berthing and anchoring. The difference between both is the location, which could be formally expressed as follows:

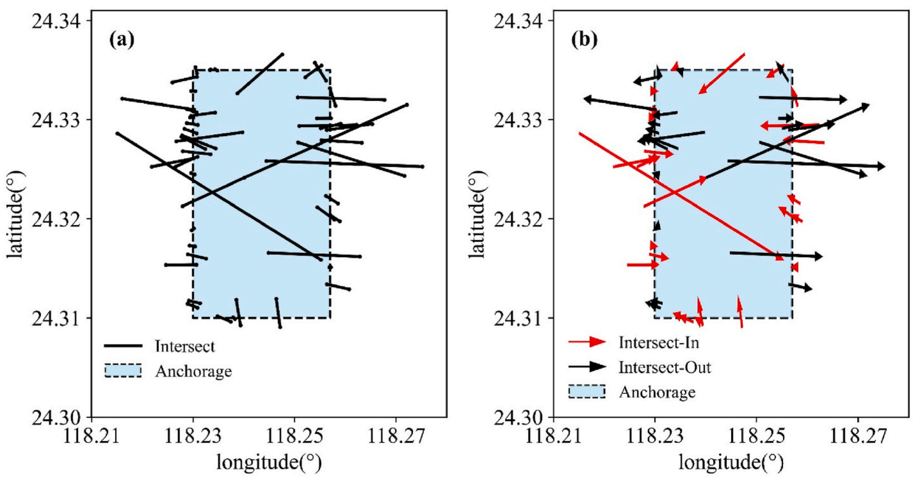


Fig. 4. Experimental comparison. (a) Original DE-9IM. A total of 49 trajectory segments intersects with the anchorage. (b) Improved DE-9IM. All intersects are detailed into 25 intersect-in and 24 intersects-out.

$$\exists AB = \{AB^1, AB^2, ..., AB^n\}, TB = \{TB^1, TB^2, ..., TB^n\}$$
$$s.t. \forall i \in [1, n], \begin{cases} AB^i = stop \\ TB^i = inside \\ I.type = Pier/anchorage \end{cases} \tag{13}$$

The semantic graph structure has unique advantages for representing ship traffic behavior, which can clearly represent the involved atomic behaviors, topological behaviors, and infrastructures and the semantic relationships among them. Through the spatiotemporal evolution of semantic graph features, we can infer the behaviors to implement the annotation of ship raw AIS trajectory data, and then index ship behavior with specific semantics efficiently, an example of "Enter" is visualized in Fig. 5. The red node denotes the traffic behavior of "Enter". Atomic behavior, shown in yellow, indicates that ship enters the main channel (i.e., green node) while keeping course and speed.

4. Experiments

4.1. Dataset

The AIS trajectory points collected from the Wuhan section of the Yangtze River and Xiamen port waters were used. We randomly selected a week to install the device and collected the AIS data from the Wuhan section of the Yangtze River. The dataset in Wuhan includes 1953 ships from December 05, 2022, to December 12, 2022, with a total of 117,799 AIS records. To test the model in a place with more complex traffic situations, the other dataset in the Xiamen port with 110,098 records of 121 ships was selected, shown in Fig. 6. The key information for constructing a spatial semantic map is of the study area, e.g., the spatial coordinates of piers, was manually extracted from ENC. To mitigate the impact of outliers, anomalies, and missing data, we implemented the following pre-processing steps.

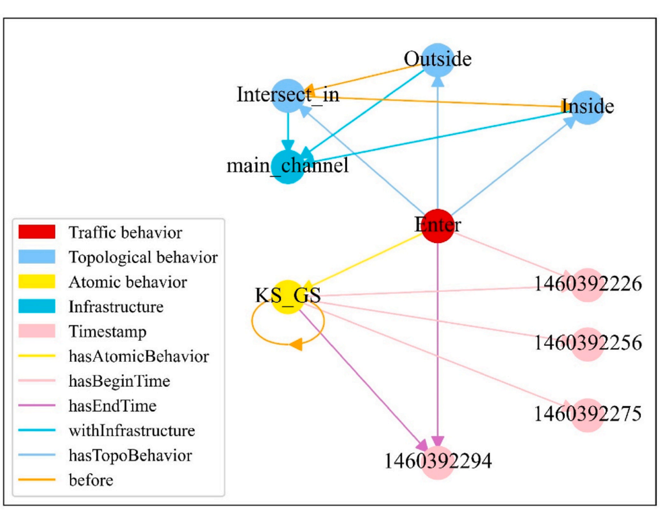


Fig. 5. Example of semantic graph for 'Enter' traffic behavior.

- Remove AIS messages with unrealistic values, such as the positions data drifting to land, speed over 40 knots, course greater than 360°, etc.
- Remove abnormal data, including repeated position and timestamp, the time interval between consecutive points is less than 6 s, etc.
- Remove noisy data that indicates ship sudden course and speed alteration that does not comply with ship maneuverability. The rate of course (ROT) between consecutive courses is used and set to 0.5°/s. For noisy speed data, an acceleration of 0.02 m/s^2 is set.

4.2. Parameter setting

Table 5 shows all parameters used for atomic behavior extraction. Thresholds are set in the inland waters and coastal waters respectively, because many differences make it inapplicable to share unified criteria, such as ship type and AIS device (Chen et al., 2018).

For inland waterways, sensitivity analysis on threshold selection of stay behavior is performed, illustrated in Fig. 7. In the choice of the number of points N, it is apparent that the overall trend declines with the increase of N in Fig. 7(a). However, after a brief period of stability, highlighted in the dashed box, the downward trend becomes dramatic, which means numerous stay points are not accurately identified when N is greater than 3. Therefore, 3 can be considered as the optimal threshold of N in inland water. As for the maximum distance between start and end points of trajectory segment ($D_{\max}$) determination, five candidates are tested with different N, shown in Fig. 7(b). The total trend shows an upward with increasing $D_{\max}$. However, it remains stable at a constant level after 200m in most cases, indicating that the change of $D_{\max}$ has little impact on the stay behavior extraction. Thus, the best choice of $D_{\max}$ is 200m. In terms of stay duration T and speed for stay V_s, parameters are set based on existing studies and maritime expert knowledge (Wen et al., 2019), which are 1h and 0.5 knots. The results of stay behavior extraction are shown as the remote sensing images in Fig. 8.

Sensitive analyses are also performed in coastal waters, presented in Fig. 9. With regard to the N in coastal water, there are no significant

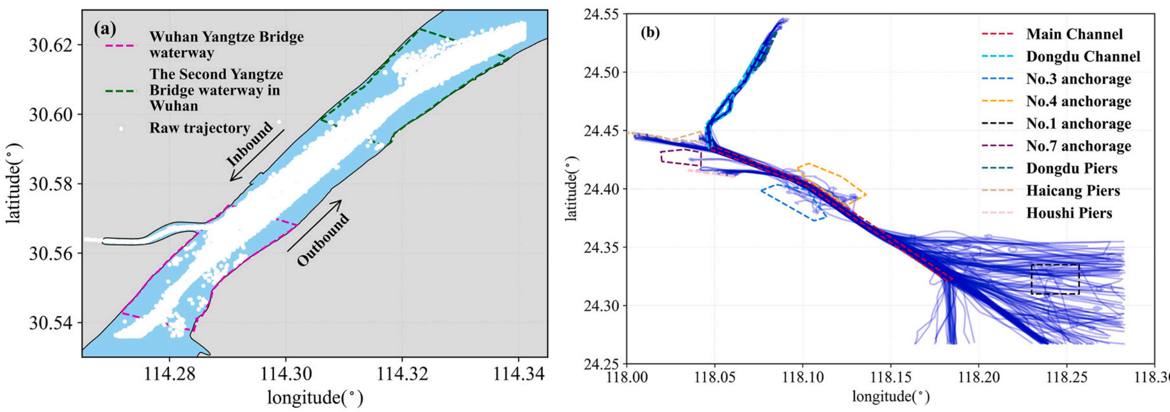


Fig. 6. AIS datasets. (a) Inland. (b) Coastal.

Table 5
Overview of parameter setting.

Parameter	Determination	Threshold	
		Inland	Coastal
Duration T	Prior knowledge and literature references	1h	2h
Number of trajectory points N	Experimental comparison	3	40
Maximum distance between start and end points of segment $D_{\max}$	Experimental comparison	200m	450m
Speed for stay V_s	Prior knowledge and literature references	0.5 knots	0.5 knots
Speed change ε	Prior knowledge and literature references	0.02 m/s^2	
Course change α	Prior knowledge and literature references	1°	

changes along with the increasing of N across all curves, see Fig. 9(a). Because duration T is set to 2h based on the existing studies (Yan et al., 2022), the N is accordingly set to 40 as the criteria of reporting interval in AIS is every 3 min when the ship is at anchor or moored or moving less than 3 knots. In terms of $D_{\max}$ selection, before 450m, the number of stopping points continues to increase with distance. However, after 450m, the trend becomes stable, even showing a decline in some cases, as shown in Fig. 9(b). Hence, the best choice of $D_{\max}$ in the coastal water is 450m. The speed threshold for stay V_s is set to 0.5 knots based on the prior knowledge and relevant literature (Van Hage et al., 2012). The results of stay behavior extraction are presented in Fig. 10.

The stay time distribution of the extracted stay behavior across two datasets is shown in Fig. 11. All extracted stay behaviors last for more than 2 h. The outliers in the figure are not anomalies, but indicate that some ships stay for a long time, even a couple of days. All extracted stay trajectories are annotated with behavior and stored in the database. Although the parameter setting between inland and coastal datasets varies much, for example, the N in coastal water is set to 40 whereas it is set to 3 in inland datasets, the distribution of two datasets indicates that each stay behavior detected is longer than 2 h, indicating the effectiveness of the proposed algorithm. The reason for the low number of N in the inland dataset can be attributed to a combination of factors, including signal congestion, low AIS transmission rate, environmental interference (Asborno et al., 2022; Guo et al., 2023), etc.

4.3. Semantic indexing

To show the application of the presented model, semantic indexing tasks in the inland waters are performed, aiming to answer questions that could not be easily answered by raw trajectories without spatial knowledge.

Question 1. How many ships in the main channel enter and leave the Wuhan Yangtze River bridge and the Wuhan Second Yangtze River bridge sequentially without stop?

Model instantiation for this case is illustrated in Fig. 12. Fig. 12(a) shows all pre-processed trajectories. The trajectory is firstly segmented and filtered by atomic behavior "move", regardless of its alteration of course or speed, and topological behaviors of "intersect-in" and "intersect-out" are sequentially considered to capture the traffic behavior of "Enter" and "Leave" bridge areas.

Fig. 12(b) displays trajectories only with sequential traffic behaviors

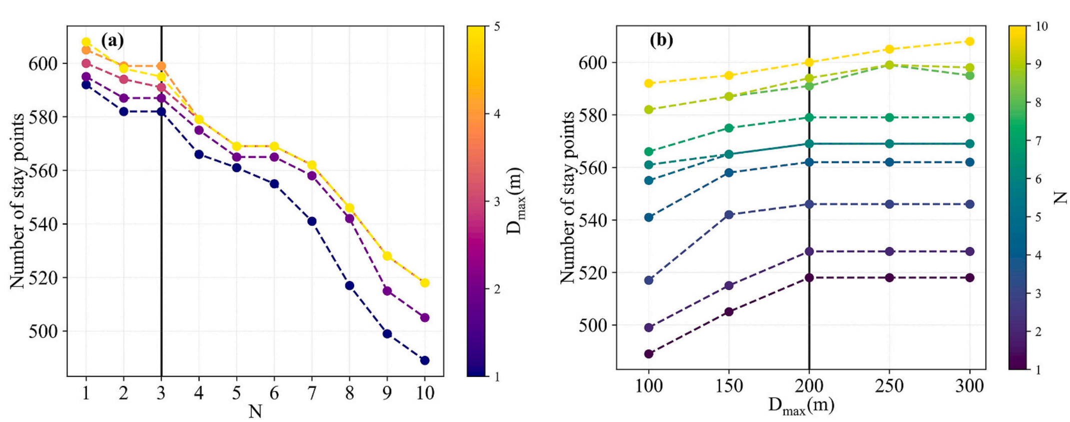


Fig. 7. Threshold selection of stay behavior extraction in inland waterways. (a) Number of points (N) determination. (b) Maximum distance between start and end points in trajectory segment ($D_{\max}$) determination in the inland waters.

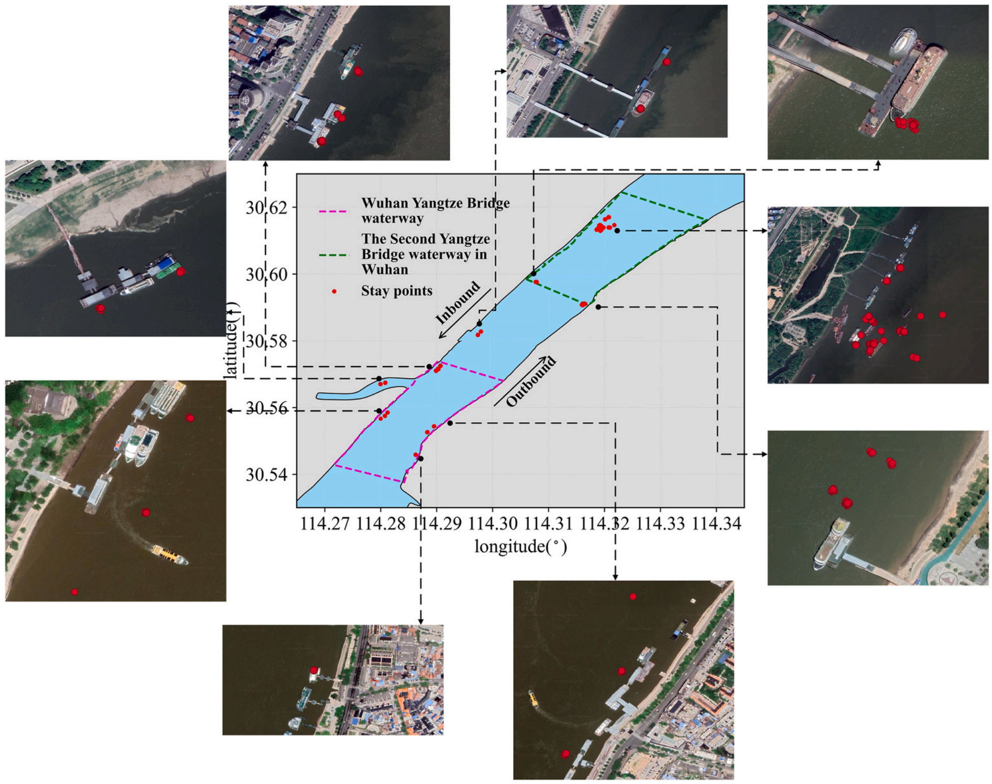


Fig. 8. Stay behaviour extraction in inland waters.

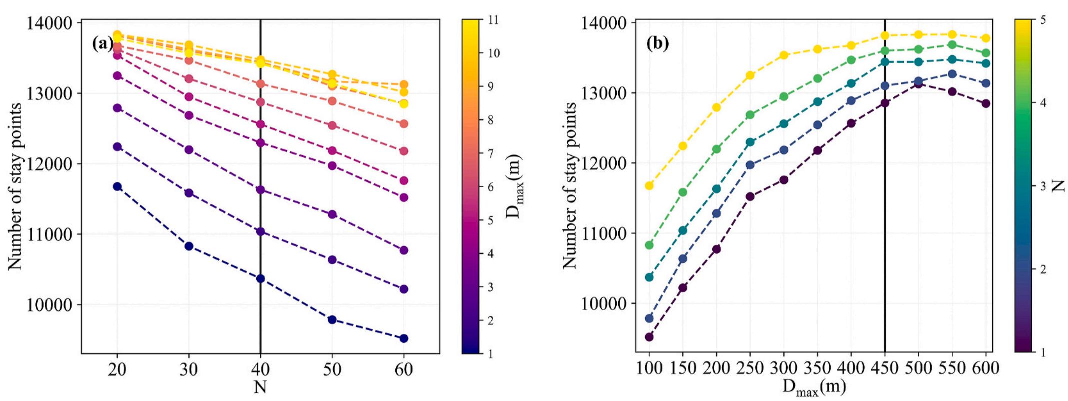


Fig. 9. Sensitive analysis. (a) Number of points (N) determination. (b) Maximum distance between start and end points in trajectory segment (D_{max}) determination in coastal waters.

of "Enter" and "Leave" in the Wuhan Second Yangtze River waterway, demonstrated in blue points. It is clear that some of the ships sail to the tributary. When another restriction is added, the graph on the right, i.e., Fig. 12(c), shows index results in pink color. Due to trajectories with stop behavior being removed, the results only keep the required trajectories.

Question 2. How many ships enter and leave the Wuhan Yangtze River bridge and the Wuhan Second Yangtze River bridge sequentially?

In this case, topological behaviors are focused. The results in different index stages are shown in Fig. 13. In Fig. 13(b), only trajectories with sequential traffic behaviors of entering and leaving the Wuhan Second Yangtze Bridge waterway are visualized in blue points. Part ships enter the Wuhan Yangtze Bridge waterway later, while others have trajectories in the tributary. After being restricted by another sequential traffic behavior in another area, target trajectories are selected, shown in Fig. 13(c) in pink color. Trajectory points in the tributary are missing compared with Fig. 13(b). Moreover, as there is no requirement on the trajectory segment between sequential traffic behaviors, trajectories with atomic behavior, i.e., "stay", between two traffic behaviors are also captured. A trajectory case is shown as an orange line in Fig. 13(c) and the segment of "stay" is visualized in red color, indicating that the model can effectively extract target trajectories with specific traffic domain knowledge.

Index results are summarized in Table 6. Stage (b) of Q2 indexes 19500 trajectory points, which is larger than that of Q1 with 19310 points. This is because the focus of Q2 is on vessels that enter and leave the bridge area waterway, which includes some vessels that stay in the bridge area after they entered, and also vessel trajectories that directly leave the area without stay, whereas the stage (b) of Q1 focuses on trajectories that do not have stay behavior in the bridge area. Similar index results occur in the stage (c).

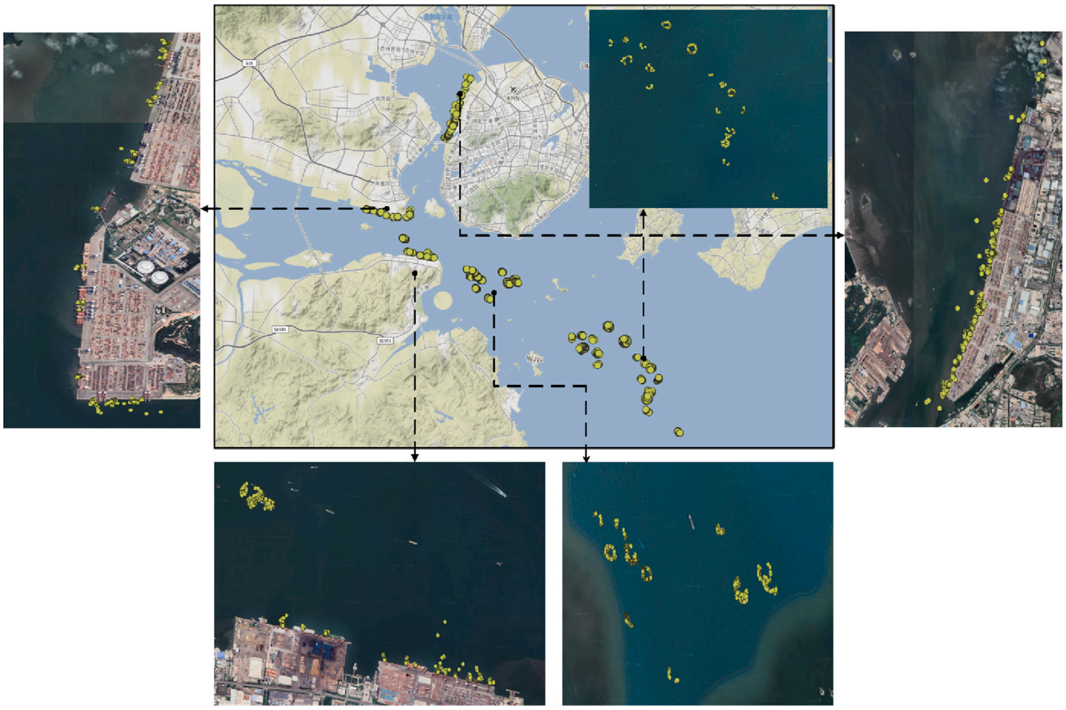


Fig. 10. Stay behaviour extraction in coastal water.

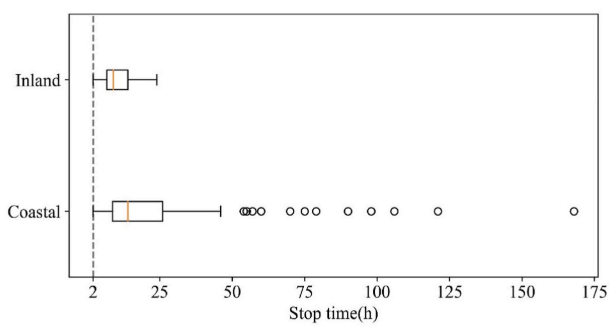


Fig. 11. Stop time distribution in inland and coastal datasets.

4.4. Performance comparison

The proposed model is compared with three other feature-based methods for similar trajectory indexing, namely DTW (Li et al., 2017), LCSS (Zhang et al., 2006), and Fréchet distance (Cao et al., 2018). Indexing is performed in the inland waters and coastal waters respectively. The indexing in coastal water is how many ships navigating in the Xiamen port following "Enter port—Berthing in Dongdu pier – Leave port" behavior sequence. The other indexing in inland waters is Question 1 on December 05, 2022.

In order to further verify the effectiveness of the presented model, precision rate, recall rate, and F_1 value are chosen as evaluation metrics. The precision rate is the proportion of the actual ship trajectories among all the trajectories retrieved by the model, which is calculated as follows:

$$precision = \frac{Correct_{trajectories}}{Correct_{trajectories} + Incorrect_{trajectcories}} \tag{14}$$

where $Correct_{trajectories}$ denotes the number of ship trajectories correctly identified, and $Incorrect_{trajectories}$ is the number of trajectories incorrectly identified.

The recall rate is the ratio of the number of ship trajectories correctly identified to the number of all ship trajectories, denoted as $All_{True_{trajectories}}$.

$$recall = \frac{Correct_{trajectories}}{All_{Correct_{trajectories}}} \tag{15}$$

The F_1 value is the weighted average of the precision rate and recall rate, which is calculated as follows:

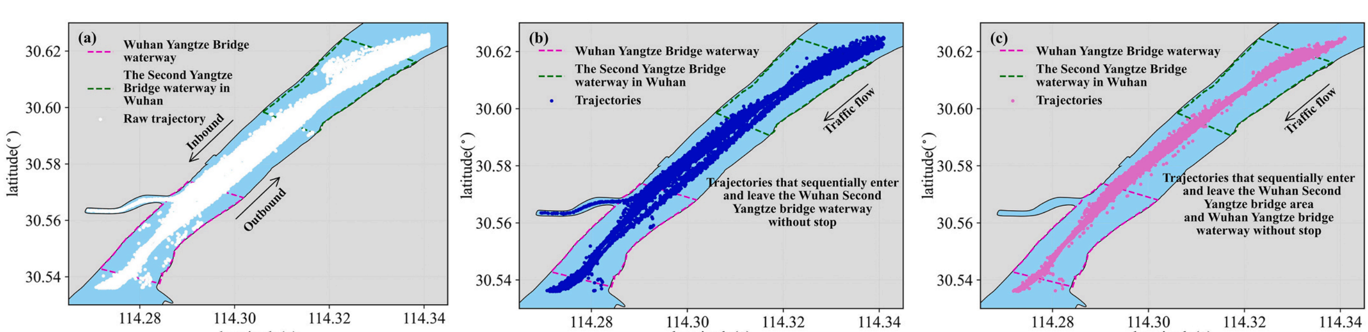


Fig. 12. Filtering Stages. (a) Raw trajectory. (b) Trajectories of entering and leaving the Wuhan Second Yangtze bridge waterway without stop. (c) Trajectories of sequentially entering and leaving two bridge waterways without stop.

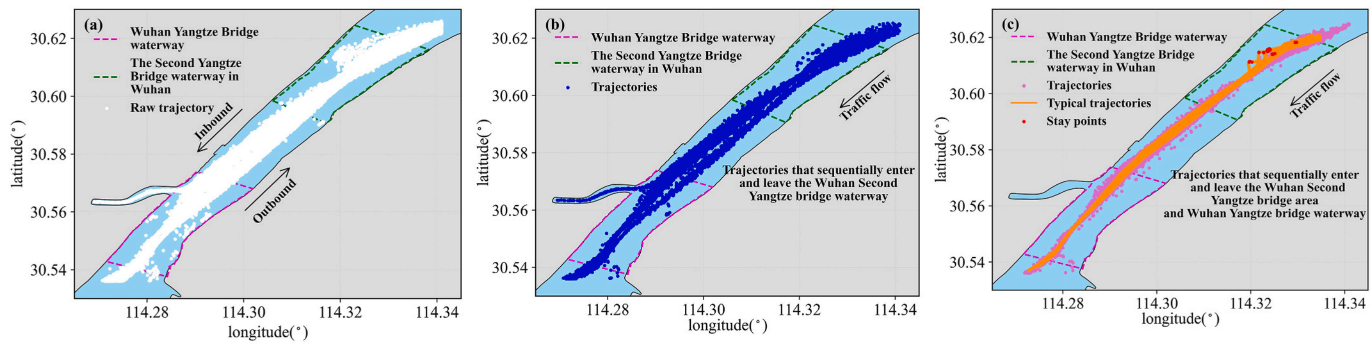


Fig. 13. Filtering Stages. (a) Raw trajectory. (b) Trajectories with sequential “Enter” and “Leave” traffic behaviors in the Wuhan Second Yangtze bridge waterway. (c) Trajectories with sequential “Enter” and “Leave” traffic behaviors in two bridge waterways.

Table 6
Number of trajectory points indexed at different steps.

Stage	Q1	Q2
(a)	69734	69734
(b)	19318	19500
(c)	16533	16682

$$F_1 = \frac{2*precision*recall}{precision + recall} \tag{16}$$

The experimental results are shown in Table 7. Overall, the indexing performance of the presented model considering contextual information outperforms the other three geometric-based methods in all datasets.

The proposed model has a recall rate of 0.89, 0.98, and F_1 value of 0.94, 0.99 in the coastal water and the inland waters datasets respectively under the premise of a guaranteed accuracy rate of 1.00, which shows that the proposed method is effective for indexing ship trajectories with behavior semantics in a big dataset.

Ship trajectory indexing baseline models (DTW, LCS, and Fréchet distance) do not consider the nautical environment, easily returning false trajectories, which decreases recognition precision. Indexing examples of Q1 from our method and DTW are compared in Fig. 14. It is clear that, as visualized in Fig. 14(a), our model can extract the whole trajectory segment that contains specific semantics, i.e., sequential “enter” and “leave” two bridge areas without stop, Even though the shape of the trajectory detected by DTW is similar to the trajectory detected by our model, the whole trajectory does not contain all behavior semantics required by Q1, shown in Fig. 14(b).

4.5. Statistic analysis of traffic behavior indexing

We also visualize the distribution of atomic behaviors in the traffic behaviors of “Enter” and “Leave” happened in the main channel, No.1 anchorage and Haicang piers in the coastal dataset, shown in Fig. 15. When ships enter the channel, most of them choose to enter from the entrance of the channel with constant course and speed, as shown in black bar in Fig. 15(a) and (b). Some of them choose to merge in the channel from the borders of the channel, which involves more left (i.e., yellow bar) or right turning (i.e.. orange bar), but do not change their speed easily. A similar situation also can be observed in Fig. 15(c) and (d) with altering course and keeping speed when ships enter and leave the anchorage. Unlike the previous two cases, ships entering and leaving pier involve more course alterations, as displayed in Fig. 15(e) and (f). These differences cannot be directly observed from raw trajectory data. Through constructing behavior semantics behind the trajectory data, rich information can be annotated to the trajectory data to facilitate further behavior-related research.

5. Discussion

5.1. Advantages and relevant applications of the proposed model

The proposed model provides a unified framework to annotate ship trajectories with behavior semantics. Table 8 compares the presented model with previous semantic models of ship trajectory.

Although most models consider navigation environment, such as grid-based contexts (Santipantakis et al., 2020), information in linked open data, e.g., GeoNames (Soares et al., 2019; Van Hage et al., 2012), or equation-based information (Wen et al., 2021), unified organization of such information is still missing. For example, the GeoNmaes database only provides basic information about the harbor, such as geographical scope, whereas the spatial semantic map proposed in this paper can organize and present detailed information about the navigation environment, i.e., attributes and interrelations. Moreover, the proposed model not only provides a common vocabulary and template for intelligent machines (Cheng et al., 2025; de Gelder et al., 2022) but can be easily maintained and reused (Song et al., 2024a,b).

With regard to spatial interaction between ship trajectory and navigation environment, the SMSB model focused on manually defined semantics, such as “inside” (Wen et al., 2019), which cannot meet the requirements of complex behavior analysis. Based on that, Wen et al. (2021) introduced the DE-9IM model to analyze interaction semantics. However, the original DE-9IM is not applicable for ship trajectory in time series. For this reason, traditional DE-9IM is improved, where each element in the DE-9IM model is associated with time information, to

Table 7
Comparison of three other feature-based ship trajectory indexing methods.

Study area	Method	Marked trajectories	Detected trajectories	Matched trajectories	Precision rate	Recall rate	F_1 value
Coastal water dataset	DTW	48	62	41	0.66	0.85	0.74
	LCSS	48	57	38	0.67	0.79	0.72
	Fréchet distance	48	50	30	0.60	0.63	0.84
	Proposed model	48	43	43	1.00	0.89	0.94
Inland waters dataset	DTW	72	72	56	0.78	0.78	0.78
	LCSS	72	67	44	0.65	0.61	0.63
	Fréchet distance	72	78	61	0.78	0.85	0.81
	Proposed model	72	71	71	1.00	0.98	0.99

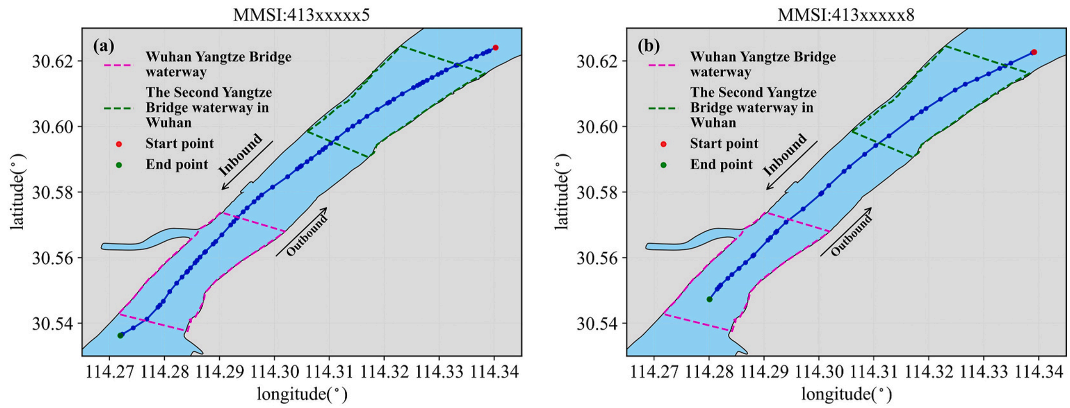


Fig. 14. Case comparison between (a) our method and (b) DTW.

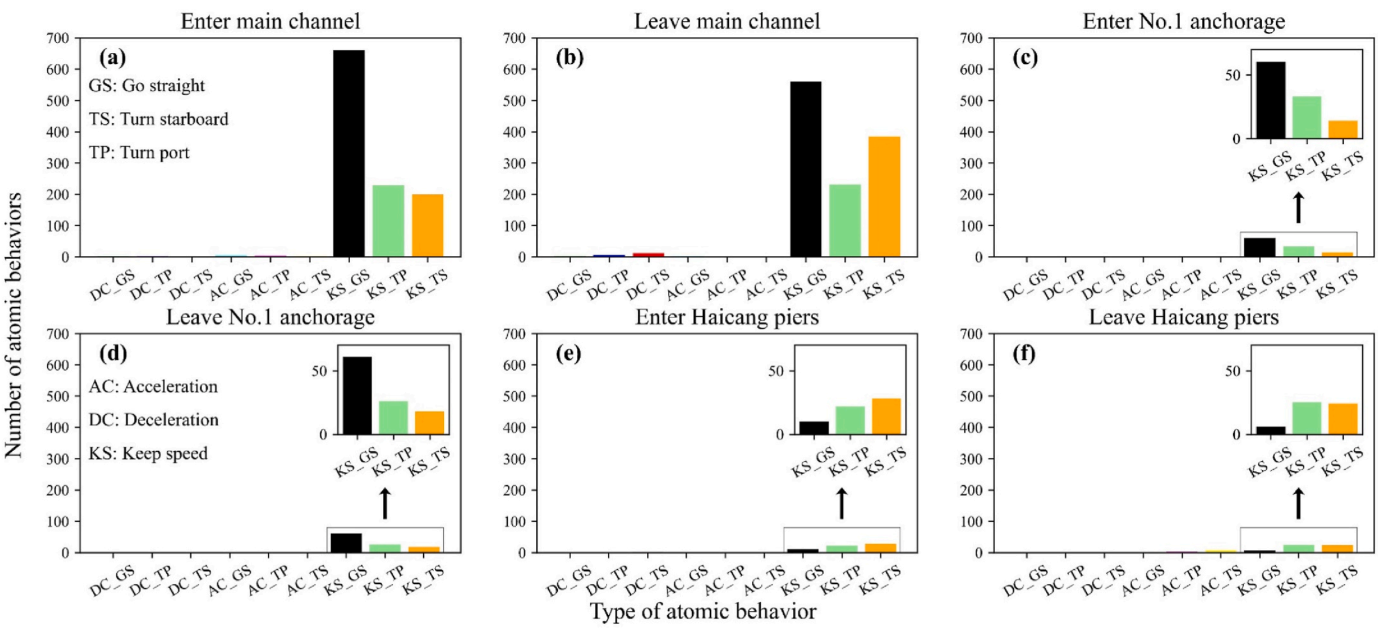


Fig. 15. Statistic distribution of atomic behavior in the traffic behaviors of (a) "Enter main channel"; (b) "Leave main channel"; (c) "Enter NO.1 anchorage; (d) "Leave NO.1 anchorage; (e) "Enter Haicang piers"; (f) "Leave Haicang piers" in the coastal dataset.

Table 8
Qualitative comparison of other semantic models of ship trajectory.

Model	Main segmentation concepts	Support for Navigation environment	Support for topological interaction
SEM(Van Hage et al., 2012)	Event	Yes	No
CRISIS(Soares et al., 2019)	Point	Yes	No
SPARTAN(Santipantakis et al., 2020)	Segment	Yes	No
SMSB(Wen et al., 2019)	Segment	Yes	No
Wen et al. (2021)	Segment	Yes	Yes
Proposed model	Segment	Yes	Yes

calculate detailed topological intersections between trajectory and navigation environment, expressing the directional interaction semantics in trajectory. As a result, spatial intersection is annotated on ship trajectory to help interpret ship semantic behaviors.

The proposed model has various potential applications.

One application is to support explainable trajectory prediction and planning tasks. Existing ship trajectory prediction and planning models are mainly fed with raw trajectory data (Li et al., 2024c; Li and Yang, 2023), e.g., longitude and latitude, unable to generalize to another place because the model needs to be re-trained and re-tested. Trajectory only contains spatiotemporal data. Annotating such data with meaningful semantics, e.g., maneuvering and interaction with the environment, can capture higher-level information reflecting ordinary practice and good seamanship (Zhang et al., 2023), etc. By applying learning-based models, such as Transformer, etc, interrelationships among sequential semantics, rather than spatiotemporal points, can be obtained to make better predictions and provide explainable results.

Furthermore, the model can support navigation scenario understanding for autonomous ships. The understanding of the navigation scenario for autonomous ships is a critical module to ensure navigation safety (Van Baelen et al., 2022; Zhou et al., 2024), of which behavior interpretation is a critical task. High-level information, such as intention (Jia and Ma, 2023), can be inferred from behavior semantics, i.e., turning starboard of give-way ship in encounter scenarios indicating the intention of passing astern, decision-making can be performed, such as path planning, to ensure safety.

5.2. Limitations and challenges

In this section, the limitations of this research are given from the perspective of data preprocessing, parameter setting, and manual annotation of modeling, respectively, as well as challenges are also demonstrated.

(1) Dataset. In this study, trajectory datasets from inland and coastal waters are utilized. Due to the limitations of onboard equipment, AIS data always in low sampling rate, which brings uncertainty to ship behavior interpretation and limits the ability to detect navigational patterns. To mitigate the limitations of low sampling rates, data fusion techniques (e.g., integrating radar data, VTS, or motion sensors) and advanced interpolation methods should be employed to reconstruct missing trajectory data so as to improve the utilization of AIS data for behavior interpretation.
(2) Parameter. In this paper, ship atomic behaviors are extracted by setting numeric thresholds. Although the analysis of optimal parameter selection is performed, the criterion for parameter setting requires advanced research. This paper only calculates the numerical changes in raw trajectory data for behavior extraction, whereas other factors, such as ship property and meteorological condition, are not well considered. Zhou et al. (2020) used AIS data to study ship behavior characteristics under the impact of wind and current, in which the results showed that ships with diverse sizes behaved quite differently under various conditions of wind and current. Therefore, how to adaptively set parameters for behavior extraction with consideration of a changeable navigation environment remains a challenge.
(3) Modeling. This paper provides a structural semantic map of the nautical area to integrate spatial information into ship trajectory for behavior interpretation. However, the semantics of nautical infrastructure are manually extracted, which is inefficient. Hence, how to automatically extract and develop nautical spatial semantic maps based on multiple-source data and advanced sensors, such as ENC, LIDAR, and SAR (Liu et al., 2023; Thombre et al., 2022), is a promising work. This potential work not only benefits behavior extraction with domain knowledge but flavors the development of intelligent waterborne transportation, such as autonomous navigation (Lisowski, 2023) and collision avoidance (Zhang et al., 2023; Zhong et al., 2022). Besides, in the computation of topological behavior, the direction of the trajectory segment is not sufficiently considered. For example, a ship right crosses the channel and merges in the channel both have the topological behavior of “intersect-in”, but with different semantics.
(4) Experiments. The proposed model is applied in area with relatively simple traffic conditions and the model focuses more on single ship navigation. In practice, ship behavior interpretation is not only related to the navigational environment but affected by other ships. Therefore, more complex traffic situations should be considered to improve the model.

6. Conclusion

Ship behavior interpretation and annotation on massive AIS trajectories is a crucial issue in autonomous navigation system. However, existing studies are insufficient to comprehensively organize and annotate ship semantics on a raw trajectory, especially in terms of spatial interactions between ship trajectory and navigational environment, hindering comprehensive interpretation of ship semantic behavior from the trajectory. To this end, a representation framework of ship semantic behavior is proposed.

This study proposes a framework to abstract and organize higher-level behavior semantics from raw trajectory, and interactions between ship and navigation environment. The semantics abstracted from the raw trajectory is called atomic behavior, which reflects the maneuvering interpretation of trajectory, such as stop and move. With regard to semantics from the navigational environment, a spatial semantic map is constructed to attach attributes of each infrastructure, such as channel, and to build the interrelations among them. Furthermore, a model improved from DE-9IM is developed to calculate and represent the spatial interaction semantics between ship trajectory and navigation environment, turning out directional topological interactions for behavior annotation. Finally, semantics with regard to ship maneuvering and topological interactions are combined to annotate higher-level traffic behavior on trajectory. Experiments of indexing on inland and coastal datasets indicate that the proposed framework can effectively capture required trajectories with specific semantic behavior. Compared with the traditional feature-based trajectory indexing method, the proposed method performs better on trajectory indexing tasks. The trajectories annotated by the proposed model may be utilized for further behavior-related research.

In the future, this work will be extended with several goals. Firstly, an effective inland and coastal regions AIS trajectory data preprocessing method will be developed for accurately capturing ship traffic behavior with domain knowledge. Secondly, adaptive parameters learning methods for behavior annotation, e.g., move and stop, across different datasets will be investigated by leveraging advanced data mining techniques. Thirdly, the model will be further improved, especially in the automatic construction of spatial semantic maps, orientation-related semantics between ship trajectory and navigation environment, and the semantics of interactions with surrounding ships, for comprehensive semantic annotation on the trajectories in the place with complex traffic conditions.

CRediT authorship contribution statement

Shunqiang Xu: Writing – original draft, Conceptualization. **Liang Huang:** Supervision, Conceptualization. **Yamin Huang:** Writing – review & editing, Conceptualization. **Yuanqiao Wen:** Supervision, Project administration, Funding acquisition. **Xiaodong Cheng:** Methodology, Formal analysis. **P.H.A.J.M. van Gelder:** Writing – review & editing, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix A. Pseudocode of stop behaviors detection

Algorithm 1 Stop behavior detection

Input:
Trajectory points, $P = (< \varphi_i, \lambda_i, s_i, t_i > | i = 1,2,..,n)$
Radius of earth $\boldsymbol{R}$; Duration of time $\boldsymbol{T}$; Number of points $\boldsymbol{N}$; Maximum distance between start and end point $\boldsymbol{D_{max}}$; Speed threshold for stay $\boldsymbol{V_s}$
Output:
Trajectory segments labelled with stop behavior $\boldsymbol{S_s}$

Initialize $i = 0, j = 1$
while $i < n$ do
　while $j < n$ do
　　if $d_{i,j} < D$ then　/* $d_{i,j} = 2R * arcsin\sqrt{sin^2\left(\frac{\varphi_j - \varphi_i}{2}\right) + cos(\varphi_j)cos(\varphi_i)sin^2\left(\frac{\lambda_j - \lambda_i}{2}\right)}$ */
　　　$j = j + 1$
　　end if
　end while
　if $t_j - t_i > T$ and $j - i > N$ then
　　for $k = i$ to j do
　　　if $s_k < V_s$ then
　　　　$s_k \rightarrow S_s$
　　　end if
　　end for
　end if
　$i = j$
end while
return S_s

Appendix B. Pseudocode of move behaviors detection

Algorithm 2 Move behavior detection

Input:

Trajectory points $P = (< \varphi_i, \lambda_i, s_i, c_i, t_i > | i = 1,2,..,n)$
Angle deviation threshold $\boldsymbol{\theta}$
Speed deviation threshold $\boldsymbol{\varepsilon}$

Output:

Trajectory segments labelled with move behavior $\boldsymbol{S}_{\mathrm{m}}$

Initialize $j = 2$, $i = j - 1$
while $j <= n$ do
    if $s_j - s_i > \varepsilon$ and $c_j - c_i > \theta$ then
        $TS\_Acc \rightarrow s_{i:j}$
    elif $s_j - s_i > \varepsilon$ and $c_j - c_i < -\theta$ then
        $TS\_Acc \rightarrow S_{i:j}$
    elif $s_j - s_i > \varepsilon$ and $|c_j - c_i| < \theta$ then
        $GS\_Acc \rightarrow S_{i:j}$
    elif $s_j - s_i < -\varepsilon$ and $c_j - c_i > \theta$ then
        $TS\_Dec \rightarrow S_{i:j}$
    elif $s_j - s_i < -\varepsilon$ and $c_j - c_i < -\theta$ then
        $TP\_Dec \rightarrow S_{i:j}$
    elif $s_j - s_i < -\varepsilon$ and $|c_j - c_i| < \theta$ then
        $GS\_Dec \rightarrow S_{i:j}$
    elif $|s_j - s_i| < \varepsilon$ and $c_j - c_i > \theta$ then
        $TS\_Ks \rightarrow S_{i:j}$
    elif $|s_j - s_i| < \varepsilon$ and $c_j - c_i < -\theta$ then
        $TP\_Ks \rightarrow S_{i:j}$
    elif $|s_j - s_i| < \varepsilon$ and $|c_j - c_i| < \theta$ then
        $GS\_Ks \rightarrow S_{i:j}$
    end if
    $s_{i:j} \rightarrow S_m$
end while
return S_m

Appendix C. Pseudocode of topological behaviors detection

Algorithm 3 Topological behavior detection

Input:

$P_i = (< \varphi_i, \lambda_i > | i = 1,2,..,m)$, trajectory points

$\mathrm{I} = (< \varphi_k, \lambda_k > | k = 1,2,..,n)$, infrastructure

Output:

B^T, trajectory segments with topological behavior

Initialize $j = i + 1$

if l_{ij} intersect I then # intersect, in, and out can be achieved by using DE-9IM algorithm

  if p_i in I and p_j out I then

    $B_i^T \rightarrow$ ′ intersect-out ′

  end if

  if p_i out I and p_j in I then

    $B_i^T \rightarrow$ ′ intersect-in ′

  end if

  if p_i out I and p_j out I then

    $B_i^T \rightarrow$ ′ cross ′

  end if

end if

if l_{ij} out I then

  $B_i^T \rightarrow$ ′ outside ′

end if

if l_{ij} in I then

  $B_i^T \rightarrow$ ′ inside ′

end if

return B_i^T

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