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Maritime Traffic Complexity Evaluation In Complex Waters

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Abstract

Maritime traffic surveillance and management have long been critical focal points in the maritime traffic field. The escalating complexity of traffic situations, marked by frequent multi-ship encounters, presents formidable challenges in achieving precise Maritime Situational Awareness (MSA), especially in intricate intersection waters. Therefore, this paper aims to develop an advanced methodology to enable maritime traffic complexity analysis and further enhance the interpretability of regional traffic situations. The first step involves constructing a conflict risk estimation model, adeptly accommodating both ship maneuverability and ship motion dynamics. Subsequently, numerous complex network metrics, including motif structural indicators, are employed to unveil the intricate nested interactions among multiple ships from various spatial perspectives. To address the collective effects among these indicators and establish hierarchical classifications of traffic complexity levels, a PCA-FCI assessment model is introduced. Comprehensive experiments, utilizing AIS data from the intersection area of Yangshan Port, is conducted to thoroughly evaluate the effectiveness of these models. The experimental results unequivocally demonstrate the capability of the proposed approach to comprehensively comprehend the entire traffic situation and issue timely warning alerts. As a result, this methodology holds immense promise for enhancing the intelligence of maritime surveillance systems.

Keywords: maritime safety, intelligent surveillance, ship traffic complexity, motif based network indicators

1. Introduction

Surveillance and management of maritime traffic are consistently at the forefront of research efforts in the field of maritime transportation. A pivotal component within the emerging Intelligent Transportation Systems (ITSs) is the development of intelligent Maritime Situational Awareness (MSA) techniques that take into account ship movement behaviors, collision risk estimation, and collision risk control. Notably, recent technological advancements, including Artificial Intelligence (AI), Blockchain, 5G, and big data, are rapidly transforming and enhancing the complexity of modern maritime transportation systems (Li et al., 2023; Li and Yang, 2023). In this evolving landscape, the maritime industry is undergoing a transition from traditional mechanical systems to digital systems. This transition marks the dawn of an era where achieving system intelligence and perception automation becomes increasingly feasible. In this context, there is a growing demand for innovative MSA tools to facilitate the establishment of ITSs and the automation of ship navigation.

Assessing and evaluating the regional traffic situation is widely acknowledged as an effective tool in supporting intelligent maritime surveillance and management. These assessments provide a quantitative foundation for revealing the overall operational status of traffic at a macro-level, playing a crucial role in guiding and controlling anti-collision efforts (Xin et al., 2022b; Zhang et al., 2022). Nevertheless, the accurate assessment of traffic situations has become increasingly complex due to the rising volume of maritime traffic and the inherent dynamics of ship motion behaviors, especially in complex intersection areas. Maritime management authorities often designate these regions as official precautionary zones, which exhibit distinct characteristics, such as elevated traffic densities, a diverse composition of maritime traffic, and the presence of dynamic spatiotemporal ship movements (Xin et al., 2023b, 2022a). Consequently, these zones frequently witness risky traffic behaviors and multiple interrelated conflicts with nested structures, which present substantial challenges for maritime operators in their efforts to quantitatively comprehend the overall traffic conditions.

In response to the increasing need to improve the understanding of traffic situations, a multitude of techniques have been developed for estimating and assessing collision risks (Cao et al., 2023; Yu et al., 2023). These methodologies assist in identifying potentially hazardous scenarios and devising strategies to resolve conflicts. The widespread deployment of the Automatic Identification System (AIS) and the availability of extensive trajectory data have enabled the analysis of "ship traffic complexity", an emerging concept that facilitates a comprehensive grasp of overall traffic conditions. Particularly, complex network theory has gained popularity in analyzing traffic complexity, owing to its ability to unveil the topological properties of intricate interactions among multiple ships. Notable examples include the utilization of various complex network indicators to characterize the overall complexity of maritime traffic (Sui et al., 2020), explore both the topological and evolutionary characteristics of traffic (Xin et al., 2022b), and pinpoint critical target vessels for monitoring purposes (Sui et al., 2022). Research in this domain has illustrated its significant effectiveness in quantifying levels of traffic congestion, collision risks, and complex interactions among multiple vessels. Nonetheless, the unique traffic characteristics found in complex intersection waters present challenges to the practical applicability of these methods:

To begin with, achieving precise real-time evaluation of collision risk for pairs of ships is a foundational requirement in the analysis of regional traffic complexity. However, the practical application of existing models faces formidable challenges due to factors such as varying ship maneuverability and dynamic ship motion behaviors. Integrating these elements into a collision risk assessment framework has the potential to create an adaptable approach for obtaining accurate risk assessments. Yet, this remains an unresolved challenge.

Moreover, the assessment of regional traffic complexity goes beyond the mere scrutiny of simple pairwise collision risks. It demands a deeper understanding of the navigational complexity within scenarios characterized by multiple interrelated conflicts. Neglecting these characteristics fundamentally hinders the accurate interpretation of real regional traffic patterns. While some studies have made progress in revealing basic traffic topological properties within specific spatiotemporal scenarios, they provide an incomplete view of the nested interdependencies among multiple ships and face challenges in achieving reliable classification of traffic complexity levels (Sui et al., 2021, 2020). In essence, accurately characterizing traffic complexity from a topological structural perspective and subsequently classifying complexity levels are still largely unexplored and demand immediate attention.

Considering these research gaps, a comprehensive model for understanding traffic complexity should include factors such as the dynamic risk associated with ship pairs in the presence of environmental disturbances and diverse ship movements. It should also account for the complex joint spatiotemporal interactions among multiple ships and offer a detailed assessment of complexity levels. Unfortunately, the field of maritime traffic complexity research remains relatively unexplored, and there are no existing studies that have presented a comprehensive solution to addressing these multifaceted challenges. Hence, the focus of this study is dedicated to the development of an integrated solution aimed at improving the interpretation of traffic scenarios and providing guidance for global collision risk management. The contributions of this research are outlined below.

1. An innovative ship domain-based conflict prediction model is designed to accurately assess the risk of conflict between pairs of ships in intersecting water areas. This model takes into account various factors, including the manoeuvrability of the ships and their potential motion dynamics, which ensures its applicability across a wide range of encounter scenarios.
2. This research presents a novel framework for modelling traffic complexity, aiming to quantify the intricate topological dependencies that arise in interdependent conflicts within specific regional water areas. In contrast to existing models that can only extract basic topological information using well-known complexity metrics, the proposed framework pioneers the use of advanced motif structure-based metrics to achieve a more detailed characterization of the structural complexity inherent in regional traffic conflicts.
3. To evaluate traffic complexity comprehensively, an approach that combines Principal Component Analysis (PCA) with the Fuzzy Clustering Iterative (FCI) method is developed to allow to classify different levels of traffic complexity effectively. It can eliminate redundant information from various complexity metrics, while also providing a hierarchical description of traffic complexity levels.

The rest of this paper is structured as follows: Section 2 introduce the proposed methodology for modelling and evaluating maritime traffic complexity. Section 3 encompasses the case demonstrations and application analysis. Section 4 outlines the conclusions.

2. Methodology: Maritime traffic complexity modelling and evaluation

In Figure 1, the primary processing modules of the proposed methodology for evaluating regional traffic complexity are presented. These modules are divided into three distinct functional components: 1) Ship-Pair Conflict Risk Estimation Module: This module is responsible for estimating the conflict risk between any pair of ships. It serves as the foundational component upon which the regional traffic complexity modeling and evaluation rely. 2) Traffic Complexity Modeling Module: The motif structure-based indicators are employed to quantify the topological complexity that arises among multiple dependent conflicts. 3) Traffic Complexity Evaluation Module: Building upon the previous modules, this module utilizes the PCA-FCI model to synthesizes multiple motif-structure based indicators, enabling precise classification of traffic complexity levels. Detailed technical insights into each of these modules will be elaborated in the subsequent subsections.

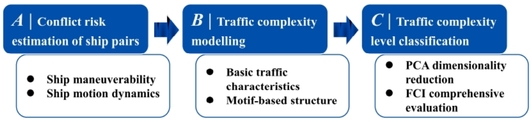

Fig. 1. Research framework.

2.1. Conflict risk prediction for ship pairs

Accurately assessing collision risks between pairs of ships is a fundamental aspect of traffic complexity analysis. Various innovative concepts, such as near-miss (Zhang et al., 2015) and ship conflicts (Weng et al., 2012; Xin et al., 2021), have been proposed to characterize potential collision risks involving ship pairs. In the present study, conflicts serve as the foundation for the analysis of traffic complexity.

In general terms, a conflict is defined as a situation in which approaching ships would breach their minimum safety distance within a forward-looking time horizon (Hao et al., 2018). To detect conflicts, this study employs a Quaternion Ship Domain (QSD) model, which incorporates the influence of ship maneuverability. Recognizing that ships may change their motion behaviors, such as performing turning maneuvers, during encounters stemming from various factors like uncertain navigational intentions, an enhanced Closest Point of Approach (CPA)-based method is adopted. This method accounts for the potential dynamics of ship movements, thereby being able to accurately determine their actual closest approaching points within a foreseeable time horizon.

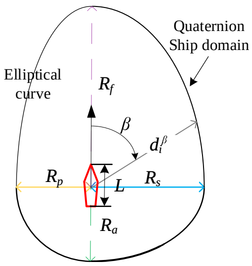

Fig. 2. Example of a quaternion ship domain.

Several geometric ship domain models have been introduced in the literature (Szlapczynski and Szlapczynska, 2017). However, among these models, the Quaternion Ship Domain (QSD) model stands out as the most advanced and practical one. The QSD model places significant emphasis on ships' maneuverability, taking into account their speeds and sizes (Bakdi et al., 2021; Wang, 2010). In Figure 2, *Rf*, *Ra*, *Rs*, *Rp* represent the domain radii in the fore, aft, starboard, and port directions, respectively. These parameters are influenced by the maneuverability of the ship and are considered as risk factors. Their determination can be outlined as follows:

$$\begin{cases} Rf = \left(1 + 1.34\sqrt{{k_{AD}}^2 + \left(\frac{k_{DT}}{2}\right)^2}\right)L \\ Ra = \left(1 + 0.67\sqrt{{k_{AD}}^2 + \left(\frac{k_{DT}}{2}\right)^2}\right)L \\ Rs = (0.2 + k_{DT})L \\ Rp = (0.2 + 0.75k_{DT})L, \end{cases} \tag{1}$$

where L stands for the ship's length, and k_{AD} and k_{DT} represent the coefficients linked to advance (AD) and tactical diameter (DT), respectively. The specific values of k_{AD} and k_{DT} offer valuable information regarding the ship's maneuverability attributes, which are influenced by both the ship's length and its real-time speed (see (Wang, 2010) for details).

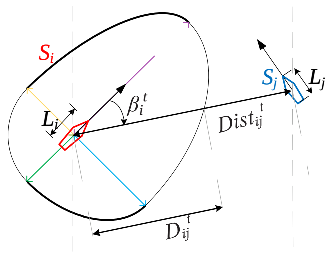

Fig. 3. Example of a ship-pair encountering situation.

By leveraging the above four radius parameters, a practical QSD model at any given point in time can be established, enhancing the ability to evaluate conflict risks. Ship domain-based conflict detection is typically categorized into four safety criteria (Szlapczynski and Szlapczynska, 2017). In this study, the third criterion is adopted, which states that neither of the domain areas of the encountering ships should be breached. This choice is driven by its ease of implementation and its consideration of the characteristics of both encountering ships. To go beyond the conventional binary evaluations of ship domain-based conflicts, which typically classify encounters as either safe or dangerous, a spatial risk model that incorporates an exponential decay function is introduced. This model is allowed to derive a more nuanced conflict risk score, which generates a continuous value falling within the range of 0 to 1 (Bakdi et al., 2021). Given two encountering ships, as depicted in Figure 3, the distance (i.e., D_{ij}^t) from the center of S_i to its domain boundaries along the line connecting the two ships can be calculated as follows:

$$D_{ij}^t = \left(\frac{1+tan^2\beta_i^t}{\frac{4}{[(1+\mathrm{sgn}x)\cdot R_{f,i}^t+(1-\mathrm{sgn}x)\cdot R_{a,i}^t]^2}+\frac{4\cdot tan^2\beta_i^t}{[(1+\mathrm{sgn}y)\cdot R_{s,i}^t+(1-\mathrm{sgn}y)\cdot R_{p,i}^t]^2}} \right)^{1/2} \tag{2}$$

where β_i^t represents the polar angle measured in a clockwise direction from the heading of S_i at time t, and the sign functions sgn$x$ and sgn$y$ are defined as follows:

$$\mathrm{sgn}x = \begin{cases} 1, & \beta \in (-\pi/2, \pi/2) \\ -1, & \beta \in [-\pi, -\pi/2) \cup (\pi/2, \pi) \end{cases}$$

$$\mathrm{sgn}x = \begin{cases} 1, & \beta \in [0, \pi/2) \cup (\pi/2, \pi) \\ -1, & \beta \in [-\pi, -\pi/2) \cup (-\pi/2, 0) \end{cases}$$

Based on the above, an instantaneous risk score with S_i as the own ship can be calculated by employing the following exponential decay function:

$$IRS_{ij}^t = e^{-\left(\frac{Dist_{ij}^t}{D_{ij}^t}\left(\ln\left(\frac{1}{r_0}\right)\right)^{\frac{1}{3}}\right)^3} \tag{3}$$

where $Dist_{ij}^t$ represents the distance between S_i and S_j at time t, and the decaying parameter r_o is set to 0.5 (Wang, 2010). It is evident that the smaller the value of $Dist_{ij}^t/D_{ij}^t$, the higher the IRS_{ij}^t. In a similar vein, one can determine the value of IRS_{ji}^t with S_j as the own ship. Since the values of IRS_{ij}^t and IRS_{ji}^t may not align due to the e varying degrees of domain invasion with different ships as the own ship, the maximum value between them is used as the instantaneous conflict risk between the encountering ships, as depicted below:

$$ICR_{ij}^t = \max(IRS_{ij}^t, IRS_{ji}^t) \tag{4}$$

It is crucial to highlight that (4) quantifies conflict risk at a precise time instance, whereas conflict encompasses the potential risk of encounters over a prediction horizon. As such, in this study, conflict risk is defined in terms of the maximum of ICR_{ij}^t over a finite look-ahead period (Hernandez-Romero et al., 2019), as expressed below:

$$CR_{ij} = \max_{t\in[0,T]} ICR_{ij}^{t} \tag{5}$$

where T denotes the prediction time horizon.

In accordance with (5), the calculation of instantaneous conflict risk at every time moment $t \in [0, T]$ throughout the entire duration presents a considerable computational burden. Consequently, this study opts to calculate the instantaneous conflict risk solely at the moment of minimum passing distance between ship pairs. To account for potential variations in ship movement dynamics, an enhanced Closest Point of Approach (CPA) method is employed for predicting this closest approaching points. Differing from the conventional CPA approach, which assumes that encountering ships will keep a constant speed in the near future, this method effectively incorporates the ships' turning behaviors. It accomplishes this by representing the dynamic future trajectories of the ships using a series of waypoints. Lines connecting successive waypoints form the future sailing route of the ships. The enhanced CPA method computes CPAs between all pairs of consecutive waypoints and then identifies the smallest CPA among them. Subsequently, the conflict risk at their closest approaching points based on the spatial risk model can be computed.

2.2. Ship traffic complexity modelling

After assessing conflict risks among ship pairs within a specified area of interest, the topological structure of ship traffic interactions becomes discernible. This structure can be elucidated through the lens of graph theory, wherein individual ships are represented as nodes, and conflicts between ship pairs are depicted as edges. The conflict risk values associated with these edges serve as weights. Building upon this foundation, the complex network metrics, including motif-based structural indicators, are adopted to unveil the intricate nested interactions among multiple ships from various spatially dependent perspectives.

Previous research efforts (Sui et al., 2021, 2020; Xin et al., 2023a, 2022b; Zhang et al., 2019) have applied a diversity of network indicators to assess the complexity of ship traffic. These indicators used in this study include both macroscopic and microscopic metrics. Macroscopic metrics, such as number of ships and conflict, serve to reveal fundamental regional traffic characteristics. Additionally, in contrast to employing traditional microscopic network metrics that provide basic topological information, the motif-based indicators are introduced to offer a more detailed characterization of structural properties within a traffic complexity graph.

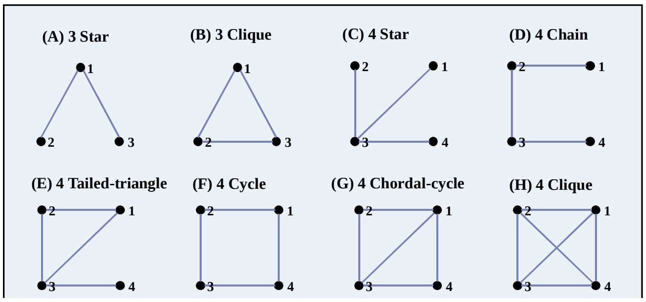

Fig. 4. Illustration of 2 types of three-node motifs and 6 types of four-node motifs.

Motif structures were initially introduced to capture higher-level structural information by exploring distinct connectivity patterns involving multiple nodes within a complex network (Milo et al., 2002). The exploration of motif structures provides a deeper understanding of nested interconnections among nodes, transcending basic topological structure analysis. Hence, they hold significant potential for revealing essential structural attributes inherent in complex networks. Most studies focus on the applications of three-node or four-node motif structures (Xu et al., 2023). This study therefore employs both three-node and four-node motifs to unveil rich topological information within a traffic complexity network. Figure 4 illustrates the structural graphs of these motifs. In conducting traffic complexity analysis, one can statistically identify the occurrences of these different motif structures within a network. A higher frequency of these structures indicates a more complex traffic situation.

Consequently, a total of 10 indicators are employed. These indicators collectively facilitate a comprehensive understanding of complex traffic situations.

2.3. Traffic complexity level classification

Evaluating regional traffic complexity comprehensively by integrating multiple complexity indicators presents a significant challenge, primarily due to the inherent interplay and interdependence among these indicators. To address this challenge, this study employs a combination of PCA and FCI methods. PCA is used to address the joint effects among indicators, while FCI establishes a hierarchical classification of traffic complexity levels.

PCA is a well-established data-driven technique commonly used for dimensionality reduction. It performs multivariate analysis to reduce the dimensionality of the data while preserving as much valuable information as possible. Given the potential presence of high correlations among the complexity indicators adopted, conducting PCA analysis for dimensionality reduction is a crucial step. For a given set of traffic scenario samples denoted as $X = (x_{ij})_{n\times m}$, where x_{ij} represents the ith complexity indicator corresponding to the jth traffic scenario, n is the number of samples, and m represents the number of indicators, standardization is the initial step to ensure that the indicators are on a consistent scale. This standardization process is performed based on the following equation:

$$\hat{x}_{ij} = \frac{x_{ij}-u_j}{\sigma_j}\bigg|_{j=1:m} \tag{6}$$

where $\hat{x}_{ij}$ is the standardized value of x_{ij}, u_j and σ_j are the mean and standard deviation of (x_{1j}, x_{2j}, …, x_{nj}) respectively. Subsequently, by performing PCA, the original standardization data $\hat{X}$ can be projected into a new feature space using the constructed projection matrix, as shown below:

$$Y = \hat{X}W \tag{7}$$

where $Y = (y_{ij})_{n\times k}$ denotes the transformed dataset, and $W = [v_1, v_2, \ldots, v_k]$ constitutes the projection matrix with v_k signifying the kth largest eigenvalue of the covariance matrix of $\hat{X}$.

On the above basis, the classification of traffic complexity levels can be further conducted using FCI. As opposed to these traditional methods tied to evaluation criteria, this approach performs well in providing a robust hierarchical analysis for high-dimensional assessment issues, without necessitating prior information (He et al., 2011). The fundamental principle of this method lies in optimizing membership assignments of assessment samples across different performance standards, which, in the context of this study, correspond to traffic complexity levels. This optimization is based on an objective function, as elaborated below:

$$\min\left[F\left(u_{ri}, s_{jr}\right)\right] = \min\left\{\sum_{i=1}^{n}\sum_{r=1}^{c}\left(u_{ri}{}^{2}\sum_{j=1}^{k}(y_{ij} - s_{jr})^2\right)\right\} \tag{8}$$

where $U = (u_{ri})_{c\times n}$ denotes the membership matrix for the sample set, $S = (s_{jr})_{m\times c}$ denotes the class centre matrix for complexity levels, c is the number of complexity levels. Equation (10) aims to minimize the quadratic sum of the Euclidean distances between all samples and different fuzzy class centers. The optimization step for (8) can be found in the work of (He et al., 2011).

As a result, the primary steps for conducting traffic complexity evaluation are outlined as follows:

Step 1. Extract traffic scenarios based on real AIS data in the studied waters and calculate their complexity indicators to construct the sample matrix $X = (x_{ij})_{n\times m}$;

Step 2. Utilize (6) to standardize the $X = (x_{ij})_{n\times m}$ to ensuring uniform scaling;

Step 3. Implement PCA to obtain the projected data matrix $Y = (y_{ij})_{n\times k}$ using (7);

Step 4. Perform FCI for different values of c to search for the optimal c, and then obtain the optimal $U = (u_{ri})_{c\times n}$ and $S = (s_{jr})_{m\times c}$;

Step 5. Assess the complexity level for each traffic scenario using the following equations:

$$RTC_i = \arg\max_{\{r=1,2,\cdots,c\}} u_{ri} \tag{9}$$

where RTC_i reveals the traffic complexity level determined by the maximum membership of the i-th traffic scenario.

3. Case study and analysis

3.1. Research area and data collection

In order to assess the effectiveness of the proposed traffic complexity methodology, a intersection area within Yangshan Port is slected as the studied site. This particular region plays a pivotal role in facilitating the passage of large-scale ships entering and departing from Yangshan Port (refer to Figure 5). It represents a typical intersection water area where multiple ship encounters frequently occur. To gather the necessary data for this study, three months' worth of AIS data spanning from April to June 2020 is collected. The preprocessing of this AIS data comprises two primary steps. First, the outlier elimination techniques and trajectory consistency methods (Kang et al., 2018; Zhao et al., 2018) are employed by referring to previously established works. Subsequently, a linear interpolation is conducted to ensure that the extracted traffic scenario at any given moment is complete. Through these preprocessing steps, substantial dataset of reliable and effective traffic scenarios can be obtained. This dataset will serve as the foundation for the analysis and evaluation of traffic complexity methodology.

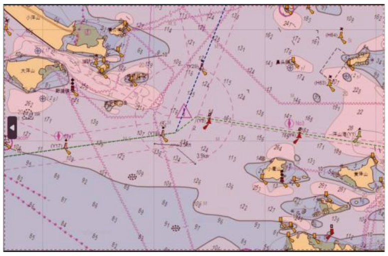

Fig. 5. Research water area.

3.2. Traffic topology modelling analysis

Figure 6 (a) provides a visual representation of the topological configuration of a particular traffic scenario derived from historical AIS data within the designated research zone. This configuration has been formulated based on the assessment of conflict risks between any pairs of ships. Within the diagram, the blue dots denote the spatial arrangement of ship traffic, while the red lines signify instances of conflict between pairs of ships. The thickness of these red lines correlates with the degree of conflict risk. Notably, it becomes apparent that intricate nested conflicts are prevalent among multiple ships, a phenomenon primarily attributed to the elevated traffic density and frequent interactions among multiple ships within this geographical region.

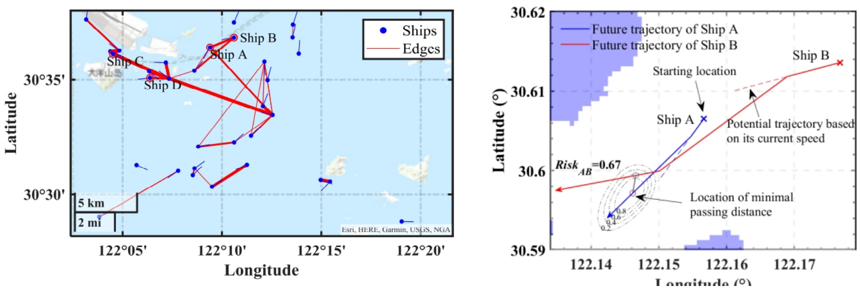

Fig. 6. Illustration of traffic situation at one specific moment. (a) Visualization of ship traffic topology; (b) illustration of detailed conflict analysis between Ships *A* and *B*.

The foundational step in the analysis of regional traffic complexity revolves around the accurate assessment of conflict risk between pairs of ships. Validating the effectiveness of the proposed conflict estimation model is of utmost importance in this regard. The proposed model takes into consideration the influence of both ships' manoeuvrability and the dynamic characteristics of ship movements. To illustrate the incorporation of these two critical factors, refer to Figure 6 (b). In this figure, the 'x' symbols denote the current positions of Ships A and B, while the solid lines represent their future trajectories based on their navigation plans. For the experimental analysis, the navigation plans of each ship, represented as sequences of waypoints, are extracted from historical AIS trajectory data using the Douglas-Peucker (DP) algorithm. Building upon this foundation, an enhanced Closest Point of Approach (CPA) method is adopted to identify the nearest approaching positions of Ships A, B, marked as 'o' in Figure 6 (b). Subsequently, the conflict risk between these two ships are quantified as 0.67 using the spatial risk model that incorporates the QSD. The QSDs depicted in the figure are constructed by taking into account the manoeuvrability limits related to the real-time navigation speed of each ship. It is worth noting that the efficacy of the QSD model in accommodating ships' manoeuvrability limits has been previously demonstrated in the work of (Wang, 2010). In contrast, employing the classic CPA method, which assumes that encountering ships adhere to linear trajectories as indicated by the dotted lines in Figure 6 (b), would erroneously predict that these ships will move away from each other in the near future. This prediction does not align with reality, as the two ships are actually headed for a crossing encounter. Such disparities can lead to confusion among practitioners in assessing genuine conflict risks. Consequently, the improved CPA model holds practical significance within the research area, primarily owning to its incorporation of dynamic ship motion characteristics.

3.3. Training results of complexity classification model

To build the PCA-FCI evaluation model, it relies on a vast dataset comprising traffic scenarios extracted from historical AIS data as the training set. Initially, Figure 7 visually depicts the cumulative variance explained by the principal components derived from PCA processing. Typically, the first few principal components that collectively account for a substantial portion of the variance, often surpassing 95%, are kept. Notably, in this instance, the first 3 principal components elucidate 95.73% of the variance, signifying a strong correlation among the selected complexity indicators. This observation underscores the importance of dimensionality reduction as a prerequisite for the subsequent classification of traffic complexity levels. Consequently, the first three principal components are preserved for further FCI training, which help discern and categorize traffic complexity levels.

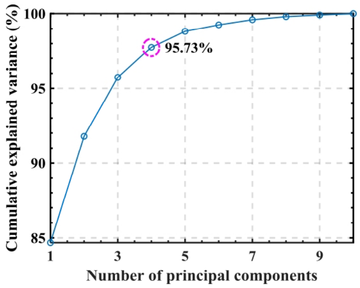

Fig. 7. Cumulative explained variance after PCA processing.

Figure 8 provides further insights into the results obtained during the FCI training process, considering different numbers of complexity levels as input parameters. As depicted in the figure, the elbow method identifies 'c = 4' as the optimal number of complexity levels. Consequently, the traffic complexity is classified into four distinct groups: Low Complexity (LC), Medium Complexity (MC), High Complexity (HC), and Extremely High Complexity (EHC).

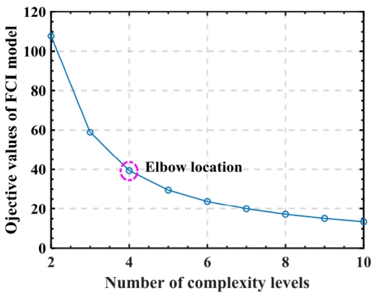

Fig. 8. Relationships between number of complexity levels and objective values.

3.4. Illustration of traffic complexity assessment

Figure 9 provides an illustrative example with a 100-minute traffic complexity evaluation within the research area. As depicted in Figure 9 (a), the membership distributions of different complexity levels shown significant temporal evolution, which provides a nuanced hierarchical depiction of traffic conditions. Figure 9 (b) illustrates the evolution of the comprehensive complexity evaluation indicator. These evaluation results collaboratively assist in the comprehension of regional traffic situations. Notably, these figures reveal the temporal intervals characterized by elevated traffic complexity, spanning approximately from the 30th to the 45th minute. This insight provides valuable guidance for maritime operators in identifying potential instances of heightened complexity, thereby bolstering their situational awareness. Additionally, Figure 10 furnishes detailed evaluation results for specific time points, specifically at t = 1, 11, 21, and 31 minutes. These outcomes offer a comprehensive exposition of each scenario's traffic topological structure, complexity indicator values, membership distributions of complexity levels, and the comprehensive assessment indicator value. As a whole, these insights foster a more thorough grasp of the traffic complexity evaluation process, offering robust support to maritime controllers in designing and implementing reliable strategies for managing and mitigating high-complexity traffic situations.

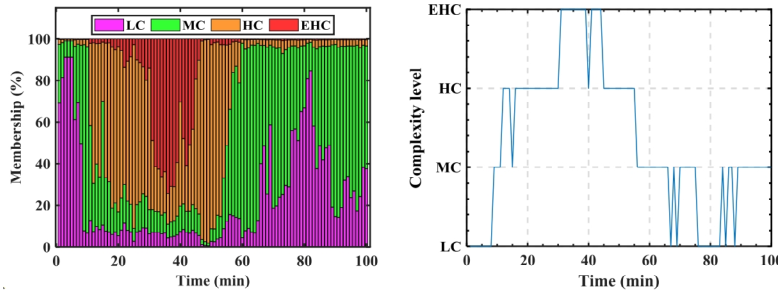

Fig. 9. A case illustration of traffic complexity evaluation. (a) Membership distribution of traffic complexity over time; (b) traffic complexity evaluation indices over time.

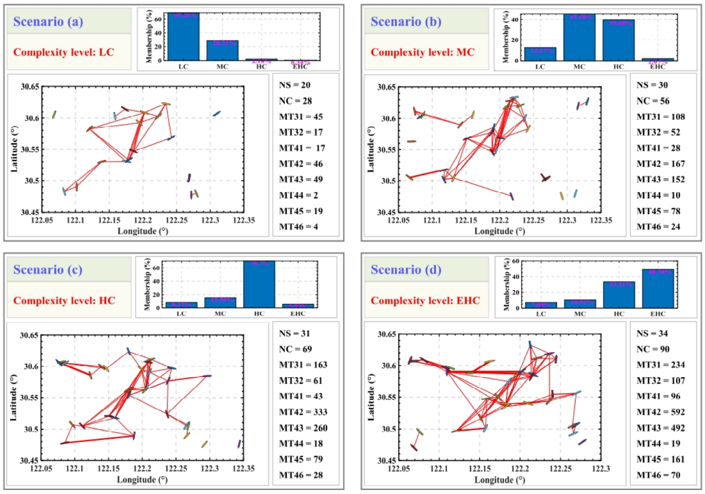

Fig. 10. Traffic complexity evaluation analysis at time t = 1, 11, 21, and 31 min.

4. Conclusion

In this study, an advanced traffic complexity methodology is developed aimed at facilitating the comprehensive interpretation of the overall traffic conditions within a specific water area of interest. This methodology introduces several innovative features: 1) A novel conflict risk estimation approach is designed to incorporate the influence of both ship manoeuvrability and ship motion dynamics; 2) the utilization of traffic complexity measurement indicators, specifically motifs, enables a more detailed characterization of the intricate structural complexity inherent in multiple nested conflicts; 3) the PCA-FCI assessment model not only considers the joint effects among these indicators but also establishes a hierarchical classification of traffic complexity levels simultaneously. To validate the effectiveness of the proposed methodology, several experiments are conducted using real-world data. These experiments serve to demonstrate and validate the superiority of the approach. Importantly, the proposed methodology enhances the interpretability of traffic patterns, particularly when maritime operators are confronted with high-complexity situations. It facilitates a more nuanced understanding of traffic situations, further supporting the deployment of targeted strategies and manoeuvring guidelines aimed at reducing traffic complexity on a global scale. Consequently, the proposed methodology provides valuable support to maritime surveillance operators in advancing operational safety management without necessitating additional investments in infrastructure upgrades. Furthermore, it holds the promise of seamless integration into intelligent maritime surveillance systems, contributing significantly to the evolution of smart ports.

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