MODELLING AND SYSTEMATIC EVALUATION OF MARITIME TRAFFIC SITUATION IN COMPLEX WATERS

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A thesis submitted in partial fulfilment of the requirements of Liverpool John Moores University for the degree of Doctor of Philosophy

March 2023

Abstract

Maritime Situational Awareness (MSA) plays a vital role in the development of intelligent transportation support systems. The surge in maritime traffic, combined with increasing vessel sizes and speeds, has intensified the complexity and risk of maritime traffic. This escalation presents a considerable challenge to the current systems and tools dedicated to maritime traffic monitoring and management. Meanwhile, the existing literature on advanced MSA methods and techniques is relatively limited, especially when it comes to addressing multi-ship interactions that may involve hybrid traffic of manned ships and emerging autonomous ships in complex and restricted waters in the future. The primary research question revolves around the challenge faced by current collision risk models in incorporating the impact of traffic characteristics in complex waters. This limitation hampers their effectiveness in managing complex maritime traffic situations.

In view of this, the research aims to investigate and analyse the traffic characteristics in complex port waters and develop a set of advanced MSA methods and models in a holistic manner, so as to enhance maritime traffic situation perception capabilities and strengthen decision-making on anti-collision risk control. This study starts with probabilistic conflict detection by incorporating the dynamics and uncertainty that may be involved in ship movements. Then, the conflict criticality and spatial distance indicators are used together to partition the regional ship traffic into several compact, scalable, and interpretable clusters from both static and dynamic perspectives. On this basis, a systematic multi-scale collision risk approach is newly proposed to estimate the collision risk of a given traffic scenario from different spatial scales. The novelty of this research lies not only in the development of new modelling techniques on MSA that have never been done by using various advanced techniques (e.g., Monte Carlo simulation, image processing techniques, graph-based clustering techniques, complex network theory, and fuzzy clustering iterative method) but also in the consideration of the impact of traffic characteristics in complex waters, such as multi-dependent conflicts, restricted water topography, and dynamic and uncertain ship motion behaviours.

Extensive numerical experiments based on real AIS data in the world's busiest and most complex water area (*i.e.*, Ningbo_Zhoushan Port, China) are carried out to evaluate the models' performance. The research results show that the proposed models have rational and reliable performance in detecting potential collision danger under an uncertain environment, identifying high-risk traffic clusters, offering a complete comprehension of a traffic situation,

and supporting strategic maritime safety management. These developed techniques and models provide useful insights and valuable implications for maritime practitioners on traffic surveillance and management, benefiting the safety and efficiency enhancement of maritime transportation. The research can also be tailored for a wide range of applications given its generalization ability in tackling various traffic scenarios in complex waters. It is believed that this work would make significant contributions in terms of 1) improving traffic safety management from an operational perspective without high financial requirements on infrastructure updating and 2) effectively supporting intelligent maritime surveillance and serving as a theoretical basis of promoting maritime safety management for the complex traffic of mixed manned and autonomous ships.

Acknowledgements

This thesis is the culmination of a three-year Dual-PhD project between Liverpool John Moores University (LJMU) and Wuhan University of Technology (WUT), China. I would like to express my heartfelt gratitude to the people and organizations who have supported and accompanied me throughout my doctoral journey.

First and foremost, I would like to thank my principal supervisor, Professor Zaili Yang, for his unwavering support, constant encouragement, patient guidance, and valuable technical suggestions throughout my research journey. More importantly, his working attitude and passion towards academic research have impressed and inspired me to keep going and bravely face all kinds of difficulties. I owe him a great deal of gratitude for giving me the opportunity to join the PhD program at Liverpool Logistics, Offshore and Marine (LOOM) Research Institute. It is a great honour for me to have been under his supervision. I would also like to express my appreciation to my co-supervisors at LJMU, Dr. Sean Loughney and Professor Jin Wang, for their kind assistance and constructive feedback in helping me complete the thesis.

I owe special thanks to my supervisory board in China, Professor Kezhong Liu and Professor Jinfen Zhang at WUT, for their extraordinary support during my research. They provided me with the opportunity to be involved in various funded projects, enhancing my knowledge. Moreover, they generously dedicated their time, sharing their experiences, perspectives, and insights. Without their contributions, this research would not have been possible.

I would like to thank my colleagues and friends whom I met at LJMU. I really enjoyed my time with them. Many thanks to them for enriching my study and life in Liverpool and making it filled with laughter.

This research has been supported and funded by the Faculty of Engineering and Technology (FET) of LJMU, and the China Scholarship Council (CSC). I would like to acknowledge the funding agencies for their financial assistance, which has made it possible for me to pursue my doctoral research and complete this thesis.

Last but not least, I am very grateful to my family for their support and encouragement throughout my doctoral research. Their unwavering belief in my abilities and their willingness to lend a listening ear have been a source of motivation and inspiration.

While this list of acknowledgements is by no means exhaustive, I would like to express my heartfelt gratitude to everyone who has played a role in my journey to complete this thesis.

Table of Contents

List of Figures

List of Tables

AHP	Analytic Hierarchical Process
AIS	Automatic Identification System
ANLS	Alternating Non-negative Least Squares
ANN	Artificial Neural Network
BCR	Bow Crossing Range
CC	Clustering Coefficient
CD	Conflict Detection
CDR	Conflict Detection and Resolution
CPA	Closest Point of Approach
CRI	Collision Risk Index
CTPA	Collision Threat Parameter Area
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DCPA	Distance to Closest Point of Approach
ETA	Estimated Time of Arrival
FCI	Fuzzy Clustering Iterative
GRNN	Generalized Regression Neural Network
IMMKF	Interacting Multiple Model Kalman Filter
IMO	International Maritime Organization
IoT	Internet of Things
KDE	Kernel Density Estimation
KF	Kalman Filtering
KS	K-Shell Decomposition
LOA	Length Overall
MASS	Maritime Autonomous Surface Ships
MC	Monte Carlo
MP	Multilayer Perceptron
MSA	Maritime Situational Awareness
NE	Number of Edges
NMF	Non-negative Matrix Factorization
NN	Number of Nodes
OOW	Officer on Watch
OPTICS	Ordering Points To Identify The Clustering Structure
PDF	Probability Density Function
POA	Projected Obstacle Area
RMS	Root Mean Square

RV	Reachable Velocity
SNMF	Symmetric Non-negative Matrix Factorization
SOLAS	Safety of Life at Sea
SVM	Support Vector Machine
TCPA	Time to Closest Point of Approach
VCRO	Vessel Conflict Ranking Operator
VO	Velocity Obstacle
VS	Vertex Strength
VTS	Vessel Traffic Service

CHAPTER 1 INTRODUCTION

This chapter offers a general analysis of the research background, providing a practical perspective on the needs and demands of new MSA techniques. It then presents an overview of the research objectives, followed by a statement of the research necessity and challenges encountered during the research process. Additionally, the scope and layout of the thesis, as well as the methodology employed in the study, are outlined and presented. Furthermore, the research contribution is illustrated, showcasing the theoretical and practical significance of the proposed models.

1.1 Research Background

Maritime transportation surveillance and management have been gaining considerable attention due to their paramount role in reducing accidents, improving the economy, and protecting the ocean environment. Advanced technologies and policies related to perception, communication, digitization, and automation have accelerated the revolutionization of the maritime transport industry (Li and Yang, 2023). Particularly, various modern and intelligent technologies and systems such as the Internet of Things (IoT), cloud computing technologies, Automatic Identification System (AIS), navigation aids and decision support systems have been deployed and incorporated into maritime transportation surveillance (Li et al., 2023). They present great potential to aid maritime authorities in proactive maritime traffic monitoring and surveillance. Meanwhile, large investments are conducted in maritime industrial projects to digitize maritime operational platforms, reduce manning requirements, and implement autonomous technology (Register, 2017; Rivkin, 2021). Following the promising development trend, the current maritime industry is evolving from conventional mechanical systems to digital systems with autonomous modules moving towards a reality (Ashraf et al., 2022; Bakdi et al., 2021).

On the other hand, the breadth of the surveillance areas and the diversity of ship motion activities (*e.g.*, sailing, berthing, anchoring, and refuelling) bring significant challenges to the practical applications of current maritime surveillance systems and tools. With respect to the transport demand growth, the application of super large-scale ships, the development of ship speed and ship types, the development of emerging technologies (*e.g.*, autonomous ships), and the impact of non-classical risks (*e.g.*, COVID-19), maritime traffic situations have become increasingly complicated and sophisticated, particularly in complex waters (*e.g.*, ports) (Fang et al., 2018; Shi and Weng, 2021; Yu et al., 2019; Zhou et al., 2022). Figure 1.1 illustrates the traffic distribution visualisation in some complex port waters, *i.e.*, Yangtze Estuary and Ningbo_Zhoushan Port in China. These waters are exposed to highly complicated traffic situations involving high traffic density, high encountering frequency, restricted water topography, and dynamic ship motion behaviours. These traffic characteristics put tremendous pressure on practical monitoring tasks for maritime surveillance operators. As a result, new advanced MSA techniques have to be developed and implemented urgently to cope with the ever-growing complexity of maritime traffic situations. In practice, MSA serves as the initial stage of maritime surveillance and management, aimed at enhancing comprehension of the traffic scenario and identifying potentially hazardous events. By integrating advanced MSA tools into the maritime surveillance system, it becomes possible to alleviate the workload of maritime operators and enhance their capabilities when confronted with highly complex traffic situations. Consequently, these tools offer valuable insights to aid the establishment of the intelligent transportation system and autonomous navigation system, which can ensure the safety and efficiency of ship navigation and safeguard the marine environment.

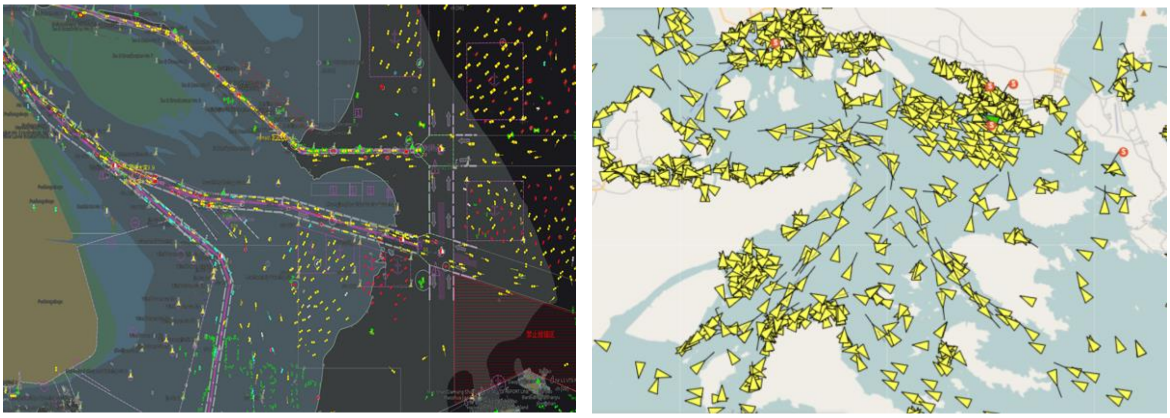


Figure 1.1. Visualisation of ship traffic distribution in Yangtze Estuary and Ningbo_Zhoushan Port.

Based on the demand to enhance the operational monitoring over busy waters of interest, a variety of techniques and approaches have been proposed to undertake traffic situation qualification and estimation (Chen et al., 2019; Huang et al., 2020; Yu et al., 2020a). They offer insights on providing a quantitative foundation for maritime surveillance and issuing early collision warnings to support anti-collision decision-making. With the rapid development of AIS and the increased accessibility of a vast amount of ship movement information (*i.e.*, AIS data), accurate maritime situation assessment and characterisation have become possible and further attracted widespread attention in recent years (Du et al., 2020b; Tu et al., 2017). Apart from uses in maritime situation analysis, advanced applications of AIS data in maritime safety-related studies have been witnessed, including maritime traffic pattern extraction (Li et al., 2020, 2022), maritime anomaly detection (Rong et al., 2019, 2022), ship destination prediction (Zhang et al., 2020), and ship path optimization (Tavakoli et al., 2021; Yu et al., 2021; Zaccone and Martelli, 2020). While the application of AIS data contributes to the improved analysis and modelling of ship motion behaviours, the increasingly complex traffic situations associated with multi-dependent ship interactions and the growth of ship spatio-temporal movement uncertainty remained unaddressed. More specifically, the development of an intelligent MSA method necessitates the comprehensive consideration of spatio-temporal dynamics and uncertainty of ship motion, maritime geographical features, and the intricate interrelationships among multiple ships. Consequently, the theoretical challenges involved in developing such an MSA method are substantial, given the multitude of constraints inherent in complex dynamic waters. One effective approach is to leverage big data mining techniques in conjunction with machine learning algorithms to solve these constraints. The success of this endeavour holds significant benefits in the form of an intelligent transportation support system for future hybrid traffic scenarios. Addressing this challenge promptly is of utmost importance.

1.2 Research Objectives

The primary research questions of this research are the obstacle encountered by current collision risk models in effectively incorporating the influence of traffic characteristics in complex waters, while also achieving a comprehensive evaluation of the entire traffic situation across various spatial scales. Consequently, the aim of this study is to develop and employ a range of novel Maritime Situational Awareness (MSA) techniques and models. These methodologies will enable the consideration of both the intricate traffic characteristics in complex waters and the multi-scale collision risk, thereby ensuring their applicability and delivering a multi-view risk evaluation when applied in complex traffic situations. These developed techniques and models will provide practical insights and implications to maritime surveillance operators, ship navigators, and port stakeholders, enabling them to enhance maritime traffic situation perception capabilities and strengthen decision-making on anti-collision risk control. Meanwhile, they will also significantly contribute to supporting intelligent port construction and lay a solid foundation for the future coexistence of mixed manned and autonomous ships. To achieve the aim, the following subsidiary objectives need to be critically solved, including:

1. To reveal the technical deficiencies and challenges in maritime traffic situational perception and AIS data applications in maritime traffic surveillance through a systematic literature review. (Chapter 2)

2. To develop a probabilistic Conflict Detection (CD) approach that can integrate the effects of dynamics and uncertainty inherent to ship spatio-temporal motion to detect collision danger more precisely and reliably in complicated dynamic situations. (Chapter 3)

3. To design a static ship traffic partition method that can partition the regional ship traffic into several compact, scalable, and interpretable groups to decrease the difficulty of regional maritime situation interpretation and capture potential high-risk traffic clusters. (Chapter 4)

4. To propose a dynamic ship traffic partition method that produces temporal stable and consistent traffic clusters to facilitate the continuous implementation of collision control strategies. (Chapter 5)

5. To establish a multi-scale collision risk model that can capture traffic conflict patterns under different spatial scales to provide a complete comprehension of a given traffic scenario. (Chapter 6)

1.3 The Statement of the Research Necessity and Challenges

In terms of a systematic literature review and research question summary (*i.e.*, objective 1 in Section 1.2), four technical models are established (*i.e.*, objectives 2-5). These models are proposed for different situational awareness demands in complex waters. The research gaps, necessity and challenges of developing each model are stated in the following:

1) Technical model 1: A probabilistic conflict detection model

Conflict detection requires incorporating the ship's spatio-temporal motion dynamics and uncertainty. This is because a conflict is defined as a situation in which the minimum safe separation between two ships is violated over a finite prediction horizon (Hao et al., 2018; Hernández-Romero et al., 2020; Matsuno et al., 2015). In other words, it is detected based on the future predicted trajectories of encountering ships. However, most collision risk estimation studies are highly dependent on the assumptions that the encounter ships would sail linearly, or that their future trajectories can be entirly predetermined, overlooking the influence of ship motion dynamics and uncertainty (Huang et al., 2020; Xiao et al., 2019a). These assumptions are the detriments of discovering the actual collision danger, resulting in their inapplicability in complex waters. In practice, the dynamics and uncertainty of potential ship movements are inevitable and subject to the influence of navigation plans or intention, environmental disturbances, and technical errors, *etc*. Therefore, the application performance of these existing models becomes questionable and arguable when applied to a complex water area involving dynamic and changeable ship motion behaviours.

To address the above issues, it is essential to develop a new capable model that incorporates the spatial-temporal motion dynamic uncertainty to conduct collision risk detection. This study develops a novel CD approach from a probabilistic risk viewpoint to adapt to the traffic motion characteristics in complex waters. Probabilistic CD modelling faces the following challenges.

1.1) How to construct the dynamic and uncertain ship motion prediction model, *i.e.*, how to predict the Probability Density Functions (PDFs) of future prediction trajectories.

1.2) How to accurately and effectively compute the conflict probability based on uncertain ship future trajectories.

2) Technical model 2: A static traffic partitioning model

The comprehension and interpretation of a regional maritime traffic situation are fundamental to maritime traffic safety surveillance and management. However, most state-of-the-art studies focused on near-miss collision risk between/among ships (Chen et al., 2019; Huang et al., 2020) (*e.g.*, technical model 1) but encountered challenges in detecting and capturing the high-risk multi-ship encounters. In complex waters with heavy traffic, maritime surveillance operators need to interpret the regional maritime traffic pattern complexity and identify the real-time high-risk areas involving complex multi-ship encounters. The lack of advanced tools to support traffic situational awareness requires maritime surveillance operators to capture high-risk multi-ship encounters based on their intuition and experience, which significantly increases their workload on practical monitoring tasks. One of the realistic solutions is to develop a practical maritime traffic partitioning approach to partition the whole maritime traffic scenario into several interpretable traffic clusters, in which the ships in the same cluster have high spatio-temporal interrelationships while the ships between different clusters have low spatio-temporal interactions (Zhen et al., 2021). Undoubtedly, it can reduce the difficulty of understanding the whole traffic situation, facilitate the proactive identification of potential high-risk traffic clusters, and further assist in guiding ship anti-collision risk management.

Nevertheless, the literature on maritime traffic partitioning is an emerging research topic and extremely limited compared with road transportation network partitioning (Gu and Saberi, 2019; Ji and Geroliminis, 2012; Saeedmanesh and Geroliminis, 2016). The most related studies are to detecting clusters of encounter ships through the density-based clustering algorithm (Liu et al., 2019a; Zhen et al., 2017, 2021). These models suffer from some drawbacks like ignoring or simplifying ship dynamics, only concerning traffic density, and having difficulty in discovering the traffic clusters with varying densities (Xin et al., 2022a). Particularly, the complicated ship traffic characteristics and the multiple dependent conflict-related interrelationships in complex waters hinder their applicability and practical usability. More concretely, the following issues need to be solved to develop an effective and reliable traffic partitioning technique:

2.1) How to incorporate the multi-dependent interrelationships among ships into the traffic partitioning process.

2.2) How to consider the influence of water topography on spatial distance measures in restricted waters.

2.3) How to choose effective clustering techniques to adapt to the unique and stochastic characteristics of maritime traffic.

3) Technical model 3: A dynamic traffic partitioning model

Currently, the limited maritime traffic partitioning or multi-ship encountering detection works have been mainly conducted from a static perspective by utilizing the snapshot traffic information at a given time (*e.g.*, technical model 2). However, it is paramount to undertake traffic partitioning in the dynamic domain since maritime traffic is a strongly time-variant process. It is crucial to examine the traffic partitioning issue over time from the temporal perspective to uncover the co-behaviours and interaction patterns during the evolution and dissolution of traffic clusters (Saeedmanesh and Geroliminis, 2017). More importantly, the generation of temporal stable traffic clusters can ensure the temporal smoothness of implementing a cluster-based anti-collision control scheme. Therefore, it is necessary to develop a dynamic traffic partitioning model that can handle the temporal evolving maritime traffic. On this basis, the temporal consistent traffic clusters can be extracted from a time series of traffic networks, thereby facilitating the internal relation analysis of traffic clusters in both spatial and temporal domains and helping observe the cluster propagation from a macroscopic perspective. Meanwhile, the temporal traffic clusters that have been extracted can be used to create a series of testing scenarios that simulate real-world navigation conditions, thereby facilitating comprehensive Maritime Autonomous Surface Ships (MASS) testing and verification (Bakdi et al., 2021).

Nevertheless, the traffic partitioning and scenario extraction when incorporating temporal information present the following challenges, which are:

3.1) How to incorporate the traffic dynamic evolution characteristics into the traffic partitioning process.

3.2) How to track the evolutionary traffic scenarios efficiently and accurately from the historical successive traffic networks.

4) Technical model 4: A multi-view collision risk estimation model

Technical models 2 and 3 pay attention to decomposing the regional traffic complexity and capturing traffic clusters. However, how to evaluate the traffic situations associated with complex interactions of traffic clusters remains unsolved. This has a bad impact on assisting surveillance operators in explicitly identifying and monitoring the critical high-risk traffic clusters, which further influences strategic maritime risk management. A reliable and robust collision risk model should be able to evaluate the traffic collision risk under any spatial scale (*e.g.*, individual, multi-ship, and regional traffic collision risk), thereby offering complete comprehension for a traffic situation. Unfortunately, there has not been any systematic approach that can conduct maritime collision risk evaluation under multiple spatial scales. Most existing studies (Chen et al., 2019; Huang et al., 2020) can only process and establish collision risk models from a single scale. As a result, these works reveal the deficiencies in capturing the traffic collision risk patterns under different spatial granularity.

Although an effective multi-scale collision risk evaluation model can assist surveillance operators in improving their cognitive abilities in complex traffic situations, it requires the full interpretation of multiple dependent interrelationships associated with the dynamic co-behaviour of multiple encountering ships. Specifically, the following questions need to be coped with to effectively incorporate the multi-scale traffic patterns into collision risk evaluation modelling.

4.1) How to explicitly reveal the complexity of a regional traffic scenario associated with the dependent conflict relations among multiple ships.

4.2) How to specify the correlation between the micro-level and macro-level collision risk to achieve a proper combination of the multi-scale risk patterns.

4.3) How to adaptively extract the optimal multi-ship clusters at different scales for risk assessment.

4.4) How to choose a proper method to conduct the comprehensive evaluation of multiple traffic risk/complexity indices.

The above challenges and solutions will be further elaborated on in the Background Information part of each technical chapter.

1.4 Research Scopes and Methodology of the Thesis

The research scope and core of the thesis is maritime traffic situation awareness and management in complex waters. The intention is to develop a holistic MSA framework to enhance intelligent traffic safety surveillance and management from an operational perspective for both ship navigators and maritime operators. The proposed methods and models pioneer the application of some new techniques (*e.g.*, SNMF and FCI) and new concepts (*e.g.*, maritime traffic partition and multi-scale collision risk), thereby offering new valuable insights into the maritime surveillance and management from different perspectives. They are particularly innovative when considering the influence of complex traffic behaviours on supporting practical risk analysis within a complex traffic environment and the future coexistence of mixed manned and autonomous ships.

The methodological view on advanced maritime traffic situation perception in the thesis can be divided into two streams: collision risk estimation and maritime traffic partitioning. On the one hand, a probabilistic conflict detection method is developed to support reliable and efficient collision danger identification under spatio-temporal uncertainty of ship movements. On the other hand, a graph-based traffic partitioning methodology from both static and dynamic perspectives is developed to decompose the whole traffic complexity and ease the design and implementation of collision control strategies. Finally, the above models are synthesised together through an integrated framework to support the collision risk estimation under any spatial scale. Figure 1.2 presents a graphical flowchart to describe the logical backbone of the developed methodology. The detailed explanations of their relationships and the thesis layout are depicted in the following.

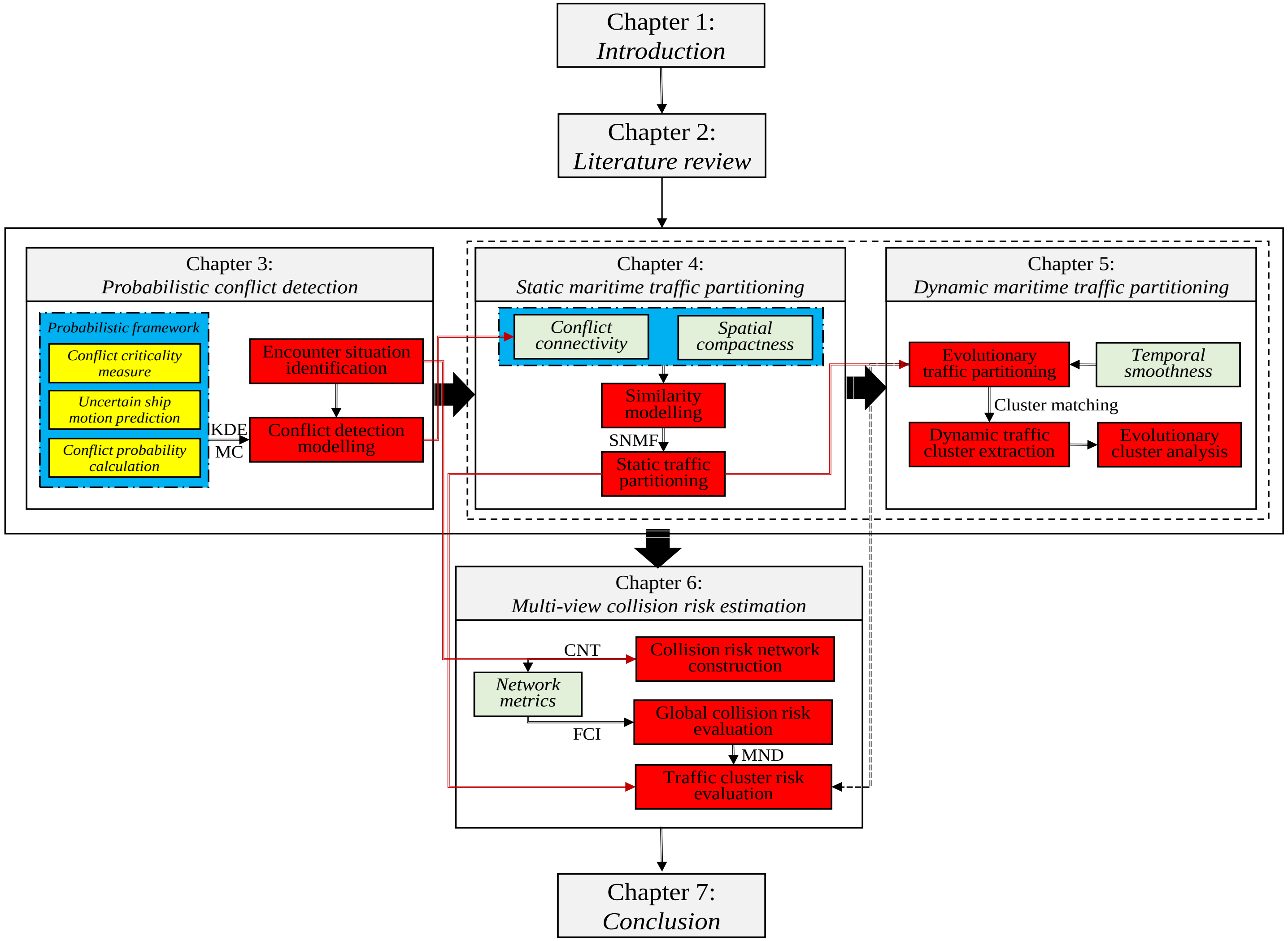


Figure 1.2. Research structure.

The thesis is compiled into seven chapters. Following the introduction of the basic information of the research, such as background, objectives, research necessity, and contributions in **Chapter 1**, **Chapter 2** reviews the important literature closely related to ship collision risk and AIS data application in maritime traffic surveillance, and then presents a critical analysis and discussion of the current research gaps. The focus and essence of the thesis are encapsulated in **Chapters 3-6**. An introduction of the relevant theories and methods tailored to the objectives and aims of the research is presented in detail in the following.

Collision risk estimation is regarded as the first basic module to support reliable risk control and management. **Chapter 3** develops a probabilistic framework to incorporate the influence of ship spatio-temporal dynamics and uncertainty on collision detection. The proposed framework involves three important components: a conflict criticality measure model, an uncertain ship motion prediction model, and a conflict probability calculation model. A classical ship domain model (Fujii and Tanaka, 1971) adaptive to restricted waters is first used to characterise the conflict between ships. Then, an uncertain trajectory prediction model, which serves as a prerequisite for potential collision detection and evaluation, is designed by modelling the ship motion as a deterministic motion correlated with the ship navigation plan plus a stochastic component fitted by the Kernel Density Estimation (KDE) method. Regarding conflict probability computation, a two-stage Monte Carlo (MC) simulation model is deployed to achieve a fast and accurate estimation of the conflict criticality. In addition, an improved Closest Point of Approach (CPA) method is applied to conduct encounter situation identification, which focuses on capturing target ships that are spatially positioned close to the own ship soon for conflict risk estimation.

However, the conflict detection model in **Chapter 3** concentrates on risk estimation at a local level. It reveals deficiencies in estimating large-scale traffic situations associated with complex interactions of traffic clusters. Therefore, **Chapter 4**, as the other research branch in parallel with the risk estimation, aims to develop an optimal maritime traffic partitioning model to improve the interpretation of a regional traffic situation, especially from a maritime surveillance perspective. The proposed model considers both the conflict criticality used in **Chapter 3** and the spatial distance between ships to generate conflict-connected and spatially compact traffic clusters. First, a composite similarity model that synthesizes the two indicators is introduced. Particularly, the real spatial distance between ship pairs is measured based on a newly formulated maritime traffic route network learned through maritime knowledge mining. Then, the similarity measure result is fed into a robust graph clustering mathematical framework known as SNMF to produce traffic clusters with a balanced size where the intra-cluster similarity can be maximized but the inter-cluster similarity minimized. The traffic partitioning results will offer useful insights for maritime operators to understand the traffic situation.

Chapter 5 makes two main extensions based on the proposed methodology in **Chapter 4**. In this chapter, a dynamic traffic partitioning model is first developed to detect temporal stable traffic clusters, in which both the current traffic partition quality (*i.e.*, the two indicators adopted in **Chapter 4**), and the temporal smoothness associated with the historical partitioning structures are considered in the partitioning process. It can support the continuous implementation of traffic cluster-based risk control strategies. Based on that, a traffic cluster matching strategy is designed to extract a series of similar clusters across successive time snapshots. The proposed matching strategy can help extract a variety of realistic and sufficient multi-ship encounter scenarios for traffic evolutionary analysis and intelligent navigation algorithm testing and verification.

Based on the proposed models in the previous chapters, **Chapter 6** develops a systematic multi-scale collision risk evaluation framework to comprehensively estimate the collision risk under different spatial scales. An improved CPA-based model in **Chapter 3** is first adopted to determine the interactions between any ship pair. Then, five network indicators from the Complex Network Theory (CNT) are used to characterise the regional traffic risk/complexity from different aspects, and the FCI method is utilized to provide a full evaluation for the multiple index synthesis. Subsequently, a node deletion method is adopted to identify the risk contribution of any single or multiple ships to the whole traffic situation. Meanwhile, the traffic partitioning model developed in **Chapter 4** is used to search for the optimal spatial scales (*i.e.*, the multiple ships with high spatial interrelationships) for risk evaluation. In this way, the collision risk of any single ship, multiple ships, and regional traffic in a given traffic situation can be comprehensively evaluated.

Chapter 7 summarises the main demands for the current MSA and highlights the novel modelling methodology and the associated implications of this study. The research limitations and the future improvements arising from the proposed methods are further outlined and suggested.

1.5 Research Contributions

This research offers valuable insights and contributions for maritime surveillance operators (*e.g.*, maritime management authorities and port safety-related departments) and ship navigators from both academic and industrial perspectives:

1) Academic contributions

1.1) The proposed probabilistic CD scheme characterises and quantifies the conflict criticality more accurately and reliably by incorporating both the dynamic and uncertain characteristics of the spatio-temporal movements of multi-ships. Compared with traditional approaches, the proposed scheme is capable of handling various encountering scenarios in complex maritime traffic waters, such as busy ports, thereby facilitating ship drivers and maritime safety authorities to obtain real-time and reliable alarms of potential collisions (Chapter 3).

1.2) An AIS data-driven procedure is designed to extract the spatio-temporal uncertainty patterns of ships from the historical trajectories. It is found that the position and course uncertainty components do not follow the commonly used Gaussian distributions and their correlations are not significant. Their PDFs are further fitted through the KDE method and the outcomes are then inserted into the ship motion model to help in providing exact distribution patterns of prediction trajectories (Chapter 3).

1.3) A two-stage Monte Carlo (MC) simulation algorithm is proposed to enhance the efficiency of the computation of conflict probability. Experimental results show that the proposed algorithm only requires much lower computational costs to yield the same approximation accuracy as the direct Monte Carlo method. In addition, this algorithm can be easily combined with other collision risk or conflict assessment models that integrate more influencing factors on minimal safety distance among ships, such as diverse "ship domain" (Im and Luong, 2019; Szlapczynski and Szlapczynska, 2016; Wang, 2013; Wang and Chin, 2016; Zhang and Meng, 2019), "synthetic index" (Li et al., 2015; Ożoga and Montewka, 2018; Wang et al., 2017; Zhang et al., 2015; Zhen et al., 2017), and "minimum distance to collision" (Montewka et al., 2010), *etc*., without having side effects on its fundamental advantages. In other words, it has a wider scope of application for conflict probability computation (Chapter 3).

1.4) The proposed maritime traffic partitioning model incorporates the multi-attribute interrelationships (*i.e.*, conflict connectivity and spatial compactness) among ships into the partitioning process. The sensitive analysis accounts for the trade-off of the multiple properties of spatio-temporal interactions, making it desirable to strike a balance among these considered criteria (Chapter 4).

1.5) The proposed approach makes use of historical AIS data to generate a data-driven representation of a maritime traffic route network. It contributes toward capturing the traffic clusters with real spatial compactness by using the length of the shortest path of ship pairs on the network instead of the traditional physical distance, thus ensuring the adaptation to the traffic scenarios in restricted geographical waters (Chapter 4).

1.6) With respect to optimal traffic partitioning, a graph-based clustering technique known as SNMF using the Newton-like algorithm is extended to produce ideal traffic clusters with balanced sizes. It is flexible and scalable to handle various traffic scenarios beyond the maritime sector by optimizing the graph clustering objectives (Chapter 4). In addition, the graph-based clustering technique is embedded into the multi-scale collision risk framework to extract the traffic conflict patterns under different spatial scales. It accounts for the spatio-temporal dependencies among multiple ships, making it desirable to adaptively select the optimal scopes for risk evaluation (Chapter 6).

1.7) To produce reliable and temporal consistent traffic clusters over time, the temporal smoothness regularization is embedded into the SNMF framework to handle the temporal-varying feature of maritime traffic. It provides a practical way to easily accommodate such information fusion as the traffic partition quality and the temporal partition smoothness (Chapter 5).

1.8) To track the evolution and structure of dynamic traffic clusters over time, an effective cluster-matching strategy is introduced for efficiently identifying dynamic clusters in multiple snapshots. It is independent of the selection of traffic partitioning algorithms, allowing accurate mappings between traffic clusters across different time snapshots (Chapter 5).

1.9) A multi-scale collision risk evaluation framework is proposed for the first time by synergizing a sequence of modelling techniques. While different from the traditional models that process collision risk on a single scale, it can capture the conflict patterns under different spatio-temporal granularity (Chapter 6).

1.10) A regional/global collision risk evaluation model is developed to characterise the topological characteristics associated with the interaction structures of the entire ship traffic situation in complex waters. It also pioneers the application of a node deletion method in revealing the aggregation effect of multi-ship risk interactions on the entire traffic situation (Chapter 6).

2) Industrial contributions

2.1) The proposed methodology can aid maritime surveillance operators in enhancing maritime intelligent awareness capabilities and proactively making timely and efficient decisions to control ship collision risks. It degrades the difficulty of MSA by dividing the whole maritime traffic situation into several clusters, proactively discovers the high-risk/density multi-ship encounters, offers a complete view analysis for a traffic situation from multiple spatial scales, and facilitates the design of strategic traffic management strategies based on the discovery of high-risk/density traffic clusters.

2.2) The proposed methods and models are of significant value for ship navigators to conduct intelligent collision avoidance. They provide insightful knowledge by focusing on the potential conflicts among ships across different adjoining waters in advance from a global traffic network perspective. It would convert the current ship anti-collision practice from being dependent on local ship-pair analysis to being handled at a global/regional level, so the collision risks of multi-ship encounters can be better controlled. The proposed methods therefore have the potential to serve as a theoretical basis for promoting the ongoing coexistence of manned and unmanned ships.

2.3) This study also brings significant benefits to strengthening port competitiveness and sustainability. The deployment of the developed advanced MSA techniques in autonomous and intelligent systems in ports is a key determinant of attracting port users and investment. Evidently, the ships will be more willing to give priority to the ports with high-end port services. It therefore makes a significant contribution to achieving the competitive advantages of the port over its competitors.

CHAPTER 2 LITERATURE REVIEW

This chapter presents a systematic overview of the works related to maritime traffic safety and surveillance. First, the critical analysis and discussion of the research on ship collision risk, especially the works on collision risk detection and estimation, are presented. Following this, the latest progress on various AIS data-based situational awareness technologies for better maritime safety surveillance is summarised and discussed. The research gaps are finally summarised to reveal the value and significance of the works to be conducted in the subsequent chapters.

2.1 Research related to Ship Collision Risk

Ship collision risk has long been an active research area in the field of maritime traffic management. A growing number of researchers have been working on quantifying ship collision probabilities, severity and/or risk, taking different approaches and from different perspectives. A complete and recent survey can be found in (Chen et al., 2019; Du et al., 2020b; Huang et al., 2020). They are at large categorised into the groups of statistical analysis of historical maritime accidents, risk modelling and analysis, and collision risk detection and estimation.

Among such literature, collision risk detection and estimation are among the hottest topics because they constitute an integral part of maritime traffic safety management and serve as a prerequisite for potential real-time collision risk detection. Therefore, one of the focuses of this study is collision risk detection and estimation in complex port waters. The works related to statistical analysis of historical maritime accidents, and risk modelling and analysis are briefly reviewed in Section 2.1.1 since it is not the focus of this study. The collision risk detection and estimation are further divided into two parts from both micro-level (Section 2.1.2) and macro-level (Section 2.1.3) perspectives to contextualise one of the primary works of this study.

2.1.1 Ship Collision Analysis and Modelling

Statistical analysis of historical maritime accidents is one of the fundamental methods to identify the relations between collision frequencies (and/or damage consequences) and risk factors (*e.g.*, ship attributes, environmental factors, human behaviours, technical failures, and traffic situations (Chauvin et al., 2013)). Information such as accident databases and accident investigation reports is used to support these studies (Chen et al., 2019). To derive knowledge about which factors are highly associated with ship collision risks, some techniques such as correspondence analysis, logistic regression, and stochastic process analysis were employed to predict the probabilities of event-related and environment-dependent accidents (Bye and Aalberg, 2018; Kujala et al., 2009; Qu et al., 2012), providing insights on the conditions under which maritime traffic accidents may occur. Unfortunately, this type of research strongly relies on historical accident data (Yu et al., 2019), which sometimes may not be fully available. When concentrating on small research sea/water areas, the occurrence frequency of collision accidents is usually rare and is often insufficient for supporting rational statistical analysis (Du et al., 2020b). This issue becomes more worrisome when focusing on investigating and revealing the influence of a large number of the known risk factors influencing ship collision accidents. Therefore, it is essential to adopt additional sources of information to understand the forming mechanism of ship collision risks.

Compared with accident statistical analysis, collision risk modelling (Kulkarni et al., 2020; Li et al., 2012) integrates multiple sources of information, including expert knowledge, historical data, computer simulation results, *etc*. It involves two important components in terms of the frequency or probability of ship collision accidents and associated potential consequences. The methods used in this category consist of ones such as Macduff (Macduff, 1974), Pedersen (Pedersen, 1995), Fault tree (Martins and Maturana, 2013; Xi et al., 2017), Bayesian networks (Fan et al., 2020; Goerlandt and Montewka, 2015a; Yu et al., 2020a), and ordered probit model (Weng et al., 2018). They contribute to the identification of the contributing factors, estimation of the accident causation probability, and analysis of their inter-relationships. The findings aid maritime surveillance operators in understanding the possible collision frequencies and consequences. Nevertheless, this group of research provides little value for real-time collision risk detection and collision warning.

2.1.2 Micro-Level Collision Risk Detection and Estimation

In recent years, various non-accident criticality measurement concepts, such as traffic conflict (Lei, 2020), near-miss (Zhang et al., 2016; Zhang et al., 2015), and collision candidates (Chen et al., 2018), have been proposed to detect and characterise potential dangerous encounter events from the micro perspective, *i.e.*, the collision risk between ship pairs. Relevant works for micro-level collision risk detection are categorised into three groups: 1) ship-domain-based methods; 2) synthetic index methods; and 3) dangerous region-based methods.

1) Ship domain-based methods

The ship domain refers to the safety zone around a ship within which all other ships remain clear unless authorised. It is employed to estimate collision risks and detect potential conflicts in terms of violation or overlap of the safety zones of encountering ships. To be specific, conflict detection based on the ship domain model can be divided into the following four safety criteria (Szlapczynski and Szlapczynska, 2017):

1) The domain area of a target ship should not be invaded by that of the own ship.
2) The domain area of the own ship should not be invaded by that of a target ship.
3) Neither of the domain areas of the encountering ships should be invaded.
4) The domain areas of the encountering ships should not overlap, *i.e.*, the domain areas should keep mutually exclusive and the safety spacing should equal the sum of the distance from each domain boundary to its corresponding ship centre.

The above definitions reflect the interpretation of different scholars regarding the safety criteria. In fact, the selection of the safety criteria is critical because they directly affect the minimal allowed distance between encountering ships.

In recent years, the advances in diversified intelligent technologies and increasing AIS data sources have contributed to the development of various ship domain models with different shapes (*e.g.*, circular and elliptical (Fujii and Tanaka, 1971; Szlapczynski and Szlapczynska, 2016), polygonal (Wang and Chin, 2016), quaternion (Liu et al., 2021; Wang, 2013), projected

(Goerlandt and Kujala, 2014) and risk-based (Zhang and Meng, 2019) domains), methodologies (*e.g.*, empirical, knowledge-based, and analytical domains (Szlapczynski and Szlapczynska, 2017; Zhang and Meng, 2019)), and factors considered (*e.g.*, ship attributes, ship manoeuvrability, knowledge and condition of navigators, and environmental conditions (Liu et al., 2016; Wang and Chin, 2016)). These models and methodologies work well in quantitatively examining candidates with collision potential and undesired consequences, identifying collision risk hotspots, and deriving relations between collision candidates and extra information (*e.g.*, historical accident databases and accident investigation reports). Thus, in this study, a conflict criticality metric is designed based on ship domain models to characterise the conflicts among encountering ships.

Although these advanced domain models can assist in improving the collision risk evaluation accuracy, the high model complexity impedes their practical usefulness in real-time when considering the computational overhead (Bakdi et al., 2021). Additionally, the applications of a domain model for collision evaluation require its combination with the trajectory prediction approaches because of its technical incompetence in motion prediction. Hence, it is promising to develop a fine-grained ship motion prediction model to combine it with the ship domain models for a proper solution to address this limitation.

2) Synthetic index methods

Synthetic index methods formulate mathematical or black-box models to synthesize the indices that reveal the spatio-temporal proximity level between encountering ships. It quantifies when and how close the encounter ships will be during the look-ahead horizon. The two most common indices, namely the Distance to Closest Point of Approach (DCPA) and Time to Closest Point of Approach (TCPA), were initially synthesised using techniques such as a binary state (*i.e.*, safe/dangerous) (Liu et al., 2006), linear regression (Chin and Debnath, 2009), and fuzzy theory (Lee and Rhee, 2001) to measure the Collision Risk Index (CRI). In this context, some researchers have improved and extended the synthesis by considering more proximity factors (*e.g.*, relative bearing, relative speed, ship manoeuvrability, ship motion patterns, and stability conditions (Fang et al., 2018; Gil et al., 2019, 2020; Gil, 2021; Öztürk et al., 2021; Zhang et al., 2017, 2021), adopting advanced fusion techniques (*e.g.*, Analytic

Hierarchy Process (AHP) (Zhao et al., 2016), Multilayer Perceptron (MP) (Ahn et al., 2012), Support Vector Machine (SVM) (Gang et al., 2016), and Dempster-Shafer evidence theory (Li and Pang, 2013)), and ensuring their applicability for various encountering scenarios (Goerlandt et al., 2015). They have reliable and practical performance in assisting in noticing potential collisions and issuing an earlier alert in open sea.

In these models, the Vessel Conflict Ranking Operator (VCRO) methods developed by (Zhang et al., 2016; Zhang et al., 2015) have gained much popularity in the maritime traffic domain. These methods work well in revealing more generic characteristics of the ship encounters by adopting a mathematical function to synthesize the influential factors such as relative speed, distance, intersection angle, and ship size. Further extensions by incorporating the ship speed and course patterns are conducted by Fang et al. (2018) to achieve a robust estimation of the possible near-miss collision risk in port waters. In addition, two other impact parameters, Bow Crossing Range (BCR) and the Time to BCR, have gained much attention owing to their effectiveness in supporting collision evaluations in crossing scenarios (Goerlandt et al., 2015; Zhang et al., 2015). For example, Gil et al. (2022) have revealed that the combination of the BCR and CPA can cope with various encounter situations to achieve effective early collision warnings.

In reality, most currently commercial systems adopt this type of method to detect potential collisions due to its simple implementation and relatively reliable performance (Xiao et al., 2020). However, the critical analysis of this type of method reveals that most of them adhere to a fundamental hypothesis that the ships will maintain a constant speed during the look-ahead period (Huang et al., 2020; Xiao et al., 2019a). Such a fundamental assumption may lead to inaccurate estimations of collision risk, which limits their practical applicability in complex waters. More specifically, when ships perform manoeuvres (*e.g.*, course or speed change) during the encountering process, these methods will offer unreliable estimation results. In addition, it is very challenging for them to provide an explicit explanation of the CRI results due to the interaction effects among different risk factors. Improvements are possible by exploiting the spatial-temporal dynamic features of ship movements that correlate with actual collisions in complicated encountering scenarios.

3) Dangerous region-based methods

Dangerous region-based methods are dependent on the collection of the sets of ship's course or speed that will result in potential collision danger with other ships. A collision warning is then issued if the ship's dynamic attributes fall into these sets. Classical solution approaches for dangerous region identification can be categorised into Velocity Obstacle (VO) (Huang et al., 2018), Projected Obstacle Area (POA) (Larson et al., 2006), and Collision Threat Parameter Area (CTPA) (Lenart, 2015).

Among them, VO has gained much popularity because of its simple operation and excellent performance in the search for collision-free schemes. Examples include integrating the ship domain with VO (Szlapczynski and Szlapczynska, 2015), developing probabilistic VO and generalised VO algorithms by loosening the linear ship motion assumption and taking ship manoeuvrability into consideration (Huang et al., 2018, 2019), extensions that consider the entire encountering process when detecting collision candidates (Chen et al., 2018), and time-varying collision risk estimation using the percentage of overlap between the VO set and the Reachable Velocity (RV) set (Huang and van Gelder, 2020). These studies demonstrate their strengths in detecting collision dangers in dynamic traffic situations and can be applied in generalised scenarios.

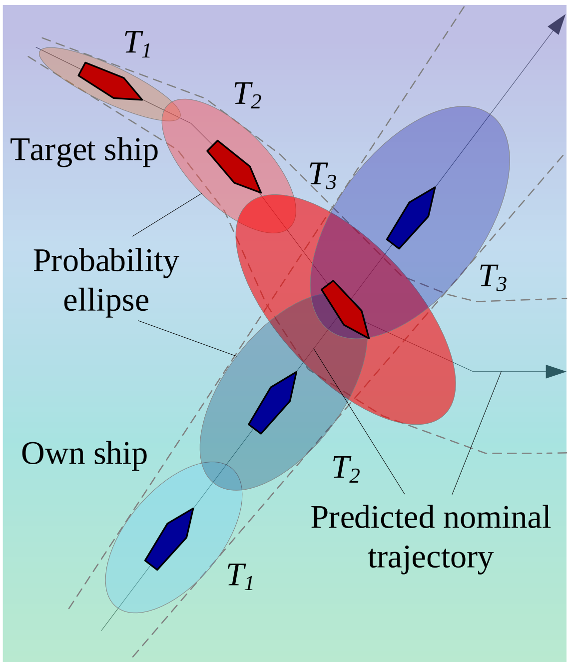


Figure 2.1. Illustration of a ship-pair encounter.

However, there are still unresolved issues from the following perspective. Owing to the non-negligible computational burdens of mapping from the spatial-temporal proximity of the ship pairs to their velocity space, it is difficult to integrate them with the complex prohibit region models holistically. As a result, they are generally combined with simple risk measurement models, such as constant minimum safe distance and circular ship domain, for real-time collision detection (Huang et al., 2018, 2019). This has been deemed the main weakness of unveiling collision risk differences under different ship encounter situations.

The above literature on micro-level ship collision risk detection and estimation reveals valuable insights for ship navigators and maritime authorities to propose and implement effective risk mitigation measures. The advantages and limitations of these models are summarised in Table 2.1. However, the increasingly complicated traffic conditions have required researchers to develop new advanced technologies. More concretely, few studies can simultaneously cope with the dynamic and uncertain characteristics of ship motion. Most of them assumed that the encountering ships maintained constant velocity or that the ship's future trajectories could be accurately obtained when undertaking CD. However, it is challenging to precisely estimate a ship's future trajectories given the uncertainty caused by environmental disturbances, navigation plans or intentions, and physical and human factors. Particularly, the prediction uncertainty and/or errors are prone to increase gradually over time (Park and Kim, 2016; Rong et al., 2019). A ship-pair encounter scenario is illustrated in Figure 2.1, in which the spread of the probability ellipses representing the predicted position uncertainty grows in time. Consequently, these methods are not applicable to complex waters associated with high traffic density, variant manoeuvring behaviour, and unique geographical characteristics. The influence of trajectory uncertainty on collision risk estimation has attracted the attention of researchers in the field of air traffic. Many studies in this research domain (Hao et al., 2018; Zhang et al., 2020) suggested that incorporating traffic dynamic and uncertain behaviours is essential to conduct Conflict Detection and Resolution (CDR). They estimated the collision risk by developing probabilistic CD models to incorporate the impact of trajectory uncertainty. Therefore, one of the aims of this study is to develop a ship conflict detection model from a probabilistic risk viewpoint to handle the ship movement dynamics and uncertainty.

Table 2.1. A summary of micro-level collision risk detection and estimation approaches.

Category	Advantages	Limitations
Ship domain-based methods	1) support various domain shapes to reveal the minimum safe distance between ships. 2) allow for the consideration of various situations and environment-related factors.	1) need high computational costs when using highly complex ship domain models. 2) require its combination with the trajectory prediction approaches for collision detection.
Synthetic index methods	1) support the quantification of when and how close the encounter ships will be in the future. 2) easily to be implemented in real traffic navigation surveillance systems.	1) hold a critical assumption that the ships will keep an unchanged speed when encountering others. 2) cannot provide an explicit explanation of the CRI results.
Dangerous region-based methods	1) allow for finding proper collision-free solutions. 2) can be applied in dynamic traffic scenarios.	1) have difficulty in combining with complex risk measure models. 2) perform poorly in unveiling collision risk differences under different ship encounters.

2.1.3 Macro-level Collision Risk Detection and Evaluation

Compared with the micro-level risk estimation, there is much less literature on macro-level collision risk evaluation and measurement. The real-time collision risk assessment based on global/regional maritime traffic in busy water areas has rarely been investigated to date, thereby offering little insight into ship collision risk from a global perspective. Only a small number of research studies have built regional/global risk models by taking density complexity into consideration (Zhang et al., 2019), incorporating the collision risk and contribution of each ship (Liu et al., 2019a), integrating the unpredictability and irregularity of maritime traffic time sequences (Zhang et al., 2022), and taking into account the evolutionary and structure properties of ship traffic networks (Xin et al., 2022b). In practice, an effective regional traffic collision risk model requires continuous assessment of the traffic complexity associated with multi-dependent ship interactions. In heavy-traffic and complex water, the behaviours of ship traffic are spatially correlated with the structure of traffic conflicts. For instance, the countermeasures used by ship *A* to avoid conflict with ship *B* could increase the risk of conflict with the other nearby ships (*i.e.*, *C* and *D*) in the same water. That is why many research communities paid attention to collision avoidance with multiple target ships (Liu et al., 2022; Zhang et al., 2021, 2022). Therefore, the development of a reliable regional traffic collision risk model is challenging when considering the sophisticated traffic co-behaviours and interactions in a traffic scenario.

Within this context, some researchers started to attach importance to a new concept called "ship traffic complexity" (Sui et al., 2020; Wen et al., 2015; Zhang et al., 2022). It is a relatively new research topic in the maritime domain, with the work of (Wen et al., 2015) who pioneered the quantitative assessment of traffic situations. However, in the aviation research field, air traffic complexity has been long-standing and applied for diverse purposes, including measuring the workload of traffic controllers (Cao et al., 2018), enhancing airspace capacity (Flener et al., 2007), assisting controllers in decision-making and conflict resolution (Radanovic et al., 2018), and implementing traffic situation assessment (Wang et al., 2016). Due to the limited research on traffic complexity in the maritime traffic field, both relevant works in the air and maritime traffic fields are critically analysed in the following.

At an early stage, traffic density was treated as the basic feature for characterising traffic complexity (Sridhar et al., 1998). Evidently, it is insufficient to capture the complete picture of complexity because many factors, including traffic flow characteristics and space structure associated with the overall traffic complexity (Cao et al., 2018) are not considered. For example, Figure 2.2 illustrates two ship traffic scenarios with the same traffic density (Note that this figure is merely an illustration and does not accurately represent the actual number of ships considered in the thesis). The traffic situation in Figure 2.2 (a) encounters more difficulties in controlling potential conflicts because many ship pairs will converge soon. In contrast, most ship pairs in Figure 2.2 (b) show a dispersed trend and thus correspond to relatively low traffic complexity. Consequently, many types of complexity metrics, such as Interval Complexity (IC) (Flener et al., 2007) and Input–Output (IO) approach (Pallottino et al., 2002), were formulated for traffic complexity assessment. Their critical design entails rationally screening and aggregating the complexity factors through a variety of combination means (Prandini et al., 2011). To reflect between-aircraft influence relationships, researchers have intensively studied complexity from the perspective of complex systems. They mathematically described the between-aircraft proximity (*e.g.*, approaching effect and potential conflict) in terms of the traffic tracking information (*e.g.*, location and velocity) to reveal the irregularity and disorder of the entire traffic situation using fractal dimension, topological entropy, and Lyapunov exponent (Delahaye et al., 2004; Delahaye and Puechmorel, 2010; Lee et al., 2009). These studies provided insights into traffic complexity but ignored the structural differences in interactions among aircraft.

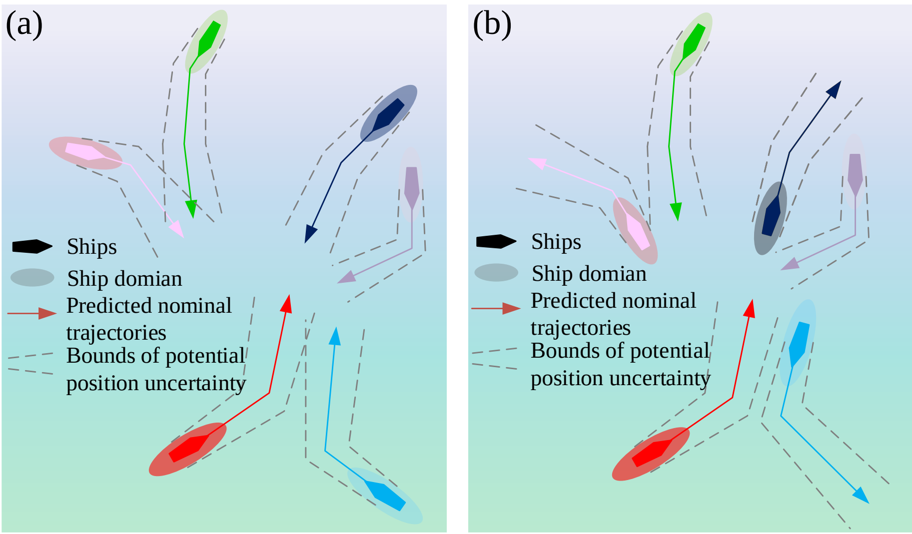


Figure 2.2. Illustration of ship traffic encounter situations in complex waters.

Complex network theory is an important theoretical framework for characterising complex systems and revealing the topological properties of system structures. It is a useful tool for investigating the relations between different parts in a system to help understand the pattern and behaviour characteristics created by interacting elements. Many systems allow the deployment of complex network theory by abstracting component units as interactions between units (Barabási and Albert, 1999; Boccaletti et al., 2006). With the rapid development of complexity science, complex network theory has become more prevalent across many traffic research topics, including vulnerability and resilience analysis of air transportation networks (Wong et al., 2020), dependence relation recognition between air traffic network structure and safety events (Carro et al., 2019), difficulty measurement that controllers encounter in different traffic situations (Wang et al., 2016), and quantitative assessment of marine traffic systems (Sui et al., 2020), from a macroscopic or microscopic perspective. As air and maritime traffic have all the characteristics of time-variable complex systems, there has been a growing trend towards microscopic traffic network complexity modelling using complex network theory. They (Sui et al., 2020; Wang et al., 2016) characterised air/maritime traffic as a complex network by denoting aircraft/ships as nodes and between-aircraft/ship-pair conflict relations as edges, and then used topological metrics to highlight the overall network performance to enhance operators' perception capabilities for traffic operation situations.

Despite their popularity, the practical applications of the above models have been limited, especially for works in the maritime traffic domain. A summary of some typical ship traffic complexity or regional collision risk models is presented in Table 2.2. The main limitations include:

1) Most of the above studies developed collision risk or traffic complexity models from a single scale, *i.e.*, merely focusing on regional collision risk. However, maritime collision risk evaluation in a busy water area exhibits significantly distinct properties in different spatial scales. Obviously, it is inadequate to reveal the collision risk patterns under different spatial granularity and comprehensively interpret the entire traffic situation by only processing the collision risk in one specific spatial scale. To the author's best knowledge, there has not been any systematic approach incorporating the multi-scale traffic properties into the maritime collision risk evaluation in the literature.

2) The interactions or conflict relations between ship-pairs are formulated based on ideal hypotheses, such as regular or constant traffic moving speeds and no environmental disturbance in traffic motion. However, the changeable traffic movements are detrimental to exploiting real traffic conflict patterns, especially for complex traffic scenarios.

3) Most of the studies merely concentrated on the overall complexity of the traffic situation but overlooked the investigation of how much influence each single ship or traffic cluster has on the regional traffic network. A thorough complexity evaluation that enables the

identification of key influential ships/clusters is of significant value for facilitating conflict resolution.

4) The multiple indicator evaluation approaches for network indicator synthesise in these models are more dependent on assessment standards and unsuitable for processing high-dimensional data. Advanced new traffic complexity or regional collision risk evaluation techniques that can accommodate big traffic data to better identify traffic complexity or collision risk patterns and support traffic alerts is essential and promising.

These challenges are yet to be addressed in the current literature. An overall solution will, therefore, no doubt, require a new holistic framework involving the advanced models performed jointly. However, it is, in return, very beneficial to develop a feasible and reliable regional traffic collision risk evaluation model from both theoretical and practical perspectives. This study, therefore, aims to propose a new collision risk evaluation approach to achieve a proper combination of both the global and local risk patterns, to offer a complete comprehension of a traffic situation as well as to cope with the limitations in the current works. This will shift the paradigm of the current ship collision risk avoidance practice by moving from a single to a multi-level analysis.

2.2 AIS Data Applications in Maritime Safety Surveillance

Owing to its high sampling frequency, wide coverage, and accessibility of rich information, the applications of AIS data have attracted growing attention from academic circles and bring great potential to maritime traffic behaviour analysis and ship collision risk characterisation. In particular, the improvements in data acquisition, storage, and processing have resulted in an increasing number of practical and advanced applications of AIS data in navigation safety-relevant research. A detailed literature review of AIS data applications has been documented in (Svanberg et al., 2019; Xiao et al., 2019a; Yang et al., 2019). This subsection is dedicated to investigating the latest progress of AIS application on maritime traffic safety surveillance. More specifically, it focuses on the following aspects: 1) The overview of AIS data in Section 2.2.1; 2) maritime traffic pattern mining and knowledge extraction in Section 2.2.2; 3) maritime traffic prediction in Section 2.2.3; and 4) maritime traffic partitioning in Section 2.2.4.

Table 2.2. Related works about ship traffic complexity or regional collision risk models.

Methods	Research focus	Model considering multi-view collision risk	Model handling dynamic traffic	Model identifying key influential ships	Model adaptive to water areas	Traffic information dimension	Model considering influencing factors
Wen et al. (2015)	Marine traffic complexity	No	No	No	Open sea	One (space)	Traffic density, ship dynamic attributes
Zhang et al. (2019)	Regional ship collision risk	No	No	No	Open sea	One (space)	Traffic density, ship dynamic attributes, ship domain
Sui et al. (2020)	Marine traffic complexity	No	No	No	Open sea	One (space)	Ship dynamic attributes, traffic topological features
Liu et al. (2019)	Regional ship collision risk	No	No	No	Open sea	Two (time and space)	Ship domain, collision avoidance manoeuvre
van Westrenen & Ellerbroek (2015)	Single ship complexity in multi-ship situation	No	No	No	Open sea	Two (time and space)	Ship domain, conflict resolution space

2.2.1 The Overview of AIS Data

The AIS was created in the 1990s, with the aim of decreasing ship collisions and improving navigation safety (Yang et al., 2019). It broadcasts and receives messages based on a receiver installed in a ship, allowing the nearby ship movements and costal information to be tracked and monitored. Moreover, the AIS can support the communication between ships and coastal authorities over a large area. Within the Safety of Life at Sea (SOLAS) convention in 2002, the International Maritime Organization (IMO) enforced all ships above 300 gross tonnage and all passenger ships to be deployed with an AIS transmitter system to facilitate the transition and exchange of all message types. This requirement was further extended to most commercial ships in 2010 and fishing ships in 2014. As a result, the AIS system becomes a reliable and rich information source for maritime traffic monitoring purposes.

The messages broadcast by the ships' AIS transceivers can be divided into three categories: dynamic messages, static messages, and voyage-related messages (Svanberg et al., 2019). Dynamic messages are transmitted every 2-12s that depend on the speed of a ship when it is underway, and every 3 min when it is moored or at anchor. The automatically and continuously updated dynamic information includes time, ship location, speed, course, *etc*. Static messages are transmitted every 6 min, regardless of the navigational status. They are almost never changed, involving information such as MMSI, ship type, ship size, ship name, *etc*. Voyage-related messages are manually stored and processed with a transmission frequency of 6 min, including information on such as draught, destination, and Estimated Time of Arrival (ETA) at the destination, *etc*. A detailed classification and description of the AIS messages are provided in Table 2.3.

Indeed, the AIS system not only enhances maritime safety through the updating of navigation information, but also offers an easy-to-access and powerful database for maritime researchers and practitioners. The AIS data in a given water area can be collected to construct a source of big data for maritime traffic analysis and exploration. However, it is not immune to data errors and inaccuracies due to technical malfunctions and failures, data transmission, poor sensor calibration, or other causes (Yang et al., 2021). For example, static and voyage-related information can be manually and incorrectly entered into the systems, while dynamic information produced by the sensors can be erroneous during data collection, transmission, and reception. Therefore, it is essential to eliminate the possible errors/noises before the data application.

Table 2.3. Classification and description of AIS messages.

Data field	Type	Description
Time stamp	Dynamic	Second field of UTC time
Longitude	Dynamic	Longitude in decimal degrees
Latitude	Dynamic	Latitude in decimal degrees
SOG	Dynamic	Speed of ship over ground (knots)
COG	Dynamic	Course of ship over ground (degrees)
True heading	Dynamic	Heading of ship (degrees)
Rate of turn	Dynamic	How fast the ship is turning, right or left range from 0-720° per minute
Navigational status	Dynamic	The status includes at anchor, underway, moored, *etc*.
MMSI	Static	Maritime Mobile Service Identify, identification number
Ship type	Static	The predefined ship types
Ship size	Static	Length and width of the ship
Ship name	Static	Name of ship
Call sign	Static	Ship radio call sign
Draught	Voyage-related	Current draught of the ship, ranging from 0.1-25.5 m
Destination and ETA	Voyage-related	Name of destination and estimated time of arrival at destination

To detect and filter the incorrect and inaccurate information inherent in the AIS data, various technical methods were developed to remove the noises, such as the data pre-processing procedure (Qu et al., 2011), error elimination method (Kang et al., 2018), and spatial logical integrity method (Zhao et al., 2018). In addition, due to the irregular, heterogeneous, and varying transmission frequencies of trajectory messages, some trajectory interpolation techniques, such as linear interpolation (Zhang et al., 2019), were designed to capture navigational traffic information at the same snapshot. In this study, a systematic data pre-processing procedure is constructed through the combination of the above models to ensure the effectiveness and reliability of the collected data.

2.2.2 Maritime Traffic Pattern Mining

Maritime traffic pattern mining is one of the most widely investigated research topics related to big AIS data applications. It is dedicated to maritime traffic knowledge extraction and traffic characteristic analytics and exploitation, thereby serving as a prerequisite for intelligent maritime monitoring and surveillance. Maritime traffic pattern mining relies on various data mining techniques to undertake maritime traffic analytics, traffic pattern exploration, and knowledge extraction. Classical solutions to traffic pattern mining involve vector-based, grid-based, and statistics-based approaches (Rong et al., 2021, 2022; Xiao et al., 2019a).

1) Vector-based methods

The vector-based methods extract the network waypoints (*i.e.*, nodes) and routes (*i.e.*, edges) to formulate the maritime traffic network, allowing the ship motions and traffic patterns over busy waters of interest to be characterised as a high compactness graph-based representation (Xiao et al., 2019a). Typically, the pre-processing of ship trajectories is a prerequisite for traffic network construction through clustering algorithms. Theoretical maritime traffic network modelling involves two important components. One component is to adopt clustering techniques such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Arguedas et al., 2017) and Ordering Points To Identify the Clustering Structure (OPTICS) (Rong et al., 2022; Yan et al., 2020) to extract the waypoints, including static points (*e.g.*, port and anchorage area), and entry and exit points. The other component uses a maritime route learning method to detect the ship trajectories following identical itineraries. Leveraging the established maritime geographical networks, they contribute to supporting maritime traffic surveillance (Arguedas et al., 2014), assisting in anomaly detection (Rong et al., 2022), facilitating route planning (Pallotta et al., 2013), and helping to understand maritime traffic patterns (Arguedas et al., 2017). However, maritime traffic following regular behaviour patterns is the basic premise for the applications of these methods, and it is highly problematic. They reveal the weaknesses when configuring the water areas where the traffic patterns are hard to categorise (Fiorini et al., 2016). Moreover, precise traffic network generation also heavily depends on effective waypoint clustering and extraction. Further detailed modelling that incorporates more traffic features, such as course and speed distribution, should be developed to effectively differentiate the traffic features and improve the accuracy of geographical networks.

2) Grid-based methods

The grid-based methods discretize the target maritime traffic area into indexed grids. Each grid is attached with essential property statistics (*e.g.*, traffic density, course and speed) to characterise the maritime traffic scenarios. The intention is to construct the gridded database to reduce the data scale and facilitate efficient retrieval and search operations of maritime knowledge. Based on the gridded database, various maritime traffic layers, such as traffic route information and traffic distribution information, can be established to identify the traffic spatial-temporal patterns (Ristic, 2014), differentiate the anomalous behaviours (Osekowska et al., 2014), investigate the traffic motion mechanism for maritime situation prediction (Tsou, 2010), and discover correlations between the local traffic pattern and near collision hotspots (Rong et al., 2021). For example, Xiao et al. (2017) populated the AIS data into structured grids to support the application of a clustering algorithm to extract the waterway and waypoint patterns. However, these methods are only suitable for small-scale waters and cannot tackle the intense computational load required to support the analysis in large-scale water areas (George et al., 2011). Additionally, the prior determination of the grid size is a problematic issue that highly depends on the local traffic features.

3) Statistics-based methods

The statistics-based methods analyse the traffic characteristics and conduct quantitative modelling to reveal the distribution profile of traffic properties. Examples include the identification of distribution characteristics of ship traffic (Xin et al., 2019; Yu et al., 2020b; Wu et al., 2018; Xiao et al., 2015), the capturing of hot-spot water areas (Wu et al., 2016), the investigation of temporal variations of density maps (Shelmerdine, 2015), the correlation examination between different traffic attributes (Kang et al., 2018), the analysis of spatio-temporal behaviours of ship trajectory (Ahmed et al., 2022; Li et al., 2018), and the visualisation of maritime traffic situations (Greidanus et al., 2016). These studies set the foundations for enhancing maritime traffic situation interpretation, determining important traffic parameter thresholds, and facilitating anti-collision decision-making. Notably, these works mainly support the fundamental statistical analytics of traffic features. For more advanced traffic characteristic exploration, they need to work with other advanced technologies to support high-level MSA. For example, Rong et al. (Rong et al., 2019) developed an uncertain ship motion prediction approach for trajectory anomaly detection by combining the ship acceleration distributions with a data-driven non-parametric Bayesian model.

Working towards MSA, all three categories of approaches provide essential prior knowledge for monitoring, analysing, and understanding the maritime traffic situation. They show great potential for tackling challenging traffic scenarios in complex waters and assisting in maritime traffic surveillance and management. Table 2.4 presents a summary of maritime traffic pattern mining methods. Thanks to the rich information in the AIS-based trajectory data and the improvement in data quality, this study conducts AIS data-based maritime traffic knowledge mining in complex waters from the following aspects:

1) Extract ship motion uncertainty patterns in Section 3.3.2.3.
2) Identify traffic conflict spatio-temporal distributions in Section 3.4.3.3.
3) Capture maritime navigable water areas and establish a maritime traffic network in Section 4.3.1.2.
4) Track multi-ship encountering scenarios in Section 5.4.1.
5) Determine the number of regional collision risk levels in Section 6.3.2.2.

It should be noted that the above maritime knowledge mining methods highly rely on the batch analysis of historical maritime data sets (*e.g.*, months or years) to provide essential knowledge for maritime surveillance and management (Xiao et al., 2019a, 2020). However, they offer fewer guidelines for maritime management authorities and operators to comprehend traffic situations in real-time. Therefore, some works associated with real-time maritime surveillance based on AIS data application are presented in Sections 2.2.3 and 2.2.4.

Table 2.4. A summary of maritime traffic pattern mining methods.

Category	Advantages	Limitations	Knowledge usage
Vector-based methods	1) allow the traffic patterns to be described compactly. 2) help characterise the regional traffic through a graph-based traffic network.	1) have difficulty in handling water areas where traffic patterns are hard to categorise. 2) highly depend on the precise waypoint clustering and extraction.	Maritime traffic surveillance. Anomaly detection. Route planning. Maritime traffic visualisation. Traffic prediction. Other advanced MSA.
Grid-based methods	1) allow the traffic information to be stored in individual grids by discretizing the target maritime traffic zone into a grid-decomposed geographical space. 2) support efficient retrieval and search operations of maritime knowledge.	1) more adaptive to small-scale waters. 2) need the prior determination of the grid size. 3) normally require that the size of each cell is unified.	
Statistics-based methods	1) help conduct quantitative modelling for traffic features. 2) allow revealing the distribution profile of traffic properties. 3) enable determining important traffic parameter thresholds.	1) only support basic statistical analytics of traffic features. 2) require to be combined with other techniques for more advanced traffic characteristic exploration.	

2.2.3 Maritime Traffic Prediction

Maritime traffic prediction employs reasonable input and output to construct mathematical functions or models for prediction applications. It is among the most recent and relevant research topics because it is one of the indispensable components for proactive traffic surveillance and management (Gan et al., 2016, 2017; Xiao et al., 2019b; Zhang et al., 2022). Many types of machine learning-based techniques and algorithms, such as SVM (Qi and Zheng, 2016), random forest (Young, 2017), associative learning (Rhodes et al., 2007), and exponential smoothing model (Sang et al., 2016), have been applied to predict the ship trajectory prediction based on the rich historical ship trajectory data. Apart from the above machine learning-based methods, neural network techniques have been widely explored in ship navigation state and trajectory forecasting due to their strong knowledge mining and prediction ability (Liang et al., 2021, 2022). Advanced neural networks for ship trajectory prediction have involved Artificial Neural Network (ANN) (Daranda, 2016; Sang et al., 2016), Generalized Regression Neural Network (GRNN) (Borkowski, 2017), Back-Propagation (BP) network (Xu et al., 2012), neuro-evolution ANN (Łącki, 2016), and generic ANN (Daranda, 2016; Young, 2017). These works focus on how to rationally make use of the data training sets, *e.g.*, AIS trajectory-based data, to construct a prediction model with proper input and output.

In terms of different data training sets, the neural network-based models can be classified as one-time training (Daranda, 2016) and adaptive training procedure (Borkowski, 2017). The one-time training procedure needs to exploit information from all historical traffic data collected over a long time. It is a typical off-line training process that can incorporate all situations that may happen. On the contrary, the adaptive training procedure needs to update the prediction model by keeping training the latest collected trajectory information. This type of method normally performs more precisely in most cases because it provides an incremental way to learn the model structure (Xiao et al., 2020). On the other hand, it also requires a high computational cost due to the adaptive training process. Hence, the two types of neural network-based models demonstrate different merits in terms of prediction accuracy, efficiency, and practical usage. In the context of maritime intelligence surveillance, traffic prediction, collision detection, and conflict resolution constitute the base of the operational authorities' task, while traffic prediction is the first basic module and is fundamental to providing precise collision estimations and supporting practical collision evasion actions. Therefore, these trajectory prediction methods enhance MSA and safety management capabilities to a large extent by facilitating the perception of forthcoming traffic situations. For example, some research studies (Rong et al., 2022; Xiao et al., 2017) developed ship trajectory prediction models to estimate future traffic hot-spots (*e.g.*, traffic speed and density) to assist in collision alerts and route planning.

Nevertheless, the above prediction approaches are developed based on a pre-assumption that the future ship trajectory can be fully and precisely predicted without considering the ship motion uncertainty. As mentioned in Section 2.1.2, the uncertainty of potential ship movements is inevitable and subject to the influence of navigation plan or intention, environmental disturbances, and technical errors, *etc*. Regarding this issue, Kalman Filter (KF) is a preferred prediction technique that considers the ship motion uncertainty as white noises (Huang et al., 2020). In the road traffic field, the holonomic models, kinematic models and KF technique were incorporated together to figure out the ship motion dynamics and uncertainties (Shah et al., 2016). In the meantime, various variations of KF, such as probabilistic filter (Wilthil et al., 2018), extended KF (Fossen, 2018), and Interacting Multiple Model Kalman Filter (IMMKF) have been used for road trajectory prediction. These models have rational and reliable performance in accurate trajectory prediction within a short period but encounter challenges in handling the trajectory changes caused by the ship manoeuvre behaviours (Lefèvre et al., 2014).

According to the survey by Huang et al. (2020), one type of trajectory prediction method, namely interaction-aware prediction, is the most accurate approach, compared with the physics-based, manoeuvre-based prediction models. This is because this category of methods assumes that ships estimate each other’s trajectories by exchanging their navigation plans or intentions through communications, whereas each ship has more relevant information related to its own future trajectory. Several recent studies (Chen et al., 2018, 2019; Zheng et al., 2016) have taken the advances of this type of method in theory to obtain the planned trajectories via “route exchange”, thereby supporting ship train formations in cooperative multi-ship systems. In light of this, the uncertain trajectory prediction in this study is conducted by assuming that each ship obtains other ships' navigation plans or planned trajectory information through interaction. Then an uncertain ship prediction model is developed by modelling the ship motion as a deterministic motion correlated with the ship navigation plan plus a stochastic component given by various perturbations. Different from the existing works that assume the distribution of traffic motion uncertainty components follow the commonly used Gaussian (or approximated Gaussian) distributions (Cho and Kim, 2017; Park and Kim, 2016; Rong et al., 2019; Yepes et al., 2007), this study extracts the real ship spatio-temporal uncertainty patterns from the historical trajectories based on an AIS data-driven procedure.

2.2.4 Maritime Traffic Partitioning

Because of economic globalization, the transport demand growth, and the development of emerging technologies (*e.g.*, autonomous ships), maritime traffic situations have become increasingly complicated and sophisticated, especially in complex waters (*e.g.*, ports). The traditional MSA methods, such as ship trajectory prediction and collision risk estimation, reveal challenges in handling the ever-growing complexity of traffic scenarios. Therefore, new advanced MSA techniques and tools are urgently needed for better maritime traffic surveillance and ship collision risk management.

Within this context, detecting clusters of encounter ships based on real-time AIS-based trajectory information has become an emerging research topic (Liu et al., 2019a; Zhen et al., 2017, 2021). It can enhance maritime surveillance capabilities and relieve surveillance operators' management pressure by identifying potentially multiple encountering ships with high spatio-temporal interactions. However, the literature on identifying real-time high-risk multi-ship encounters in complex water areas is still extremely limited, despite its crucial role in decreasing the difficulty of situational awareness and further guiding ship anti-collision risk management. Additionally, the current relevant research in the maritime domain applied the density-based clustering algorithm, *i.e.*, DBSCAN, to detect clusters of encounter ships and filter out the relatively safe ships, suffering from some drawbacks, as follows:

1) Only the spatial distance among ships is considered when conducting maritime traffic clustering, which is insufficient to reveal the complex dependencies of encounter ships. To

reflect different aspects of ship traffic interactions simultaneously, it is of paramount importance to identify the encountering traffic clusters by fully considering the multiple dependent interrelationships (*e.g.*, spatio-temporal proximity and conflict severity) among ships.

2) These works detected traffic clusters or multi-ship encounters based on traditional Euclidean/physical distances among ships but yet considered the influence of restricted geographical waters on the spatial distance calculation. Evidently, it is problematic to overlook the effects of water topography on spatial distance measurement because the two spatially close ships (of a short distance) may be blocked by obstacles, *e.g.*, islands and skerries, especially in complex port waters.

3) The adopted clustering techniques (*i.e.*, DBSCAN) of these works reveal challenges in figuring out various interrelationships (*e.g.*, conflict severity) among ships as well as discovering the traffic clusters in waters with varying traffic densities. The high complexity of ship spatio-temporal distribution, the unpredictability of ship motion behaviours, and the restricted geographical waters jointly create difficulties in pioneering an effective traffic clustering model. These unique and stochastic characteristics in maritime traffic justify the deficiencies of direct applications of arbitrary clustering techniques, as they often produce error-prone clustering solutions.

4) These studies ignored that the traffic situation dynamically evolves with time. Obviously, the interaction among ships would change over time. However, the current works detect the traffic clusters by only considering the traffic interactions at moment in time, which would produce unstable and inconsistent traffic clusters over time. This is detrimental to the continuous implementation of cluster-based anti-collision risk management strategies. However, a new dynamic traffic clustering model that can generate temporal stable traffic clusters will also facilitate the exploration of evolutionary co-behaviours among multiple participating ships.

Regarding the above issues, recent advances in urban transportation network partitioning using graph-based clustering techniques offer valuable insights (Gu and Saberi, 2019; Ji and

Geroliminis, 2012; Saeedmanesh and Geroliminis, 2016, 2017). Specifically, road network partitioning focuses on segmenting a heterogeneous traffic network into several spatially connected, homogeneous, and compact-shaped sub-regions in terms of indices like link speed and density. For example, both static and dynamic road network partitioning in Saeedmanesh and Geroliminis (2017) are explored, which has shown much attractiveness in decomposing traffic network complexity, identifying the congested network regions, and capturing the process of congestion formation and dissolution.

Inspired by the relevant works in the road traffic field, it is essential to develop a practical maritime traffic partitioning approach to partition the whole maritime traffic scenario into several interpretable traffic clusters to enhance maritime surveillance ability in a given high-traffic water area and ease the design and implementation of traffic safety management strategies. However, the literature review indicates that no maritime traffic partitioning using graph-based clustering techniques based on multiple properties of spatio-temporal interactions among ships is available in the literature. There have not been any relevant research findings reported on dynamic maritime traffic partitioning considering the evolutionary characteristics of ship traffic as well. Therefore, this study attempts to combine the graph-based clustering framework associated with the complex multi-attribute interrelationships among ships, as a hybrid pioneer, to investigate maritime traffic partitioning from both static and dynamic perspectives.

2.3 Research Gaps and Challenges

In summary, ship collision risk detection and estimation remain an active research topic while at the same time the increasingly complicated traffic conditions have required researchers to develop new advanced technologies. In the meantime, there remains much potential for making advanced use of AIS-based trajectory data to conduct intelligent MSA. The demands and needs for developing new technologies can be justified by the following limitations and challenges:

1) Limitations and challenges related to ship collision risk detection and estimation

1.1) There has been little collision risk estimation research that accounts for the dynamics and uncertainty involved in ship motion.

1.2) There has not been any systematic approach incorporating the multi-scale traffic properties into the maritime collision risk evaluation.

1.3) The current studies ignored the exploration and exploitation of the importance and contribution of single ship or multiple ships to the entire traffic risk in a given complex water, which provides little insight into risk management from a global surveillance perspective.

2) ***Limitations and challenges related to AIS data application in maritime surveillance***

2.1) The existing trajectory prediction methods revealed deficiencies in modelling the uncertain patterns of ship movements.

2.2) Detecting clusters of encounter ships is specific to the distance relations between ships without explicitly considering other spatio-temporal interrelationships, *e.g.*, conflict severity, which cannot incorporate the complex dependencies of encounter ships into traffic cluster detection.

2.3) The current traffic cluster detection models overlooked the effects of water topography on real spatial distance measurement, *i.e.*, assuming no obstacles exist between ships.

2.4) Advanced traffic cluster techniques that focus on the interactions among ships rather than the ships' own attributes are promising in maritime traffic partitioning.

2.5) Tracking temporal stable traffic clusters in dynamic maritime traffic brings interesting new challenges but shows potential to facilitate the continuous implementation of cluster-based anti-collision risk management strategies.

These research gaps must be filled and challenges dealt with to improve the situational awareness capability and ensure ship anti-collision safety. Therefore, four technical models in the subsequent chapters are developed as follows:

1) A probabilistic conflict detection model in Chapter 3 to solve limitations 1.1 and 2.1.

2) A static traffic partitioning model in Chapter 4 to handle limitations 2.2, 2.3 and 2.4.

3) A dynamic traffic partitioning model in Chapter 5 to cope with limitation 2.5.

4) A multi-view collision risk model in Chapter 6 to overcome limitations 1.2 and 1.3.

These new advanced technologies aided by big AIS data are expected to promote maritime traffic surveillance intelligence and ship navigation automation by integrating traffic characteristics in complex waters.

CHAPTER 3 PROBABILISTIC COLLISION DETECTION APPROACH UNDER SPATIO-TEMPORAL MOVEMENT UNCERTAINTY

In this chapter, a probabilistic conflict detection approach is proposed to estimate potential collision risk in various encounter situations. To do so, the spatio-temporal dependent patterns of ship motions are newly considered through quantifying the trajectory uncertainty distributions using AIS data. In the meantime, the estimation accuracy and efficiency are assured by employing a two-stage Monte Carlo (MC) simulation algorithm, which provides the quantitative bounds on the approximation accuracy and allows for a fast estimation of conflict criticality. Several real experiments are conducted using the AIS-based trajectory data in Ningbo-Zhoushan Port to demonstrate the feasibility and superiority of the proposed new approach. The results show that it enables the effective detection of collision risk timely and reliably in a complicated dynamic situation. They therefore provide valuable insights on ship collision risk prediction as well as the formulation of risk mitigation measures.[1]

3.1 Introduction

Maritime transportation plays a significant role in global economic development. However, the growing shipping traffic volume over the past decades has resulted in high maritime traffic densities or complexity (Chai et al., 2017; Yu et al., 2019, 2021), particularly in the waters near ports. It makes ship collisions appear among the most frequently occurring maritime accident types (Weng et al., 2018; Zhang et al., 2017). In particular, due to their high traffic volumes, such water areas as the Singapore Strait, the Ningbo-Zhoushan Port, and the Northern Baltic Sea are exposed to an extremely complicated traffic situation, in which heavy traffic, high maritime transportation dynamics and changeable ship motion behaviours often occur. This leads to increasing concerns on the incompetency of traditional risk approaches to maritime conflict detection and challenging demands on new capable models for ship collision risk

[1] This chapter contributed to journal paper [1].

perception.

In response to such concerns, a variety of methods have been developed for the quantitative analysis and detection of ship collision risk (*e.g.* (Chen et al., 2019; Du et al., 2020b; Goerlandt and Montewka, 2015b; Huang et al., 2020; Kulkarni et al., 2020; Li et al., 2012; Tu et al., 2017)). They provide a quantitative basis for implementing ship collision risk mitigation strategies. In recent years, one class of collision risk estimation methods that detect potential dangerous encounter events from AIS data using the concepts like "conflict" (Debnath and Chin, 2010; Weng et al., 2012; Weng and Shan, 2015) or "near miss" (Zhang et al., 2015, 2016, 2020) has attracted much research interest. However, the majority of them estimate the collision risk with a strong assumption that the engaged ships will keep the observed velocity in the near future, or the ship trajectories can be accurately predicted in advance, overlooking the effects of the dynamic and uncertain characteristics of ship motions. This strong assumption often results in inaccurate conflict or near-miss assessment in reality, especially under highly complicated and dynamic traffic situations. This is because some ships may take one or more turning manoeuvres during the encountering process constrained by their navigation plans or water topography. Moreover, it is extremely hard to accurately predict the ship trajectories due to the uncertainty by various influencing variants such as environmental, physical, and human factors. Furthermore, the prediction uncertainty and/or errors are prone to increase gradually over time (Park and Kim, 2016; Rong et al., 2019). Thus, the performance of these models on risk analysis and prediction becomes questionable and arguable in some practical cases. Another research gap that needs to be addressed in urgency is that most of the current ship collision risk research is targeted on ship-pairs and fails to detect potential conflict in multi-ship encounter scenarios. It therefore hinders their applications in congested waters where multi-ship encounters are frequently occurring (Liu et al., 2019b). Consequently, a dynamic risk estimation model, that can incorporate the spatial-temporal motion uncertainty of multiple ships, becomes essential in order to realize the real-time and accurate evaluation of ship collision risks under high uncertainty.

This study aims to develop a probabilistic risk approach for ship CD that 1) is adaptive to multi-ship encounters in high traffic waters and 2) can take into account the effects of uncertainty (or potential variations) inherent to the spatial-temporal motion of ships. By doing so, a novel CD approach is proposed from a probabilistic risk viewpoint, where an AIS data-driven analysis is conducted to extract the engaged ship trajectory uncertainty distributions. Compared to the empirical modelling of the PDFs of trajectory uncertainty components as Gaussian distributions (Lee et al., 2009; Matsuno et al., 2015; Park and Kim, 2016; Prandini et al., 2000; Rong et al., 2019), this work pioneers to identify the time-dependent position and course uncertainty patterns by mining the trajectory information from historical AIS data. Based on the predicted ship trajectories, the conflict criticality in multi-ship encountering is estimated. Given that the addition of ship motion uncertainty in the model makes the computation of conflict probability very costly, a two-stage MC simulation algorithm is designed and incorporated to efficiently estimate the conflict criticality, while providing the quantitative bounds to ensure the estimation accuracy. The performance of the proposed approach is finally experimentally validated by using real AIS-based trajectory data in port.

More specifically, the rest of the chapter is organized as follows. Section 3.2 details the difficulties and solutions of constructing a probabilistic CD model. In Section 3.3, the proposed probabilistic CD approach is introduced in detail, including the conflict criticality measure, ship motion modelling, and conflict probability estimation. In Section 3.4, the spatio-temporal uncertainty patterns of ship trajectories are extracted and fitted, and the effectiveness and applicability of the proposed models are tested and demonstrated using real data-based experiments. Conclusions are summarised in Section 3.5.

3.2 Problem Statement

In general, the currently available CD methods can be mainly divided into two classes: deterministic and probabilistic (Matsuno et al., 2015). The deterministic approach projects the current state into the future along a single trajectory, *i.e.*, the future trajectories are assumed to be fully known in advance. This class of methods is simple and straightforward but overlooks the trajectory deviations caused by various sources of uncertainty. Currently, the majority of the existing collision risk estimation research in the maritime sector falls within this category, as reviewed in Section 2.1.2. The probabilistic approach describes the potential variations of the predicted trajectories by using PDFs, from which the probability of a conflict is computed. Thus, this type of approach can better reflect the reality and is more effective to estimate collision risks under a high level of uncertainty. As the probabilistic CD is a relatively emerging topic under development in the maritime transportation domain, the relevant research in all traffic and transport fields (*e.g.*, air) is critically analysed.

According to the statement in Section 1.3, probabilistic CD modelling faces two challenges when being applied in a real environment.

1) How to construct the dynamic and uncertain ship motion prediction model

The uncertain ship trajectory forecasting normally includes two important components: the deterministic motion component and the stochastic motion component. The deterministic motion component associated with the navigation plans or planned trajectory information (including dynamic information of future trajectories) can be easily obtained through communications between ships, as stated in Section 2.2.3. The stochastic component reveals various perturbations influencing the ship movements, *i.e.*, the PDFs of future prediction errors. Commonly, the position and/or heading course prediction errors in the literature are assumed to be Gaussian (or approximated Gaussian) distributions with zero mean (Cho and Kim, 2017; Park and Kim, 2016; Rong et al., 2019; Yepes et al., 2007) and their variances are expected to grow linearly or quadratically with time (Jilkov et al., 2018; Paielli et al., 2009; Park and Kim, 2016; Prandini et al., 2000). However, these hypotheses may be problematic and need to be verified, to avoid any false conflict estimation and wrong conflict avoidance decision. In addition, there is some probabilistic CD research that takes into account the trajectory uncertainty using the reachable sets (Huang and van Gelder, 2020; Yang et al., 2016; Yu et al., 2019). Despite that, they can provide the reachable domain boundaries of all possible future ship or aircraft movements but cannot offer the specified probability distribution of the potential states in the reachable sets. AIS data, as a valuable source of information, is widely adopted for knowledge extraction in the maritime traffic domain (see Section 2.2.2), Hence, it is promising to extract the ship spatio-temporal motion uncertain patterns from historical AIS data.

2) How to compute the conflict probability based on uncertain ship future trajectories

Conflict probability computation methods in the literature are categorised into Analytical approximations (Baek and Bang, 2012; Hwang and Seah, 2008; Liu and Hwang, 2011), MC simulation (Jilkov et al., 2018), Gridding methods (Hao et al., 2018; Huang and van Gelder, 2020; Yu et al., 2019), and Markov chain approximations (Prandini and Hu, 2006). Each type of method has its own strengths and weaknesses (see Table 3.1). In these methods, the MC simulation is the least restrictive because it enables the non-stationary and non-Gaussian processes, any dependencies and scenarios involving multiple ships to be modelled and evaluated (Blom et al., 2001). In addition, it also allows the combination with any types of conflict measure models (Kochenderfer et al., 2010). Hence, it is used to perform the conflict probability computation task in multi-ship scenarios with a complex conflict measure model. However, it is recognized that the assessment through MC simulation tends to be computationally intensive due to the slow convergence in the process of obtaining accurate results (Prandini and Watkins, 2005). It is therefore of great importance to improve the efficiency of the MC simulation when using it in this work.

Table 3.1. Comparison of the relevant conflict probability computation methods (Mitici and Blom, 2018; Prandini and Hu, 2006; Prandini and Watkins, 2005).

Methods	Analytical approximations	MC simulation	Gridding methods	Markov chain approximations
Number of ships involved in the model	Ship pair	Multi-ship	Multi-ship	Ship pair
Model allows non-stationary processes	No	Yes	Yes	No
Model allows non-Gaussian processes	No	Yes	Yes	Yes
Model allows dependency between variables	No	Yes	Yes	Yes
Type of conflict measure models	Circular	Any	Circular	Circular and elliptical
Computational costs	Very low	High	Very High	Low

This study proposes a probabilistic CD approach to address the above challenges by developing both an AIS data-driven procedure for ship motion uncertainty pattern mining and a two-stage MC simulation algorithm for efficient and accurate conflict probability computation. As a result, it will facilitate the ship navigators and maritime authorities to detect collision risks in complex maritime traffic waters.

3.3 Methodology: A Probabilistic Conflict Detection Approach

The probabilistic CD approach is characterised by the blocks shown in Figure 3.1. First, the basic concept of ship conflict and its criticality measure model are introduced to assess how safe the current ship encounter is. Secondly, the ship position in the look-ahead time horizon is predicted by incorporating the information on the ship navigation plan and the disturbances affecting the ship motion. Various sources of uncertainty may cause deviations of the prediction position. Thus, the PDFs of trajectory uncertainty components are extracted using historical AIS data to model the future trajectory probability distribution at each instantaneous time. Thirdly, the conflict probabilities in multi-ship encounters are computed based on the prediction position distributions to decide whether to issue an alert or not. For each ship, the minimal passing distances with its nearby ships are first computed based on the improved CPA method, to identify which target ships need to be concerned for potential collision risk calculation. After that, the conflict probabilities with these ships are estimated using a fast-improved MC algorithm implementation.

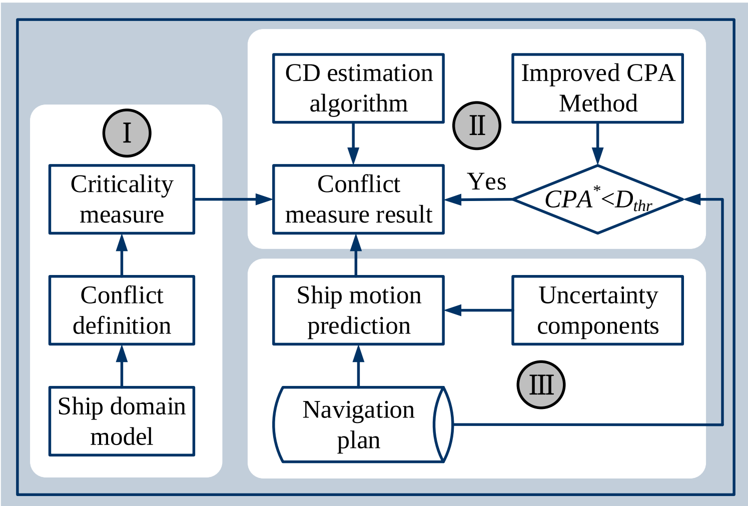


Figure 3.1. The framework of probabilistic conflict detection for encountering ships.

3.3.1 Conflict Definition and its Criticality Measure

A conflict occurs when the trajectories of two ships are predicted to violate a given set of prescribed separation distances. In this study, ship conflict is defined based on the ship domain model. An example of conflict identification is illustrated in Figure 3.2. In this figure, ships A and B are considered to be in conflict if the following formula is held in the near future.

$$Dist_{AB}(t) \leq SD_A(t) + SD_B(t) \tag{3-1}$$

where SD_A and SD_B are the distances from each ship centre to the boundaries of their ship domain area, and $Dist_{AB}$ is the distance between the own ship and target ship. The widely used ship domain model from (Fujii and Tanaka, 1971) that is suitable for the restricted areas with high-density traffic is adopted, which is an ellipse with a long radius of 6 L (L is the ship's Length Overall (LOA)) and a short radius of 1.6 L. In fact, the shapes and sizes of ship domains are heavily dependent on the study water's traffic density and traffic rules. An alternative approach is to design a ship domain model based on particular water areas' AIS data mining (Wang and Chin, 2016; Zhang and Meng, 2019), to determine the relationship between such impact factors as ship attributes, navigational environment and human factors, and domain sizes. However, the main concern in this study is to identify and quantify the conflict in a multi-ship encounter under the presence of ship motion uncertainty. It is the probability that the ship trajectories experience the violation of a set of the minimum allowed distances, thus causing a conflict.

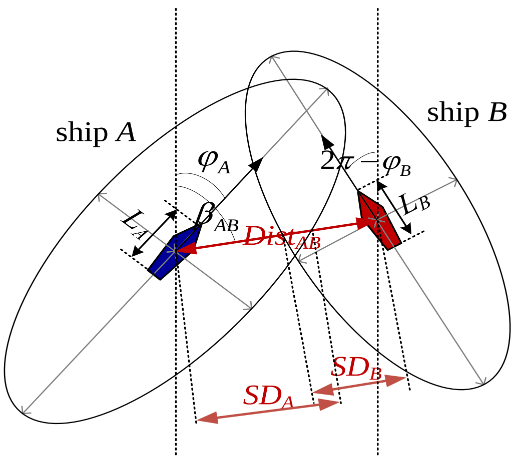


Figure 3.2. Definition of ship conflict.

The instantaneous probability of a conflict at time t ($PC(t)$) is given by the probability that the separation of the two ships is smaller than or equal to the prescribed separation distance, *i.e.*, $Dist(t) \leq SD_A+SD_B$, as follows:

$$PC(t) = \Pr[L(t) \leq 0] = \int_{-\infty}^{0} f_{L(t)} dL(t) \tag{3-2}$$

where $f_{L(t)}$ represents the PDF of $Dist(t)$-$SD_A(t)$-$SD_B(t)$.

To characterise an appropriate supporting metric to measure the criticality of a conflict ($C(\gamma)$), it is declared based on the maximum value of the conflict probabilities over a prediction horizon. This criterion has been widely adopted in the air traffic domain (Hernandez-Romero et al., 2019; Jilkov et al., 2018; Yang et al., 2016), as follows:

$$C(\gamma) = \max_{t\in[0,T_{CDH}]} PC(t) \tag{3-3}$$

where T_{CDH} is the predicted time horizon. Note that the CD horizon (*i.e.*, T_{CDH}) is set to be 15 minutes in terms of the work presented by Bakdi et al. (2021), as this study pays attention to the CD in the medium-term time horizon, *i.e.*, the order of tens of minutes.

3.3.2 Model of the Ship Motion

The uncertain trajectory prediction is a prerequisite for potential collision detection and evaluation. As mentioned in Section 2.2.3, the interaction-aware prediction method is adopted because of its high accuracy. That is, the planned trajectory information or navigation plans are assumed to be obtained based on the interaction among ships (Chen et al., 2018, 2019). Furthermore, an uncertain ship prediction model is developed by modelling the ship motion as a deterministic motion correlated with the ship navigation plan plus a stochastic component given by various perturbations. The details of the ship motion model are presented in the following subsection.

3.3.2.1 Ship Absolute Motion

Typically, a ship navigation plan consists of a sequence of waypoints $WP_{i=1, 2..., n+1}$, which specifies a piecewise linear nominal trajectory. For conflict estimation, the nominal ship trajectory is first computed with the assumption that each ship follows its navigation plan moving along the line connecting successive waypoints with a prescribed speed. Then, the position uncertainty is added to the nominal trajectory, from which the occurrence probability of conflict can be computed. As a result, the ship motion model in this study is composed of the following three components: 1) a continuous dynamic describing the laws of physics of the ship motion; 2) a discrete dynamic associated with the navigation plan; and 3) a stochastic component given by the ship motion uncertainty caused by environmental disturbances such as wind, waves, and currents, as well as mechanical and human factors.

Building on the above model, the predicted position of ship *A* in the future *T* moment can be expressed as follows:

$$\vec{S}_A(t_c + T) = \vec{S}_A(t_c) + \int_{t_c}^{t_c+T} \vec{V}_A(t)dt + R(\varphi_A(T)) \cdot \vec{Q}_A(T) \tag{3-4}$$

where t_c is the current time instant; $\vec{S}_A(t_c)$ is the initial position of ship *A*; $\vec{V}_A(t)$ denotes the nominal speed of ship *A* at time *t*, which is a piecewise constant function associated with the navigation plan; $R(\varphi_A(T))$ is the rotation matrix associated with the ship's nominal heading course $\varphi_A(T)$; and $\vec{Q}_A(T) = [Q_{A,x}(T); Q_{A,y}(T)]$ represents the uncertain components of ship prediction position. More details about Eq. (3-4) can be seen in Appendix A.

3.3.2.2 Ship Relative Motion

As the conflict occurrence probability is highly dependent on the relative motion between the encountering ships, the distance between them is first given as follows.

$$Dist_{AB}(t) = ||\vec{S}_A(t) - \vec{S}_B(t)|| \tag{3-5}$$

In addition, the ship domain boundary relations between encountering ships also have a significant effect on the conflict criticality (see Figure 3.2). Thus, the distance from the centre of ship *A* to its ship domain boundary along the line between the positions of the two ships is given by the following expression.

$$SD_A(t) = \left(\frac{1 + tan^2(\beta_{AB}(t) - \varphi_A^T(t))}{\frac{1}{{R_{L,A}}^2} + \frac{tan^2(\beta_{AB}(t) - \varphi_A^T(t))}{{R_{S,A}}^2}} \right)^{1/2} \tag{3-6}$$

where $\beta_{AB}(t)$ represents the predicted relative course of the position of ship B over that of ship A at time t (see Figure 3.2), $R_{L,A}$ and $R_{S,A}$ are the length of the semi-major axis and semi-minor axis of ship A's domain ellipse, and $\varphi_A^T(t)$ denotes the predicted heading course of ship A at time t. As the ship's course may vary slightly when sailing along the route derived from the navigation plan under the effect of various disturbances, its prediction uncertainty component has also been considered due to its significant impact on the length of SD_A. As a result, $\varphi_A^T(t)$ can be described as follows:

$$\varphi_A^T(t) = \varphi_A(t) + \alpha_A(t) \tag{3-7}$$

where $\alpha_A(t)$ represents the predicted course error component at time t, which will be introduced in detail in Section 3.3.2.3. In a similar way, the length of SD_B can also be obtained.

3.3.2.3 Extraction of Ship Position and Course Uncertainty Patterns

One of the most important tasks in the ship motion modelling is to identify the distribution functions of uncertainty components influencing the ship motion (*i.e.* $Q_{A,x}$, $Q_{A,y}$ and α_A in Eqs. (3-4) and (3-7)), since the accuracy of the estimated $C(\gamma)$ relies on the predicted ship state distributions to a large extent. To tackle this issue, an AIS data-driven procedure is designed to determine the PDFs of position and course uncertainty components. It consists of four steps: 1) Identification of trajectories' turning points; 2) Extraction of position and course prediction errors; 3) Correlation test of uncertain component data sets; and 4) PDF fitting of uncertain components.

To be more specific, the AIS data trajectories' turning points are first identified as the waypoints of ship navigation plans in terms of the Douglas–Peucker (DP) algorithm (Douglas and Peucker, 1973). This algorithm can compress line data in one trajectory by splitting them recursively to retain the important trajectory positions. Due to its great performance in running speed and accuracy, it has been widely used in ship trajectory compression (Zhang et al., 2016; Zhao and Shi, 2018). Therefore, it is adopted to simplify the trajectories and identify the ships' turn points. The details about the DP algorithm design can be found in Du et al. (2020a).

On the above basis, each ship's future nominal trajectory can be predicted based on their current state and the identified turn points. By computing the differences between the nominal prediction trajectory and the real trajectory from historical AIS data, the position and course prediction errors at each time moment over the predicted time horizon are extracted. An example of error computation is given in Figure 3.3. In this figure, points *A* and *A*' represent the predicted nominal position and the real position at time *t*, respectively. Considering a route-fitted coordinate system with *u* aligned with the ship's nominal sailing direction and *v* perpendicular to it, the ship's prediction position errors in its vertical and horizontal directions can be computed, as follows:

$$\Delta P_x'(t) = \sin\varphi\,(t) \cdot \Delta P_x(t) + \cos\varphi\,(t) \cdot \Delta P_y(t) \tag{3-8}$$

$$\Delta P_y'(t) = -\cos\varphi\,(t) \cdot \Delta P_x(t) + \sin\varphi\,(t) \cdot \Delta P_y(t) \tag{3-9}$$

where $\varphi(t)$ is the ship's predicted nominal course in time t, $\Delta P_x(t)$ and $\Delta P_y(t)$ represent the predicted longitudinal and lateral position errors on the original geographic coordinate system. As for the course error, it can be easily extracted based on the difference between the nominal prediction course and the real course. In this way, the data sets of the ships' nominal prediction position and course errors for every minute over the prediction time horizon can be collected. Since the correlations between these error data sets have an important impact on the evaluation accuracy when computing the probability of a conflict, the Pearson correlation coefficient is adopted to measure the dependence between each pair of data sets with the same time, before performing dataset PDF fitting.

Finally, the Kernel Density Estimation (KDE), a non-parametric estimation method (Silverman, 1986), is adopted to identify the PDFs of these data sets, through the following equation:

$$g(x) = \frac{1}{K'}\sum_{i=1}^{K'} \phi_h(x - x_i) = \frac{1}{K'h}\sum_{i=1}^{K'} \phi_h(\frac{x - x_i}{h}) \tag{3-10}$$

where ϕ_h is a kernel function with window bandwidth h that satisfies $\phi_h(x)>0$ and $\int_R \phi_h(x)\,dx = 1$, K' denotes the number of elements in the data set to be investigated within the bandwidth h. In this study, the Gaussian kernel is employed to determine the PDFs.

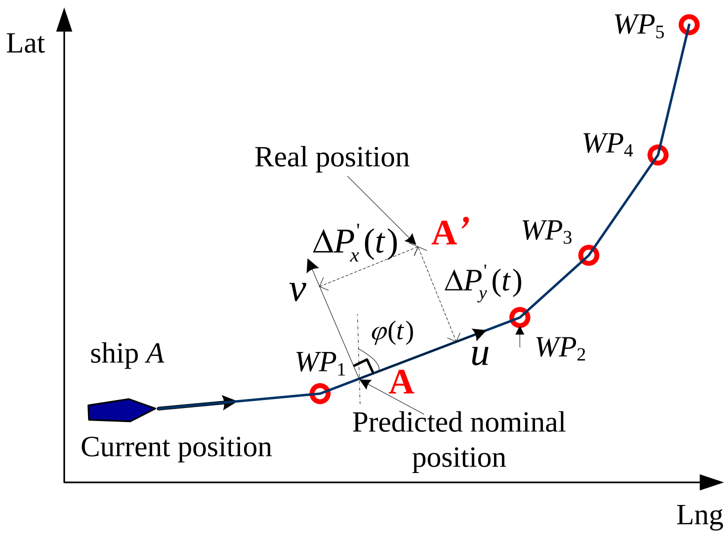


Figure 3.3. Illustration of computation of position and course prediction errors.

It should be noted that the $Dist_{AB}$, SD_A and SD_B in Eq. (3-1) are functions of the position and heading course prediction error components ($Q_{A,x}$, $Q_{A,y}$, $Q_{B,x}$, $Q_{B,y}$, α_A and α_B), so that whether Eq. (3-1) is held is a probabilistic event and its occurrence probability needs to be determined based on probability computation methods.

3.3.3 Conflict Probability Estimation

In reality, the Officer on Watch (OOW) needs to detect target ships with potential collision risk from a huge number of sailing ships within a given busy water before conducting ship conflict or collision risk estimation. For that, an improved CPA method is adopted to extract target ships spatially positioned close to the own ship in the near future, then a two-stage MC simulation algorithm is presented to estimate the $C(\gamma)$ level in multi-ship encounters.

3.3.3.1 Identification of Target Ships with Potential Collision Risk

The traditional way to calculate the minimum passing distance of two encountering ships is based on the CPA method. However, as mentioned in Section 2.1.2, this approach is used with the assumption that the ships are sailing linearly without changes in heading and speeds. To tackle this issue, an improved CPA-based method is adopted to cope with non-linear ship motion cases. Appendix B presents the equations for the calculation of minimum passing distance between ships. As a preliminary step of conflict probability estimation, the identification of potential conflict ships is undertaken based on the nominal prediction trajectories derived from the navigation plans. After obtaining the values of minimum passing distance, it can be preliminarily identified whether there are potential collision risks between the encountering ships in the near future.

3.3.3.2 Computation of Conflict Criticality in Multi-Ship Encounters

One of the biggest obstacles in the implementation of the CD approach is the computation of the probability of conflict occurrence, since there exists no derived analytical solution for $PC(t)$ in Eq. (3-2). The MC simulation is used for a solution (Mitici and Blom, 2018). Applications of a direct MC simulation are often computationally intensive, and hence speed-up improvement for direct MC is essential for certain online applications.

For a typical MC simulation, it consists of two loops, one for sampling iterations and the other for trajectory propagation (Yang et al., 2004). In the sampling iteration loop, it generates N groups of samples of random variables in terms of their prescribed PDFs, and each group of samples is then inserted into the stochastic model to find a deterministic solution. By using the ensemble of the deterministic solutions, one can finally obtain an estimated value. As the value of N in the sampling iteration loop defines the accuracy of the estimated solution, it needs to look for ways to improve the computation efficiency of direct MC from the trajectory propagation loop. In general, the values of conflict probabilities of encountering ships over a finite look-ahead time horizon tend to exhibit a sharp spike at some time instant, whereas they are relatively small elsewhere. In view of the fact that only the maximum value of the conflict probabilities over the prediction horizon requires to be estimated exactly, one can roughly extract the time points with higher conflict probabilities before executing a large number of iterations. Based on this principle, a two-stage MC simulation algorithm is developed to efficiently estimate the conflict criticality, in which the quantitative bounds on the approximation accuracy is also provided.

To determine how many iterations (N) are adequate to guarantee a desired accuracy of the estimation, Hoeffding's inequality (Prandini and Watkins, 2005) that describes the relation between N and the estimated accuracy is first given as follows:

$$N \geq \frac{log(2/\delta)(b-a)^2}{2\varepsilon^2} \tag{3-11}$$

where ε denotes the accuracy, 1-δ represents the confidence, a and b represent the lower and upper bounds of estimated values, which are 0 and 1, respectively. This inequality indicates that for finite N, one can ensure a certain accuracy ε for the estimator with confidence 1-δ. In this study, the accuracy is designed as 1% to provide an accurate conflict warning for practical applications. It requires a total of 15,000 iterations to achieve this accuracy with a confidence $1\text{-}2\times10^{-3}$.

Algorithm 3.1. Two-stage MC simulation algorithm.

Input: PDFs of random variables in different time moments $Q_x^{(t)}$, $Q_y^{(t)}$ and $\alpha^{(t)}$, number of iterations in the first stage N_{MC1}, number of iterations in the second stage N_{MC2}, prediction time horizon T, number of ships N.
Output: $C(\gamma)$
1: // Extract time point with higher conflict probabilities for ship A
2: **For** t = 1, 2,…, T **do**
3: Generate random sample vectors for each ship~$\{Q_{l,x}^{(t)}$, $Q_{l,y}^{(t)}$ and $\alpha_l^{(t)}$: $l = A, B, \ldots, N\}$ // length of sample vectors N_{MC1}
4: Compute the values of vectors $SD_A, SD_B, \ldots, SD_N$; $Dist_{AB}, \ldots, Dist_{AN}$ based on generated random sample vectors
5: c = count($SD_A + SD_B > Dist_{AB}$ || ,…, || $SD_A + SD_N > Dist_{AN}$)
6: $PC_1(t) = c/N_{MC1}$
7: **End for**
8: Find and rank the time points whose probability values are larger than $\max\{PC_1(t)\}-2\times[\log(2/\delta)/(2\times N_{MC1})]^{0.5}$, and then store at most the first two time points into T_2
9: // Execute a large number of iterations for time points in T_2
10: **For** $t \in T_2$ **do**
11: Repeat step 3-6 to obtain $PC_2(t)$ // length of sample vectors N_{MC2}
12: $PC(t) = (PC_1(t)\times N_{MC1}+PC_2(t)\times N_{MC2})/(N_{MC1}+N_{MC2})$
13: **End for**
14: $C(\gamma)=\max\{PC(t)\} \quad t\in T_2$

Algorithm 3.1 provides a detailed description of the proposed two-stage MC simulation algorithm. At the first stage, the conflict probability at each time instant over the prediction time horizon is computed roughly with a relatively small number of samples (*e.g.*, 1,000 iterations). Then the time points which may have the maximum probability of conflict are extracted and ranked in combination with the quantitative bounds on the approximation error obtained from Eq. (3-11). In this process, at most the first two ranked time points are retained for further accurate conflict probability computation when facing the cases where many time points are extracted, since retaining too many time points will increase the computational burden in the second stage. It should be pointed out that the cases that are required to extract too many time points usually occur when the estimated $C(\gamma)$ is small. In practice, if the estimated maximum conflict probability in the first stage is far below the threshold of conflict warning, it is not necessary to continue the conflict probability computation in the second stage, so as to reduce the waste of computational resources. In addition, the bounds derived from Eq. (3-11) are generally conservative (Prandini and Watkins, 2005), which means the real number of time points that may have the maximum conflict probability is less than the actually extracted. Therefore, it is acceptable to retain a small number of time points for the second stage. On the above basis, a more accurate $C(\gamma)$ can be obtained with a large number of iterations in the second stage. It is noteworthy that this approach is generic and can be adaptive to multiple ships (see lines 3-6 in Algorithm 3.1).

3.4 Applications and Case Study Results

3.4.1 Case Description and Data

To evaluate the effectiveness and feasibility of the proposed methodologies (including the technical models in Chapters 3-6), the Ningbo-Zhoushan Port is considered as the test site. It is a unique deep-water port with some of the densest traffic in the world in terms of cargo throughput (see Figure 3.4). There are more than 620 production berths, including approximately 170 large-scale berths above 10,000 tons and more than 100 super large-scale deep-water berths above 50,000 tons. The restricted geographical regions, various ship types, diversified movement behaviour, and the presence of complex environmental conditions expose it as a complicated and challenging scenario for maritime traffic risk analysis and management. These attributes jointly pose great challenges for maritime supervisors in effective MSA. Therefore, it is highly desirable to make use of this complex water area to validate the proposed methodologies.

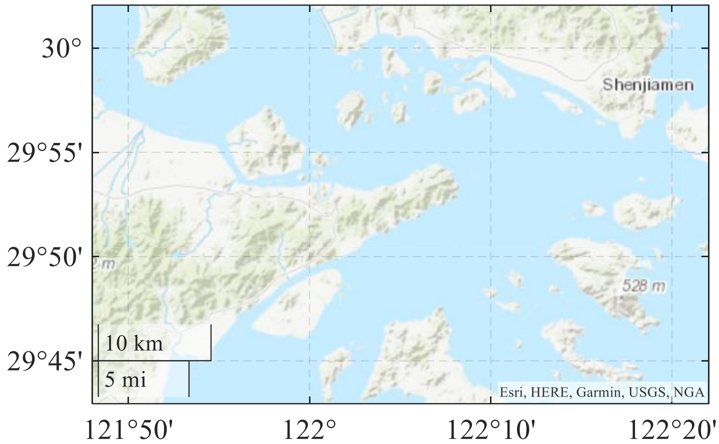


Figure 3.4. Hub area of Ningbo-Zhoushan Port, China.

The AIS-based ship trajectory data in the Ningbo-Zhoushan Port is deployed to constitute the input to maritime traffic analysis. A total of two months of AIS messages from 01/10/2018 to 30/11/2018 is collected, with the region under analysis bounded between latitudes 29°43'N-30°02'N and longitudes 121°52'E-122°22'E. The data source is collected from the Shanghai Maritime Safety Administration and is solely used for research purposes. In this study, the AIS data is composed of the following fields: MMSI number, time, longitude, latitude, SOG, COG, type, length, and breadth. As the ships such as fishing ships, pilot boats, and tugboats often exist together for their missions and may not abide by conventional maritime safety rules, the AIS messages of general merchant ships, including cargo ships and tankers, are used for experimental analysis.

Given that AIS information errors are inevitable because of various technical issues or other causes, a systematic data pre-processing procedure is implemented to cleanse the data. It includes the following steps: noise elimination of each ship attribute (Kang et al., 2018), trajectory extraction and separation, trajectory consistency confirmation (Zhao et al., 2018), and trajectory interpolation (Zhang et al., 2019), *etc*. In this way, it can reconstruct clean and accurate traffic trajectories for experimental analysis. More operation details for data pre-processing can be found in Appendix C.

After pre-processing the original data, the results can be validated through trajectory visualisation. Figure 3.5 presents the visualisation results of partially processed trajectories, revealing the absence of abnormal track points in each trajectory and the elimination of crossing land and unrealistic tracks along the border. This demonstrates a substantial improvement in track consistency quality.

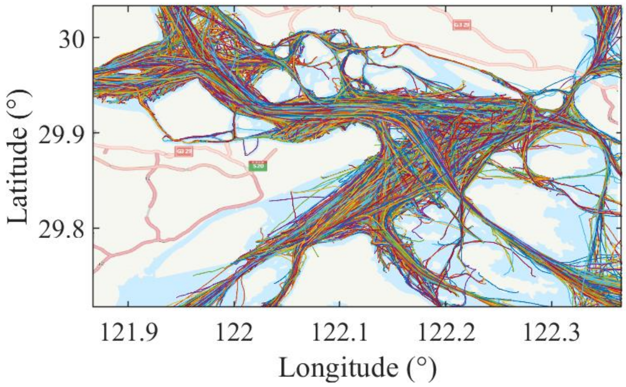
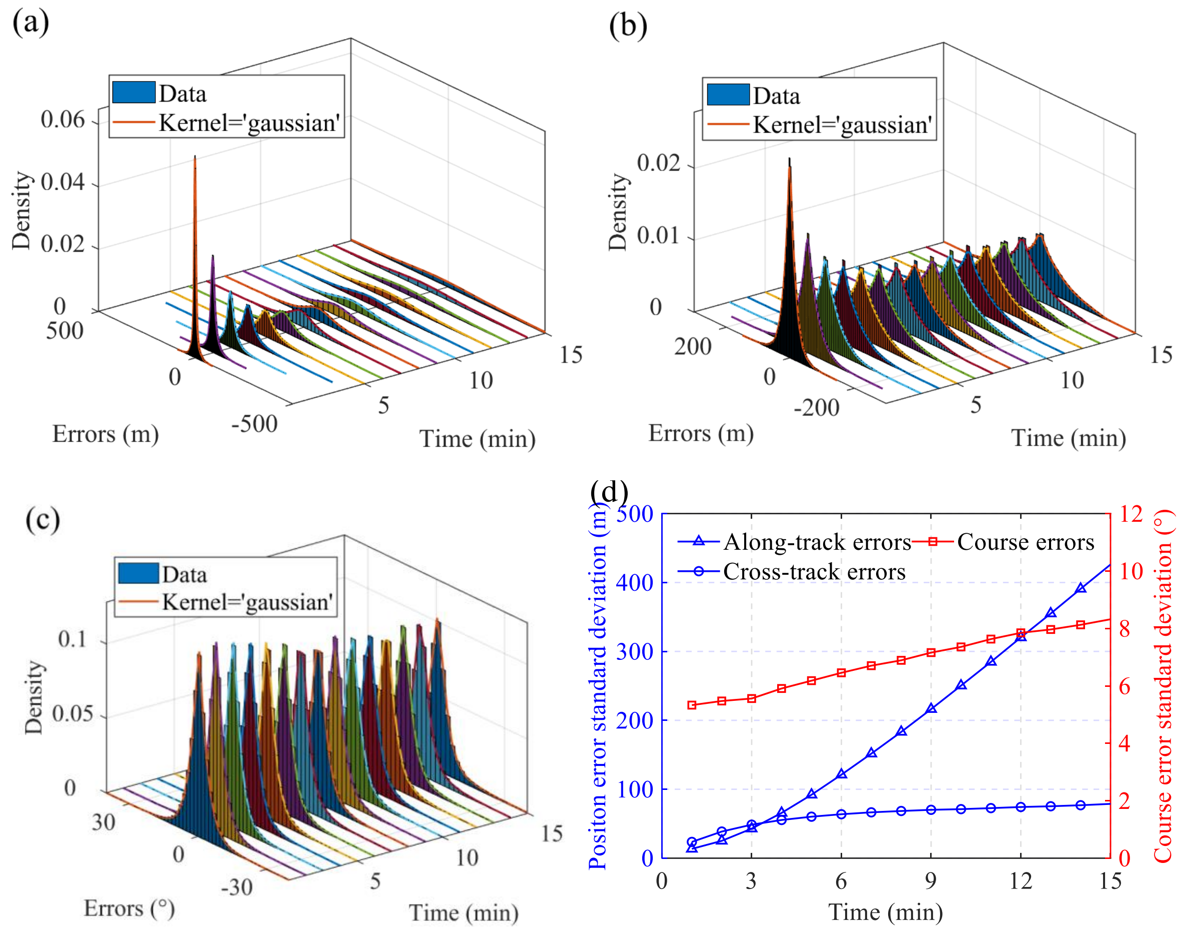


Figure 3.5. The ship trajectory visualisation after pre-processing.

3.4.2 Fitting Distribution Functions of Ship Position and Course Uncertainty Patterns

In this study, the data sets of the ships' nominal prediction position and course errors for every minute over a 15 min prediction horizon (the collision-warning time is set to be 15 min) are collected, by utilizing each ship's trajectory for error sampling. The Pearson correlation results show that except for the high correlation coefficients between the horizontal position errors and course errors in 1 and 2 minutes (larger than 0.4), the remaining data set pairs are insignificantly correlated and satisfy the hypothesis of no correlation with a significance level of 5% (Hollander et al., 2013). For simplicity, all error data sets are assumed to be statistically independent. In fact, this assumption is feasible for practical application since the extracted prediction errors in the first two minutes are smaller compared with those with prediction times larger than 2 min, which are relatively less influential to the $C(\gamma)$ outputs.

To check whether the position or course error data sets agree with a normal distribution, the Jarque–Bera test (Jarque and Bera, 1980) is selected for experimental testing. It is found that none of the position or course error data sets fits a Gaussian distribution. That is to say, the hypothesis that the Gaussian distribution can be utilized to reflect the trajectory prediction uncertainty is inaccurate in the maritime domain (Lee et al., 2009; Matsuno et al., 2015; Park and Kim, 2016; Prandini et al., 2000; Rong et al., 2019). In addition, some typical density distribution functions such as *t* Location-Scale, Stable, Logistic, Extreme Value and Generalized Extreme Value are also considered. The Kolmogorov-Smirnov test (Massey Jr, 1951) is used to measure how well these distributions fit the collected data sets. The results show that these distribution functions are still not appropriate because all *P*-values obtained using the Kolmogorov-Smirnov test are below 0.05. Consequently, the PDFs of these data sets are finally identified using the KDE method, because it has obvious superiority in fitting any distribution shape (Zhang and Meng, 2019). The corresponding fitting results are illustrated in Figure 3.6.



(a) Time-dependent PDFs of along-track prediction errors; (b) time-dependent PDFs of cross-track prediction errors; (c) time-dependent PDFs of course prediction errors; (d) standard deviations of position and course errors over the prediction time horizon.

Figure 3.6. PDFs of trajectory prediction errors.

Figures 3.6 (a)-(c) depict the error data set's PDF fitting curves along with their normalized bar charts for every minute over a 15 min look-ahead horizon. All these curves are approximately symmetric, with sharp turning points occurring near 0 and progressively descending to both sides. From Figure 3.6 (a), it is noticeable that the curves rapidly become lower and wider with time, indicating that the along-track prediction uncertainty grows significantly in time. In contrast, the cross-track error PDF curves exhibit a significantly different trend. According to Figure 3.6 (b), the curves change over time considerably in the initial stage but basically remain stable for the rest of the time horizon. As for the fitting curves of the course errors (see Figure 3.6 (c)), there are no significant changes with time.

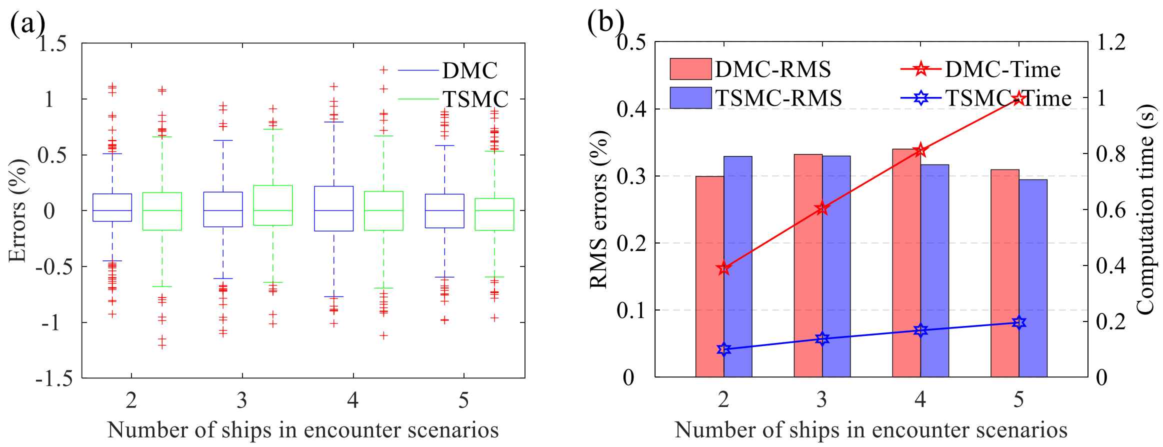
To further identify the change rates of these error data sets, the standard deviations for different uncertainty components over time are presented in Figure 3.6 (d). It can be found that the variations of standard deviations with time are basically consistent with those of fitting curves. Both the along-track and course error standard deviations grow linearly with time, in which the latter increase at a slower speed, while the cross-track error standard deviations increase fast initially but remain at a lower growth rate for prediction times longer than 3 min. In addition, it can be observed that the standard deviation of along-track errors is significantly larger than that of cross-track errors, especially as time goes on, reflecting the fact that the prediction trajectories in the vertical direction have a higher level of uncertainty. By embedding the PDFs obtained above into the CD approach, the real-time identification of the $C(\gamma)$ levels can be achieved.

3.4.3 Experiments and Results

In this subsection, several real experiments are performed to test and demonstrate the performance of the proposed probabilistic CD approach. It starts by checking the accuracy and efficiency of the proposed two-stage MC through comparison with direct MC. Then, two ship encounter scenarios including one ship-pair encounter and one multi-ship encounter derived from AIS data are introduced to explain how the proposed method is suitable for high traffic waters with complicated encounter situations. Applications of the proposed method on both real-time CD and off-line collision risk Hot-Spot identification are finally described.

3.4.3.1 Computational Performance Comparison

Figure 3.7 provides the error statistics for the accuracy and computational costs computed by the Direct MC (DMC) and two-stage MC (TSMC) with the different number of ships in encounter scenarios. For the computation of estimation errors of the two methods, the values obtained by performing the DMC simulation with 1,000,000 iterations are regarded as the true values. According to Figure 3.7 (a), there is no significant difference in the Boxplot of error statistics of the two methods, and almost all sampled results based on the two methods have an error within 1%. Furthermore, in terms of the Root Mean Square (RMS) errors of the estimated accuracy (see Figure 3.7 (b)), it can be found the proposed TSMC slightly underperforms the DMC with the different number of encountering ships. However, in terms of the performance of running efficiency, the proposed method has a huge advantage. It is clear from Figure 3.7 (b) that compared with the DMC, which is computationally demanding, the computational costs of the proposed method are much lower, and the advantage becomes more obvious with the increasing number of ships. That is, the proposed method requires much lower computational costs to yield the same accuracy as the DMC. Therefore, the proposed method can greatly enhance the computational efficiency while ensuring the accuracy of the approximate solution.

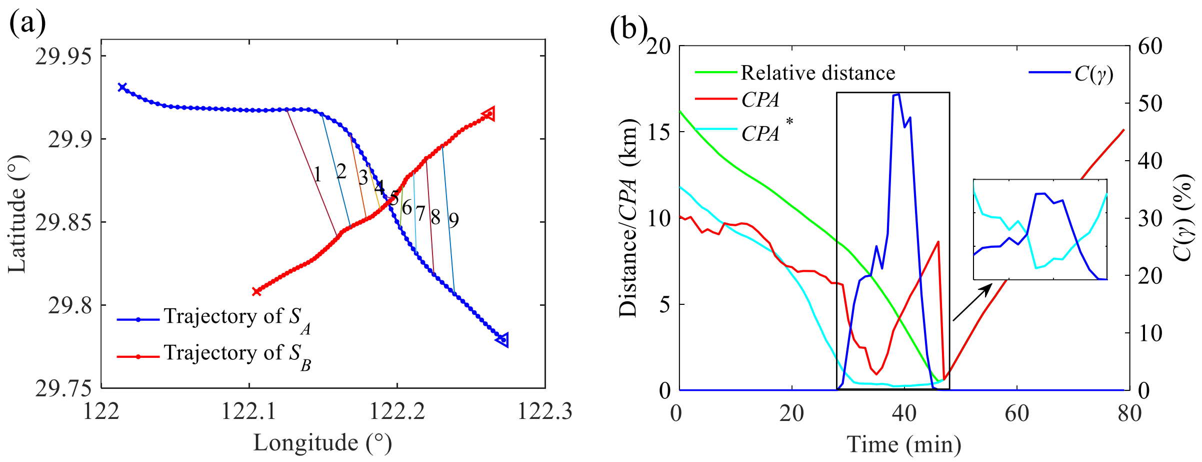


(a) Boxplot of estimation error distributions for DMC (N=15000) and TSMC (N_{MC1}=1000, N_{MC2}=14000); (b) RMS errors and computational costs for DMC and TSMC.

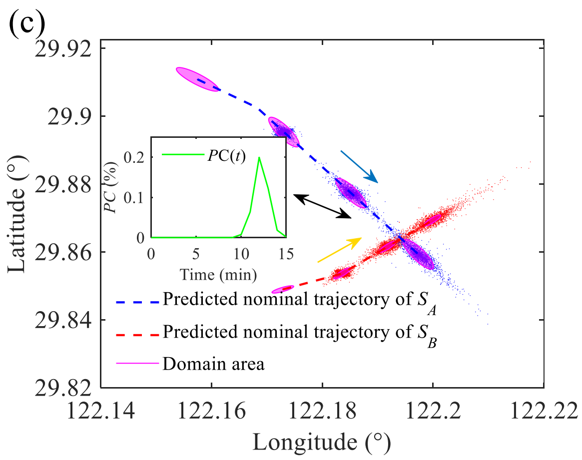
Figure 3.7. Comparison between DMC and TSMC in accuracy and computation efficiency.

3.4.3.2 CD Approach Test based on Ship Encounter Scenarios

To test the performance of the proposed CD approach under the condition that the encountering ships have changeable spatio-temporal motion behaviours, a ship-pair encounter scenario derived from the historical AIS data is presented (see Figure 3.8). The lines in Figure 3.8 (a) are the trajectories of the ship-pair involved in the encounter, where 'x' marks the ships' starting locations and '△' their final locations. It can be seen that one ship basically sails linearly, while the other has a turning behaviour during the encounter.



(a) Trajectories of ship pair; (b) risk variable evolutions of ship-pair encounter;



(c) illustration of prediction trajectories and *PC* of ship-pair at time t = 33 min.

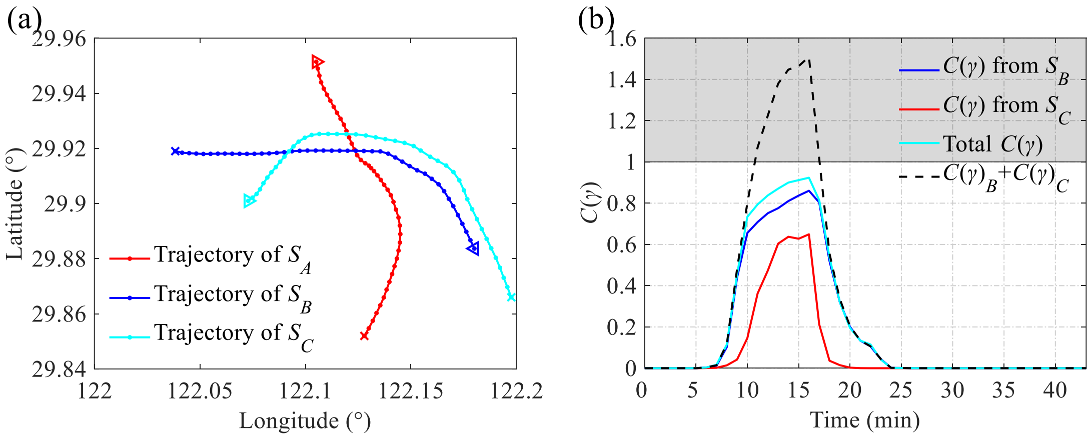
Figure 3.8. A ship-pair encounter scenario.

Figure 3.8 (b) displays the risk variable evolutions over time for the encounter scenario. In the figure, the $C(\gamma)$ has a negative relation with the minimum passing distance (CPA^*) over a 15 min look-ahead time horizon (to be in line with the setting of prediction time in the CD approach) computed by the improved CPA method, which coincides with the common sense that a smaller minimal passing distance corresponds to a higher conflict probability. However, when comparing the $C(\gamma)$ with the minimum passing distance (CPA) computed by the original CPA technique, one cannot obtain similar results. It is found that CPA experiences two troughs due to the turning action of ship A, which may confuse ship navigators in identifying collision dangers. Obviously, the original CPA technique becomes ineffective for this encounter scenario. This can be attributed to the fact that the CPA technique is performed with the assumption that ships are sailing linearly without changes in heading and speeds. As a result, all CPA-based collision risk assessment methods may provide false collision alerts, which hinders their applications in highly dynamic traffic situations.

In addition, one interesting phenomenon that must be mentioned is that the $C(\gamma)$ has dropped to 0 before the distance between the ship-pair reaches the minimum. This is due to the fact that the ship conflict does not happen at the minimal distance, and their subsequent movements follow a diverging trend. However, when the two ships are approaching, the $C(\gamma)$ shows an upward trend and reaches a high level because of the potential conflicts caused by the uncertainty inherent in the ship spatio-temporal movements. Consequently, the proposed CD approach can detect the potential conflicts in advance by taking into account both the dynamic and uncertain characteristics of ship motion, thus providing exact and timely collision warning.

Figure 3.8 (c) provides an example to demonstrate how to obtain the $C(\gamma)$ under the presence of ship motion uncertainty. In the figure, the dash lines represent the nominal prediction trajectories over the prediction horizon, the pink ellipses are the ship domain areas in terms of the nominal prediction positions at prediction time 0, 5, 10 and 15 min, and the scattered points represent the potential position distributions at the corresponding prediction time due to ship spatio-temporal movement uncertainty. By incorporating the potential position distributions into the two-stage MC simulation algorithm, the PC at each prediction time slice can be computed (see the subgraph in Figure 3.8 (c)) and the corresponding $C(\gamma)$ can be finally obtained.

To further validate the proposed CD approach in multi-ship encountering cases, a three-ship encountering scenario derived from the historical AIS data is selected for experimentation. The trajectories and the $C(\gamma)$ levels of the scenario are plotted in Figure 3.9 (a) and (b). In Figure 3.9 (b), the cyan curve represents the total $C(\gamma)$ of ship A in the multi-ship encounter, while the blue curve and red curve represent the $C(\gamma)$ of ship A with ship B and ship C, respectively. It can be observed that the total $C(\gamma)$ of ship A is higher than that with any single target ship. This finding meets the general knowledge about collision risk, *i.e.*, a ship involved in multi-ship encounters usually faces greater risks than those involved in ship-pair encounters. Moreover, the total $C(\gamma)$ of ship A is not the sum of the $C(\gamma)$ with each single target ship, which can be verified by comparing the cyan line with the dotted line. In fact, the difference between the above two lines represents the probability of all encountering ships involved in conflicts. Therefore, not only can the proposed CD approach detect the own ship's conflict probability in multi-ship encounters, but also it can provide the occurrence probability of the multi-ship conflict.



(a) Trajectories of multiple ships; (b) $C(\gamma)$ in the multi-ship encounter scenario.

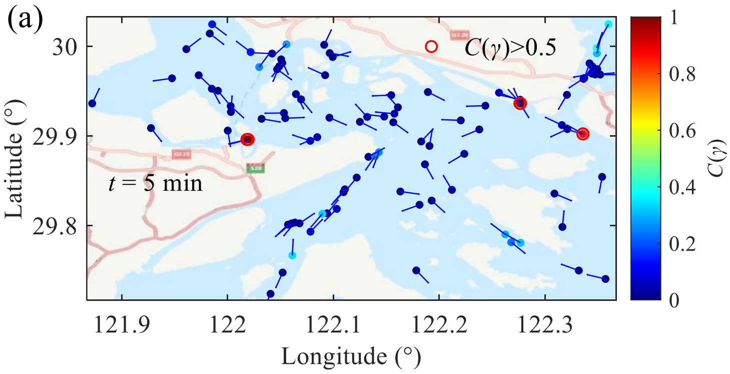
Figure 3.9. A multi-ship encounter scenario.

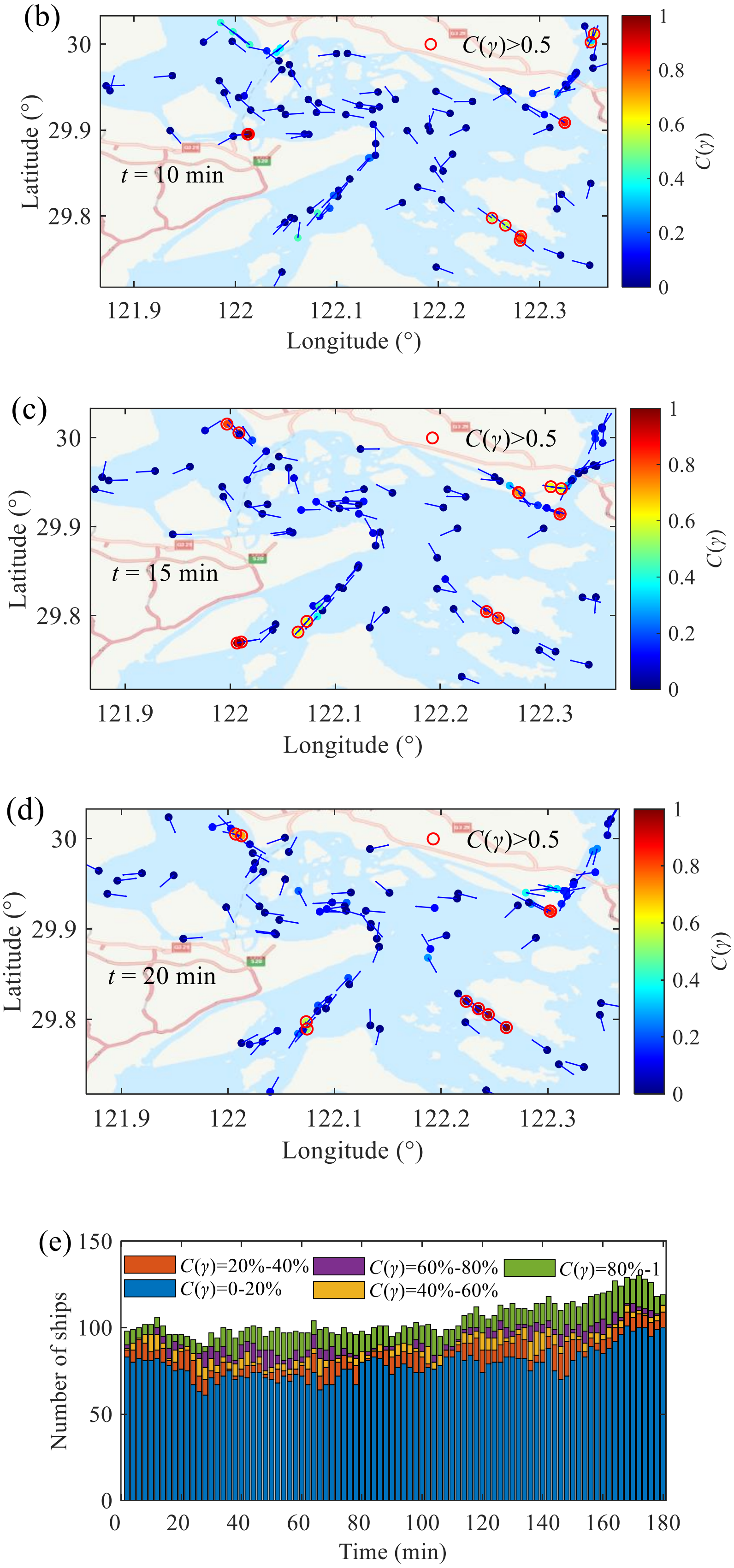
3.4.3.3 Application of the Proposed Probabilistic CD Approach

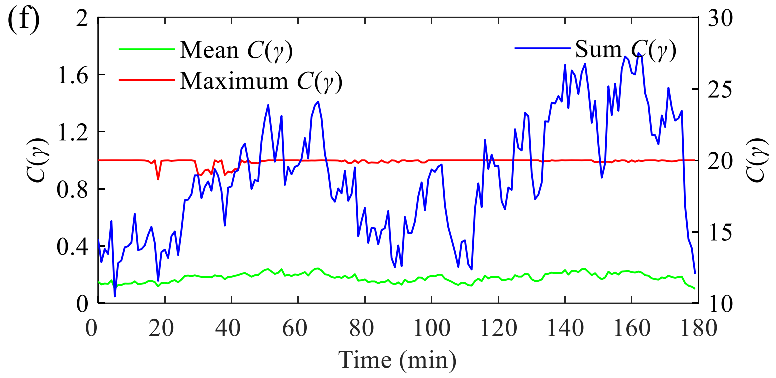
From the practical viewpoint of application, the proposed CD approach has the potential to be applied to both real-time conflict estimation and off-line identification of conflict distribution characteristics. Thus, its online application in risk estimation is demonstrated through a case study. Then, the spatio-temporal features of the conflicts are studied in terms of the conflict distributions in space and time.

Figure 3.10 provides an example of the conflict evolution of ship traffic over time within the study area. In Figure 3.10 (a)-(d), the points show the ships' positions, the blue lines represent the ships' heading course, and the points' colours display the ships' real-time $C(\gamma)$ levels. From these figures, it is easy to find which ships will face high conflict probabilities in the near future (these ships with $C(\gamma)$ levels larger than 0.5 are circled with red circles), thereby providing ship navigators with early warnings of potential collisions. Figure 3.10 (e) further depicts the compositions of ship traffic involved in different severity levels of conflicts. According to the figure, it can be observed that the number of ships generally shows an upward trend with time, and it can be also easily seen how many ships are involved in high severity levels of conflicts at different time moments. Thus, from the perspective of maritime safety authorities, the proposed CD approach can assist them in monitoring and offering hazard warnings for high collision risk ships as well as facilitate them to implement risk mitigation measures in a timely manner.

In addition, the $C(\gamma)$ evolution of ship traffic in terms of their mean, maximum and sum is also investigated. It is seen from Figure 3.10 (f) that both the mean and maximum $C(\gamma)$ curves fluctuate slightly over time, and the latter basically remains stable at 1, implying that dangerous ship encounters occur at each time moment. In contrast, the sum $C(\gamma)$ changes considerably as time goes on, primarily because the number of ships at different times varies greatly. By taking advantage of the three measures' ability to reflect the individual or total ship encountering conflicts, the traffic management centre could better understand the real-time collision risk and traffic complexity comprehensively, so as to improve their working ability when facing dangerous traffic situations caused by high traffic intensities.



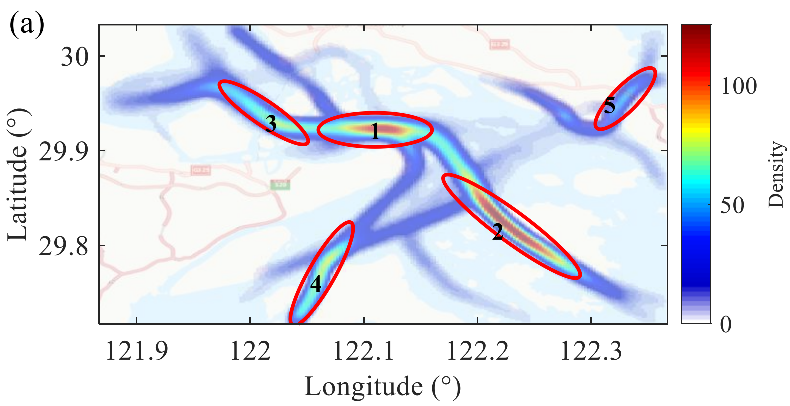

(b)
$C(\gamma)$>0.5
t = 10 min
Latitude (°)
Longitude (°)
$C(\gamma)$
(c)
$C(\gamma)$>0.5
t = 15 min
Latitude (°)
Longitude (°)
$C(\gamma)$
(d)
$C(\gamma)$>0.5
t = 20 min
Latitude (°)
Longitude (°)
$C(\gamma)$
(e)
$C(\gamma)$=20%-40%
$C(\gamma)$=60%-80%
$C(\gamma)$=80%-1
$C(\gamma)$=0-20%
$C(\gamma)$=40%-60%
Number of ships
Time (min)



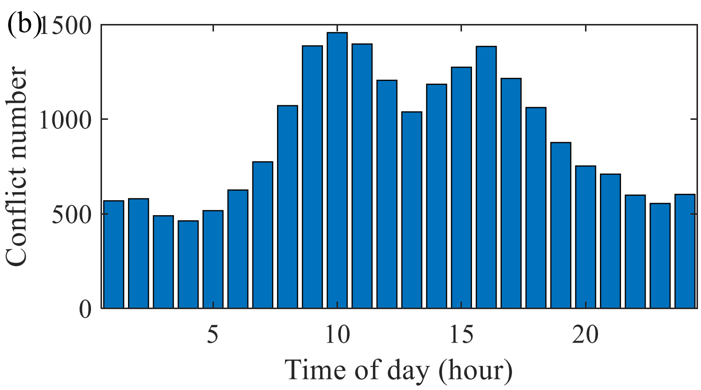
(a)-(d) Ship traffic spatial distribution and their $C(\gamma)$ levels at $t = 5, 10, 15, 20$ min; (e) compositions of ship traffic with different $C(\gamma)$ levels over time; (f) mean, maximum and sum $C(\gamma)$ curves of ship traffic over time.

Figure 3.10. Illustration of $C(\gamma)$ evolution of ship traffic for 3 hours in the study area.

Figure 3.11 illustrates the spatial and temporal distributions of ship conflict candidates within the study area. The ship conflict candidates whose real-time $C(\gamma)$ levels are larger than 0.5 are captured and retained twice per hour. As shown in Figure 3.11 (a), it can be easily seen that there are several conflict hotspot areas that are marked with red ellipses and with labels 1-5. Hotspots 1-3 belong to the main route that links the ship traffic between hub areas in the port and the outside waters, and consequently, having the largest traffic density and experiencing a high frequency of dangerous ship encounters. Particularly, hotspots 1 and 2 are associated with a higher frequency of ship conflicts compared with the other three areas. The higher conflict frequency for hotspot 1 can be explained by the fact that the ship traffic coming from other areas merges together in this area, increasing the frequency of multi-ship encounters. Besides, the frequently turning manoeuvres of ships caused by the geometry constraint within this area may also contribute to this result, since the dynamic ship movements increase the difficulty of situational awareness of ship navigators. In practice, hotspot 1 is an official precautionary area released by the Ningbo-Zhoushan Vessel Traffic Service (VTS) centre, displaying the effectiveness of the proposed CD approach on the identification of high collision risk areas to a certain extent. For hotspot 2, it is located in Xizhimen waterways, which is the main channel for the majority of large-scale ships to enter and exit the port but has narrower navigable width. Consequently, it becomes one of the riskiest areas for ship collision. The other two small hotspots (marked with number 4 and 5) are located in Fodu and Zhujiazui fairways. One possible reason for a little higher frequency of dangerous ship encounters in the two regions might also be that their narrow traffic widths result in the reduced minimal passing distances between encountering ships, thus producing lots of conflicts with high levels of severity. It should be noted that compared with the existing conflict visualisation studies (Weng et al., 2012; Weng and Shan, 2015; Wu et al., 2016) that identified the high collision risk areas based on the current state of ship-pairs, the proposed measures foresee the ships' potential conflicts in multi-ship encounters at present and in the near future time, thereby providing a different way to identify high-risk areas.



(a) Visualisation of spatial distribution of ship conflicts using KDE method.



(b) Temporal distribution of ship conflicts (The horizontal axis with label 3 corresponds to 02:00-02:59).

Figure 3.11. Spatio-temporal distribution of ship conflicts.

In addition, Figure 3.11 (b) clearly shows the number of conflict candidates against every hour of a day. A higher frequency of conflict candidates can be found during 08:00-12:00 and

13:00-17:00. This is consistent with the actual traffic situation in the regions because a higher ship traffic density occurs during the daytime. Based on the identification results of conflict distributions in space and time, both ship navigators and maritime authorities can gain valuable understanding of when and where situational awareness is enhanced during ship movements.

Our application analysis of real cases facilitates the validation of the proposed CD approach to estimate potential conflicts and identify areas with high collision risks. Therefore, its outcomes provide detailed insights on how to determine and implement appropriate conflict resolution strategies. For example, the proposed CD approach can be inserted into the optimal control algorithms to ensure the resolution of potential conflicts in a complicated dynamic situation. The proposed approach can be widely used in collision risk monitoring and control.

3.5 Conclusion

Collision risk analysis modelling in multi-ship encounters is critical for marine traffic safety management, particularly in complicated traffic waters. In this study, a probabilistic CD approach is developed to investigate the influence of spatio-temporal movement uncertainty of multiple ships on potential collision risk. The proposed approach has several unique features: 1) Both the dynamic and uncertain features of multi-ship movements are taken into account, so as to be applicable to various complicated encountering scenarios; 2) The developed conflict probability computation algorithm is efficient, accurate and having the capability to combine with any other conflict measure models (*e.g.*, diverse "ship domain" and "synthetic index") without the requirement of changing its fundamental structure; and 3) The spatio-temporal dependent patterns of ship motions correlated with actual collisions are extracted and integrated to support a robust estimate of the collision risk.

Several experiments are carried out using real AIS-based trajectory data in the Ningbo-Zhoushan Port to test the performance of the proposed CD approach. The results show that the proposed approach performs better than these traditional CPA-based approaches in detecting collision risks in a timely manner and reliably under a dynamic and uncertain traffic situation and can address multi-ship encounter scenarios. The application analysis also demonstrates its effectiveness and applicability in both real-time CD and off-line collision risk Hot-Spot identification. As a result, the proposed quantitative approach provides ship navigators, officers/captains and port management agencies with detailed insights into collision risk evaluation, helping them to facilitate the implementation of risk mitigation measures.

CHAPTER 4 STATIC SHIP TRAFFIC PARTITIONING FOR MARITIME SURVEILLANCE IN COMPLEX PORT WATERS

Chapter 3 has proposed a probabilistic conflict detection approach to detect collision danger between/among ships in a dynamic and uncertain traffic situation. However, this kind of risk estimation is conducted from a local perspective, revealing challenges in estimating large-scale traffic situations associated with complex interactions of traffic clusters at a regional level. In view of this, this chapter aims to develop a new static traffic partitioning methodology to realise ships' optimal partition of regional maritime traffic in complex port waters. It generates conflict-connected and spatial compact clusters to improve traffic pattern interpretability and ensure ship anti-collision safety. A composite similarity measure incorporating both conflict criticality (ensuring conflict connectivity) and spatial distance (ensuring spatial compactness) is first designed, in which the conflict relations of ship pairs are quantified using the probabilistic conflict detection approach in Chapter 3 and the spatial compact relations are then measured using a newly formulated maritime traffic route network by maritime knowledge learning. Subsequently, an extended graph-based clustering framework is proposed to produce balanced traffic clusters with high intra-similarity but low inter-similarity. Finally, the proposed methodology is comprehensively demonstrated and tested using the AIS trajectory data in the Ningbo-Zhoushan Port. Experimental results reveal that the proposed methodology 1) has reliable and rational performance in decomposing the whole traffic situation in complex port waters; 2) can identify the high risk/compact traffic clusters; and 3) is generic enough to tackle various traffic scenarios in complex geographical waters.[2]

4.1 Introduction

Maritime safety management has always been regarded as one of the essential concerns due to the intolerable ramifications when maritime traffic accidents occur. Economic globalization

[2] This chapter contributed to journal paper [4].

associated with the rapid boom in transportation demand has made maritime traffic more sophisticated, especially in restricted waterways and heavy-traffic ports. This change brings significant challenges to maritime operational authorities on maritime traffic safety management, particularly when the fast development of emerging autonomous ships is considered, which could potentially increase the occurrence likelihood of ship collisions without an effective solution to be found. Although the current maritime traffic surveillance systems present a great variety of intelligent functionalities in monitoring and regulating maritime traffic behaviours (Liu et al., 2022a, 2022b), they still reveal some drawbacks in rationally interpreting maritime traffic pattern complexity and adaptively capturing real-time high-risk traffic clusters from a regional surveillance perspective (Xin et al., 2022b; Zhang et al., 2019). Accordingly, maritime traffic controllers often need to face difficulties in capturing the high-risk ship areas by their intuition and experience, significantly increasing their workload, and hindering the timely implementation of anti-collision risk control strategies.

To enhance maritime traffic safety monitoring and management, detecting clusters of encounter ships based on real-time AIS-based trajectory information has become an emerging research topic (Liu et al., 2019a; Zhen et al., 2017, 2021). It plays a significant role in improving maritime surveillance capabilities and identifying potentially multiple ship encounters. However, the existing studies suffer from some drawbacks, such as ignoring or simplifying ship dynamics, only concerning traffic density, and having difficulty in discovering the traffic clusters with varying densities (Xin et al., 2022a). Besides, the ever-growing ship spatio-temporal movement uncertainty and maritime traffic complexity further influence the state-of-the-art approach's effectiveness and applicability, especially in complex traffic scenarios involving changeable traffic behaviour. To identify the encountering traffic clusters, it is of paramount importance to fully consider the complicated ship traffic characteristics and the multiple dependent conflict-related interrelationships of encounter ships. Therefore, these research gaps must be filled to ensure ship anti-collision safety at sea.

This study aims to develop an optimal static ship traffic partition methodology to adaptively discover the multi-ship encounters from a given water area of interest. It is dedicated to partitioning the regional ship traffic into several compact, scalable, and interpretable groups, decreasing the difficulty of maritime situation interpretation, and enhancing overall maritime logistics management, especially in complex waters (*e.g.*, ports) possibly involving mixed traffic of manned and unmanned ships in the future. The first step to partition maritime traffic is to rationally interpret its pattern complexity and the interactions (*e.g.*, spatio-temporal proximity and potential conflict) among ships. Compared to the investigations in urban transportation networks (Gu and Saberi, 2019; Ji and Geroliminis, 2012; Saeedmanesh and Geroliminis, 2016, 2017), the graph-based traffic partitioning study in maritime transportation is in its infancy partially because of its traffic uniqueness in the sector, which requires to generate traffic clusters with a guarantee of both conflict connectivity and spatial compactness. Both guarantees have some theoretical implications that have not yet been well addressed in the current literature. For instance, the conflict calibration needs to incorporate the ship movement uncertain features in a dynamic traffic situation, whereas the spatial compactness measure requires extending the shortest path search approach based on a maritime traffic route network by maritime trajectory knowledge extraction. Furthermore, these two indices have to be integrated into a composite similarity measure model through an effective combination approach, in which the weights assigned to the two indices also need to be calculated based on sensitivity analysis as a trade-off parameter. Only then, can the similarity measure result be fed into a robust graph clustering approach to produce traffic clusters with balanced sizes where the intra-cluster similarity can be maximized but the inter-cluster similarity minimized. Despite the high demand on research efforts and resources, the success of this work will make significant contributions both in theory and in practice to supporting intelligent MSA by decomposing the whole traffic complexity in the surveillance area to guiding ship anti-collision risk management.

The remainder of the chapter is organized as follows. Section 4.2 explains the challenges and solutions of conducting traffic partitioning in the maritime field. In Section 4.3, the details of the developed modelling methodology are explained, including the similarity measure model, graph partitioning algorithm, and metrics development. Application performance and discussions are provided in Section 4.4. Conclusions are summarised in Section 4.5.

4.2 Problem Statement

Maritime traffic partitioning plays a significant role in 1) partitioning the whole maritime traffic scenario into several sub-clusters to improve situational awareness, and 2) assisting in capturing potential high-risk traffic clusters in a proactive way. The state-of-the-art research primarily attaches importance to collision risk estimation and evaluation between/among ships but encounters challenges in decomposing the regional traffic complexity and identifying real-time high-risk multi-ship encounters. The most relevant research in the maritime domain is to detect clusters of encounter ships, which faces several of the following deficiencies (see Section 2.2.4): 1) only considering the spatial distance relations without fully incorporating the multiple dependent interrelationships among ships; 2) overlooking the effects of water topography on spatial distance measurement; and 3) adopting improper clustering techniques to cope with the complex interactions among ships. However, failure to address these issues often leads to a negative impact on decomposing regional traffic complexity and capturing actual traffic clusters. Therefore, these issues need to be solved one by one, as follows:

1) How to incorporate the multi-dependent interrelationships among ships into the traffic partitioning process

The interaction relations between ship pairs in a given traffic scenario can be expressed in various ways, such as spatio-temporal proximity, conflict severity, approaching rate (Wen et al., 2015; Zhang et al., 2019). These multi-attribute interrelationships reflect different aspects of ship traffic interactions, in which each one contributes to a meaningful traffic pattern understanding from its own angle. A proper combination of these multiple dependent interrelationships of encounter ships will lead to improved traffic situation awareness by taking advantage of their complimentary information. In contrast, any one-attribute interaction is not sufficient to describe the underlying dependencies of encounter ships, as the works in (Liu et al., 2019a; Zhen et al., 2017, 2021). Therefore, it is meaningful and promising to construct a model that can simultaneously take into account the multi-attribute interactions in ship traffic when conducting maritime traffic partitioning.

Regarding this issue, a linear combination function is adopted to combine the multi-attribute dependence measures matrices to produce a composite dependence measure model. It provides a simple yet powerful way to describe the relationships between ship pairs when these dependence measures are presented by the same value ranges (Gu and Saberi, 2019). The composite similarity measure results can then be fed into a robust clustering framework to achieve the multi-objective traffic partitioning. In the meantime, the sensitive analysis is used to cope with the trade-off of the multi-attribute interactions, to strike a balance between these considered criteria.

2) How to consider the influence of water topography on spatial distance measures in restricted waters

Maritime traffic partitioning requires guaranteeing the spatial compactness of the produced traffic clusters to ease the design of collision risk management strategies. The traditional measure of spatial compactness is conducted in terms of the Euclidean distance (or called linear distance) between ships (*e.g.*, Liu et al., 2019b; Xin et al., 2022a; Zhen et al., 2021). However, in complex and restricted waters, the two ships spatially adjacent may not be reachable from each other. For instance, obstacles (*e.g.*, small islands) between the ships often block them. Hence, the traditional linear distance measure is not always applicable to describe the spatial compactness of traffic scenarios in complex waters involving restricted geographical features.

An appropriate way to solve this issue is to search for the shortest distance between ship pairs with reference to the maritime traffic route network as their actual spatial distance. However, unlike the road network, there are only a few customary transportation routes and traffic lanes in complex port waters, which is insufficient to measure the real spatial distance between any pair of ships. Therefore, some recent studies resorted to identifying ship traffic motion patterns based on maritime traffic knowledge extraction to formulate a complete and precise maritime traffic route network. As stated in Section 2.2.2, establishing a maritime traffic network by extracting the nodes and legs is a typical solution (Arguedas et al., 2017; Rong et al., 2022). Unfortunately, difficulties arise when they are applied to complex traffic waters where it is difficult to categorise traffic motion behaviours (Xiao et al., 2019a). Specifically, these methods can detect high-density waypoints but ignore low-density waypoints. This property makes them inefficient at extracting all ship motion patterns, which further brings difficulties in exploring the real spatial distance between ships under any situation. Therefore, this study adopts an image processing technique as an effective solution. It can capture the main skeleton of the navigable waters as the traffic route network to aid in capturing the reasonable spatial distance on the network (Lam et al., 1992).

3) How to choose effective clustering techniques to adapt to the unique and stochastic characteristics in maritime traffic

As stated in Section 2.2.4, the current research in the maritime traffic field adopted density-based clustering algorithms (*e.g.*, DBSCAN) to detect clusters of encounter ships and filter out the relatively safe ships. This category of algorithm is not suitable to cope with the complex interrelationships (*e.g.*, conflict severity) among ships and suffers from discovering the traffic clusters with varying densities. Therefore, the choice of clustering technique is crucial to produce reliable traffic partitioning solutions.

Indeed, the traffic partitioning problem can be regarded as a graph-cut issue in terms of the complex neighbouring relationships between ships. With respect to this issue, graph-based clustering represents a widely used type of clustering algorithm for solving graph partitioning problems. Different from other classes of clustering algorithms (*e.g.*, prototype-based and density-based clustering) that focus on the data set itself, the graph-based clustering algorithms assign the data samples into proper clusters in terms of the similarity/interrelationship between each pair of data samples and make no assumptions on the form of the clustering data sets. Therefore, an extended and competitive graph-based clustering technique, *i.e.*, SNMF, are adopted for graph clustering. It is a variant of Non-negative Matrix Factorization (NMF) developed by (Lee and Seung, 1999) and distinguishes different clusters by performing the non-negative lower rank approximation for a graph similarity matrix. According to the comprehensive study by Kuang et al. (2012, 2015), SNMF has the following unique features of: 1) being adaptive to more general cases by offering the flexibility to define any similarity measure that describes the data set structure well; 2) being capable of achieving higher accuracy and quality compared with other clustering algorithms including the standard forms and variations of spectral clustering, k-means, and NMF for graph clustering. These merits make SNMF appealing for graph partitioning applications. It has therefore been successfully applied in a diversity of research fields, such as community detection (Chunaev, 2020) and traffic network partitioning (Saeedmanesh and Geroliminis, 2016, 2017).

In summary, this chapter attempts to develop a holistic graph-based clustering framework involving a multi-attribute interrelation measure model, as a hybrid pioneer, to tackle the challenges that are yet to be addressed in the current literature.

4.3 Methodology: Static Maritime Traffic Partitioning

As mentioned before, the development of an optimal static ship traffic partition methodology should aid to achieve the goals of 1) extracting the traffic clusters that have shown high conflict connectivity to detect real traffic conflict patterns, and 2) generating the traffic clusters that are spatially compact to ease the design and deployment of traffic management strategies. Based on these two goals, this study involves constructing an undirected graph for ship traffic partition, in which each ship is modelled as a node and their neighbouring relationships (*i.e.*, edges) are built based on their conflict criticality and spatial distance. By doing so, the traffic partitioning problem is transformed into a graph cut problem.

The proposed partitioning methodology is dedicated to separating the network into several sub-graphs. It consists of the following major steps. Firstly, a composite similarity model that considers conflict connectivity and spatial compactness is introduced. The conflict relations are quantified by a probabilistic conflict detection approach, which can precisely estimate the conflict criticality between ship pairs by incorporating the ship motion dynamic and uncertain characteristics. The spatial compact relations, on the other hand, are measured based on a maritime traffic knowledge extraction technique. It extracts the real spatial distance between ship pairs from a derived ship traffic route network. Based on the constructed similarity model, a graph clustering mathematical framework is further utilized to group the ships with high conflict criticality and spatial compactness in clusters with balanced sizes. Additionally, four metrics are adopted to evaluate and check the performance of the proposed traffic partitioning framework. Figure 4.1 provides the associated methodological framework. The important supporting techniques embedded into each step are explained in the following subsections.

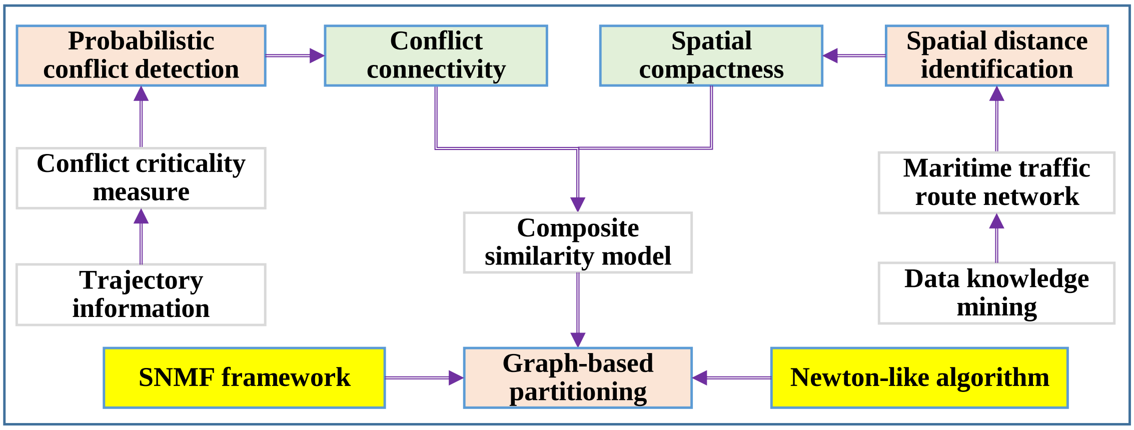


Figure 4.1. The research framework.

4.3.1 Similarity Measures and Models

The key issue of graph partitioning is how to define a similarity/adjacent measure to describe the connections/interactions between each pair of ships. This study is devoted to developing a similarity model to enable the simultaneous consideration of both the conflict relation and spatial distance of ship pairs. The similarity model comprises the following elements: 1) a probabilistic conflict criticality evaluation model to reflect the conflict relation in Section 4.3.1.1; 2) a real spatial distance identification model to define the spatial relation in Section 4.3.1.2; and 3) the developed composite similarity model in Section 4.3.1.3.

4.3.1.1 Probabilistic Conflict Detection

Collision risk qualification is an integral part of the detection of conflicting traffic clusters. Hence, the conflict criticality is measured based on the probabilistic conflict detection model in Chapter 3 to ensure the adaptation to traffic scenarios with high movement dynamics and uncertainty.

In Chapter 3, the conflict criticality measure is conducted based on the maximum conflict probability over the CD horizon. This supporting metric is used to support collision alarm when the maximum conflict probability within the detection time period exceeds the predefined threshold (Hernandez-Romero et al., 2019; Jilkov et al., 2018; Yang et al., 2016). However, this chapter focuses on revealing the risk interactions between ships from both spatial and temporal perspectives. Hence, the conflict criticality over the CD horizon is quantified by considering both the maximum $PC(t)$ (see Eq. (3-2)) with $0 < t \leq T_{CDH}$ (T_{CDH} is the CD horizon) and its corresponding occurrence moment. The first indicator reveals the highest intensity of a potential conflict, while the second indicator represents the urgency of a traffic case needing immediate conflict resolution actions. Indeed, these two indices play equally significant roles and are equivalent to the two commonly used indices, *i.e.*, DCPA and TCPA, in maritime traffic navigation (Cho et al., 2020; Hu et al., 2019). Therefore, an exponential function that refers to the work in (Hu et al., 2019; Wang et al., 2018) is utilized to synthesize the outlined indices as follows:

$$C(\gamma) = MPC^{1+\left(\frac{t_{MPC}}{T_{CDH}}\right)} \tag{4-1}$$

where *MPC* represents the maximum conflict probability during the CD horizon, and t_{MPC} denotes the occurrence moment of the maximum conflict probability.

4.3.1.2 Real Spatial Distance Identification

The real spatial distance identification consists of two important components: one is the traffic route network extraction, the other is the spatial distance computation based on the derived traffic route network. The flowchart demonstrating the traffic network representation learning and real spatial distance computation is presented in Figure 4.2. The detailed procedure is given as follows:

Firstly, the KDE is applied to distinguish the navigable and unnavigable water areas. It estimates the spatial probability distribution of ship traffic based on real historical AIS data. The relevant formula is shown in Eq. (3-10) in Chapter 3. The entire investigated water area is divided into a series of grids. For each grid, if its spatial probability distribution value of ship traffic is larger than a defined threshold, it represents a navigable area. Otherwise, it is unnavigable. The determination of the grid size and threshold is analysed in Section 4.4.2.

Leveraging on the probability distribution results obtained using the KDE, the whole investigated water area can be transformed into a binary image comprising of grids with 1 representing the navigable area and 0 representing the unnavigable area. The image processing operation is applied to the binary image to extract the image skeleton (Lam et al., 1992). Compared with the approaches that perform maritime traffic network abstraction based on node and edge extraction, it is more easily implemented by using the morphological algorithms in the MATLAB toolbox. Through the execution of the morphological algorithms, a network skeleton that provides a compact, structured, and precise traffic route description can be built.

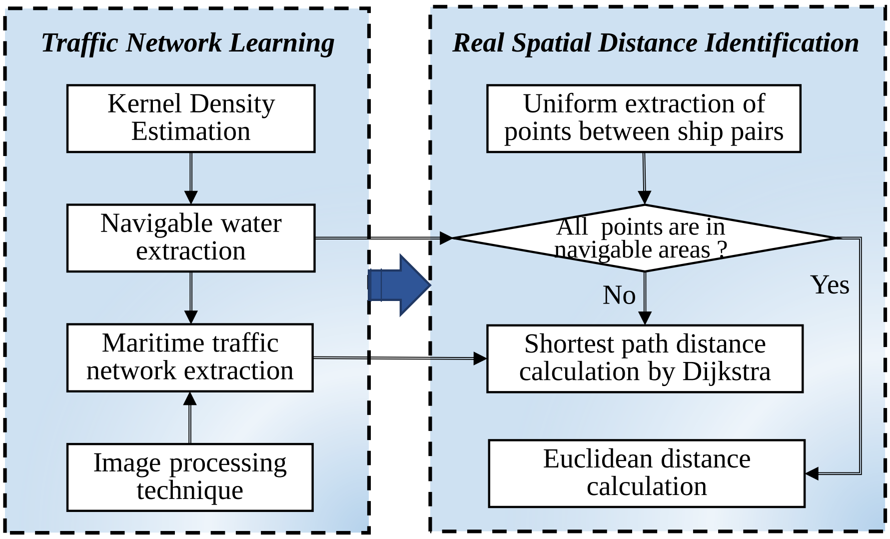


Figure 4.2. Flowchart of traffic network representation learning and real spatial distance computation.

After obtaining the traffic network representation, it can be employed to identify the real spatial distance between ship pairs. The procedure implementation comprises the following steps. First, several points are evenly sampled on the connection lines between the ship pairs to identify whether they fall into the navigable areas. In this study, the number of sampled points for any ship pairs is set to 10 for easy implementation. If all these points are in the navigable areas, the real spatial distance between ship pairs is calculated in terms of the Euclidean distance; otherwise, the nearest point on the traffic route network that each ship is close to is searched for. Then, Dijkstra's algorithm is applied to calculate the shortest path distance between the two points. In this way, the procedure offers the potential to support generating actual spatial compact traffic clusters.

4.3.1.3 Composite Similarity Measure Model

Furthermore, the conflict relation and distance relation measures can be merged to fulfil the spatial compactness and conflict connectivity requirements simultaneously. As mentioned above, the two measure indices are combined through a linear combination method for clustering purposes. Note that the value ranges of conflict criticality between ship pairs fall within [0, 1] (*i.e.*, Eq. (4-1)). Hence, the conflict connectivity similarity W_{ij}^{c} between ships *i* and *j* can be defined as equal to their conflict criticality. However, the real distance between ship pairs varies significantly (*e.g.*, tens of nautical miles). A compactness similarity W_{ij}^{d} that allows its value range to be in line with W_{ij}^{c} is therefore defined by transforming the real distance between a ship pair as follows:

$$W_{ij}^{d} = \begin{cases} 1, & Dist_{ij} \le D_1 \\ \left(\dfrac{D_1}{Dist_{ij}}\right)^{\beta}, & D_1 < Dist_{ij} < D_2 \\ 0, & Dist_{ij} \ge D_2 \end{cases} \tag{4-2}$$

where $Dist_{ij}$ is the real spatial distance between the two ships, β is a scaling parameter, and D_1 and D_2 are two user-specified parameters that put the spatial compact relations into three categories, *i.e.*, high, medium, and negligible compact relations. According to Eq. (4-2), if the real spatial distance falls within D_1, the ship pairs are regarded as high compact and W_{ij}^{d} is set to be 1. If the real spatial distance is between D_1 and D_2, the compact similarity is monotonically decreasing based on an exponential mathematical expression. If the real spatial distance exceeds the threshold D_2, the compact relation between ship pairs is negligible. Overall, Eq. (4-2) has the following properties: 1) exhibits a normalisation effect to ensure that W_{ij}^{d} falls within [0, 1]; 2) offers flexibility to control the relations between W_{ij}^{d} and $Dist_{ij}$ by using β (*e.g.*, a larger β results in a high decline rate, and vice versa); and 3) produces a sparse similarity matrix to simplify the optimization complexity of graph partitioning by setting 0 similarities for ship pairs with extremely large spatial distance.

A composite similarity measure is further defined to put different weights for W_{ij}^{d} and W_{ij}^{c} through a linear combination way, as follows:

$$W_{ij} = W_{ij}^{c} \cdot \alpha + W_{ij}^{d} \cdot (1 - \alpha) \tag{4-3}$$

where W_{ij} denotes the similarity between ships i and *j*, and α is a trade-off weighting coefficient. This model explicitly considers the above two similarity measures and helps systematically describe the multi-interrelationships among ships in a whole investigated water. However, the conflict connectivity and spatial compactness indices may conflict with each other because the conflict criticality between ship pairs is not totally dependent on their real spatial distance. The indices such as ship size, speed, and spatial approaching rate of encountering ships also have an impact on the conflict relations. This means that the weighting coefficient α is essential, playing an important role in achieving a trade-off between the two indices. For instance, a higher α that puts more weight on conflict connectivity may result in spatially non-compact clusters. Consequently, the optimization of α is investigated and discussed based on the sensitivity analysis in the experimental subsection (see Section 4.4.3).

4.3.2 Static Maritime Traffic Partitioning

4.3.2.1 The SNMF Framework

Static traffic partitioning makes use of the snapshot information of the traffic network at a particular time. It processes a static graph without considering the temporal dependency of traffic networks over time. This study adopts the graph-based clustering model, *i.e.*, SNMF, as a solution. The symbols used in the model are provided in Table 4.1. The relevant model details are elaborated on below.

Table 4.1. The symbols used in the traffic partitioning model.

Symbol	Definition and Explanation
G	maritime traffic network with node set V and edge set E
W	the similarity matrix for G
D	diagonal matrix with $D_{uu} = \sum_{v=1}^{N} W_{uv}$.
L	Laplacian matrix, $L = D\text{-}W$
W_{uv}	the element at u^{th} row v^{th} column in W
X'	the transpose of matrix X
H	the clustering membership matrix
$\boldsymbol{Tr}$(W)	the trace of matrix W
$\widetilde{W}$	the normalized W, $\widetilde{W} = D^{-1/2}WD^{-1/2}$
A	the whole data set for G
$\{A_c\}_{c=1}^{k}$	the traffic clusters for G
$vol(A_o)$	the number of nodes in subset A_o

For a typical graph partitioning problem, the objective function is inherently consistent, which is mathematically equivalent to a trace maximization formulation (Kuang et al., 2015), as follows:

$$\max_{H\geq 0, H^T H = I} \boldsymbol{Tr}(H^T W H) \Leftrightarrow$$

$$\min_{H\geq 0, H^T H = I} \boldsymbol{Tr}(W^T W) - 2\boldsymbol{Tr}(H^T W H) + \boldsymbol{Tr}(H^T H) \Leftrightarrow \tag{4-4}$$

$$\min_{H\geq 0, H^T H = I} \|W - HH^T\|_F^2$$

where $W \in \mathbb{R}^{N\times N}$, $H \in \mathbb{R}^{N\times k}$ subject to $H \geq 0, H^T H = I$, N is the number of data samples, and k represents the desired number of clusters. It is an NP-hard problem to find the optimal solution to minimize the graph clustering objective (Eq. (4-4)) due to the two constraints on H.

As a result, there are two algorithms to solve the NP-hard issue, which are spectral clustering and SNMF. In theory, SNMF and spectral clustering are two highly relevant approaches according to the graph clustering objective but adopt fundamentally distinct ways to optimize the objective function. They attempt to loosen one of the constraints on H to obtain a tractable formulation. More concretely, spectral clustering retains the orthogonality constraint, while SNMF keeps the non-negativity constraint. These two relaxed versions result in significantly different approaches for solving the optimization problems in Eq. (4-4). The orthogonality constraint in spectral clustering requires that each data sample falls within one cluster only. In contrast, by removing the orthogonality constraint in SNMF, the data sample can be assigned to several clusters with different membership values. In Zass and Shashua (2005), it was verified that the non-negativity constraint on H plays a more crucial role than the orthogonality constraint. Additionally, Ding et al. (2005) have pointed out that keeping the non-negativity constraint by SNMF brings about a near orthogonality approximation of the columns in matrix H. This property is beneficial and promising for SNMF to effectively figure out the graph partitioning problem.

To partition maritime ship traffic into balanced groups with similar sizes, the commonly used objective function termed Normalized Cut (*Ncut*) (Shi and Malik, 2000) is adopted to produce the proper clusters. In Bach and Jordan (2006), it was proved that the normalized cut can be expressed as follows:

$$Ncut = k - \boldsymbol{Tr}\left[H^T\left(D^{-\frac{1}{2}}WD^{-\frac{1}{2}}\right)H\right] = \boldsymbol{Tr}(H^T D^{-\frac{1}{2}}LD^{-\frac{1}{2}}H) \tag{4-5}$$

In terms of the derivation in Eq. (4-4), the minimization of *Ncut* can be achieved by using the normalized similarity matrix $\widetilde{W}$ to replace the W in the third formula in Eq. (4-4). Consequently, given the normalized similarity matrix $\widetilde{W} \in \mathbb{R}_+^{N\times N}$, the desired number of clusters k, and the non-negativity constraints on $H \in \mathbb{R}_+^{N\times k}$, the graph clustering optimal model for SNMF can be formulated as follows:

$$\underset{H\geq 0}{\arg\min}\left\|\widetilde{W} - HH^T\right\|_F^2 \tag{4-6}$$

The purpose of SNMF is to search for a symmetric non-negative lower rank approximation *H* for the matrix $\widetilde{W}$. For an optimal matrix *H*, each column can be considered as the membership degree of the clustering data samples belonging to one cluster. Accordingly, the clustering assignments of the data samples can be directly identified in terms of the largest entry in each row in the low-rank matrix *H*.

4.3.2.2 The Optimization Algorithm for SNMF

Different optimization approaches can be contemplated for solving the minimization problem described in Eq. (4-6), such as the Newton-like algorithm (Gu and Saberi, 2019; Kuang et al., 2012), the Alternating Non-negative Least Squares (ANLS) algorithm (Kuang et al., 2015), and interior-point theory (Saeedmanesh and Geroliminis, 2016). In this study, the optimization problems are directly solved by implementing the Newton-like algorithm. The pseudocode of the Newton-like algorithm can be found in (Gu and Saberi, 2019; Kuang et al., 2012). It is suitable for small-size issues (*e.g.*, $N < 3000$) and can produce accurate solutions with higher-quality clustering results. Despite that, it may encounter a local minimum solution due to its sensitivity to the initialization of *H*. Regarding this issue, the Newton-like algorithm is performed many times with the randomly sampled initial *H* to find a global minimal solution or at least guarantee a near-global minimum. The detailed algorithmic steps for static traffic partition can be found in Appendix D.

4.3.3 Metrics Development

The performance evaluation is crucial to ensure the effectiveness of the proposed methodology. Therefore, four metrics are introduced to evaluate and compare the traffic partitioning results.

The first adopted metric is 'NcutSilhouette' (*NS*) (Ji and Geroliminis, 2012), which is expressed as follows:

$$NS_k(A_o, A_p) = \frac{\sum_{u \in A_o} \sum_{v \in A_p} (1 - W_{uv})^2}{vol(A_o) vol(A_p)} \tag{4-7}$$

where A_o and A_p represent two cluster sets, k denotes the number of clusters. Here $NS_k(A_o, A_p)$ measures the average quadratic dissimilarity between clusters A_o and A_p. Similarly, determining whether the ships in one cluster are properly grouped is measured using the following metric:

$$NS_k(A_o) = \frac{NS_k(A_o, A_o)}{NSN_k(A_o, A_q)} \tag{4-8}$$

where $NSN_k(A_o, A_q) = \min\{NS_k(A_o, A_p) | A_p \in A, A_p \neq A_o\}$, and A_q denotes the most relevant cluster with A_o. This metric measures the ratio of intra-cluster dissimilarity ($NS_k(A_o, A_o)$) over inter-cluster dissimilarity ($NS_k(A_o, A_q)$). Evidently, $NS_k(A_o) < 1$ indicates that cluster A_o is properly separated. Furthermore, the overall performance for a given traffic partitioning can be evaluated in terms of the average NS_K of all partitioned clusters, as follows:

$$NS_k = \frac{\sum_{o=1}^{k} NS_k(A_o)}{k} \tag{4-9}$$

A small NS_k value implies that the overall traffic scenario is well partitioned.

Additionally, the graph-based measure, *Ncut* (*i.e.*, Eq. (4-5)), is employed to evaluate the comprehensive partitioning quality. This metric also considers both the similarity between different clusters and the similarity within the cluster. It is subsequently expressed as *NC*. The smaller the value of *NC* is, the better quality the partitioning scheme has.

Note that the above two comprehensive metrics are highly dependent on the designed similarity model (*i.e.*, Eq. (4-3)). They cannot directly examine the spatial compactness and conflict connectivity of partitioning results because of the influence of the super parameters (*e.g.*, α) in the similarity model. Therefore, two specific metrics associated with these two criteria are further presented. With respect to the conflict connectivity, it can be calibrated based on the degree that the ship pairs with conflicts are segmented into different clusters, as follows:

$$f_1 = \sum_{i=1}^{N_{vc}} C(\gamma)_i \tag{4-10}$$

where N_{vc} denotes the number of ship pairs with conflicts that are arranged into different clusters, and $C(\gamma)_i$ represents the conflict criticality of ship pair i. A smaller f_1 value suggests that more ship pairs with conflicts are effectively clustered into the same group. Regarding spatial compactness, NS_k can still be applied by using the real spatial distance to replace the dissimilarity in Eq. (4-7), expressed as f_2 in the following experimental section. The smaller the f_2 value, the smaller the spatial distance within the clusters is and the larger the spatial distance between the clusters is. This suggests that the spatial compactness of the traffic partitioning is well fulfilled.

4.4 Case Study: Implementation and Results

In this subsection, the effectiveness of the proposed static traffic partitioning methodology is evaluated and discussed. Section 4.1 illustrates the offline training results of the ship traffic route network in the investigated water area. In Section 4.2, several sensitivity analyses on the super parameters in the proposed methodology are performed. Section 4.3 illustrates how the proposed approach assists in intelligent MSA and capturing high-risk traffic clusters. Section 4.4 conducts model comparison and validation to highlight the superiority of the proposed methodology. Furthermore, discussion and insights are analysed in Section 4.5.

4.4.1 Ship Traffic Route Network Extraction and Analysis

Based on the procedure in Section 4.3.1.2, the navigable/unnavigable regions and ship traffic route network can be identified and derived through maritime knowledge mining from the historical AIS data. In theory, a smaller grid size that discretises the entire research waters is associated with a higher visualisation resolution. However, the extracted traffic route network is extremely complex when the grid size is too small, which will further result in a heavy computational burden for the identification of the shortest path distance on the network. Hence, the grid size is set to be 1.25×10^{-3} ° after making a trade-off between the visualisation resolution and computational burden. Besides that, the threshold distinguishing the navigable areas from unnavigable areas is determined by observing the matching effect between unnavigable waters and real land. When the threshold falls within [0.2, 0.4], the unnavigable waters and real land keep goodness-of-fit, and the corresponding visualisation basically remains stable. Therefore, the threshold is finally set to 0.3.

Figure 4.3 illustrates the identified unnavigable regions and the derived ship traffic route network. The dark red areas represent the unnavigable regions, while the blue lines indicate the traffic route network. It is found that the blue lines effectively describe the skeleton of the navigable areas, which reveals its goodness-of-fit. This precise and structured representation of the maritime traffic network allows the real spatial distance between ship pairs to be measured. To enlighten the use of the derived network for real spatial distance computation, an example of how to identify the spatial relations of ship pairs based on the graph-based topology is presented in Figure 4.4. In the figure, ships B and C are separated from A by obstacles. The Real Spatial Distance (RSD) between ships A and B based on the route network and Linear Spatial Distance (LSD) are 6.43 and 4.51 nautical miles (nm), respectively. It is evident that the distance of a ship pair should be better measured by the length of their shortest path on the route network instead of using the physical distance because of the obstacles between them. The route network contributes to identifying the real spatial distance in complex waters as a first step toward recognizing actual spatial compact traffic clusters.

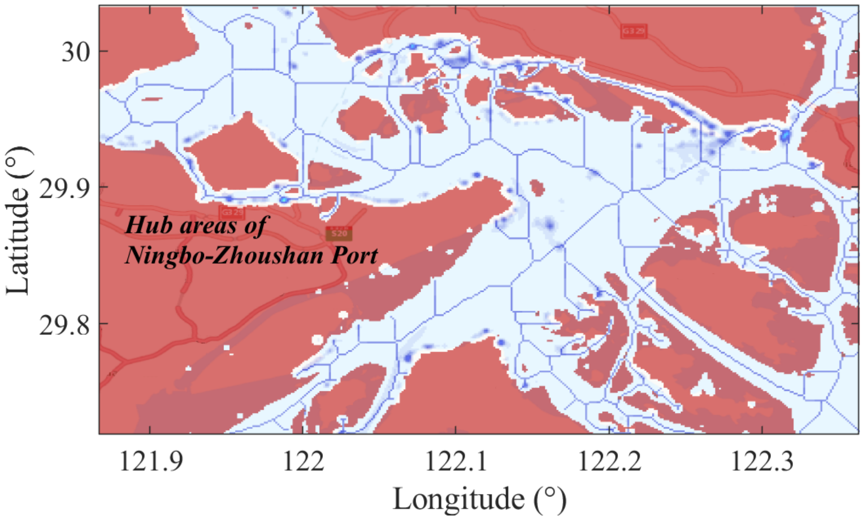


Figure 4.3. The identified unnavigable regions based on KDE and extracted ship traffic route network based on image processing technique in Ningbo_Zhoushan port.

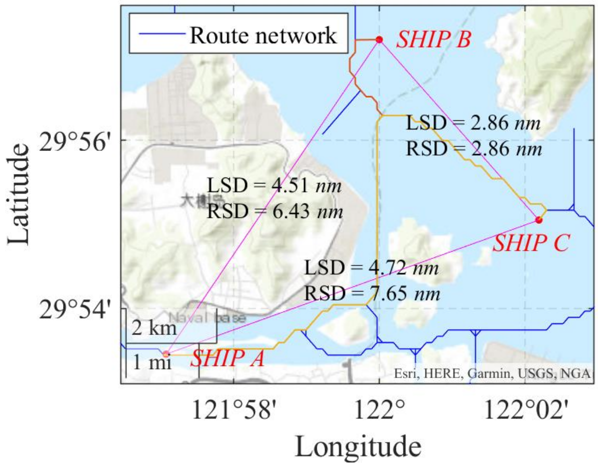


Figure 4.4. An example of real spatial distance computation based on the formulated traffic route network.

4.4.2 Sensitivity Analyses on Different Design Parameters

According to the methodology subsection, four super parameters need to be determined to obtain the optimal traffic partitioning results, which are D_1, D_2, β, and α. The first three come from the compactness similarity measure model (Eq. (4-2)), while the fourth one is the trade-off weighting coefficient used to balance the spatial compactness and conflict connectivity (Eq. (4-3)). Their optimal values are respectively confirmed based on the following sensitivity analysis.

4.3.1 Distance Measure Parameters

In the maritime field, when the distance between ship pairs is larger than 6 nautical miles, they are not considered to be in an encountering situation (Cho et al., 2020; Zhang et al., 2016). Hence, D_2 is directly set to be 6 nautical miles to distinguish the encountered and non-encountered ship pairs. On the other hand, the alarm procedure is normally activated when the predicted distance between ship pairs is smaller than 1 nautical mile in open sea (Hu et al., 2019). Considering the high density and greater tolerance for a small encountering distance in complex port waters, four values within 1 nautical mile are selected for D_1, which are 0.125, 0.25, 0.5, and 1 nautical mile. As for β, it is set as 0.5, 1, 2 and 3 to control the decline rate of S_{ij}^{d} with $Dist_{ij}$. Figure 4.5 illustrates the average f_1 and f_2 of the tested traffic scenarios using different combinations of D_1 and β. Based on the Pareto principle in multiple objective optimizations that one is not dominated by others if at least one objective is better, three optimal combinations of (0.125, 2), (0.125, 3), and (0.25, 3) that are non-dominated by any other combination constitute the Pareto front. It is also observed that both D_1 and β have profound impacts on the partitioning quality in terms of the change degree of f_1 and f_2, indicating the necessity to perform sensitivity analysis to find the optimal combinations. Notably, f_1 is more sensitive to these two parameters than f_2 in terms of its higher fluctuations.

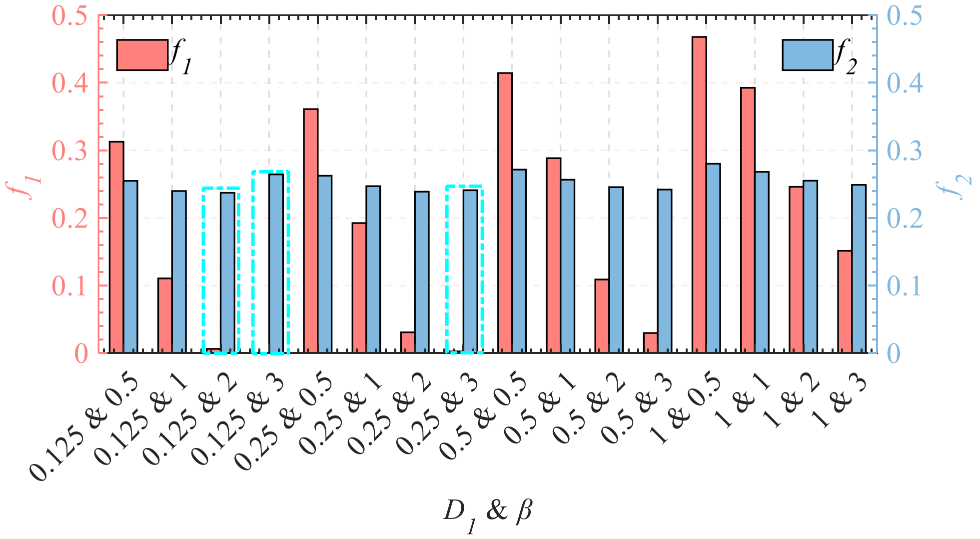


Figure 4.5. Average f_1 and f_2 of the partitioned traffic scenarios with various combinations of D_1 and β.

To further identify the best D_1 and β, the performance of each pair of super parameter combinations is compared. For combinations A and B, their domination relations for each traffic scenario sample can be identified. Then the percentage that each one dominates another in all experimental traffic scenario samples is calculated, and the one with a higher percentage is better than another one. By doing so, the number of times that each combination dominates other combinations can be counted. According to Figure 4.6, the combination of D_1 = 0.125 and β = 2 dominates all other 15 combinations. It should be noted that when D_1 = 0.125, f_1 keeps falling while f_2 first decreases and then increases with β. This indicates that β = 2 is not necessarily the point leading to the best model performance. Therefore, the combinations of (0.125, 1.5) and (0.125, 2.5) are further compared with (0.125, 2). It is found that the combination of (0.125, 2) is still better than the other two. These results enable us to determine the optimal parameter combination as 0.125 and 2 by observing the relevant turning points.

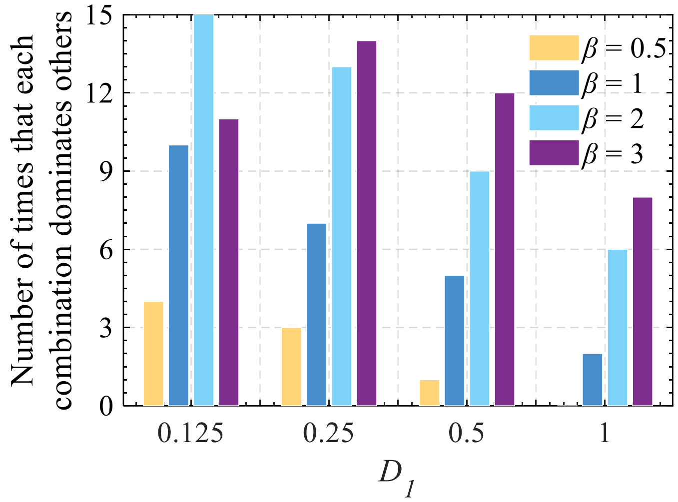


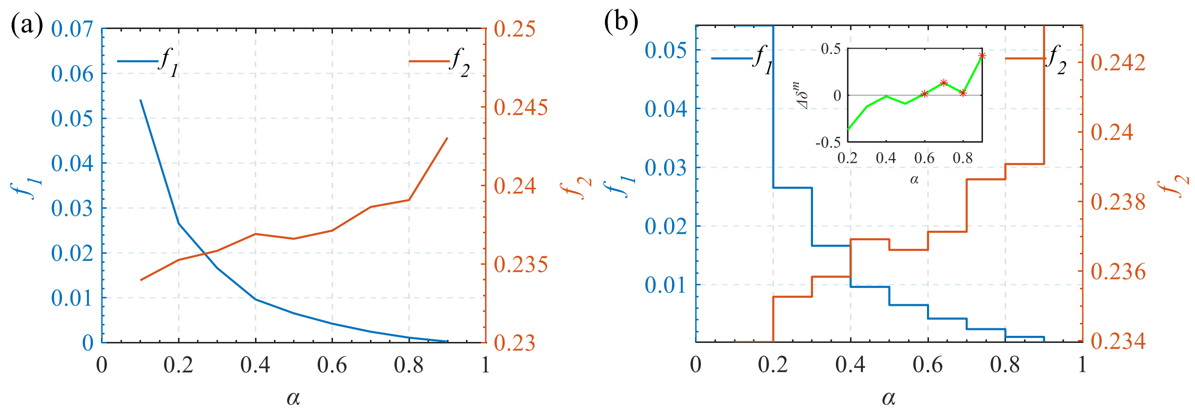
Figure 4.6. Traffic partitioning performance comparison with respect to various combinations of D_1 and β.

4.3.2 Composite Similarity Weight Coefficient

The weight coefficient α is fundamental to supporting a good trade-off between the two considered traffic clustering criteria. Therefore, the traffic partitioning results with different α are analysed. In Figure 4.7 (a), an increasing α results in a decrease/improvement in f_1 and in an increase/deterioration in f_2, implying the conflicting relations between the conflict connectivity and spatial compactness. When α is lowered, more penalty is imposed on the compactness dissimilarity and vice versa. Therefore, an appropriate way is applied to determine the optimal α. It is based on the principle that the increase of α should lead to a more substantial improvement in one metric than the deterioration in another. The change degree of the metric improvement/deterioration from $(m\text{-}1)^{\text{th}}$ to m^{th} α is calibrated using the following equation:

$$\Delta\delta^m = \frac{\bar{f}_1^m - \bar{f}_1^{m-1}}{\left|\bar{f}_1^M - \bar{f}_1^1\right|} + \frac{\bar{f}_2^m - \bar{f}_2^{m-1}}{\left|\bar{f}_2^M - \bar{f}_2^1\right|} \tag{4-11}$$

where $\bar{f}_1^m$ and $\bar{f}_2^m$ represent the average f_1 and f_2 for the m^{th} α, m = 1, 2, …, M (M denotes the number of values of α). In Eq. (4-11), the first term measures the improvement degree (negative index) in f_1 while the second term measures the deterioration degree (positive index) in f_2. Additionally, the normalization is conducted by using the denominators to make the change degree of the two metrics comparable in the same scale. Hence, when $\Delta\delta^m < 0$, it implies a whole improvement gained by increasing α and vice versa. From Figure 4.7 (b), f_1 starts to decline slowly while f_2 starts to increase rapidly when α reaches up to 0.6. More exactly, $\Delta\delta^m$ remains larger than 0 when $\alpha \geq 0.6$ (see the subfigure in Figure 4.7 (b)). It means that the increase in α from 0.6 would not improve the whole partitioning performance. Therefore, a sensible balance between the two conflicting objectives is achieved by using $\alpha = 0.6$.



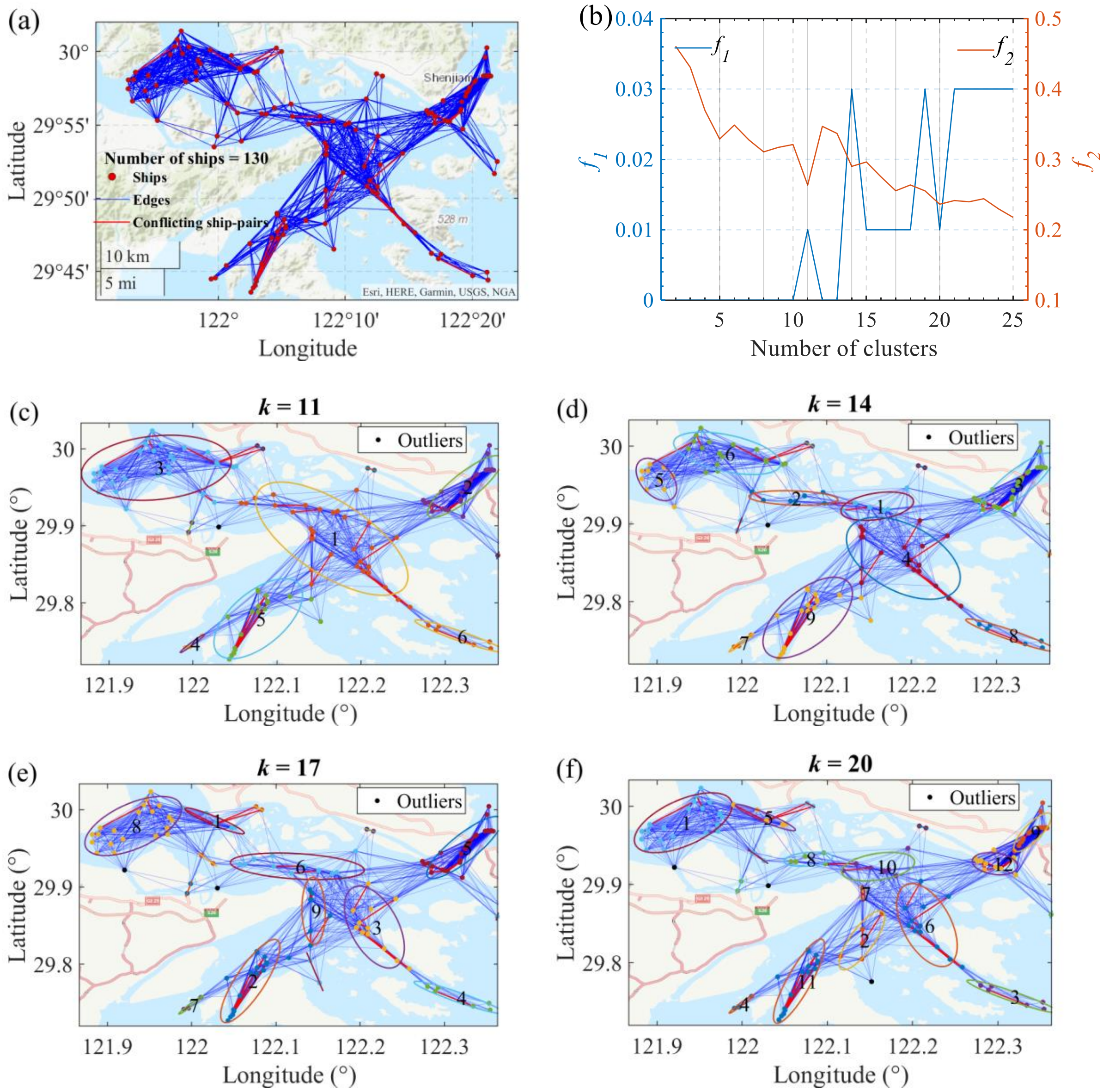
(a) average f_1 and f_2 with different α; (b) increase/decrease degree in f_1 and f_2 with the increase in α.

Figure 4.7. Sensitivity analysis of composite similarity weight coefficient α.

4.4.3 Application Results and Analysis

In this subsection, the effectiveness of the proposed static traffic partitioning methodology is demonstrated based on the real cases. It started by highlighting the application effect on decomposing the whole traffic complexity through a specific maritime traffic scenario. Then a traffic evolution scheme is analysed to display how the proposed methodology sheds light on enhancing maritime traffic surveillance and guiding ship collision risk management.

Figure 4.8 illustrates the ship traffic partitioning results for a traffic scenario with high traffic density at one moment. In Figure 4.8 (a), the visualisation of the graph representation of traffic relations is displayed. The red points represent the ships, the blue lines represent the similarities (*i.e.*, $W_{ij} > 0$) between ship pairs, and the red lines indicate that the ship pairs have conflicting interactions. Because the number of clusters for a clustering issue needs to be determined in advance, the values of f_1 and f_2 when performing clustering with different numbers of clusters are presented in Figure 4.8 (b). Four traffic partitioning results in terms of multiple troughs of orange polyline in Figure 4.8 (b) are exhibited (see Figure 4.8 (c-f)). It is evident from these figures that the produced traffic clusters are spatially compact, while at the same time most of the conflicting ship pairs are assigned to the same clusters, illustrating the good properties of the outlined methodology. In the meantime, it is found that there are complicated conflicting relations among ships (*e.g.*, Clusters 2 and 3 in Figure 4.8 (e)), hence much attention should be paid to the spatio-temporal interactions of multiple ships instead of focusing on the interactions between ship pairs. Additionally, the clustering quality is robust with respect to different numbers of clusters, and more outliers (*i.e.*, the produced clusters with one ship, which can be regarded as safe ships) tend to be filtered out with the increase in the number of clusters. This implies that instead of focusing on a single number of clusters, one can conduct a multi-view analysis by exploring clustering performance of a traffic scenario with different input numbers of clusters. Overall, the proposed methodology performs well in partitioning the whole ship traffic into several high spatial compact and conflict-connected clusters.



(a) Visualisation of ship traffic network; (b) f_1 and f_2 with different numbers of clusters; (c)-(f) traffic partitioning results when the numbers of clusters are 11, 14, 17 and 20.

Figure 4.8. Illustration of ship traffic partitioning results at one moment.

The properties of the generated clusters in Figure 4.8 (d) and (f) are examined and analysed in more detail. Here the clusters with a number of ships smaller than 3 are not labelled. The number of ships and *NS* (Eq. (4-8)) of each produced cluster are shown in Figure 4.9 (a) and (c). It is found that the values of *NS* of all produced clusters are smaller than 1, implying the traffic scenario is properly partitioned. Then Figure 4.9 (b) and (d) present each cluster's traffic density and sum of conflict criticality. The traffic density of each cluster is measured based on the average density of the ships in one cluster and one can refer to (Tan et al., 2016) about the density definition. As shown in these figures, the clusters with high density/conflict severity can be easily found, *e.g.*, Cluster 3 in Figure 4.9 (b) and Cluster 9 in Figure 4.9 (d). This indicates the necessity of decomposing the whole traffic scenario instead of directly implementing MSA from a global perspective. Regarding the practical application of the proposed methodology, one can check the risk/density indices of partitioned traffic clusters to assist surveillance operators in paying more attention to the critical traffic clusters. In this way, the proposed traffic partitioning methodology is supportive for improving situational awareness and identifying high-risk/density areas.

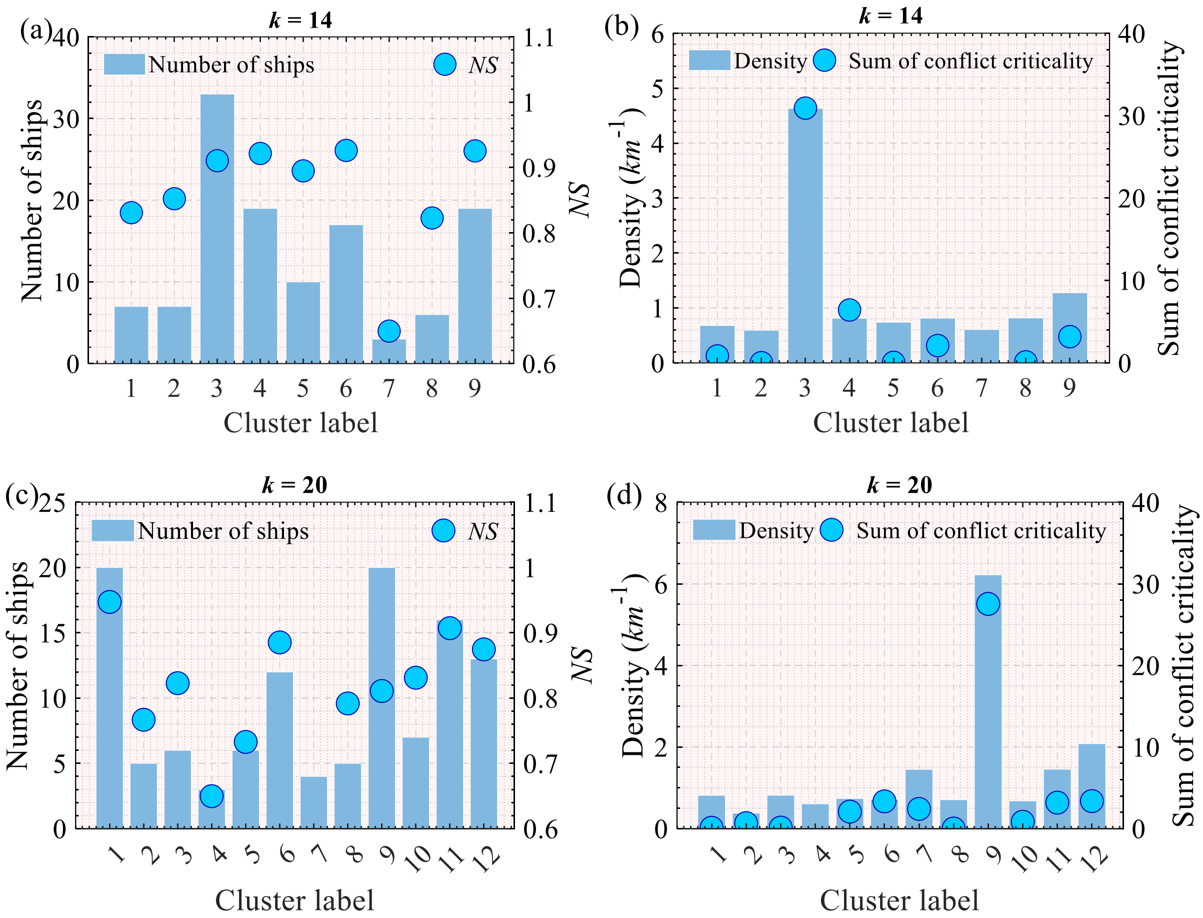


Figure 4.9. Feature statistics of each cluster in Figure 4.8 (d) and (f), including the number of ships, *NS*, traffic density and the sum of conflict criticality.

To illustrate how the proposed methodology enhances maritime operational monitoring and provides vital support in anti-collision decision-making over the water areas of interest, the evolution of density and conflict criticality of both the whole ship traffic situation and generated traffic clusters is provided in Figure 4.10. Here the maximum density and conflict criticality of traffic clusters generated at each moment are exhibited. The number of clusters adopted for partitioning all traffic scenarios at different moments is 15. From Figure 4.10, two interesting findings are revealed. First, the whole traffic density is unfeasible to assist in comprehending the traffic situation due to its slight fluctuations with time. Based on this indicator, maritime operators may encounter difficulties in issuing timely warnings. By contrast, the density of generated traffic clusters varies over time, which can facilitate maritime operators and regulators in identifying when and where they are in high traffic complexity. Second, the conflict criticalities of the whole ship traffic scenario and the traffic clusters show consistent trends. Notably, they are very close during some periods, *e.g.*, 130-150 min. This implies that the conflicting ship pairs have a high probability of being in the same cluster. That is, the traffic partitioning approach can effectively group the ships with high conflict relations into one cluster, which further provides a practical foundation for maritime operators to devise and implement anti-collision risk control strategies. These observations highlight the necessity and effectiveness of the traffic partitioning approach in strengthening MSA and supporting collision risk control.

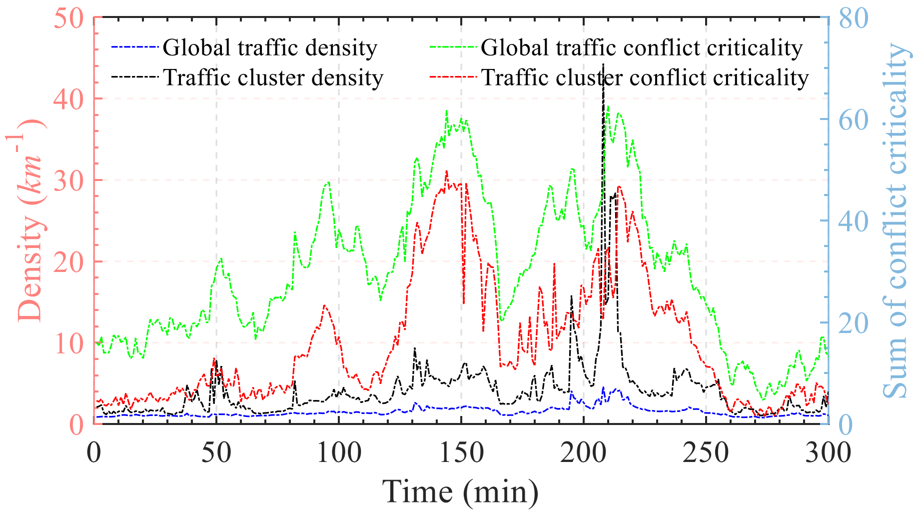


Figure 4.10. Density and conflict criticality evolution of whole ship traffic and traffic clusters over five hours.

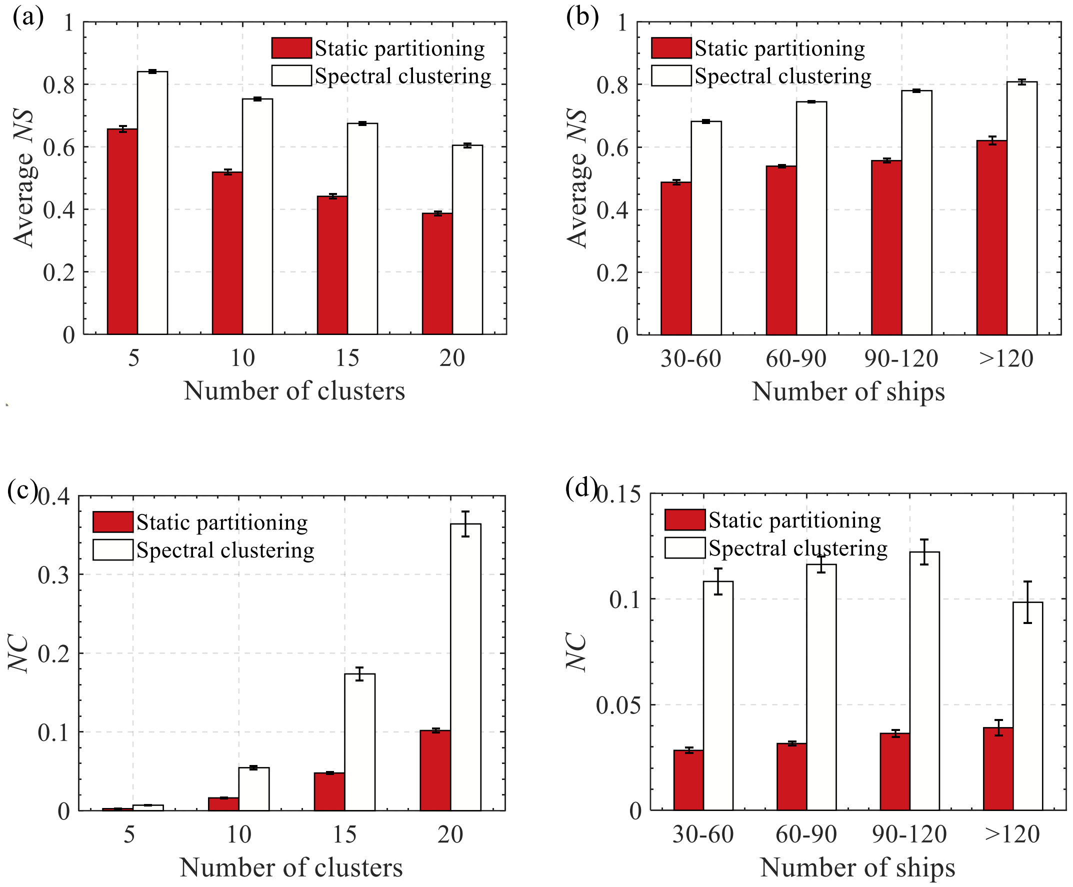
4.4.4 Model Comparison and Validation

The model comparison and validation are essential for the practical application of the modelling methodology. Therefore, the proposed methodology is first compared with the widely used graph-based algorithm (*i.e.*, spectral clustering) to exhibit the superiority of the SNMF framework. Subsequently, the functionality and utility of the functional modules (*i.e.*, the composite similarity model) are tested and examined.

Table 4.2 presents a comprehensive comparison between the proposed methodology and spectral clustering. As shown in the table, the overall performance of the proposed methodology is better than that of spectral clustering in terms of multiple evaluation metrics. The reason is mainly because of the good properties of the SNMF framework and the fact that the orthogonality constraint has a smaller influence on it. Note that other classes of clustering algorithms like prototype-based and density-based clustering are not considered for comparison because they focus on each data sample's features. For instance, *k*-means algorithm performs clustering based on the cluster centres, which is meaningless when the spatial distance between ships is measured by the length of their shortest path on the route network instead of Euclidean distance. The DBSCAN algorithm requires identifying the core samples and has difficulty in handling data sets with varying densities. Therefore, they are not very feasible for traffic partitioning based on the interactions/similarities between ships. To further evaluate the generalization ability of the proposed methodology, extensive comparisons of the two approaches with different numbers of clusters and ships are conducted. As shown in Figure 4.11, the proposed methodology remains superior to spectral clustering under all kinds of situations with respect to both the average *NS* and *NC*. These results confirm the stability and scalability of the SNMF framework.

Table 4.2. A comprehensive comparison between SNMF and spectral clustering.

Clustering algorithms	Average *NS*	*NC*	f_1	f_2
SNMF	0.535	0.032	0.006	0.371
Spectral clustering	0.741	0.115	0.157	0.538

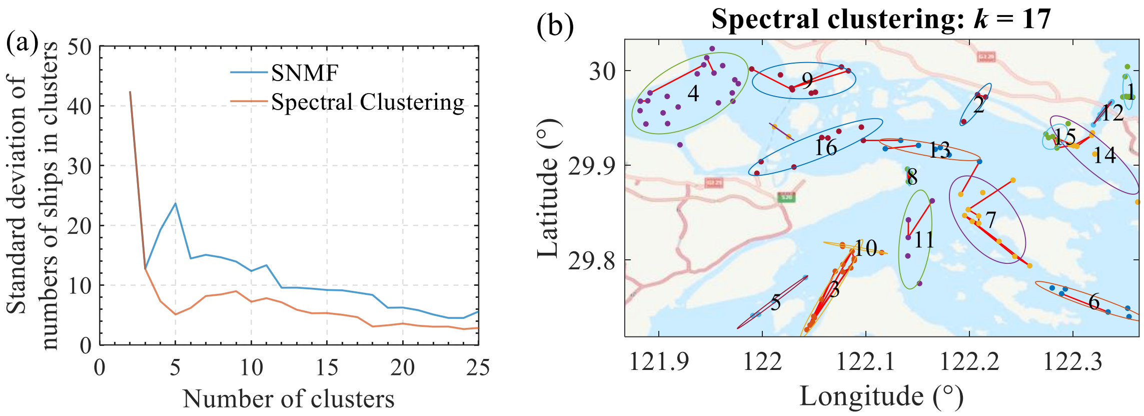


(a-b) Average *NS* comparisons; (c-d) *NC* comparisons.

Figure 4.11. Performance comparison between the proposed methodology and spectral clustering with different numbers of ships and clusters.

One interesting observation is that compared with SNMF, spectral clustering works better in producing clusters with balanced sizes. For example, by making use of the traffic scenario in Figure 4.8 (a), the standard deviations of the generated clusters' numbers of ships from the two algorithms are compared (see Figure 4.12 (a)). It is evident that the standard deviations of spectral clustering are smaller. Figure 4.12 (b) presents the visualisation of the partitioning results using spectral clustering when the number of clusters is 17. It is found that spectral clustering segments Cluster 5 in Figure 4.8 (e) into 4 clusters, thereby generating more balanced clusters. Despite that, spectral clustering ensures the balanced size of clusters by sacrificing the high connections between ships to some extent. That is why its clustering quality is inferior to that of SNMF. By contrast, SNMF performs well in capturing traffic clusters with high connections/similarity while simultaneously filtering out the outliers (*i.e.*, safe ships).

Particularly, one can observe how the high connection traffic clusters expand and shrink with the decrease or increase in the number of clusters, which can help devise multi-layered strategies for conflict resolution. This is obviously not achievable by spectral clustering.



(a) The standard deviations of generated clusters' numbers of ships when implementing the two algorithms for the scenario in Figure 4.8 (a); (b) clustering results using spectral clustering.

Figure 4.12. Comparison between SNMF and spectral clustering in terms of the balance of cluster sizes.

As the designed composite similarity model is among the most critical methodological contributions in this work, the functionalities and utility of key modules in the model are tested and analysed from the following two aspects. Firstly, a traffic scenario is displayed, where using the Euclidean/physical distance encounters issues in ensuring good clustering quality (see Figure 4.13 (a)), while the proposed spatial distance measure model could be potentially better (see Figure 4.13 (b)). As shown in Figure 4.13 (a), ships i and j are surrounded by obstacles and have negligible interactions with other ships. However, they are grouped into clusters, indicating that the Euclidean distance is not appropriate for complex waters with restricted geographical characteristics. In contrast, by using the shortest path length on the derived traffic route network as the distance measure criteria, ships i and j in Figure 4.13 (b) can be identified as outliers. Besides, it is found that Group k in Figure 4.13 (b) is also well separated by using the newly proposed distance measure model. These comparisons reveal that the ship traffic should be more reasonably grouped based on their real spatial relations instead of their physical distance. As a result, the proposed spatial distance measure model leads to a significant improvement of the traffic partitioning performance.

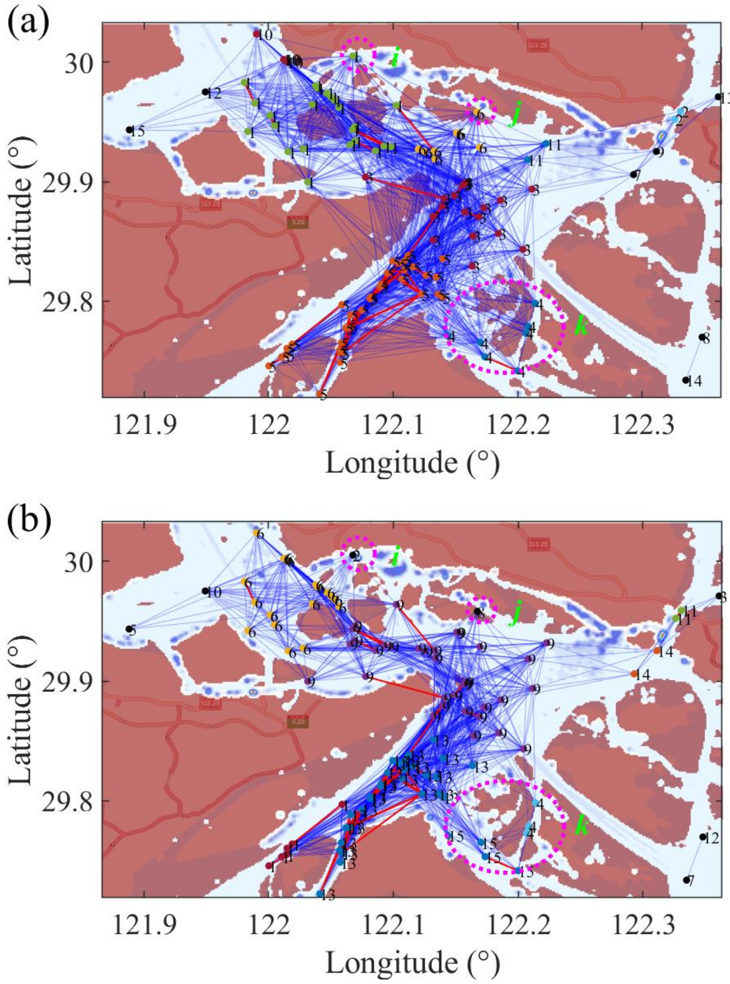


Figure 4.13. A comparison of clustering results when using (a) Euclidean distance and (b) real spatial distance based on the formulated traffic route network.

Another traffic scenario is used to examine the necessity of considering both the spatial compactness and conflict connectivity indices. Figure 4.14 illustrates a clustering performance comparison in which one conducts clustering only based on the compactness similarity model, whereas another uses the composite similarity model. From Figure 4.14 (a), the generated traffic clusters are highly spatial compact, but the ships in conflict are not guaranteed to be assigned to the same clusters. For example, the ships with conflict relations in Circles i, j, and p are not well grouped, which is detrimental to discovering conflicting interaction patterns among ships. On the other hand, it is found from Figure 4.14 (b) that the conflicting ships are well clustered while the spatial compactness is maintained properly as well. Indeed, Figure

4.14 (a) provides an extreme scenario with the weighting coefficient $\alpha = 0$, while Figure 4.14 (b) makes a good trade-off between spatial compactness and conflict connectivity. It must be mentioned that the conflict-based interactions among ships receive more attention from ship navigators and maritime operators than the distance-based interactions. This is because high conflicting relations explicitly indicate the potentially dangerous situation, while high-density relations merely mean the traffic situation is busy and complicated. Therefore, both the conflict connectivity and spatial compactness indices are critical to improving the traffic partitioning quality. In summary, the designed bi-objective similarity model is more desirable as it allows the two indices to be considered simultaneously.

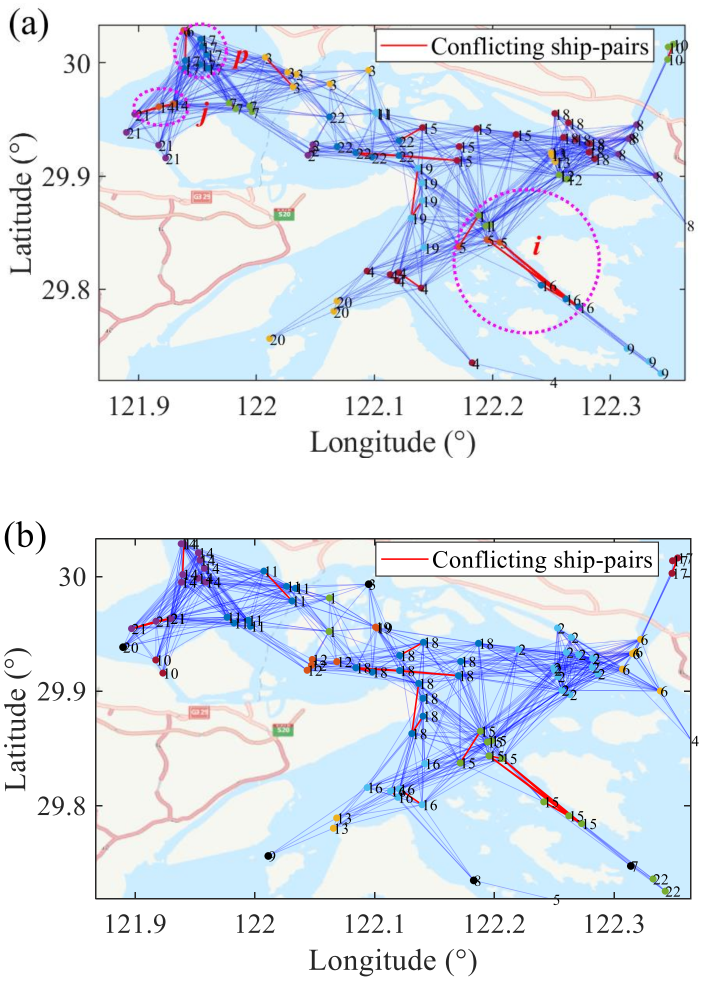


Figure 4.14. A comparison of clustering results when using (a) compactness similarity model only and (b) composite similarity model.

4.4.5 Discussion and Insights

This study conducts a comprehensive experimental analysis and validation for the proposed traffic partitioning methodology, covering from sensitivity analysis of super parameters and application case demonstration to model comparison as well as an examination of key modules' functionality.

Based on the experimental analysis, three methodological insights can be drawn. First, performing MSA in terms of global traffic situation evaluation indices is not constantly recommended for maritime operators because these indices will likely provide less insight into the comprehension of the traffic situation. By contrast, traffic partitioning could improve traffic pattern interpretability and facilitate the discovery of high-risk/density traffic clusters. Second, the incorporation of both spatial compactness and conflict connectivity as well as the influence of water geographical features into traffic partitioning could help obtain a full understanding of the actual multi-attribute interrelationships among ships. However, the existing studies (Liu et al., 2019a; Zhen et al., 2017, 2021) have not addressed either of these two issues. Thirdly, the proposed methodology can be easily tailored and applied to any port and waters because of its strong applicability and robustness to such complex port waters involving high traffic density, dynamic ship movements, and restricted geographical characteristics. Therefore, the proposed methodology and experimental results provide practical implications to maritime surveillance operators and ship navigators in strengthening maritime traffic situation understanding and implementing collision risk control.

4.5 Conclusion

Developing advanced MSA techniques and tools is one of the essential components of emerging intelligent ports and autonomous ships. This study proposes an optimal static ship traffic partitioning methodology that captures conflict-connected and spatial compact traffic clusters to enhance situational awareness and support collision risk management. The developed methodology has been embedded with several unique features: 1) the multi-attribute interrelationships among ships are considered, including their conflict relation and spatial distance; 2) it identifies the exact spatial distance based on maritime traffic knowledge extraction, enabling the methodology to be adaptive to complex geographical waters; and 3) a more competitive graph-based clustering formulation is employed to support robust traffic partitioning.

Extensive numerical experiments with real AIS-based data are conducted to demonstrate the practicality and superiority of the proposed methodology. Based on the in-depth case applications, model comparison, and validation of key modules, its potential to strengthen maritime traffic situation interpretation as well as its good generalization ability and stability have been proved. It sheds valuable light on supporting intelligent maritime surveillance and promoting autonomous anti-collision risk management. Furthermore, it provides the possibility and applicability for the intelligent maritime safety management of both manned ships and MASS as well as their hybrid traffic. As a result, the proposed methodology can be applied in the maritime autonomous navigation system to aid in automatic situation awareness and updates.

Nevertheless, maritime traffic in port areas experiences strongly dynamic behaviour during different times of the day. The influence of traffic evolution over time on traffic partitioning should not be underestimated. It is essential to develop a dynamic traffic partitioning technique to produce realistic and consistent partitioning results that are less sensitive to traffic evolution. In this way, it can facilitate the continuous implementation of anti-collision risk management strategies for the detected traffic clusters. The details of the dynamic traffic partitioning model are elaborated on in Chapter 5.

CHAPTER 5 DYNAMIC SHIP TRAFFIC PARTITIONING INCORPORATING TEMPORAL SMOOTHNESS FOR SAFETY SURVEILLANCE AND MANAGEMENT IN COMPLEX PORT WATERS

This chapter presents a methodology that builds upon the study presented in Chapter 4, offering an effective and powerful means to cope with the influence of dynamic evolution characteristics of ship traffic on traffic partitioning. The methodology comprises two main components. The first is the dynamic traffic partitioning model, which combines the SNMF framework with a temporal smoothness regularization. This model produces stable traffic clusters that are less sensitive to traffic evolution. The second component is a scalable cluster matching strategy, which is developed to track the evolution and structure of dynamic traffic scenarios by extracting a series of similar clusters across successive time snapshots. To evaluate the methodology's performance, maritime traffic data obtained from the Ningbo-Zhoushan Port is used in application demonstration and validation. Experimental results reveal that the new approaches can detect temporal stable and consistent traffic clusters, thereby facilitating the continuous implementation of risk control strategies. Moreover, the methodology performs well in extracting a variety of realistic and sufficient multi-ship encounter scenarios for traffic evolutionary analysis. They offer new insights into enhancing maritime anti-collision control capability and supporting traffic cluster evolutionary behaviour exploration.

5.1 Introduction

The research work in Chapter 4 mainly deals with the identification and discovery of traffic clusters in a specific time moment, in which the traffic situation at a given time slice enables it to be described as several spatially compact and conflict-connected multi-ship encounters. It offers an effective and reliable tool for maritime operators to decrease the difficulty of interpreting the whole traffic situation within a surveillance area and to discover the high-risk traffic clusters in a proactive way. Meanwhile, maritime traffic partitioning is also a prerequisite for the implementation of traffic risk control and management strategies. It can help to determine the constraint boundary (*i.e.*, the nearby ships that need to be considered when taking conflict avoidance action) of a conflict resolution strategy by assigning the ships with high interactions into one cluster (Yang et al., 2017). However, the static traffic partitioning approach in Chapter 4 ignores the importance of incorporating the dynamic evolution characteristics of ship traffic, which may not provide sufficient support for anti-collision strategy implementation in a highly dynamic situation.

Indeed, maritime traffic is a time-variable complex system, where both the ships and their interactions would evolve over time due to short-term variations and long-term drift (Li et al., 2022; Rong et al., 2022). For instance, new ships enter the maritime regulatory region, existing ones leave it, or interrelationships (*e.g.*, spatial distance and conflict criticality) between members are established or terminated as time goes by. These unpredictable dynamic characteristics would significantly affect the stability and consistency of generated traffic clusters over time, which is detrimental to the continuous and efficient implementation of cluster-based anti-collision risk management strategies. In a real-world traffic scenario, a traffic guidance scheme (*e.g.*, a collision avoidance manoeuvre) usually takes a while to complete. To ensure the temporal smoothness of implementing a traffic control scheme, a dynamic traffic partitioning that can handle the temporal evolving maritime traffic is essential. That is, an excellent traffic partitioning scheme should not only match the current interactions among ships well, but also not deviate too significantly from the recent historical partitioning results. Therefore, discovering stable and consistent traffic clusters in dynamic maritime traffic is an important research task with new interesting challenges.

On the other hand, dynamic traffic partitioning is crucial for studying traffic cluster evolution patterns over time. It enables the examination of key events such as birth, growth, contraction, merging, splitting, and death of a traffic encountering scenario (Dakiche et al., 2019). Hence, advanced techniques are needed to track dynamic traffic scenarios, which involve conducting traffic cluster matching at consecutive time steps to form a sequence of snapshot clusters ordered by time. In the meantime, the rapid development of MASS brings new emergent properties to the maritime transportation domain, which requires the proper assessment and tests before implementation (Bakdi et al., 2021). The extracted dynamic traffic scenarios involving complex spatio-temporal multi-ship interactions can form a complete set of realistic navigation scenarios for MASS testing and verification. Therefore, combining a new dynamic traffic partitioning model with an effective traffic cluster matching strategy has the potential to promote a navigation automation system.

This chapter aims to develop a dynamic traffic partitioning and a traffic scenario extraction model that can 1) produce realistic and consistent partitioning results that are less sensitive to the temporally evolving characteristics of maritime traffic and 2) extract the dynamic traffic scenarios to track their evolution and structure in multiple time snapshots. To achieve the purposes, dynamic traffic partitioning must consider both the current traffic partition quality and the temporal smoothness associated with the historical partitioning structures to obtain reliable and stable traffic clusters to aid the continuous implementation of risk control strategies. On this basis, a simple but effective cluster matching method can be designed and used to effectively track the dynamic traffic scenarios from the dynamic traffic partitioning results. The research framework is shown in Figure 5. The success of the proposed methodology will enhance intelligent maritime traffic management by facilitating anti-collision decision-making to control multi-ship collision risks and support the evolution analysis of traffic interactions.

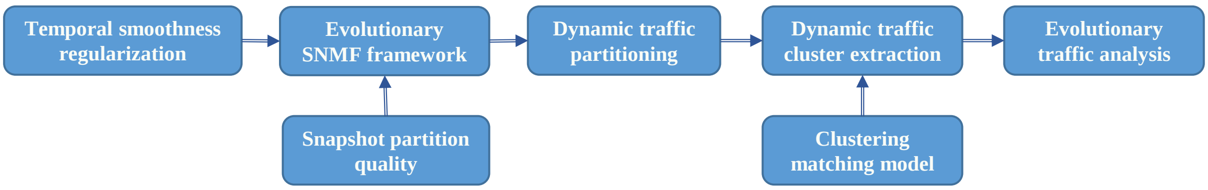


Figure 5.1. The research framework.

The rest of this chapter is organised as follows. Section 5.2 discusses the challenges and solutions regarding dynamic traffic partitioning and dynamic traffic scenario extraction. Section 5.3 elaborates on the details of the proposed dynamic traffic partitioning method. In Section 5.4, the proposed dynamic traffic scenario extraction strategy is described in detail. The application performance and validation are demonstrated in Section 5.5. Finally, this chapter is concluded in Section 5.6.

5.2 Problem Statement

As reviewed in Section 2.4, there have not been any relevant research findings reported on dynamic maritime traffic partitioning that generates temporally stable and consistent traffic clusters, despite its crucial role in supporting the continuous implementation of anti-collision risk management strategies. In the road transportation network partitioning sector, researchers have highlighted the importance of investigating the traffic partitioning issue from the temporal dimension (Ji and Geroliminis, 2012; Saeedmanesh and Geroliminis, 2017). These works provide valuable insights into dynamic maritime traffic partitioning. Based on the research aims mentioned above, the following challenges must be solved.

1) How to incorporate the traffic dynamic evolution characteristics into the partitioning process

Compared with static traffic partitioning, dynamic traffic partitioning is more challenging as one must consider current clustering accuracy and temporal smoothness related to historical information simultaneously. The relevant work in the road transportation network field adjusted the cluster boundary over time based on the spatio-temporal propagation of congested pockets (Ji and Geroliminis, 2012; Saeedmanesh and Geroliminis, 2017). However, the unique temporal characteristics of the ship traffic network (*i.e.,* both the nodes and edges change over time) present a challenge for adopting this type of method. To address this issue, an evolutionary clustering-based framework (Chi et al., 2007) is adopted to conduct dynamic traffic partitioning based on the traffic networks at successive time points. It has been widely used for dynamic community detection because of its excellent performance in balancing the communities obtained in networks at consecutive snapshots (Li et al., 2021; Qin et al., 2016). The framework involves two components: Snapshot Cost (*CS*) and Temporal Cost (*CT*). *CS* measures how well the clustering results represent the current traffic network feature, where a lower *CS* indicates better clustering quality. *CT* quantifies the goodness-of-fit of the current clustering structure with respect to either historical data features or historical clustering structures, where a lower *CT* suggests a better temporal smoothness. To balance the *CS* and *CT*, a weighted linear function is generally employed as follows:

$$Cost = \gamma \cdot CS + (1 - \gamma) \cdot CT \tag{5-1}$$

where $\gamma \in [0,1]$ is a regularization parameter that controls the relative importance of the two regularization items. The setting of γ corresponding to the lower and upper bounds of [0,1] provide two extreme scenarios. When $\gamma = 1$, dynamic traffic partitioning is transformed into a static traffic partitioning problem since the temporal smoothness associated with the traffic network at the previous moment is ignored. When $\gamma = 0$, the clustering structures at the consecutive time moments are required to be identical. Therefore, the effective tuning/optimization of parameter γ contributes to a better trade-off between *CS* and *CT*, which is analysed and determined in terms of the optimisation performance in both competing objectives (see Section 5.4.1).

2) How to track the evolutionary traffic scenarios efficiently and accurately from the historical successive traffic networks

Dynamic traffic partitioning can also aid in the extraction of dynamic traffic scenarios from multiple snapshots, enabling spatio-temporal evolution analysis of multi-ship conflicts. Currently, some researchers have concentrated on extracting multi-ship encounter scenarios from massive historical AIS databases. For example, Bakdi et al. (2021) designed a hierarchical data mining method to capture a variety of realistic and sufficient traffic encountering scenarios based on big traffic data. The extracted scenarios have their unique characteristics over simulation-based traffic scenarios, which are fundamental inputs for MASS testing and verification. However, to avoid the computational intensity of direct scenario extraction from the historical data, this study captures dynamic traffic scenarios based on the dynamic traffic partitioning results from each time snapshot. The approach matches clusters with those detected in previous time snapshots based on their similarity (Asur et al., 2009; Hopcroft et al., 2004).

In the context of the approach described above, two key issues need to be considered: the cluster matching accuracy and efficiency. The traditional strategy of searching for the optimal match between clusters at different time snapshots is precise but time-consuming, such as the work in Tantipathananandh et al. (2007). This study therefore designs a greedy search procedure to efficiently and reliably identify and track dynamic traffic scenarios across different time steps. Additionally, a heuristic threshold-based model is employed to adaptively control the mapping degree between clusters in multiple snapshots.

5.3 Methodology 1: Dynamic Traffic Partitioning

An excellent dynamic traffic partitioning method should produce good partitioning results that simultaneously fit the current traffic network and do not deviate dramatically from the recent historical traffic partitioning results. To fulfil the dual objectives, a holistic evolutionary clustering method that can integrate a measure of temporal smoothness is developed, which consists of three major components: 1) a composite similarity model; 2) an SNMF based evolutionary clustering model; and 3) an extension of the evolutionary clustering model. In addition, the new metrics for performance evaluation of the dynamic traffic partitioning method are finally introduced.

5.3.1 Similarity Measures and Models

The similarity measure for ship pairs is the first basic module of maritime traffic partitioning because it describes the interrelationships and interactions among ship traffic. This chapter still adopts the composite similarity model developed in Chapter 4 to allow both the conflict relation and spatial distance of ship pairs to be measured. The relevant details can be checked in Section 4.3.1.

5.3.2 SNMF Based Evolutionary Clustering Model

As mentioned in Section 5.2, dynamic traffic partitioning needs to incorporate historical network structure information. Hence, a dynamic traffic network should be formulated in terms of the interrelations among ship traffic in successive time steps. Normally, a dynamic traffic network consists of a sequence of static traffic networks, which can be expressed as $\{G_1, G_2, \ldots, G_T\}$, where $G_t = (V_t, E_t)$ represents the traffic network at time snapshot t with node set V_t and edge set E_t. Note that the symbol definitions adopted in this chapter are identical to those provided in Table 4.1. Hence, the similarity and degree matrices for traffic network at time t can be expressed as W_t and D_t.

Once the traffic network information in consecutive snapshots is obtained, dynamic traffic partitioning can be implemented. Following the evolutionary clustering-based framework in Eq. (5-1), two crucial terms, *i.e.*, *CS* and *CT*, need to be determined. In this study, the snapshot cost *CS* is characterised by the *Ncut* in Eq. (4-5), while the temporal cost *CT* measures the difference between the clustering structures at the current time moment and at the previous time moment based on the partition distance indicator in Chi et al. (2009), as follows:

$$\begin{aligned} CT &= dist(H_t, H_{t-1}) \\ &= \frac{1}{2}\|H_t H_t^T - H_{t-1}H_{t-1}^T\|^2 \\ &= \frac{1}{2}\boldsymbol{Tr}(H_t H_t^T - H_{t-1}H_{t-1}^T)^T (H_t H_t^T - H_{t-1}H_{t-1}^T) \\ &= \frac{1}{2}\boldsymbol{Tr}(H_t H_t^T H_t H_t^T - 2H_t H_t^T H_{t-1}H_{t-1}^T + H_{t-1}H_{t-1}^T H_{t-1}H_{t-1}^T) \\ &= k - \boldsymbol{Tr}(H_t^T H_{t-1}H_{t-1}^T H_t) \end{aligned} \tag{5-2}$$

where H_t and H_{t-1} represent the clustering membership matrices at time *t* and *t-1*, respectively. Eq. (5-2) uses the clustering results at the previous time moment to guide the clustering at the current time moment. It penalizes the *CT* terms when the H_t does not fit well with H_{t-1}.

Substituting Eq. (4-5) and Eq. (5-2) into Eq. (5-1), the overall cost function can be reformulated in the following forms:

$$\begin{aligned} Cost_{Ncut} &= \gamma \cdot CS_{Ncut} + (1-\gamma)\cdot CT \\ &= \gamma \cdot k - \gamma \cdot \boldsymbol{Tr}\left[H_t^T \left(D_t^{-\frac{1}{2}} W_t D_t^{-\frac{1}{2}}\right) H_t\right] + (1-\gamma)\cdot k + (1-\gamma) \\ &\qquad \cdot \boldsymbol{Tr}(H_t^T H_{t-1}H_{t-1}^T H_t) \\ &= k - \boldsymbol{Tr}\left\{H_t^T \left[\gamma \cdot D_t^{-\frac{1}{2}} W_t D_t^{-\frac{1}{2}} + (1-\gamma)\cdot H_{t-1}H_{t-1}^T\right] H_t\right\} \end{aligned} \tag{5-3}$$

where the symbols attached subscript *t* in Eq. (5-3) represent the corresponding variables in Table 4.1 at time *t*. Note that the first term (*i.e.*, the desired number of clusters *k*) in Eq. (5-3) is constant. Therefore, minimizing $Cost_{Ncut}$ is equivalent to maximizing the second term, as shown in Eq. (5-4).

$$\min Cost_{Ncut} \propto \max \boldsymbol{Tr}\left\{H_t^T\left[\gamma \cdot D_t^{-\frac{1}{2}} W_t D_t^{-\frac{1}{2}} + (1-\gamma) \cdot H_{t-1} H_{t-1}^T\right] H_t\right\} \tag{5-4}$$

In terms of the derived formulas in Eq. (4-4), the trace optimization issue in Eq. (5-4) can be rewritten as follows:

$$\min_{H_t \geq 0, H_t H_t^T = I} \left\|\gamma \cdot D_t^{-\frac{1}{2}} W_t D_t^{-\frac{1}{2}} + (1-\gamma) \cdot H_{t-1} H_{t-1}^T - H_t H_t^T\right\|_F^2 \tag{5-5}$$

Relaxing the orthogonality $H_t H_t^T = I$ based on the SNMF framework, Eq. (5-5) is rewritten as:

$$SNMF_{Cost_{Ncut}} \propto \min_{H_t \geq 0} \left\|\gamma \cdot D_t^{-\frac{1}{2}} W_t D_t^{-\frac{1}{2}} + (1-\gamma) \cdot H_{t-1} H_{t-1}^T - H_t H_t^T\right\|_F^2 \tag{5-6}$$

The minimisation of Eq. (5-6) can be further solved by using the Newton-like algorithm mentioned in Section 4.3.2.2.

5.3.3 Extension of the Evolutionary Clustering Model

It should be noted that the above dynamic clustering framework may encounter the following limitations for its real application in maritime traffic partitioning. First, new ships join, or existing ships leave frequently in real-world traffic networks, which may result in the inconsistency between H_t and H_{t-1}. Second, the dynamic framework incorporates a single-step historical network structure information, which can only discover short-cycle stable traffic clusters. Hence, further extensions become essential to handle these issues.

With respect to the first issue, a heuristic solution is adopted to transform the H_{t-1} to the identical dimension as H_t. When old ships quit, the corresponding rows in H_{t-1} are removed to obtain $\widetilde{H}_{t-1}$ (assuming the dimensions of $\widetilde{H}_{t-1}$ is $n_1 \times k$). When new ships join, $\widetilde{H}_{t-1}$ is further extended to be $\widehat{H}_{t-1}$ (assuming the dimension of $\widehat{H}_{t-1}$ is $n_2 \times k$) using the following equation:

$$\widehat{H}_{t-1} = \begin{bmatrix} \widetilde{H}_{t-1} \\ G_{t-1} \end{bmatrix}, \text{where } G_{t-1} = \frac{1}{n_1} \vec{1}_{n_2-n_1} \vec{1}_{n_1}^T \widetilde{H}_{t-1} \tag{5-7}$$

In Eq. (5-7), the row average of $\widetilde{H}_{t-1}$ is inserted as new rows. By doing so, the generalization of the dynamic clustering framework for the addition and removal of nodes is ensured.

Regarding the second issue, the dynamic clustering framework can be extended to cover longer historical information by incorporating a series of H_i (i = 1, 2, …, t-1) at the previous time steps. Thus, Eq. (5-6) can be extended to the following form:

$$\arg\min_{H_t \geq 0} \left\| \gamma \cdot D_t^{-\frac{1}{2}} W_t D_t^{-\frac{1}{2}} + (1-\gamma) \cdot \left(\sum_{i=1}^{t-1} H_{t-i} H_{t-i}^T \right) - H_t H_t^T \right\|_F^2 \tag{5-8}$$

Indeed, even only considering one single-step historical information, the evolutionary clustering framework can combine the information across multi-step historical traffic networks to some extent. This is because the clustering structure H_t partly relies on H_{t-1}, while H_{t-1} partly relies on H_{t-2}, and so on. That is, the dynamic clustering framework provides an incremental way to detect clustering structures over time, which will be demonstrated in Section 5.5.2.

In addition, the dynamic clustering framework also gives the flexibility to handle variations in the number of clusters over time. This is due to the fact that the calculation of partition distance (*i.e.*, Eq. (5-2)) is free from the effect of the number of columns in H_t and H_{t-1} (expressed by k_t and k_{t-1}), in which k_t and k_{t-1} represent the number of clusters at the two moments. Hence, the number of clusters at time t does not require the same as that at time t-1. Based on the extension and the universality of the dynamic clustering framework, it will be flexible and generalized enough to adapt to the maritime traffic evolution characteristics.

5.3.4 Model Performance Measure Indicators

In Section 4.3.3, four metrics are employed to evaluate static traffic partitioning performance, which is also used in this chapter. Additionally, for dynamic partitioning performance verification, the temporal smoothness of clustering results at different time moments also needs to be calibrated. Here a partition difference measure index used by (Chi et al., 2007; Meilă, 2012) is adopted to quantify the distance between two clustering results as follows:

$$CT_{KM} = \sum_{i=1}^{k_t} \sum_{j=1}^{k_{t-l}} \frac{vol(A_{ij})^2}{vol(A_{i,t}) vol(A_{j,t-l})} \tag{5-9}$$

where t and t-l denote two time moments for traffic partitioning, $vol(A_{i,t})$ is the number of ships of the ith produced traffic cluster at time t, k_t represents the number of clusters generated at time t, and $vol(A_{ij})$ denotes the number of ships belonging to both clusters $A_{i,t}$ and $A_{j,t-l}$. In theory, the un-relaxed versions of distance indices in Eq. (5-2) and Eq. (5-9) hold the following relation (see (Bach and Jordan, 2006) for reference):

$$\frac{1}{2}\|H_t H_t^T - H_{t-1}H_{t-1}^T\|^2 = k - \sum_{i=1}^{k}\sum_{j=1}^{k}\frac{vol(A_{ij})^2}{vol(A_{i,t})vol(A_{j,t-1})} \tag{5-10}$$

Therefore, a higher value of CT_{KM} is associated with a higher temporal smoothness. Moreover, the distance index CT_{KM} of two identical traffic partitions equals the value of the number of clusters.

5.4 Methodology 2: Dynamic Traffic Scenario Extraction

5.4.1 Dynamic Traffic Scenario Discovery

Dynamic traffic scenario tracking involves the extraction of a series of similar clusters at different time slices. Assume that a dynamic traffic network $\{G_1, G_2, \ldots, G_T\}$ is associated with a set of T time step clusters $\{C_1, C_2, \ldots, C_T\}$, where $C_t = \{C_{t,1}, C_{t,2}, \ldots, C_{t,kt}\}$ represents the instance observations of traffic clusters at time t. Then the issue becomes the capturing of a set of dynamic traffic scenarios $DTC = \{DTC_1, DTC_2, \ldots, DTC_{k0}\}$ that are provided in $\{C_1, C_2, \ldots, C_T\}$ across successive time snapshots, where a dynamic traffic scenario DTC_i can be expressed by its constituent clusters ordered by a timeline.

In practice, the extraction of dynamic traffic scenarios can be solved by a bipartite matching approach because it concentrates on searching for optimal correspondence between the traffic clusters at consecutive time steps. However, traditional bipartite matching approaches need to perform the matching task for all possible cluster pairs at successive time snapshots, resulting in high computational complexity (Tantipathananandh et al., 2007). Therefore, a greedy search procedure is proposed to allow efficient computation through eliminating unnecessary mapping.

To measure the matching between traffic clusters in different time steps, a commonly used Jaccard coefficient for binary sets (Jaccard, 1912) is employed. Given the local clusters $C_{t,i}$ and

$C_{t+1,j}$ at time snapshots t and t+1, the matching degree between them is defined as follows:

$$MD(C_{t,i}, C_{t+1,j}) = \frac{|C_{t,i} \cap C_{t+1,j}|}{|C_{t,i} \cup C_{t+1,j}|} \tag{5-11}$$

where $|C_{t,i}|$ represents the number of ships in $C_{t,i}$. The underlying assumption is that a higher overlap of ships corresponds to a higher matching degree. Here, a matching threshold $\theta \in [0, 1]$ is adopted to determine whether $C_{t,i}$ and $C_{t+1,j}$ have the possibility of belonging to the same dynamic cluster. When $MD(C_{t,i}, C_{t+1,j})$ exceeds θ, $C_{t,i}$ and $C_{t+1,j}$ may be added into the same *DTC* based on the timeline.

Based on the matching degree metric, an effective cluster search procedure is introduced to efficiently match and capture dynamic traffic clusters in multiple snapshots. The procedure proceeds as follows. For each $C_{t+1,j}$ within each time step, the front traffic cluster $C_{t,i}$ (*i.e.* the time step clusters from C_t) which has a maximal *MD* with $C_{t+1,j}$ is selected. If $MD(C_{t,i}, C_{t+1,j}) > \theta$, then $C_{t+1,j}$ will be added to the dynamic traffic cluster containing $C_{t,i}$; otherwise, a new dynamic traffic cluster including $C_{t+1,j}$ will be created. During the process, once $C_{t,i}$ has been matched, the *MD* between $C_{t,i}$ and other local clusters in C_{t+1} do not need to be calculated. The procedure continues until all time step clusters have been processed. The detailed matching algorithm is provided in Algorithm 5.1.

Algorithm 5.1. An effective dynamic traffic cluster matching strategy.

Input: local clusters $C = \{C_1, C_2, . . . , C_T\}$ over time, matching threshold θ.
Output: dynamic traffic scenarios $DTC = \{DTC_1, DTC_2, . . . , DTC_{k0}\}$
1. **For** each subsequent step t, extract C_{t+1} from C.
2.   **For** each $C_{t+1,j} \in C_{t+1}$
3.   Calculate $MD(C_{t,i}, C_{t+1,j})$ for any unmatched $C_{t,i} \in C_t$
4.   Search for $C_{t,i}$ that has the maximal *MD* value with $C_{t+1,j}$
5.   **If** $C_{t,i}$ satisfies $MD(C_{t,i}, C_{t+1,j}) > \theta$
6.   Add $C_{t+1,j}$ into the dynamic traffic cluster containing $C_{t,i}$
7.   **Else**
8.   Create a new dynamic traffic cluster containing $C_{t+1,j}$
9.   **End**
10. **End**
11. **End**

5.4.2 Dynamic Traffic Scenario Property Evaluation

A large number of dynamic traffic scenarios can be captured from the historical AIS data based on the dynamic cluster discovery procedure. The traffic clusters associated with different sizes and time lengths will correspond to different interpretability. Hence, it is essential to adopt some measure of significance to evaluate the scenario properties. Here, two indices are considered: 1) the life cycle or longevity of a dynamic traffic scenario; and 2) the stability or consistency of node members in a dynamic traffic scenario with time. More concretely, the longevity of a dynamic traffic cluster $DTC_i = \{DTC_{i,1}, DTC_{i,1}, \cdots, DTC_{i,l_i}\}$ refer to the existing duration from its existence to disappearance, which is expressed as l_i. The stability of DTC_i is measured based on the mean Jaccard coefficient between each of its constituent step local clusters and its previous step local cluster (Greene et al., 2010), as follows:

$$Sta(DTC_i) = \frac{1}{l_i - 1} \sum_{DTC_{i,j} \in DTC_i} \frac{|DTC_{i,j} \cap DTC_{i,j+1}|}{|DTC_{i,j} \cup DTC_{i,j+1}|} \tag{5-12}$$

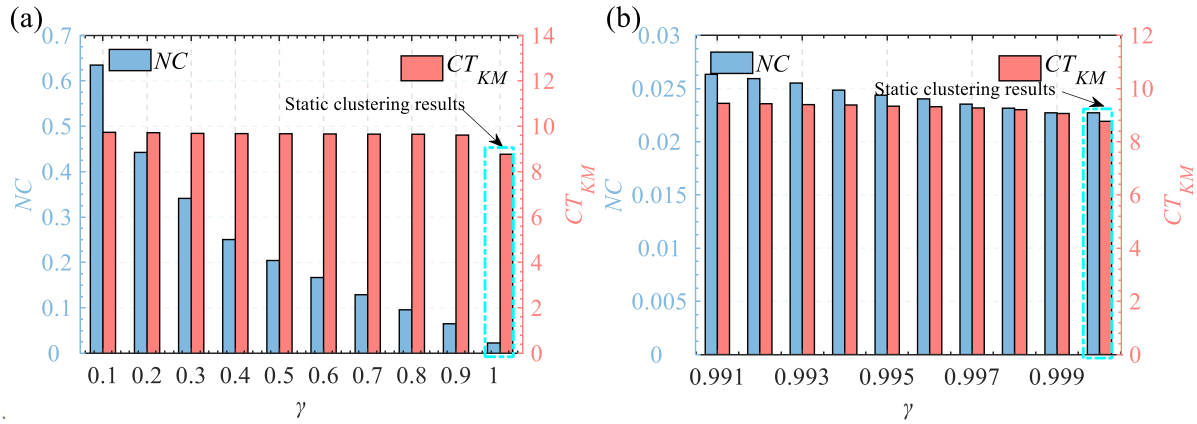
where $Sta(DTC_i)$ falls into [0,1]. This indicator quantifies the appearing frequency of the same node members between consecutive time steps. A more stable dynamic scenario will be associated with a significance score close to 1, while a less stable dynamic scenario will correspond to a significance score close to 0.

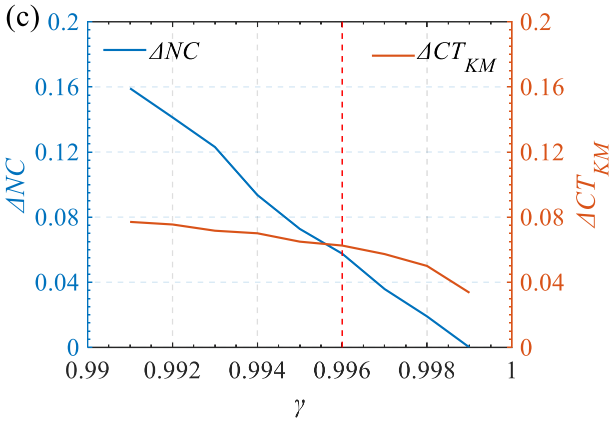
5.5 Applications and Case Study Results

In this subsection, the performance of the proposed methodology is evaluated and analysed. It is organised as follows: Section 5.5.1 illustrates the sensitivity analysis for the super parameters in the proposed methodology. Section 5.5.2 demonstrates how the dynamic traffic partitioning method captures the temporal stable and consistent traffic clusters and assists in collision risk control. In Section 5.5.3, the extracted dynamic traffic scenarios are analysed and demonstrated. Section 5.5.4 conducts a model validation and comparison analysis.

5.5.1 Sensitivity Analysis of Evolutionary Regularization Weight Coefficient

As stated in Section 5.2, the weight coefficient γ needs to be properly chosen to balance the clustering accuracy and temporal smoothness. Figure 5.2 illustrates the dynamic traffic clustering results when using different γ. In Figure 5.2 (a), when $\gamma \in [0.1\ 0.9]$, the NC indicator has inferior performance (very high NC values) compared with the static clustering results (*i.e.*, when $\gamma = 1$). On the contrary, the CT_{KM} indicator keeps relatively stable in this range. This is because the two terms adopted in Eq. (5-1) have different scales. Hence, this difference has to be considered and further performance analysis with different γ is conducted within the range of [0.9, 1]. As shown in Figure 5.2 (b), the two indicators have a relatively consistent change degree when γ falls into [0.991, 1]. To identify the optimal γ, the change degree of the metric improvement/deterioration is analysed. Different from the weight coefficient α in Section 4.4.2.1, the change degree of NC and CT_{KM} can be determined by using the static clustering results as baselines. In Figure 5.2 (c), ΔNC and ΔCT_{KM} represent the increasing degree of NC and CT_{KM} compared to the static clustering results, respectively. ΔNC quantifies the deterioration degree in NC, while ΔCT_{KM} measures the improvement degree in CT_{KM}. It is found NC decreases more quickly than CT_{KM} with the increase in γ. When $\gamma = 0.996$, the NC and CT_{KM} have close change degrees, *i.e.*, the deterioration degree in NC and the improvement degree in CT_{KM} are in balance. As a result, γ is set to be 0.996 to effectively balance the two conflicting terms.



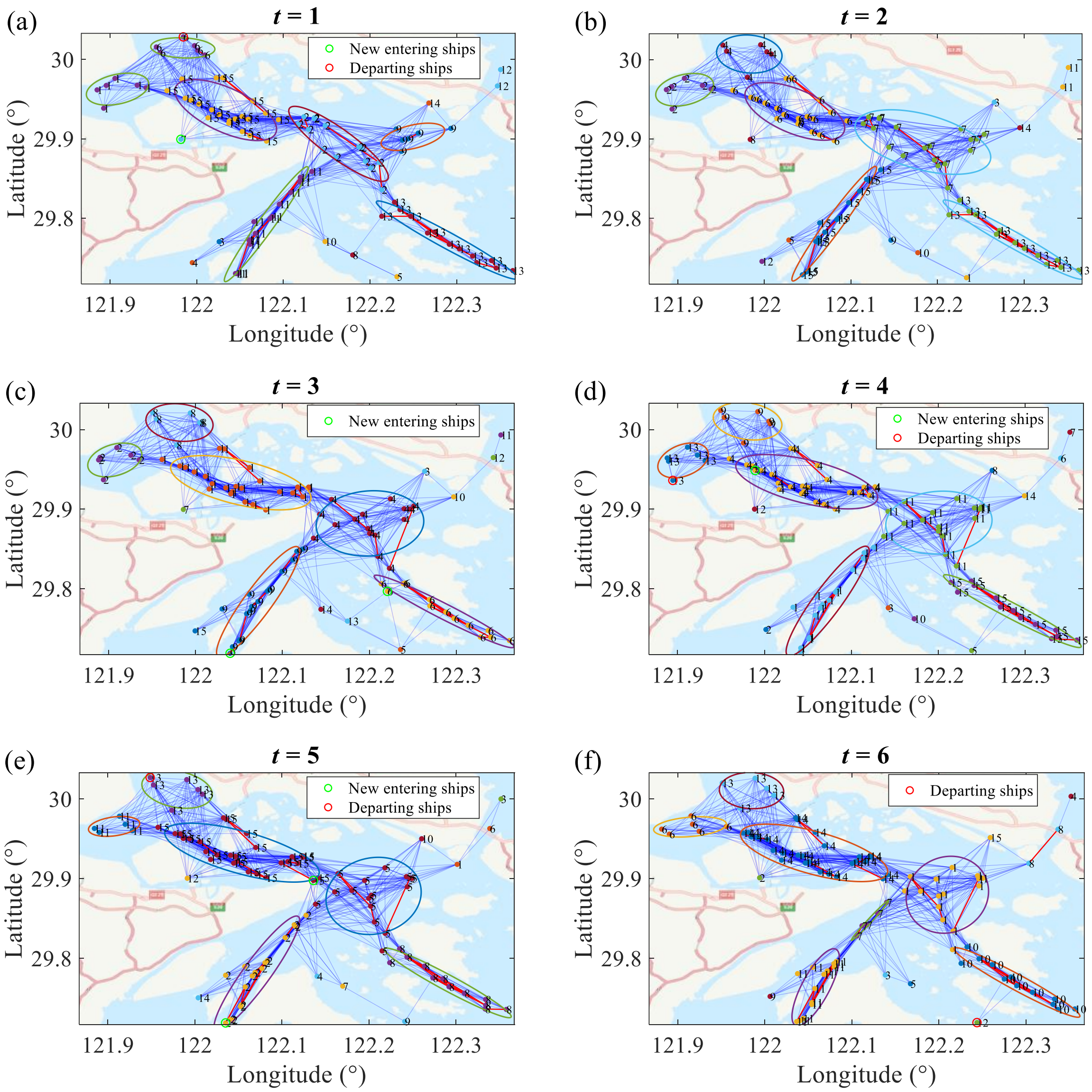


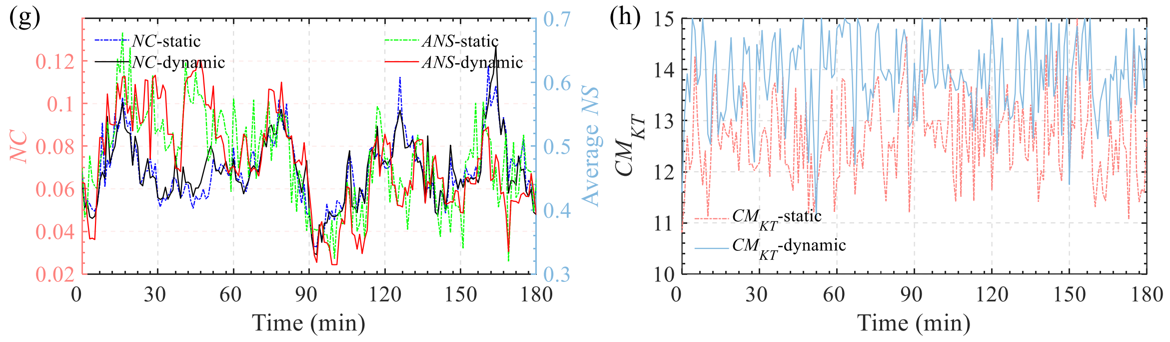
(a) Average *NC* and CT_{KM} when *γ* falls into [0.1, 1]; (b) average *NC* and CT_{KM} when *γ* falls into [0.991, 1]; (c) increase degree in *NC* and CT_{KM} with different *γ*.

Figure 5.2. Sensitivity analysis of evolutionary regularization weight coefficient *γ*.

5.5.2 Application Performance of Dynamic Traffic Partitioning

Figure 5.3 displays the dynamic partitioning results over 3 hours when using single-step historical clustering information. In Figure 5.3 (a)-(f), the visualisation of dynamic traffic partitioning at the first 6 minutes (*i.e.*, t = 1, 2, 3, …, 6 minutes) is exhibited, where the points circled with green and red circles represent the new entering and departing ships, respectively. The high frequency of the joining and leaving of ships in a short period shows the strongly time-variant process of maritime traffic. The number of clusters (*i.e.*, k) is set to 15 for partitioning the traffic scenario at each moment. It is shown from Figure 5.3 (a)-(f) that the traffic partitioning results maintain relatively good consistency with their historical clustering structures. The stable traffic clusters without significant drift over time are a prerequisite for the continuous implementation of cluster-based anti-collision strategies, which provides vital support in ensuring the safety level of maritime traffic. In the meantime, several interesting evolutionary characteristics are found. For instance, Clusters 2 and 9 at $t = 1$ merge a new Cluster 7 at $t = 2$; Cluster 3 at $t = 5$ is split into two new Clusters 7 and 11 at $t = 6$. Additionally, the boundary adjustment of traffic clusters is also found, *e.g.*, some ships in Cluster 7 at $t = 2$ are added into Cluster 4 at $t = 3$. The temporal dependencies of the generated traffic clusters show the potential to assist in exploring the evolutionary co-behaviours among multiple participating ships, which can contribute sufficient real-world scenarios to testing and verifying the new intelligent traffic management techniques, such as autonomous decision-making and physical and cyber risk assessment. Furthermore, the evolution of *NC*, average *NS*, and CM_{KT} when using dynamic and static traffic partitioning are compared and investigated. In Figure 5.3 (g), the performance of *NC* and average *NS* with dynamic traffic partitioning does not decline significantly. In particular, the *NC* values associated with dynamic traffic partitioning basically keep the same as those of static partitioning. On the other hand, the $CM_{KT}(t, t\text{-}1)$ performance of dynamic partitioning is improved to some extent compared with that of static clustering. In other words, the dynamic traffic partitioning model can detect traffic clusters that jointly maintain the fit of the current traffic features and the historical temporal evolution.

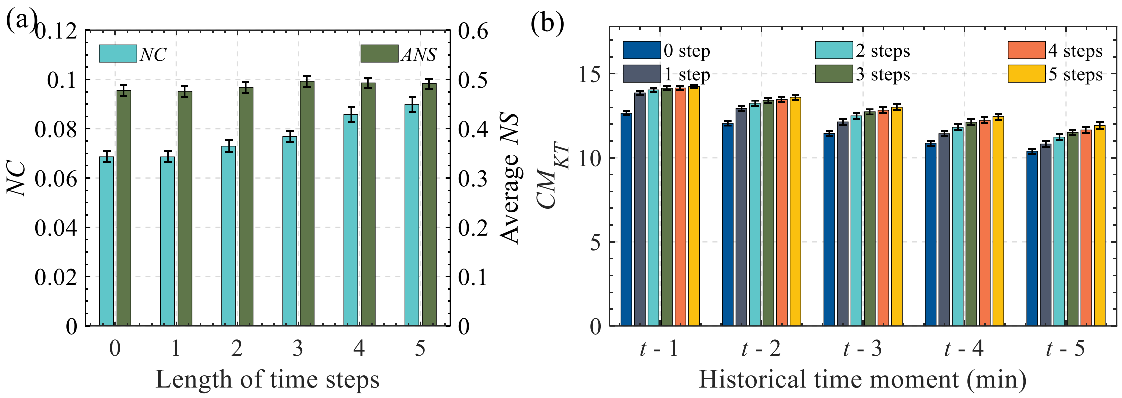




(a)-(f) Dynamic traffic partitioning results at time t = 1-6; (g) evolution of *NC* and average *NS* over 3 hours; (h) evolution of $CM_{KT}(t, t\text{-}1)$ over three hours, where $CM_{KT}(t, t\text{-}1)$ represents the partition distance between the clustering results at time t and t-1.

Figure 5.3. Dynamic traffic partitioning with a single step.

Figure 5.4 further presents the effect of dynamic traffic partitioning when incorporating multi-step historical information. The same traffic scenarios as shown in Figure 5.3 are used for the experimental analysis. In Figure 5.4 (a), the clustering quality when covering historical information across 1, 2, …, 5 snapshots is exhibited. The *NC* and average *NS* indicators grow linearly and slowly with the increase in the length of considered historical time steps, respectively. This implies that combining longer historical time steps is associated with a worse clustering quality than the current traffic feature. On the other hand, incorporating longer time steps can contribute to more consistent traffic clusters with older historical clustering results, as shown in Figure 5.4 (b). To be specific, multi-step dynamic traffic partitioning can keep significantly higher CM_{KT} with older historical clustering results compared with static partitioning, while one-step dynamic traffic partitioning can only maintain substantially higher CM_{KT} with closer historical time moments. That is, the extended dynamic model that covers longer historical information can generate more robust traffic clusters to avoid the dramatic change of traffic partition structure for a long time by sacrificing the current clustering quality to some extent. For the real-world application of the dynamic traffic partitioning model, the confirmation of the length of historical time steps can depend on the actual decision-making demands of traffic operators. For example, it can be determined based on the time required for an evasive manoeuvre of the ship in a traffic cluster.

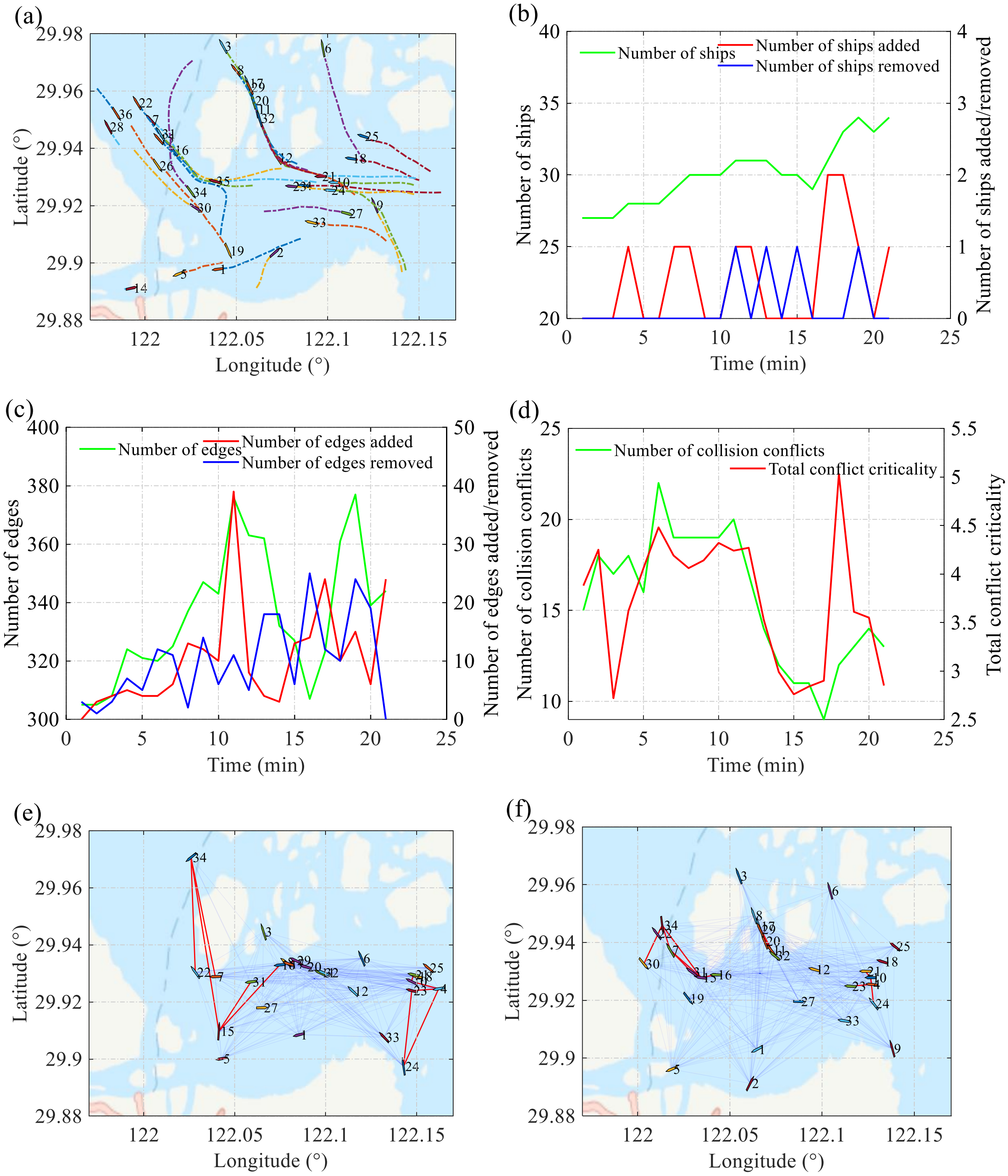


(a) Clustering quality comparison; (b) temporal smoothness comparison, where *t*-1 in the longitudinal axis represents the CM_{KT} between clustering results at time *t* and *t*-1. The error bars indicate the 95% confidence intervals of the means.

Figure 5.4. Dynamic traffic partitioning performance when incorporating multiple historical time steps.

5.5.3 Dynamic Traffic Scenario Extraction and Analysis

Figure 5.5 depicts an extracted dynamic traffic cluster scenario. It is parametrized by the following parameters: the duration of traffic scenario from appearance to disappearance, the number of ships, the number of ships added, the number of ships removed, the number of edges, the number of edges added, the number of edges removed, the total number of collision conflicts, total conflict criticality, and the topological structure of traffic interactions at each timestamp. These parameters enable a scenario to be precisely determined and characterised. Particularly, the momentary situations and their graph representation of traffic clusters at a single timestamp are given in Figure 5.5 (e) and (f). It can be found that there are lots of collision conflicts with all kinds of encounters (*i.e.*, head-on, crossing, and overtaking) at one moment. Such nested conflicts provide a good case to test the co-behaviour between autonomous and manned ships. Meanwhile, the temporal dependencies among multiple participating ships offer insights into detecting the evolution patterns and predicting the varying structure of traffic clusters over time.



(a) Trajectory of ships in the clusters; (b) change in number of ships over time; (c) change in number of edges over time; (d) change in number of collision conflicts and total conflict criticality over time; (e)-(f) graph representation of traffic networks at time t = 1 and 11 min.

Figure 5.5. An example of an extracted dynamic traffic scenario.

Dynamic traffic cluster scenarios detected are complex and critical situations that are more likely to occur in real-world settings. Compared to manually designed fictitious scenarios, they offer superior accuracy, scalability, and variety. These traffic cluster scenarios provide a sufficient real-world test set to evaluate various autonomous navigation algorithms in multiple conflict situations. For instance, an autonomous ship can plan, update, and control its trajectory based on waypoints at each moment. The detected scenarios facilitate autonomous performance evaluation by executing collected trajectory information over time.

Furthermore, the characteristics of extracted traffic scenarios are analysed from a macro perspective. To investigate the longevity of dynamic traffic scenarios in more detail, Figure 5.6 (a) depicts the distribution of scenarios' life cycles with different matching thresholds θ. It is observed that a higher value of θ leads to fewer matches between traffic clusters across different time snapshots, and consequently shorter life cycle. In addition, the stability of traffic scenarios resulting from the different values of θ is examined. As shown in Figure 5.6 (b), a more conservative matching policy associated with higher values of θ corresponds to more stable traffic scenarios. These experimental results indicate the importance of the choice of matching degree parameters, which can be determined based on user preference. The excellent performance of the cluster matching strategy on successfully tracking traffic scenarios over time with different levels of volatility is also demonstrated. It should be noted that a smaller value of θ enables many-to-many mappings between traffic clusters across different time steps, effectively capturing a wide range of events that can occur in the life cycle of a traffic scenario, including cluster merging and splitting.

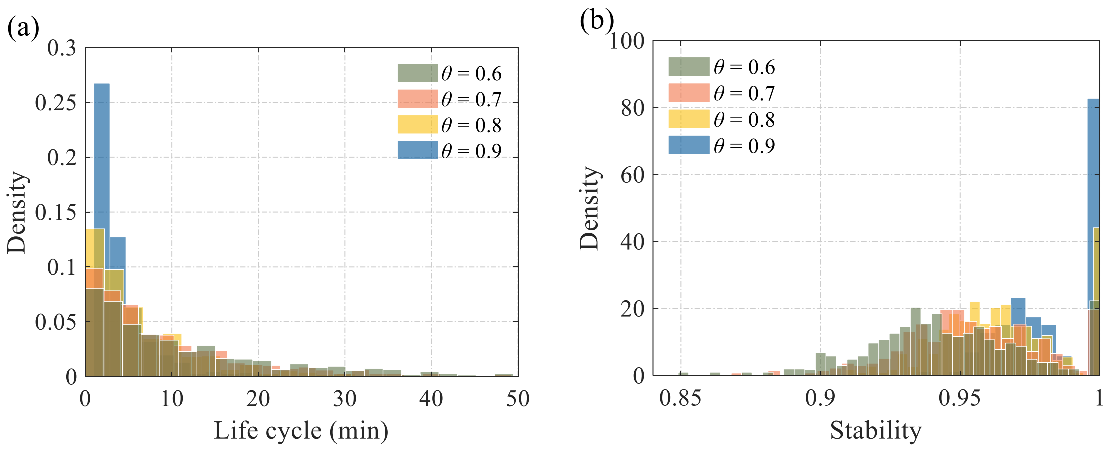
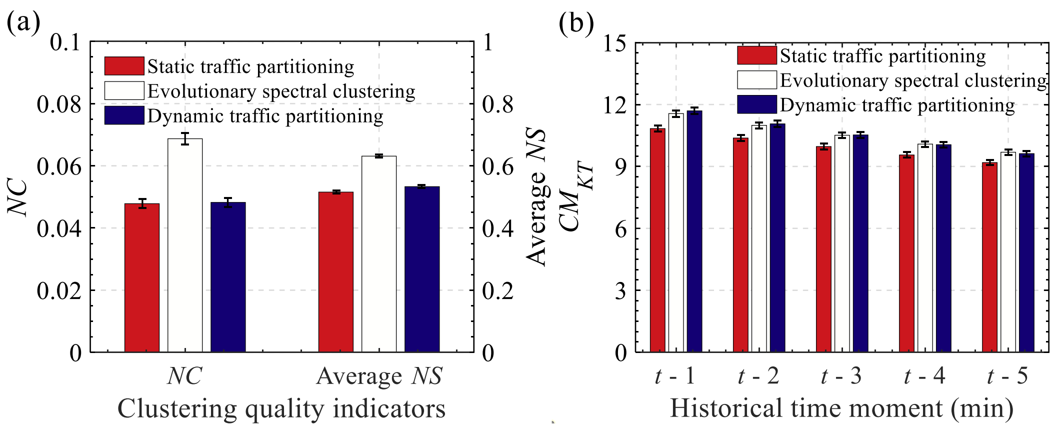


Figure 5.6. The distribution of life cycle and stability of traffic clusters with different matching thresholds θ.

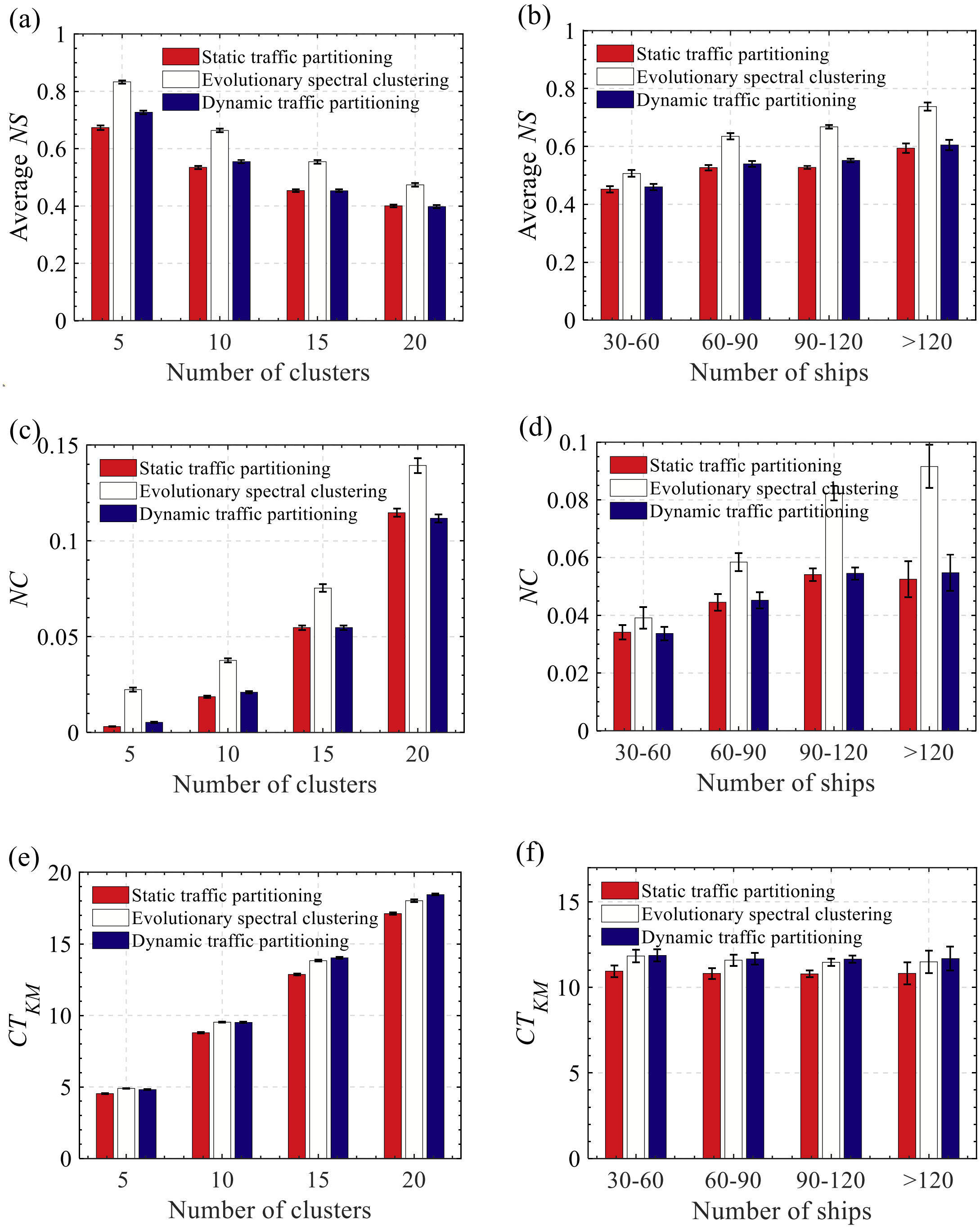
5.5.4 Model Validation

Model validation is an essential step to ensure the effectiveness of the proposed methodology. Here, the proposed dynamic traffic partitioning model is compared with the static model and evolutionary spectral clustering to illustrate its robustness and superiority. According to Figure 5.7, several phenomena can be revealed. Firstly, compared with the static model, the dynamic model shows a small deterioration in clustering quality (*i.e.*, average *NS* and *NC*) but has a considerable improvement in terms of temporal smoothness, which implies its good ability in both remaining faithful to current traffic characteristics and keeping consistency with the traffic structures at the previous snapshots. Secondly, the dynamic partitioning model yields superior results compared to the evolutionary spectral clustering algorithm. Although the evolutionary spectral clustering algorithm can also keep the temporal smoothness of generated clusters, it has worse performance in ensuring the current traffic partitioning quality. Thirdly, the dynamic framework maintains higher temporal smoothness with multiple historical snapshots. This can be attributed to the fact that each clustering structure at time t iteratively integrates the clustering structure information at time t-1. The above observations show the excellent properties of the dynamic traffic partitioning model. In addition, the model comparisons under different numbers of clusters and ships are also performed. As shown in Figure 5.8, the dynamic traffic partitioning model achieves excellent performance in capturing traffic clusters within high quality while simultaneously guaranteeing temporal dependency under various situations, which indicates its good scalability and generalization ability.



(a) Clustering quality comparison; (b) temporal smoothness comparison. Note that the dynamic partitioning uses single-step historical clustering information.

Figure 5.7. A comprehensive comparison between static traffic partitioning model, evolutionary spectral clustering model, and dynamic traffic partitioning model.



(a-b) Average *NS* comparisons; (c-d) *NC* comparisons; (e-f) $CT_{KM}(t, t\text{-}1)$ comparisons.

Figure 5.8. Performance comparison between the static traffic partitioning model, evolutionary spectral clustering, and dynamic traffic partitioning model with different numbers of ships and clusters.

5.5.5 Discussion and Insights

The static traffic partitioning approach independently addresses the risks associated with each cluster by dividing the overall traffic into several clusters. This division ensures that the design of risk mitigation strategies remains manageable, empowering vessel navigators to establish constraint boundaries for autonomous collision avoidance decision-making. Furthermore, the introduction of a novel dynamic traffic partitioning approach, considering the evolutionary characteristics of maritime traffic, provides a crucial foundation for the continuous implementation of risk control schemes within the same traffic cluster. The resulting stable and consistent traffic clusters ensure temporal smoothness in the application of cluster-based risk resolution strategies over time.

Additionally, the proposed dynamic traffic partitioning approach offers insights into investigating the co-evolutionary behaviours among multiple ships. By extracting temporally stable traffic clusters from historical AIS trajectory data, it facilitates the exploration of complex and realistic time-evolving multi-ship encountering scenarios. These scenarios provide valuable testing and verification grounds for new intelligent techniques, such as autonomous ships. This rigorous evaluation process is a critical prerequisite before the real-world deployment of these advanced techniques.

Consequently, the proposed methodology holds particular relevance in the domain of autonomous maritime anti-collision risk control. It lays a solid foundation for the future coexistence of mixed manned and autonomous ships, ensuring safe and efficient operations in maritime environments.

5.6 Conclusion

This chapter pioneers a new attempt to investigate maritime traffic partitioning from dynamic perspectives. It employs a competitive graph-based clustering formulation associated with a temporal smoothness regularization to support robust traffic partitioning. The proposed traffic partitioning method has a reliable and rational performance in capturing temporal stable traffic clusters, thereby supporting the continuous implementation of anti-collision risk control strategies. In addition, an effective cluster-matching procedure is designed to efficiently track a series of similar clusters across successive time snapshots. The extracted dynamic traffic scenarios with time series can support spatio-temporal evolution analysis of multi-ship conflicts as well as formulate a complete set of realistic navigation scenarios for MASS testing and verification. Therefore, the developed methodology shows excellent potential to enhance the operators' anti-collision control ability and facilitate the evolution analysis of multi-ship interactions.

CHAPTER 6 MULTI-SCALE COLLISION RISK ESTIMATION FOR INTELLIGENT MARITIME TRANSPORTATION SYSTEM IN COMPLEX PORT WATERS

Ship collision risk evaluation is one of the essential components of intelligent maritime surveillance systems. Traditional risk evaluation approaches, which can only aid to analyse traffic collision risk in one specific scale (*e.g.*, the CD method in Chapter 3), reveal a significant research challenge in extracting the collision risk patterns of a given traffic scenario from different spatial scales. This is detrimental to understanding traffic situations and supporting effective anti-collision decision-making, especially given the growth of maritime traffic complexity and the emergence of autonomous ships. In this chapter, a systematic multi-scale collision risk evaluation approach is newly developed to capture traffic conflict patterns under different spatial scales. It extends the application of the complex network theory and a node deletion method to quantify the interactions and dependencies among multiple ships within encounter scenarios, enabling collision risk to be evaluated at any spatial scale. Meanwhile, an advanced graph-based clustering framework from Chapter 4 is introduced to search for the optimal spatial scales for risk evaluation. Extensive numerical experiments based on real AIS data in Ningbo_Zhoushan Port are carried out to evaluate the model performance. Experimental results reveal that the proposed approach performs well in strengthening maritime situational awareness and supporting strategic maritime safety management. This work therefore sheds light on improving the intelligent levels of maritime surveillance and promoting maritime safety management in the context of future coexistence of manned and autonomous ships.[3]

6.1 Introduction

Maritime collision risk evaluation is an integral component of safety management. It is of great benefit to the safety and efficiency enhancement of maritime transportation, such as

[3] This chapter contributed to journal paper [5].

providing early collision warnings (Zhang et al., 2021), facilitating route planning (Yu et al., 2021), assist in collision avoidance (Li et al., 2019a, 2019b), and supporting the identification of risk influencing factors (Zhang et al., 2021). However, the existing models, such as the CD model in Chapter 3, encountered drawbacks in offering a comprehensive description of the entire traffic situation. In the meantime, the increasingly complex traffic scenarios, where many sophisticated traffic behaviour characteristics are incorporated together, also raise a new challenge to the applicability and effectiveness of the traditional risk evaluation methods in the literature. Notably, the accuracy and reliability of a risk evaluation model are key determinants for developing an autonomous shipping scheme. More specifically, autonomous systems generally consist of perception and control modules, where the former acts as a prerequisite to the decision-making design (Thombre et al., 2020). Therefore, new risk evaluation models are urgently needed to improve the full understanding of a given traffic scenario and enhance intelligent levels of autonomous navigation systems.

In practice, maritime collision risk evaluation in a busy water area exhibits significantly distinct properties in different spatial scales. From a micro spatial scale, the collision risk of ship pairs can be accurately measured, and the local conflict patterns are revealed with fine granularity. However, the characterisation of global multi-conflict interactions on this scale remains a difficulty. On the contrary, the global collision risk/complexity can be easily recognized from a macro spatial scale, whereas the critical details of local conflict patterns are often ignored. Intuitively, an appropriate way to solve this issue is to incorporate the multi-scale patterns into risk evaluation modelling to interpret the traffic situation comprehensively and accurately. Unfortunately, due to the high complexity of this type of research, most existing studies (Chen et al., 2019; Huang et al., 2020) established collision risk models from a single scale. There has not been any systematic approach incorporating the multi-scale traffic properties into the maritime collision risk evaluation in the literature. These existing works consequently encounter the difficulties in capturing the traffic conflict patterns under different granularity and in offering a complete comprehension of a traffic situation.

This study aims to develop a multi-scale collision risk evaluation approach to achieve intelligent MSA in complex waters. It requires full traffic situation interpretability by extracting the traffic conflict patterns under different spatial scales and incorporating multiple dependent interrelationships relating to the dynamic co-behaviour of multiple participating ships. To address these issues, a holistic framework involving a set of designed technical models is built to reveal the actual traffic patterns under different spatial scopes and scales. In the framework, the near-miss collision risk measurement of ship pairs integrates the spatio-temporal dynamics of ship movements by extending the classical CPA based approach. The complex network theory is applied to support the quantification of spatio-temporal dependencies and interactions of multiple ships. Furthermore, the constructed framework integrates the graph clustering algorithm in Chapter 4 to adaptively partition the entire ship traffic scenario into the optimal scales in terms of the spatio-temporal interrelationships among ships. Only by doing so, the traffic interaction analyses under different scales can be realised. The successful combination of these techniques will facilitate a better understanding of maritime traffic situations and promote maritime safety management in the context of developing intelligent and automated maritime traffic.

The remaining parts of this chapter are organized as follows. Section 6.2 reviews the models and methods and techniques adopted in the proposed framework. Section 6.3 describes the new methodology and elaborates on the details of the multi-scale collision risk evaluation approach. In Section 6.4, the application implementation and performance of the methodology are illustrated and discussed. Conclusions are outlined in Section 6.5.

6.2 Problem Statement

As reviewed in the Literature Review, there is an abundance of works related to micro-level collision risk analysis and evaluation, such as ship domain-based and CPA-based methods (Chen et al., 2019; Huang et al., 2020). On the contrary, the works on macro-level collision risk evaluation and assessment are extremely limited. There have not been any relevant research findings reported on multi-scale collision risk evaluation as well. An effective multi-scale collision risk evaluation model can help reveal the collision risk patterns under different spatial granularity. However, it enforces a set of techniques and methods to cope with the following questions:

1) How to explicitly reveal the complexity of a regional traffic scenario associated with the dependent conflict relations among multiple ships

The current ship collision risk models are still prone to focusing on ship pair analysis at the local level. However, in a heavy-traffic and complex water, the behaviours of ship traffic are spatially correlated with the structure of traffic conflicts. For instance, a single ship is not only influenced by its nearby conflicts, but also will be involved in the conflicts with far ships as time goes by. That is, it is essential to consider the navigational complexity of a scenario associated with multiple dependent conflicts. Within this context, there has been a growing trend toward applying the complex network theory to unveil the topological properties of traffic interactions, especially in the air transportation field (Bombelli et al., 2020; Radanovic et al., 2018; Wang et al., 2016; Zhou et al., 2021a, 2021b). It has a rational and reliable performance in investigating the interrelations among different elements in a system and capturing the co-behaviour features relating to the element interactions. In other words, the success of the complex network theory as an appropriate solution to describe the global traffic complexity stimulates this novel investigation of the dynamic interactions of ship traffic in maritime transportation.

2) How to specify the correlation between the micro-level and macro-level collision risk to achieve a proper combination of the multi-scale risk patterns

A systematic approach that can extract both the micro and macro spatial features enables the traffic situation to be described more precisely and completely. This is crucial to the intellectualization and automation of future maritime surveillance systems, especially considering its role in improving traffic pattern interpretability. Hence, much effort should be placed in analysing the correlation between the micro and macro collision risk to realise a proper combination of the multi-scale risk patterns. In the field of network analysis, many practices have shown that a node deletion method is a useful technique to characterise the relations between the whole system and its individual units (Wang et al., 2011). Notably, it has been successfully adopted to capture the crucial airports and ports in the whole traffic network (Liu et al., 2018; Wen et al., 2018). Inspired by these findings, this study extends the application of the node deletion method to investigate the aggregation risk criticality of single or multiple ships to a regional or global traffic situation, thereby achieving a desired collision risk evaluation for any single or multiple ships in a busy water area of interest.

3) How to adaptively extract the optimal multi-ship clusters at different scales for risk assessment

One difficulty with multi-scale collision risk evaluation is extracting the optimal multi-ship clusters at different scales for risk assessment. Empirically, a gridding method is a commonly used tool to discretize the target maritime traffic zone into a grid-decomposed geographical space, where the size of each cell is usually predefined and unified. This method is adaptive to the batch analysis of historical traffic data by conducting the necessary traffic feature statistics within each cell (*e.g.*, average speed, course change, and risk levels) to support maritime traffic visualisation and collision avoidance (Liu et al., 2021; Rong et al., 2021; Yoo, 2018). Unfortunately, it cannot incorporate the complicated interactions relating to the real-time multiple dependent conflicts among ships when implementing the discretization. Generally, the spatial distribution of maritime traffic is unevenly spread over the water area, and the spatial dependencies among multiple conflicts may experience high dynamics over time. As a result, the issue concerning how to adaptively recognize the optimal traffic cluster scopes based on the real-time multi-ship dependencies becomes fundamental and requires much further investigation. The graph clustering approach (*i.e.*, SNMF framework), which has been successfully used to capture congested road traffic regions (Gu and Saberi, 2019; Ji and Geroliminis, 2012; Saeedmanesh and Geroliminis, 2016, 2017), shows much attractiveness in integrating various interrelationships among the investigated objects during the clustering process. It is also applied in Chapters 4 and 5 for both static and dynamic traffic partitioning, whose excellent performance has been demonstrated and validated. Therefore, the SNMF framework is adopted to search for the optimal spatial scopes of risk assessment by partitioning the regional ship traffic into compact, scalable and interpretable traffic clusters.

4) How to choose a proper method to conduct the comprehensive evaluation of multiple traffic complexity indices

It should be noted that the complex network theory includes various lists of network indices to reveal the structural properties of a network. Therefore, the regional traffic complexity evaluation is by nature a high-dimensional, complex, and multiple-index assessment issue.

Conventional mathematical solutions to index integration include the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Liu et al., 2016), fuzzy comprehensive evaluation (Liu et al., 2019), entropy weight method (Bian and Deng, 2018), grey relational analysis (Li et al., 2015), and SVM (Xu et al., 2012), among others. These approaches provide diverse perspectives for the interpretation of index interactions and help study complex systems. However, they have been criticised for their inherent weaknesses, such as subjectivity and difficulty in determining index weights, inability to process high-dimensional data, low resolution, and the requirement of a large number of training samples (Wang and Yang, 2020). Additionally, deep learning has also be employed in the research of multi-indicator comprehensive evaluation, but it possesses limited interpretability and demands a substantial amount of labelled samples.

In comparison, the Fuzzy Clustering Iterative (FCI) approach has recently been favoured by scholars because of its merits in handling high-dimensional index vectors and demonstrating quality clustering effects for multivariate data. The essence of this approach is to search for the optimal memberships of the assessment samples against different performance standards (*e.g.*, risk levels and complexity patterns) based on the fuzzy set theory and an optimization algorithm (He et al., 2011). Compared with the above-named traditional methods, it is independent of the evaluation criteria by concentrating on the data set's characteristics and can figure out the randomness, uncertainty, and fuzziness of the data set in the evaluation process (Lu et al., 2017; Lyu et al., 2019; Wu et al., 2013). In addition, the performance of the FCI model has been verified by solving typical benchmark test problems and actual multi-index assessment cases (He et al., 2011; He and Wan, 2020). Despite this, current applications of FCI are mainly constrained in the field of complex engineering (Wang and Yang, 2020), and there is little research on applying FCI to evaluate ship traffic risk. Therefore, this study pioneers the application of FCI to perform a complexity/collision risk assessment task for regional maritime traffic.

In summary, the multi-scale collision risk qualification for ship traffic in complex waters is a very high-value but complex work. It is essential to design a system-level solution by making effective synergies of various advanced techniques to perform multi-scale collision risk assessment. Therefore, this study develops a holistic framework to cope with these needs to allow the traffic patterns under different granularity to be extracted and evaluated. It brings new insights that have not yet been revealed in the current literature from both theoretical and applied perspectives, hence making significant contributions to the formulation of operation services for intelligent maritime safety management and anti-collision solutions to autonomous ships.

6.3 Methodology: Multi-Scale Collision Risk Evaluation

Figure 6.1 presents a systematic framework of the proposed multi-scale collision risk evaluation scheme. It involves a set of techniques which work holistically to explore the correlation between the collision risk under different types of spatial granularity. These techniques are effectively integrated with a series of interrelated steps, characterised by the following modules. Firstly, an improved CPA-based model incorporating the spatio-temporal dynamics of ship movements is introduced to estimate the collision risk between ship pairs. Subsequently, a ship traffic network is established to evaluate the collision risk of the entire ship traffic in a given water area. It comprises nodes representing ships and links representing the collision risk of ship pairs which connect the nodes. In this stage of the research, five network indices from the complex network theory are used to quantify the regional traffic risk/complexity, which concerns traffic density, collision risk severity, and topological structure related to multi-ship interactions. In the meantime, an FCI method is applied to support a hierarchical and fine-grained assessment of multiple index synthesis. After these two steps, a node deletion method is utilized to examine the risk criticality of any single or multiple ships to the traffic situation as a whole, to quantitatively estimate the ship traffic risk under any spatial scale. Additionally, the graph clustering model partitions the regional/global maritime traffic in terms of the spatial interrelationships among ships, and the collision risk assessment is conducted for the generated traffic clusters accordingly. This step addresses the problem of adaptive identification of the optimal spatial scales. By doing so, the multi-scale patterns of collision risk embedded into the complete maritime traffic situation can be extracted and evaluated, thereby achieving a comprehensive evaluation of the traffic scenarios. The technical details of relevant steps are highlighted in the following subsections.

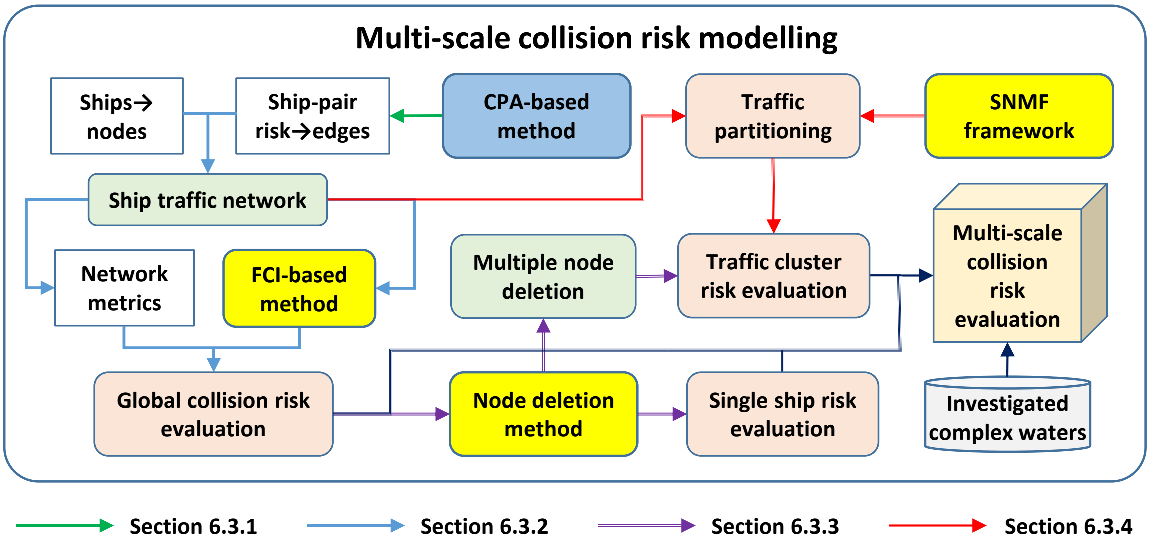


Figure 6.1. Methodological framework of multi-scale collision risk evaluation.

6.3.1 Collision Risk Evaluation of Ship Pairs

The collision risk measures of ship pairs are the basic premise of ship traffic network construction. In Chapters 4 and 5, the traffic network is built based on both the conflict criticality and spatial distance between ships. The incorporation of spatial distance relations is to help generate traffic clusters that are spatially compact to ease the design and deployment of traffic management strategies (Gu and Saberi, 2019; Ji and Geroliminis, 2012; Saeedmanesh and Geroliminis, 2016, 2017). However, this chapter only focuses on the collision risk relations between ship pairs for collision risk evaluation at any spatial scale. Although the conflict criticality in Chapter 3 is a stronger indicator of the collision risk measure between ships, its sparse nature makes it insufficient to achieve a good regional traffic partitioning for the regional ship traffic, *i.e.*, the optimal capturing of spatial scopes for risk evaluation. To be specific, there will be lots of disconnected components for a specific traffic scenario (see the red lines in Figure 4.8. (a)), which results in the difficulty of assigning all ships to different clusters. This is mainly because the probabilistic CD model adopts the more restricted ship domain model corresponding to smaller safety distance criteria to detect collision danger. As a result, the ship domain overlap between ship pairs over the look-ahead horizon would not occur frequently.

For the encounter situation analysis, the CPA-based method is also widely adopted to evaluate whether the ship pairs have collision risk during the look-ahead horizon due to its simple implementation and excellent performance when ships navigate on a straight track. Compared with the probabilistic CD model in Chapter 3, it can provide richer structural information for traffic clustering by using a relatively larger safety distance to construct a more informative and connected network. However, according to the statement in Section 2.1.2, this method calculates the DCPA and TCPA indicators relying on the strong hypothesis that the encountering ships will sail with a linear speed over a finite look-ahead horizon. In reality, the ship speed has to change in some cases due to various perturbations such as restricted waterway topography, environmental disturbances, and uncertain navigation intention, especially in complex port waters. Hence, it is necessary to describe ship pairs' relative spatio-temporal proximity relationship by incorporating their potential movement dynamics. This study adopts the improved CPA-based model to obtain the actual DPCA and TPCA under the presence of ship motion dynamics, which is adopted in Section 3.3.3.1 to detect the target ships with potential collision risk. Further details about this model can be found in Appendix B.

It should be noted that both DCPA and TCPA are fundamental to collision detection in maritime navigation, which has been explained in Section 4.3.1.1. The former reveals the severity of a potential collision, whereas the latter reflects the time duration available for the collision resolution. Similarly, an exponential function (Hu et al., 2019; Wang et al., 2018) is adopted to synthesise the two indicators, as shown in Eq. (6-1):

$$CR_{ij} = \begin{cases} \left(\dfrac{\gamma_{DCPA} - DCPA_{ij}}{\gamma_{DCPA}}\right)^{1+\frac{TCPA_{ij}}{\gamma_{TCPA}}}, & \text{if } 0 \leq DCPA_{ij} \leq \gamma_{DCPA}, 0 \leq TCPA_{ij} \leq \gamma_{TCPA} \\ 0, & \text{otherwise} \end{cases} \tag{6-1}$$

where $DCPA_{ij}$ and $TCPA_{ij}$ represent the two improved indicators between ships i and j, γ_{DCPA} and γ_{TCPA} denote the prescribed threshold values for collision detection, which are dependent on the application environment. Here, γ_{DCPA} is set to be two nautical miles in terms of the possible accepted safety distances given in (Liu et al., 2022; Wu et al., 2021). Simultaneously, γ_{TPA} is denoted as 15 minutes since this study performs collision detection at the medium-term time range with reference to the work in (Bakdi et al., 2021). Overall, Eq. (6-1) conforms to the safety requirement in maritime transportation, *i.e.*, an encounter scenario with smaller DCPA and TCPA values is more dangerous than the one with larger values, which effectively characterises the ship-pairs' spatial and temporal proximity.

6.3.2 Regional/Global Collision Risk Evaluation

Once the proximity relationships of all ship pairs are measured, the ship traffic network can be constructed. A graph $G(V_N, E_L)$ is adopted to describe the ship traffic network, where V_N denotes N ship nodes connected by L links E_L. The ship pairs with collision risk larger than 0 are connected by an edge. Each edge weight is equal to the collision risk of the connected ship pairs. On this basis, the regional/global traffic collision risk can be evaluated from the perspective of complexity based on the complex network theory. It consists of two important components: one is the selection of network metrics, which requires the full characterisation of a regional traffic situation; the other is the comprehensive evaluation of multiple metric measures, which concerns the adopted techniques and approaches with which the chosen metrics can be effectively combined to quantify the entire network collision risk. The relevant network metrics and index synthesis technique are elaborated in the following subsections.

6.3.2.1 Network Metrics

The complex network theory covers a variety of network metrics to characterise the structure-property of a network. In this study, five network metrics, including Number of Nodes (*NN*), Number of Edges (*NE*), Vertex Strength (*VS*), K-Shell Decomposition (*KS*) and Clustering Coefficient (*CC*), are used together to comprehensively reveal the global risk/complexity of a traffic scenario in a given water area. These metrics can capture distinct aspects of a ship traffic network, in which *NN* measures the traffic density in a given region, *NE* reflects the number of ship pairs that are at collision risk, *VS* quantifies the total collision risk, and *CC* and *KS* unveil the traffic network's topological characteristics related to the resolving difficulty of collisions. Their definitions are given as follows:

1. **Number of Nodes (*NN*)** is treated as the basic feature of a network. It generally serves as a practical reference for maritime operators to issue instructions. The higher the value of *NN*, the busier the traffic situation is.

2. **Number of Edges (*NE*)** refers to the number of links connecting the node pairs. It reflects the number of ship pairs with the potential for a collision in the maritime traffic network. A larger *NE* corresponds to a riskier and more complex traffic situation, and vice versa.

3. **Vertex Strength (*VS*)** represents the sum of edge weights correlated with one node. It integrates the characteristics of both the node degree and the associated edge weight, where the node degree refers to the number of nodes connecting with one specific node. Here the sum of all vertex strengths is used to unveil the total collision risk of a traffic scenario as shown in Eq. (6-2):

$$VS = \sum_{i=1}^{N} VS_i/2 = \sum_{i=1}^{N}\sum_{j=1}^{D_i} w_{ij}/2 \tag{6-2}$$

where N represents the number of nodes, w_{ij} denotes the edge weight between nodes i and j, D_i is the number of adjacent nodes to node i, and VS_i represents the Vertex Strength of node i. A high VS means that maritime traffic is more likely to encounter a hazardous situation.

4. **K-Shell Decomposition (*KS*)** is a typical technique that concerns the network structure. It partitions the network into several layers based on the coreness of the nodes. This metric works well in revealing how the nodes are grouped together and identifying the node's global important level. The nodes with dense connections are assigned with high KS_i values and the nodes in the same layer have identical KS_i indexes (see Figure 6.2). The relevant details about k-shell calculation can be found in (Zekun et al., 2019).This study adopts the maximum KS_i to reflect the difficulty level of conflict resolution caused by the traffic network topology. A larger *KS* means that lots of ships are spatially closer together with complicated interactions, and consequently, the surveillance controllers will encounter increased risk management pressure.

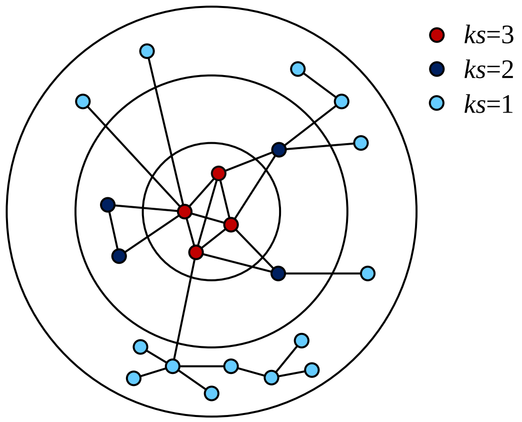


Figure 6.2. A schematic diagram of K-shell Decomposition.

5. **Clustering coefficient (*CC*)** quantifies the aggregation/clustering degree of the nodes in a graph. It can reveal how close the nodes' neighbours are to be a clique. The local *CC* of a node is denoted in Eq. (6-3):

$$CC_i' = \frac{N_\Delta(i)}{d_i(d_i - 1)/2} \tag{6-3}$$

where $N_\Delta(i)$ denotes the real number of edges between the nodes that have connections with node *i*, and $d_i(d_i - 1)/2$ reflects the theoretical maximum number of edges between these nearby nodes. However, this metric cannot coincide with the basic principle of the global collision risk modelling, *i.e.*, the increase of nodes or edges should not lead to the decline of the global risk. The example in Figure 6.3 well justifies this. It is seen that the CC_A' decreases when a new node and edge are embedded into the graph. Hence, an improved metric CC_i that removes the denominator in Eq. (6-3) is developed, which is expressed using Eq. (6-4):

$$CC_i = N_\Delta(i) \tag{6-4}$$

This new metric can quantify the complex interactions among the neighbours of one node while simultaneously meeting the global risk modelling principles. Furthermore, the sum of CC_i is used to describe the global cross-conflict degree among ships, i.e., $CC = \sum_{i=1}^{N} CC_i$. A larger CC is usually associated with more complex multiple dependent conflict-based interrelationships among ships and the corresponding conflicts within the traffic situation are harder to resolve.

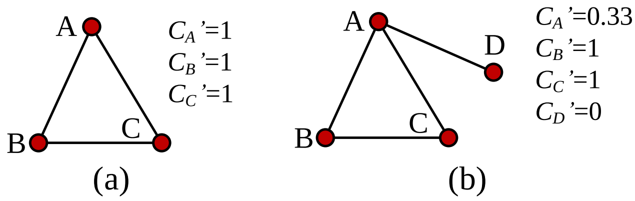


Figure 6.3. An example of clustering coefficient calculation.

6.3.2.2 Comprehensive Evaluation of Regional Collision Risk

This study adopts FCI to support a comprehensive and fine-grained evaluation of the regional collision risk. In essence, FCI represents a class of data-driven techniques. It designs an iterative procedure to optimize the objective function continuously until it finds the optimal weight vector w, clustering centre matrix S and membership matrix U (Wang & Yang, 2020). The implementation details of this model can be found in Appendix E.

One well-known problem that needs to be addressed when using FCI is identifying the optimal number of levels/classes of regional collision risk (*e.g.*, low-risk, medium- risk, and high- risk). Generally, it is strongly dependent on the users to identify it beforehand. Here, six fuzzy cluster validity indices, including Partition Coefficient (PC), Partition Entropy (PE), Modified Partition Coefficient (MPC), VFS, VXB, and VK in Wang & Zhang (2007), are adopted to measure the fuzzy clustering performance of the FCI model. In these indices, a high PC and MPC value indicates that the data set is well clustered. In contrast, a small value of the remaining indices means that a good partition is produced. More detailed explanations about the adopted validity indices are summarised in Wang & Zhang (2007).

It should be noted that the implementation of FCI is an offline training process, which comprises the following steps:

Step 1: Sample extraction, pre-processing, and normalization

Extract the sample data set of ship traffic scenarios in terms of real AIS-based trajectory data in the investigated waters. Subsequently, calculate the values of the five network indicators of each sample and construct the sample matrix A (see Appendix E). Subsequently, standardise the sample matrix to the normalised form (see Eq. E1) to perform the FCI procedure.

Step 2: Parameter initialisation

Determine the search range for the number of collision risk levels c (*e.g.*, c = 2-10).

Step 3: Implement FCI

For each number of collision risk levels c, run the FCI model repeatedly based on the normalised sample matrix. Then compute the values of the six fuzzy cluster validity indices.

Step 4: Identify the optimal *c*, *w*, *U* and *S*

Identify the optimal c based on the six fuzzy cluster validity indices and then obtain the corresponding optimal w, U and S.

After obtaining the optimal number of regional collision risk classes/levels c, optimal w, U and S, the mapping relationships between the assessment samples and the different risk classes/grades can be calibrated. Assume that u_{pj} represents the membership degree of the j^{th} regional traffic scenario belonging to the p^{th} risk level, where p = 1, 2, …, c. Then two comprehensive indicators can be used to evaluate the regional collision risk, as shown by Eq. (6-5) and Eq. (6-6):

$$RCR_j^1 = \arg\max_{\{p=1,2,\cdots,c\}} u_{pj} \tag{6-5}$$

$$RCR_j^2 = R_j \cdot w \tag{6-6}$$

where $R_j = (r_{1j}, r_{2j}, \ldots, r_{mj})$ is the normalized value of the adopted network metrics associated with the jth traffic scenario, and $w = (w_1, w_2, \ldots, w_m)$ denotes the influence weight of each network metric in which m represents the number of network indices. The former indicator reveals the regional collision risk level/class based on each traffic scenario's maximum membership. By contrast, the latter reflects a single assessment value through the weighted sum of selected network indices.

6.3.3 Risk Criticality of Single/Multiple Ships

In addition to the collision risk evaluation for ship pairs or regional/global ship traffic, the issue as to how the risk assessment under any spatial scale is realised is a remaining crucial question to answer. The node deletion method, as an effective system analytical tool, works well in quantifying the correlation between the whole network system and the single node (wang et al., 2011). Its essence is to measure each node's relative contribution by identifying the drops in the network performance resulting from the deletion of different nodes from the network. In this study, further extension and improvement are conducted for the node deletion method to explore both the risk contribution of any single and multiple dependent ships to a regional traffic situation. The contribution of the single/multiple ships to the regional collision risk can be interpreted as their risk criticality. The implementation process comprises two phases:

1. *Risk criticality of single ship*: In this phase, the drops in the regional collision risk are calculated when each ship is removed from the full traffic network separately. Suppose the regional collision risk associated with the full traffic network is given as RCR^2, and the regional collision risk when deleting the qth ship (q = 1, 2, …, ns, where ns is the real-time number of ships in the entire network) from the full traffic network is computed as RCR_q^2. Then the margin of RCR_q^2 against RCR^2 can be calculated, denoted by $SCR_q^2 = RCR^2 - RCR_q^2$. Accordingly, the risk criticality of each individual ship to the regional traffic can be estimated based on the value of SCR_q^2. Additionally, the set of $SCR^2_{\{q\ =\ 1,2,\ldots,ns\}}$ can be ranked in a descending order, so that the ships of high-risk criticality values can be captured.
2. *Risk criticality of multiple ships*: In this phase, the coupling effect of multiple ships on a regional traffic situation is analysed. It investigates the aggregation risk criticality of multi-ships by removing them simultaneously from the full traffic network. It is noteworthy that this step should be combined with a maritime traffic partition approach (Section 6.3.4) since the latter helps detect multi-ship clusters with spatio-temporal dependencies.

6.3.4 Regional Maritime Traffic Partitioning

Maritime traffic partition is a crucial component for multi-scale collision risk analysis. It can recognize the optimal spatial scopes for risk evaluation, facilitating traffic pattern exploration under different granularity. In this study, the SNMF model used in Chapters 4 and 5 is still used for optimal ship traffic partition because it has a solid theoretical foundation in addressing specific graph partition issues and demonstrates better performance than other graph clustering algorithms (Kuang et al., 2012, 2015). The similarity measure, that takes the collision risk from Section 6.3.1, as the similarity of ship pairs is fed into the SNMF model, and the detailed steps for the optimization of traffic partition can be found in Section 4.3.2.2.

It should be noted that this chapter only adopts a static traffic partitioning model to conduct model application analysis and validation. However, dynamic traffic partitioning can also be easily inserted into the multi-scale collision risk estimation framework when the evolutionary characteristics of traffic clusters are required to be considered.

6.4 Case Study: Implementation and Results

This subsection is organized as follows. Section 6.4.1 starts with the presentation of the training results for the FCI-based evaluation model. Section 6.4.2 uses a real application case to demonstrate how the proposed methodology is applied to evaluate the collision risk under different spatial scales. In Section 6.4.3, the collision risk distributions of regional traffic, single ships, and multiple ships are investigated, to assist in the identification and monitoring of critical high-risk traffic clusters. Section 6.4.4 describes the performance of a few statistics analyses of the traffic collision risk evolution, to shed light on the future collision risk estimation and control. Furthermore, the model validation and comparison analysis are conducted in Section 6.4.5.

6.4.1 Training Results of the FCI Model

A total of 4,315 traffic scenarios are extracted as the training samples, in which each of them is extracted every 10 minutes from one month of AIS data in Ningbo_Zhoushan port waters. Figure 6.4 illustrates the average validity performance of the six indices (See Section 6.3.2.2), in which each of the number of risk levels is run 20 times with randomly sampled initial w and U. It is seen that the MPC, VXB, and VK indices have the best performance when the number of risk levels is six. Consequently, the regional collision risk is divided into six levels in terms of the FCI model (Wang & Zhang, 2007), which are Very Low (VH), Low (L), Slightly Low (SL), Slightly High (SL), High (H), and Very High (VH).

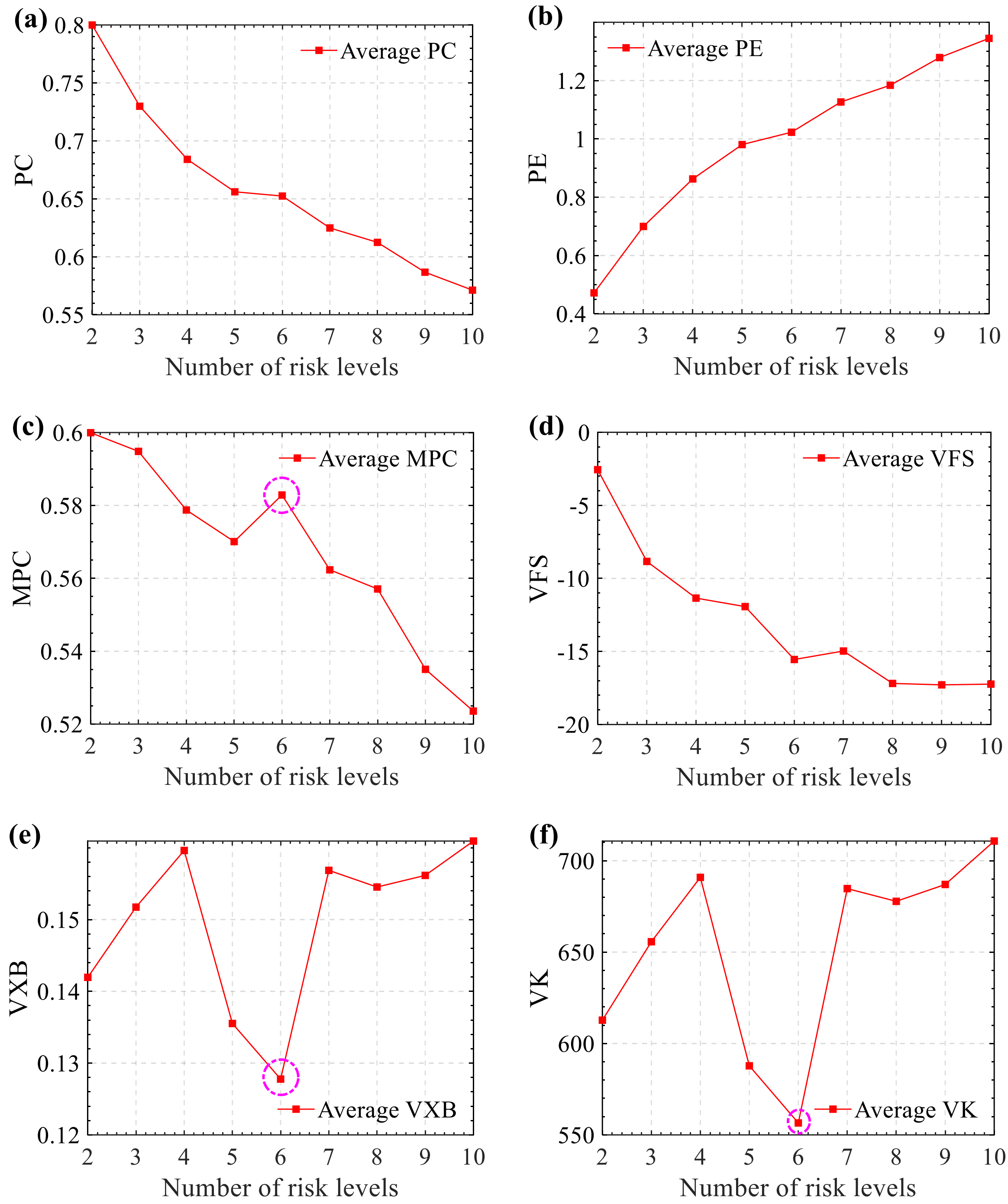
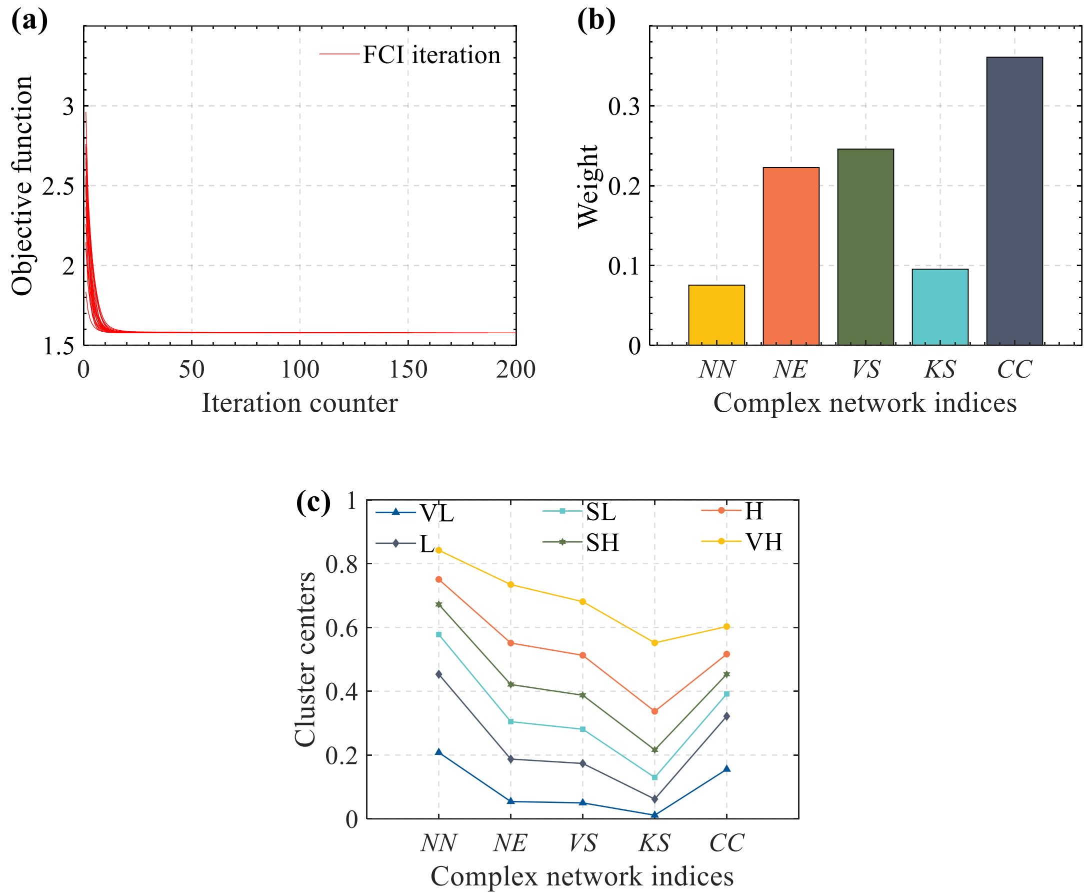


Figure 6.4. Model performance illustration with different numbers of risk levels.

Figure 6.5 further displays the optimal results of the FCI model when the number of risk levels is six. By inputting the final optimal w and S into Eq. (E.4), the membership distribution to different risk levels of new traffic scenarios can be calibrated.

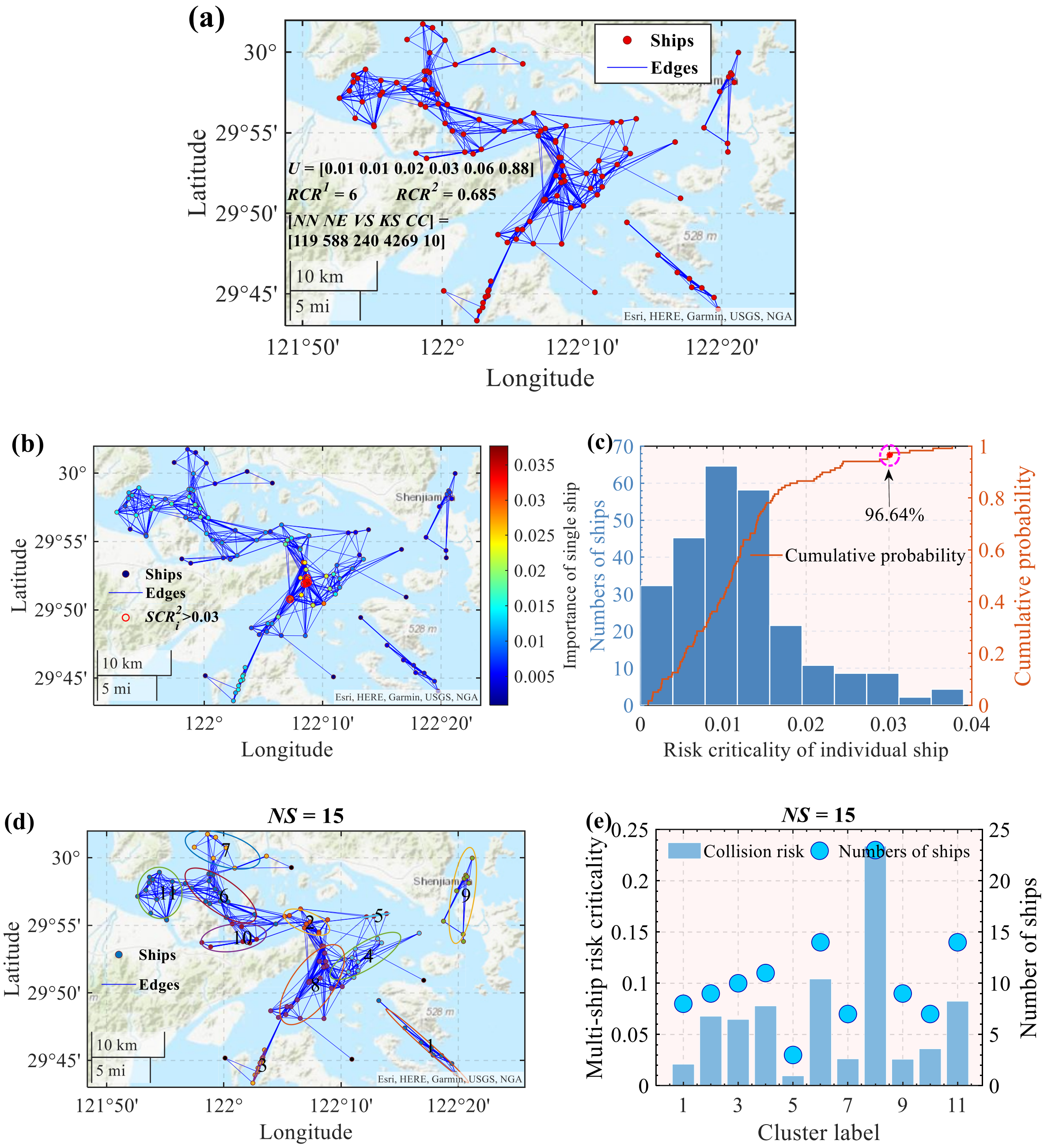


(a) Iteration optimization processes of FCI with 20 randomly initial *w* and *S*; (b) weights of five adopted network indices; (c) clustering centres of six global collision risk levels.

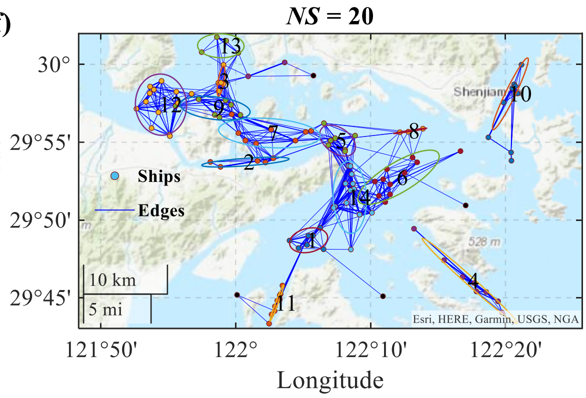
Figure 6.5. Optimal results of FCI model.

6.4.2 Application Performance Analysis

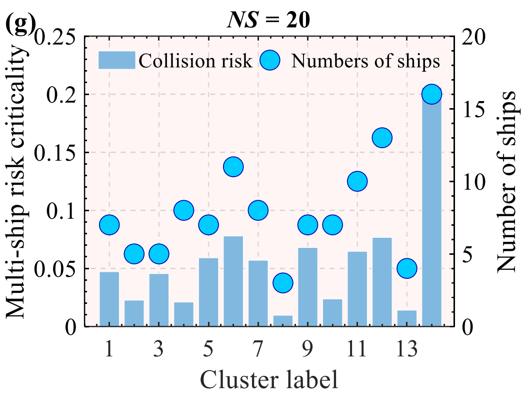
Figure 6.6 provides the multi-scale collision risk analytical results for a specific traffic scenario within the research area. In Figure 6.6 (a), the visualisation of the constructed traffic network is exhibited, where the red points stand for the spatial distribution of ship traffic, and the blue lines represent that the connected ship pairs have potential collision risk. It is found that there are complicated dependent interrelationships among ships. This phenomenon highlights the necessity of incorporating the topological indices (*i.e.*, *KS* and *CC*) to describe the multi-ship interactions, rather than merely addressing the ship-pair interactions when conducting a regional collision risk assessment. Based on the Equations in Section 6.3.2.1, the values of the adopted five network indicators for this scenario are 119, 588, 240, 4,269, and 10, respectively. The memberships belonging to different regional risk levels are then calculated as 0.01, 0.01, 0.02, 0.03, 0.06, and 0.88 in terms of Eq. (E.4) in Appendix E. These membership results show a hierarchical description of the regional collision risk. The regional risk level and value (*i.e.*, RCR^1 and RCR^2 in Eqs. (6-5) - (6-6)) are further obtained as 6 and 0.685, respectively, implying the complex situation of the analysed traffic scenario. These evaluation indicators work together to facilitate the interpretation of the regional/global traffic situations.



(f)



(g)



(a) Visualisation of ship traffic network; (b) visualisation of risk criticality of any single ship to a regional traffic situation; (c) risk criticality distribution of single ships; (d)-(g) visualisation of ship optimal traffic partition and collision risk of generated traffic clusters when *NS* = 15 and 20. Note that the generated traffic clusters with a number of ships less than three are not labelled.

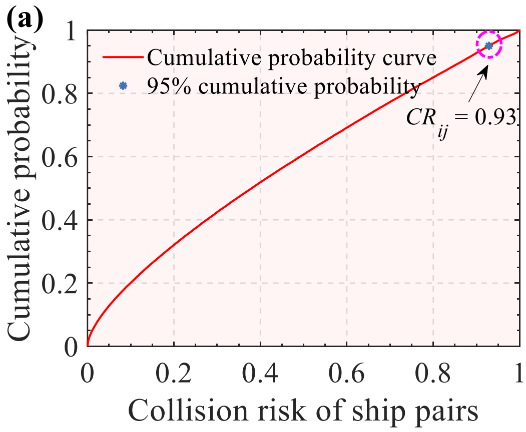
Figure 6.6. Illustration of multi-scale collision risk of ship traffic at one time moment.

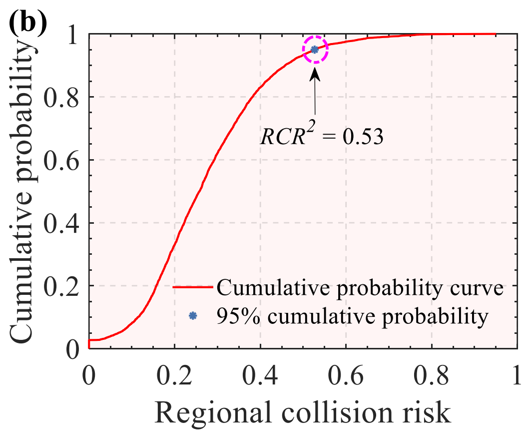
Figure 6.6. (b) displays the visualisation of the single ship criticality to the regional collision risk. According to this figure, the ships with higher criticality values can be easily captured based on their colour indices. For instance, the ships with $SCR_i^2 > 0.03$ are highlighted with red circles. This can provide valuable guidelines for ship navigators to notice potential collision risks. Besides, the single ship risk criticality value distribution is exhibited in Figure 6.6. (c). It is observed that the criticality of these ships is obviously heterogeneous and the key influential ships (*e.g.*, the ships with $SCR_i^2 > 0.03$) account for a smaller percentage. Hence, the recognition of key influential ships can provide vital support in risk management from a global surveillance perspective. More specifically, the precise guidance and manoeuvring instructions for these few critical ships can effectively aid to quickly mitigate the regional traffic complexity and consequently obtain the maximum regional collision risk reduction.

Furthermore, Figure 6.6 (d) and (f) illustrate visualisation of ship optimal traffic partition when *NS* = 15 and *NS* = 20. In these figures, the ships in the same traffic cluster are spatially compact and have highly dependent conflict-related interrelationships. This indicates the good properties of the proposed traffic partition approach in aiding to search for the optimal spatial scopes for risk evaluation. Additionally, the aggregation risk criticality and the number of ships of each traffic cluster are presented in Figure 6.6 (e) and (g). The identified multi-ship aggregation effect of each cluster on the regional traffic risk can provide a practical reference for capturing the critical traffic clusters and resolving traffic conflicts in terms of the joint guidance of the multiple ships. Therefore, the combination of maritime traffic partition and multiple node deletion methods enables us to extract and reveal the collision risk pattern under different granularity. Overall, the proposed multi-scale collision risk methodology supports a full comprehension of a specific navigation scenario.

6.4.3 Statistical Analysis of Traffic Collision Risk Characteristics

It is important to note that the traffic clusters with larger numbers of ships generally correspond to higher collision risk. This is due to the fact that a larger traffic cluster usually has a more significant aggregation risk criticality to regional traffic. Therefore, the collision risk of traffic clusters should be compared in the same order, so that the key influential ships or traffic clusters with high risk can be more reasonably recognized and monitored. In light of this, the collision risk distributions of regional traffic, single, and multiple ships are statistically analysed separately. Figure 6.7 illustrates the cumulative probability distributions of collision risk for ship pairs, regional traffic, and single ships. For example, the collision risk values corresponding to a 95% cumulative probability are chosen for a risk alert application. As a result, 0.93, 0.53, and 0.021 are the high-risk lines for the above three cases. Similarly, the collision risk criticality distributions of traffic clusters with different numbers of ships are displayed in Figure 6.8. These analytical results offer a quantitative reference to trigger an earlier alert under different spatial granularity.





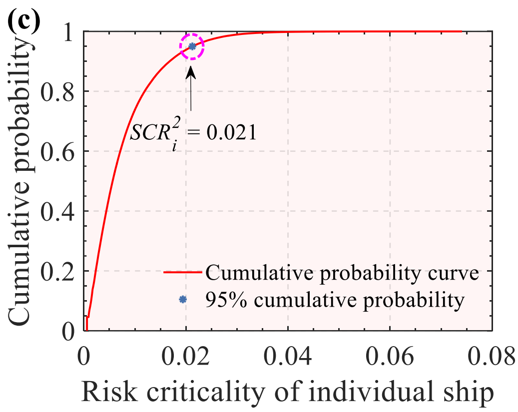


Figure 6.7. Cumulative probability distribution of collision risk.

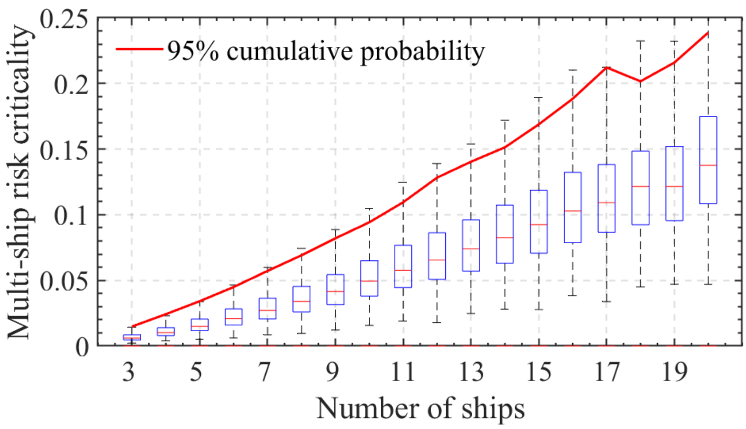
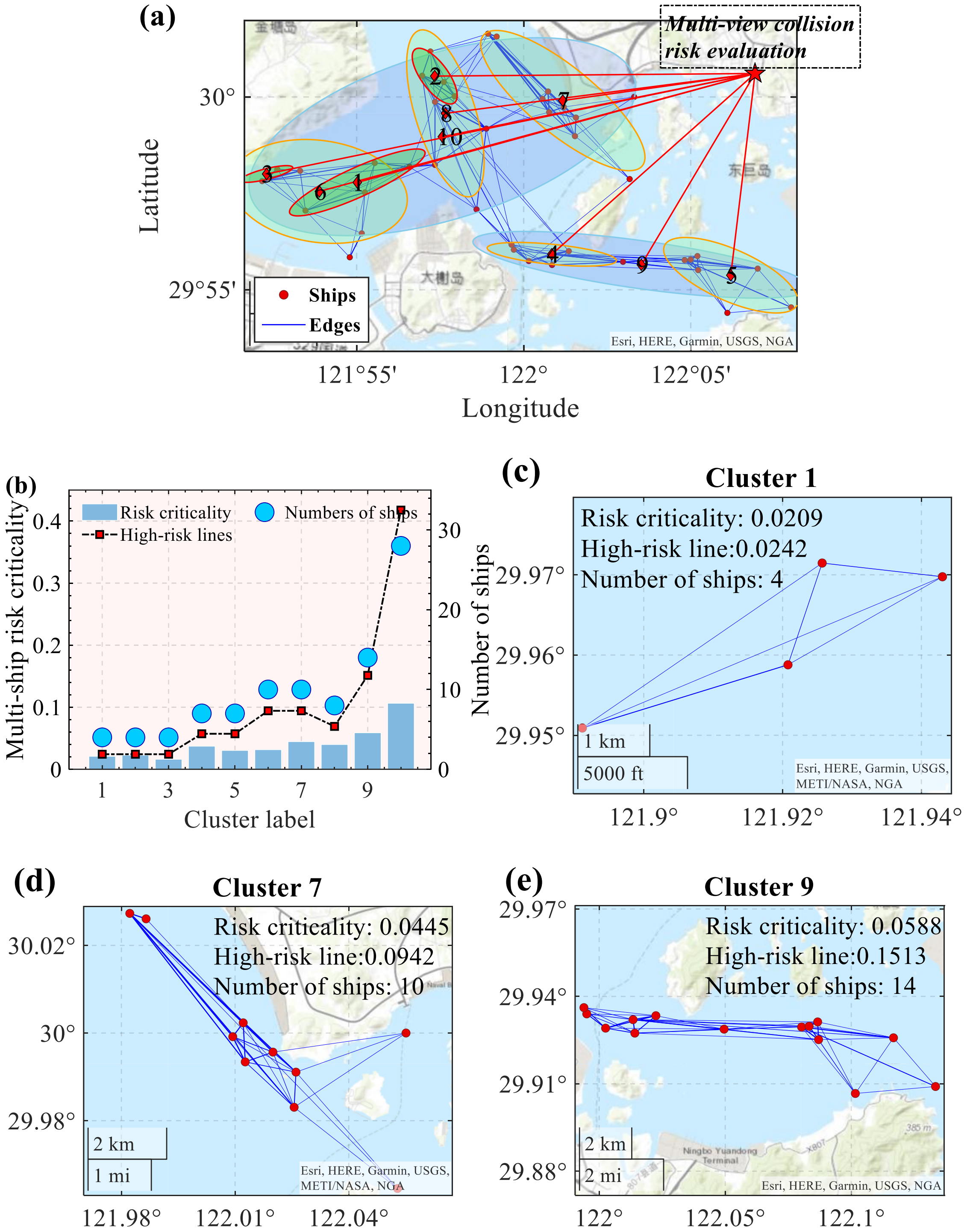


Figure 6.8. Boxplot of risk criticality of traffic clusters with different numbers of ships.

Built on the determined collision alert thresholds, Figure 6.9 presents the multi-view collision risk analysis results for a traffic scenario. In Figure 6.9 (a), the multi-scale traffic patterns are revealed, including both small-scale (*e.g.*, Cluster 3) and large-scale (*e.g.*, Cluster 10) patterns. Figure 6.9 (b) further exhibits the collision risk criticality and numbers of ships of different traffic clusters. It is seen that the risk criticality of Clusters 1 and 2 is close to the associated high-risk lines. Hence, much attention should be paid to these two clusters. In the meantime, Figures 6.9 (c)-(e) display the detailed information of Clusters 1, 7 and 9 to help better understand the generated clusters' multi-resolution features. The results reveal that the proposed methodology can proactively capture the high-risk areas under any spatial scale by integrating the determined collision alert thresholds.



(a) Visualisation of multi-view traffic clusters; (b) risk criticality and number of ships of each traffic cluster; (c)-(e) visualisation of some single traffic clusters.

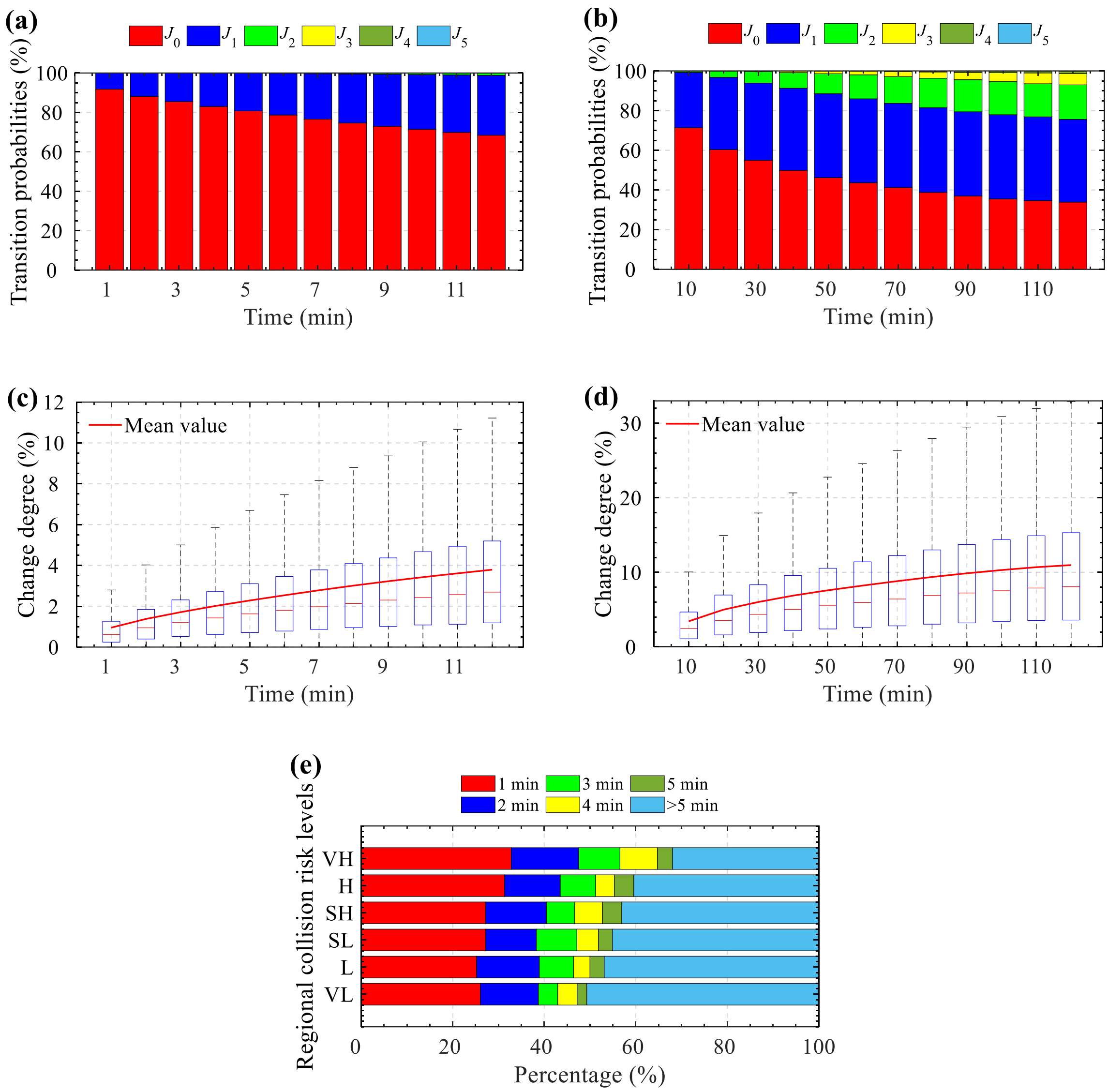
Figure 6.9. Multi-view collision risk evaluation for a traffic scenario.

6.4.4 Traffic Collision Risk Evolution

A maritime traffic situation is inherently a dynamic evolving process; hence, multi-scale collision risk patterns commonly vary with time. To fully understand the evolutionary mechanism of the traffic situation, the time-dependent characteristics of collision risk are explored from regional and individual scales.

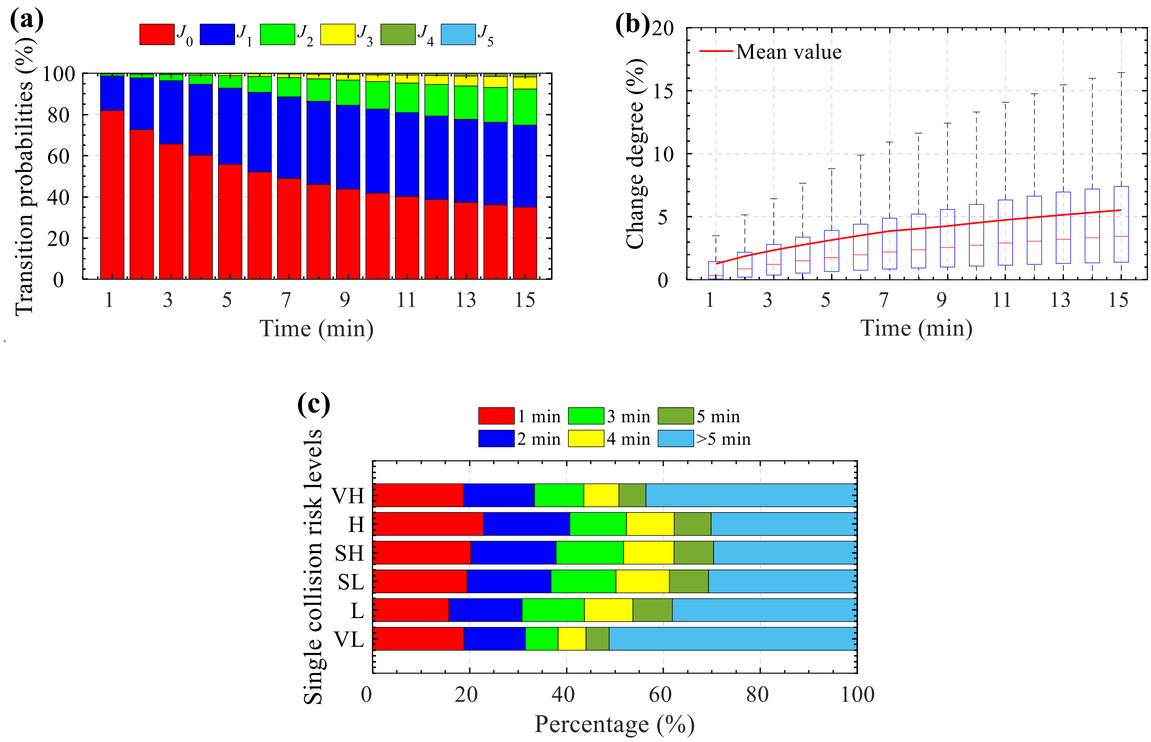
Figure 6.10 provides the evolutionary characteristics of regional collision risk. In Figure 6.10 (a)-(b), the transition probabilities between different regional collision risk levels are illustrated. Two insightful phenomena can be drawn. First, the cases that maintain the same risk levels (see the red bar in Figure 6.10 (a)) or transfer to their nearest risk levels (see the blue bar in Figure 6.10 (a)) over a short-term period almost account for 100%. Secondly, the jumping transitions, *i.e.*, the transitions beyond 1 level, start to occupy a certain proportion when the evolving time lasts for 20 minutes (see the second bar in Figure 6.10 (b)). These results imply that the regional traffic situations evolve steadily over time. Meanwhile, the change degree of RCR^2 over short-term and long-term periods is shown in Figure 6.10 (c)-(d). According to these figures, the degree of change of RCR^2 grows linearly over a short-term period, while the growth rate of change degree gradually decreases over a long-term period. This is basically in line with the evolutionary features of RCR^1 (see the change degree of red bars in Figure 6.10 (a)-(b)). Additionally, Figure 6.10 (e) illustrates the life cycle of different regional collision risk levels. The life cycle refers to the existing duration of the current risk levels/classes. It is evident that a larger risk level corresponds to a shorter life cycle. This may be attributed to the fact that when faced with a persistent high-risk situation, maritime operators should take appropriate strategies to relieve the regional traffic complexity and consequently, the high-risk traffic situation will disappear soon. These evolutionary investigations provide a basis for future prediction of a high-level maritime traffic risk situational awareness and offer insights into the design of maritime safety management strategies.

A similar evolutionary analysis is conducted for individual collision risk. To investigate the transition features and life cycle of single ship collision risk, it is equally divided into six levels in terms of the cumulative probability distribution. The corresponding statistical results are shown in Figure 6.11. Compared to the regional collision risk evolution, two different findings are revealed. First, the individual collision risk evolves faster than the regional collision risk because the jumping transitions of risk levels occur over a short period (Compare Figure 6.10 (a) and Figure 6.11 (a)). Second, the medium risk levels have a shorter life cycle than the remaining risk levels since their life cycle with the duration less than or equal to 5 min occupies a higher percentage (see Figure 6.11 (c)). This may be because SH and SL risk levels can transit to two sides while VH and VL risk levels can only transit to one side, so that the former are associated with higher dynamics and instability.



(a)-(b) Transition probabilities between different regional collision risk levels RCR^1 over short-term and long-term periods, where J_0, J_1, …, J_5 represent the transitions with 1, 2, …, 5 levels ; (c)-(d) change degree of RCR^2 over short-term and long-term periods; (e) life cycle of different regional collision risk levels, where 1 min, 2 min…, >5 min denote the life cycle with 1 minute, 2 minutes…, >5 minutes.

Figure 6.10. Regional collision risk evolution.



(a) Transition probabilities between different single ship collision risk levels over a short-term period; (b) change degree of SCR_i^2 over a short-term time; (c) life cycle of different single ship risk levels.

Figure 6.11. Individual ship collision risk evolution.

6.4.5 Model Validation

The methodological validation is an indispensable part of any modelling approach since it confirms the confidence level of the results produced. In this chapter, the model robustness validation consists of two crucial blocks: one is the reliability analysis of the multi-scale collision risk evaluation, which needs to be conducted from the perspectives of ship pair, global traffic, single ship, and multiple ships, respectively; the other is the effectiveness test of the optimal maritime traffic partition, which concerns the model performance in terms of capturing the optimal spatial scales. In fact, the performance of the maritime traffic partition model has been comprehensively verified to be reliable and robust in Section 4.4.4. Here its robustness would not be tested again. Furthermore, the remarkable performance of ship-pair collision risk evaluation based on the improved CPA model has been extensively demonstrated in Zhang et al. (2015). Consequently, the primary emphasis of this subsection lies in validating the collision risk associated with global traffic, individual ships, and multiple ships.

Firstly, the regional collision risk evaluation model is examined through two Axioms of sensitivity analysis (Fan et al., 2020; Yu et al., 2020; Zhang et al., 2013):

1) An increase or decrease in the Number of Nodes (*NN*) or Edges (*NE*) in a traffic network should result in a corresponding increase or decrease in the regional collision risk *RCR*.
2) The total influence of *NN* and *NE* should not be smaller than the change by its subsets (*i.e.*, any part of *NN* or *NE*).

Following the two Axioms, Table 6.1 shows the effects of single factor change on the *RCR*. It is observed that the increase/decrease of *NN* or *NE* results in the correspondence change in the *RCR* and their change amplitude is positively correlated. These results are in good agreement with Axiom 1. Equally, Table 6.2 presents the effects of multiple factor change. There is a more substantial variation in the *RCR* when *NN* and *NE* change together. This coincides with Axiom 2, which proves the rationality of the regional collision risk model to some extent.

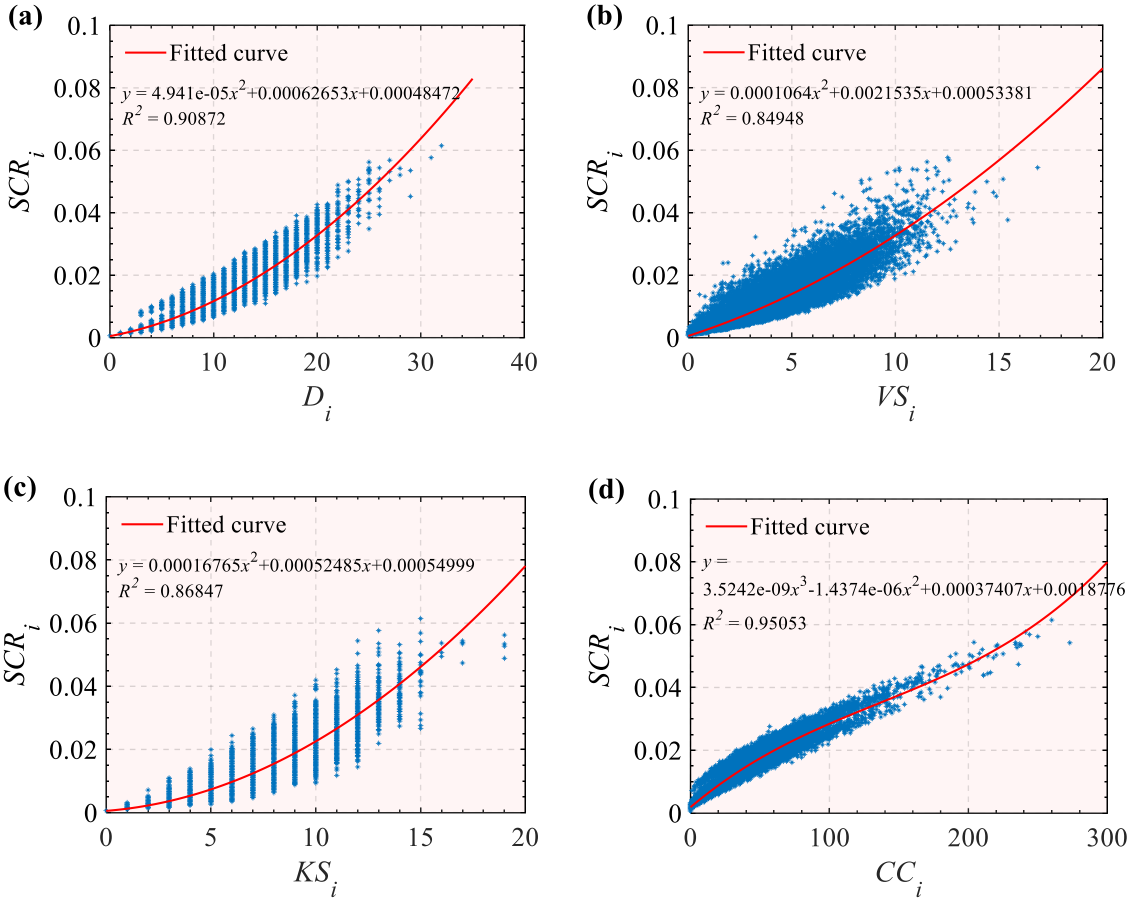
Table 6.1. Validity test (1) for regional collision risk model.

Change rate of *NN*	ΔRCR^1	ΔRCR^2	Change rate of *NE*	ΔRCR^1	ΔRCR^2
+10%	+0.46%	+1.53%	+10%	+4.88%	+6.11%
+20%	+0.85%	+3.04%	+20%	+9.69%	+12.36%
-10%	-12.83%	-16.30%	-10%	-9.73%	-12.38%
-20%	-28.02%	-32.80%	-20%	-19.46%	-23.26%

Table 6.2. Validity test (2) for regional collision risk model.

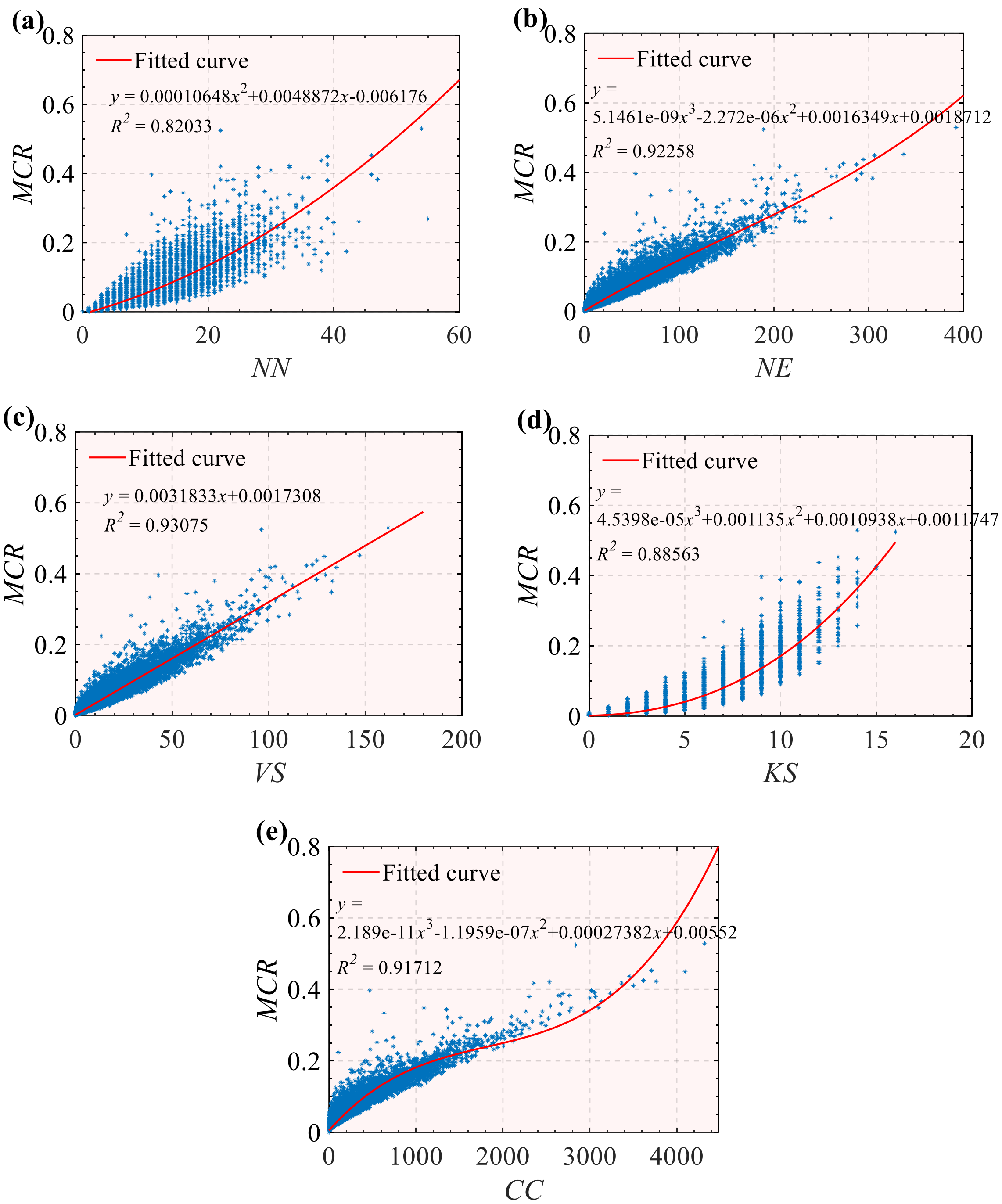
Change rate of *NN*	/	+10%	+10%	-10%	-10%
Change rate of *NE*	/	/	+10%	/	-10%
ΔRCR^1	0	+0.46%	+5.17%	-12.83%	-22.45%
ΔRCR^2	0	+1.53%	+7.55%	-16.30%	-26.48%

As for the validity examination of the individual collision risk model, the correlations between the *SCR* and the local network indices (*i.e.*, D_i, VS_i, KS_i, CC_i) are investigated, as shown in Figure 6.12. It is remarkable that the *SCR* has a significantly positive relation with each of local network indicators. These results conform to the common sense about the collision risk, *i.e.*, a single ship associated with larger local network indices should have a higher risk level than the one with smaller network indices. Simultaneously, the identical statistical analyses are carried out for the multi-ship collision risk model. According to Figure 6.13, similar responses between the Multi-ship Collision Risk (*MCR*) and the network indices can be observed, which helps further validate the model's feasibility and reliability.



(a) SCR_i vs. D_i; (b) SCR_i vs. VS_i; (c) SCR_i vs. KS_i; (d) SCR_i vs. CC_i.

Figure 6.12. Correlations between single ship collision risk and local network indices.



(a) *MCR* vs. *NN*; (b) *MCR* vs. *NE*; (c) *MCR* vs. *VS*; (d) *MCR* vs. *KS*; (e) *MCR* vs. *CC*.

Figure 6.13. Correlations between multi-ship collision risk and global network indices.

6.4.6 Discussion and Implication

Multi-scale collision risk estimation regards different spatial scales as different views to characterise the different aspects of a traffic scenario. This research is the first attempt to develop a multi-scale approach to capture the collision risk patterns under different spatiotemporal granularity. The in-depth case analysis and model validation test reveal the significant contributions of the proposed approach both in theory and in practice. The insights and implications in terms of the experimental results and analytical discussions are drawn as follows.

Firstly, traditional studies process collision risk at a fixed granularity. However, the proposed approach enables multi-resolution feature extraction of traffic scenarios, facilitating comprehensive analysis of traffic situations. This is highly significant in enhancing maritime intelligent perception capabilities, enabling informed management and operational insights to support intelligent maritime surveillance.

Secondly, the proposed method effectively identifies key influential ships or traffic clusters within a given traffic scenario, enabling proactive risk control through strategic actions. Precise strategy deployment and maneuvering instructions for these crucial ships or traffic clusters contribute to a substantial reduction in overall traffic complexity. This improvement from a global perspective enhances the working ability of maritime operators when faced with high-complexity traffic situations.

Thirdly, the proposed approach provides valuable insights into potential conflicts among ships across different adjoining waters from a global traffic network perspective. By transitioning from local ship-pair analysis to global/regional handling, the current ship anti-collision practice becomes more coordinated. This enables better control of multiple ship collision risks through coordination.

6.5 Conclusion

This chapter shifts a paradigm of ship collision risk analysis from a single scale focused scheme towards a regium involving a multi-scale collision risk study to reveal the traffic risk patterns under different spatial granularity. It synergizes a series of techniques to achieve collision risk evaluation at any spatial scale and capture the optimal spatial scope for risk analysis. The developed methodology has several unique features: 1) it incorporates the influence of ship motion dynamics on collision risk to ensure the applicability in generalized scenarios; 2) the topological characteristics of multiple ship conflicts are explicitly considered to reveal the resolving difficulty of collisions brought by traffic interaction structure; 3) it pioneers the application of node deletion method to quantify the aggregation risk criticality of any multiple ship interactions to a regional traffic situation; and 4) a competitive SNMF framework is embedded to search for the optimal traffic clusters at any spatial scale. Comprehensive experiments based on real-AIS data are performed to evaluate and check the performance of the proposed approach. Experimental results show that the proposed methodology can offer a complete comprehension of the traffic scenarios and facilitate strategic maritime safety management. Additionally, the robustness and superiority of the proposed methods are tested through a sensitivity analysis and correlation examination. This study therefore could be used in practice to support intelligent maritime perception and promote maritime system automation.

CHAPTER 7 CONCLUSIONS AND FUTURE RESEARCH

This chapter briefly summarises and discusses the current research deficiencies and demands, and the proposed models and techniques (Chapters 3 to 6). Particularly, it highlights the advantages and implications of the proposed models and methods in promoting maritime traffic surveillance intelligence and ship navigation automation. Additionally, the research limitations along with the suggestions for further improvements, as well as the future research directions are outlined and revealed.

7.1 Conclusions and Implications of the Research

Maritime traffic surveillance and management is an essential and crucial part of the rapid development of intelligent ports and autonomous ships. However, economic globalization, the considerable growth in traffic demand, and the emergence of autonomous ships have incurred more complicated traffic situations, involving dynamic traffic movements, uneven traffic spatio-temporal distribution, and multiple dependent conflicts, particularly in complex port waters. Risky and sophisticated traffic situations increasingly pose significant challenges to the safety management of maritime transportation operations. Although there is a significant appeal in assisting operators and controllers in monitoring and regulating maritime traffic dynamics, existing technologies and systems still have limitations in their practical applications due to the increasing ship traffic complexity. As a result, developing advanced MSA techniques that enable maritime controllers and ship drivers to better comprehend traffic situations and strengthen maritime traffic situational awareness is in high demand.

The critical analysis from the literature review has revealed that previous studies on ship collision risk estimation and maritime traffic situation perception ignored the influence of various traffic characteristics in complex waters on potential collision detection, rarely examined the relationships between the collision risk and the traffic topological property associated with the dependent conflict relations among multiple ships, and have difficulty in decomposing the regional traffic complexity of a given traffic scenario. Besides, most of the studies processed collision risk or traffic complexity models in one specific scale, which is inadequate to reveal the collision risk patterns under different spatial granularity and comprehensively interpret the entire traffic situation. These traditional methods encounter challenges in adapting to increasingly complex traffic situations and the development of intelligent supervision technologies. Thus, the previous chapters in this thesis develop a holistic framework to fill these research gaps and achieve advanced MSA. The applied approaches and research outcomes can be summarised as follows:

1) Developing a novel probabilistic CD framework to estimate the conflict criticality under ship motion dynamics and uncertainty (Chapter 3).

2) Constructing an AIS data-driven procedure to extract the ship motion uncertainty pattern and quantify the trajectory uncertainty distributions (Chapter 3).

3) Introducing a two-stage MC simulation model to accurately and efficiently compute the probabilistic conflict criticality (Chapter 3).

4) Adopting an image processing technique to build a traffic route network to aid in capturing the actual spatial distance between ship pairs (Chapter 4).

5) Employing an SNMF framework to partition the regional ship traffic into several spatial compact and conflict-connected traffic clusters to decompose the whole traffic complexity and search for the optimal scopes for collision risk evaluation (Chapters 4 and 6).

6) Combining the SNMF with a temporal smoothness regularization to handle the effects of the temporal-varying feature of maritime traffic on the temporal stability of generated traffic clusters (Chapter 5).

7) Designing an effective cluster-matching strategy to extract realistic and sufficient multi-ship encounter scenarios for the evolutionary analysis of dynamic traffic clusters over time (Chapter 5).

8) Developing a multi-scale collision risk evaluation framework to explore the collision risk under different types of spatial granularity (Chapter 6).

9) Applying the complex network theory to unveil the topological properties of traffic interactions in a given traffic scenario (Chapter 6).

10) Utilizing the node deletion method to characterise the correlation between the micro-level and macro-level collision risk (Chapter 6).

In summary, the objectives listed in Section 1.2 are well achieved. Moreover, the proposed methods and models show great potential as valuable and powerful tools to assist maritime operators, ship navigators, and other practitioners in traffic situational awareness and decision-making. They can be easily tailored to any waters because of their strong applicability and generalization ability to complex port waters involving dynamic ship movements, restricted geographical characteristics, and frequent multi-ship interactions. Therefore, the methods proposed in this thesis reveal the significant contributions and implications both in theory and in practice, which are drawn from the following three aspects:

1) Supporting intelligent maritime surveillance

This study provides managerial and operational insights on supporting intelligent maritime surveillance. Generally, traditional methods are prone to process the collision risk in a fixed granularity. For example, current maritime controllers undertake MSA based on the traffic density in a given water. The effectiveness of this method becomes questionable in complex port waters because the complex and sophisticated conflicts among ships are ignored. This issue will become even more worrisome once the traffic situations in ports are more complex due to the occurrence of mixed encounter situations involving both manned and autonomous ships. However, the proposed approach can achieve the multi-resolution feature extraction of a traffic scenario, offering a complete view analysis for a traffic situation. This is of great significance to enhancing maritime intelligence perception capabilities.

Moreover, the developed maritime traffic partition technique not only assists in capturing the optimal spatial scopes for risk analysis, but also decreases the difficulty of situational awareness. It helps to improve traffic pattern interpretability by decomposing the whole maritime traffic scenario into several compact and interpretable sub-clusters. On this basis, maritime management authorities can also gain detailed knowledge concerning how the collision risk is distributed in space and where it should be prioritised to mitigate risk.

Additionally, the proposed models can be used as an effective tool for tactical traffic management. For instance, when the regional maritime traffic situation is at high-risk levels, the complex traffic behaviours will induce a sharp increase in the potential conflicts among ships. Under this circumstance, maritime surveillance operators will suffer from the tremendous pressure on practical monitoring tasks and encounter challenges in designing rational measures to relieve traffic complexity. A practical way in reality is to regulate the rate of ships joining the overall traffic (that influences the quantity of the ships in a water area simultaneously) to reduce the traffic density in the surveillance area. It however needs to sacrifice traffic efficiency to a certain extent and even may ignore some local traffic conflicts. On the contrary, the identification of the key influential ships or traffic clusters through the proposed approach in this study is helpful for taking strategic actions to proactively control risk. The precise strategy deployment and manoeuvring instructions for these crucial ships or traffic clusters can contribute to a considerable decline in traffic complexity from a global perspective, which thereby improves the efficiency of maritime operators when facing high-complexity traffic situations.

As a result, this work can aid surveillance operators in promoting maritime safety management from an operational perspective without the need of either compromising traffic density and flow efficiency or new investment demand for infrastructure upgrading. It has the potential to be embedded into intelligent maritime surveillance systems to support intelligent port design and operation.

2) Promoting maritime navigation autonomy

This study also brings significant benefits to maritime navigation autonomy. Currently, ship navigators are inclined to focus on their own operations and situations rather than taking the traffic situation from a global/regional perspective. However, in a complicated encounter scenario, the measures taken by one ship to avoid a collision with another ship could pose a higher risk to others. This is because the navigational complexity of a scenario may be highly associated with multiple dependent conflicts, especially in high-traffic waters possibly involving classical manned ships and emerging autonomous ships. Therefore, the collision avoidance strategy deployment only based on nearby local ship pairs is not constantly recommended because it may render ship navigators to continuously adjust collision evasive manoeuvres due to the complex spatial dependencies among multiple conflicts. By contrast, this work captures the traffic clusters with high intra-interactions by the proposed traffic partitioning methodology, thereby aiding the traffic conflicts to be resolved from a perspective of traffic clusters instead of based on nearby local ship pairs. In other words, it makes a ground-breaking development by shifting the anti-collision control from being dependent on the ship navigator locally to taking strategic action so that the collision risks of multi-ship encounters can be better managed.

On the other hand, the division of the whole ship traffic scenario into small clusters can support tackling each cluster's risk independently, which would not make the design of risk mitigation schemes too sophisticated. It enables ship navigators to specify the constraint boundaries for the design of autonomous collision avoidance decision-making. Particularly, the new dynamic traffic partitioning approach considering the evolution characteristics of maritime traffic provides an important basis for the continuous implementation of risk control schemes in the same traffic cluster. The generated stable and consistent traffic clusters ensure the temporal smoothness of a cluster-based risk resolution strategy over time. Additionally, the proposed dynamic traffic cluster matching approach also sheds light on investigating the evolutionary co-behaviours among multiple ships by extracting the temporal stable traffic clusters from the historical AIS trajectory data. It can provide massive time-evolving multi-ship encountering scenarios that are complicated but exist in reality to enable new intelligent techniques (*e.g.*, autonomous ships) to be extensively tested and verified, which constitutes a critical step before the real-world applications of these new techniques.

Therefore, the proposed methodology would be particularly applicable in autonomous maritime anti-collision risk control and lay a solid foundation for the future coexistence of mixed manned and autonomous ships.

3) Enhancing port competitiveness

Furthermore, this study would be of great significance in enhancing port reliability and competitiveness. The deployment of the proposed approach in autonomous and intelligent systems shows the potential to reduce collision risk and mitigate port congestions and traffic delays. Evidently, port safety and efficiency are the key concerns of port stakeholders such as port operators, ship owners, and shippers. The ports with high-end port services are foreseen to attract more direct investment. Additionally, the enhancement of maritime efficiency would also mean fuel cost savings and emission reductions, which are helpful for constructing green, modern, and intelligent ports. Hence, the proposed approach is seen as a fundamental tool to make the port competitive and sustainable.

7.2 Limitations and Further Improvements

Despite the advantages and implications mentioned above, the proposed methodologies still reveal some limitations due to the research time and cost constraints. Further studies are required to improve the research from the following aspects:

1.1) The effectiveness and reliability of the proposed methodology are currently tested in a selected water area (*e.g.*, Ningbo-Zhoushan), and its generality should be further investigated in a larger scope in the future. This is of paramount importance to its practical implementation and applications.

1.2) The ship trajectory prediction method should be further extended. In Chapter 3, the proposed ship motion prediction model highly depends on the exchange of navigation plans among ships through communications. However, in reality, non-cooperative ships are unlikely to share their intention information. Some manoeuvre-based prediction techniques could be further incorporated into the model to support conflict estimation with non-cooperative ships.

1.3) The proposed method in Chapter 3 mainly emphasises the estimation of the occurrence probability of a conflict. However, it may be inadequate to comprehensively assess the navigational risk, since the potential consequence is not explicitly considered in the conflict probability. In fact, there are a large number of possible accident scenarios with distinct occurrence probabilities and consequences once involved in collisions. Therefore, an improved model which takes into account both the occurrence probability and damage consequence could facilitate ship navigators and maritime safety authorities to better understand the actual level of danger or risk of the traffic situation.

1.4) The maritime traffic partitioning approaches capture traffic clusters based on the conflict relations and spatial distance relations among ships in Chapters 4 and 5. In fact, more ship motion interactions (*e.g.*, converging/diverging trend of ship pairs and ship movement behaviour patterns) could be factored into the traffic partitioning process to help better unveil the complementary information related to ship traffic interactions.

Additionally, future research extensions can also be conducted from the following aspects:

2.1) The impact of additional factors, *e.g.*, ship type, ship manoeuvrability, human behaviours, and environmental disturbances, on the traffic collision risk could be usefully taken into consideration. It could help improve the collision risk evaluation accuracy.

2.2) The influence of the risk perception difference on probabilistic collision detection, especially for the interaction between large and small ships, could be investigated. When encountering ships that are spatially close to each other, large ships are often subject to high collision avoidance pressure and require an earlier alert. Hence, further efforts will be made to integrate the risk perception difference into the multi-scale collision risk evaluation by constructing directed ship traffic networks.

2.3) The propagation and prediction of maritime traffic risk deserve further concern. It will enhance the perception ability for forthcoming traffic situations, which is helpful for issuing an early collision alert and preventing the time lag in risk management response.

2.4) A new conflict resolution approach that can coordinate and balance the local and regional collision risk could be beneficial to guide surveillance operators to devise multi-layered strategies for hierarchical risk control purposes, which is also the final step of maritime traffic safety surveillance and management.

2.5) The application of advanced artificial intelligence techniques in autonomous maritime traffic systems warrants thorough exploration. This endeavour involves enhancing the decision-making capabilities of autonomous ships through the utilization of reinforcement learning techniques, as well as generating real-world scenarios to comprehensively test autonomous ship operations by utilizing deep learning techniques.

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APPENDICES

Appendix A. Calculation of Ship Absolute Motion

In Eq. (3-4), the first two terms represent the nominal prediction trajectory based on the sequence of waypoints derived from the navigation plan. To be more specific, assume that the navigation plan of ship A comprises n_A segments with n_A+1 waypoints, in which the first waypoint is the initial position where the prediction is made. According to the assumption that each ship moves following its navigation plan with a prescribed speed, the nominal navigation time taken in each segment, as shown in Figure A1, can be obtained by the following expression:

$$t_{A,i} = \frac{||\vec{P}_{A,d_i} - \vec{P}_{A,o_i}||}{||\vec{V}_A(t)||} \quad i = 1,2 \cdots n_A \tag{A1}$$

where $\vec{P}_{A,d_i}$ and $\vec{P}_{A,o_i}$ denote the coordinates of the origin and destination waypoints of segment i, respectively. Then the nominal prediction times at which ship A starts and ends at each segment can be recursively computed by

$$t_{A,o_i} = \sum_{j=1}^{i-1} t_{A,j} \quad i = 2,3 \cdots n_A \tag{A2}$$

$$t_{A,d_i} = \sum_{j=1}^{i} t_{A,j} \quad = 1,2 \cdots n_A \tag{A3}$$

Based on Eq. (A1)-(A3), the nominal prediction position at any specific time can be easily computed.

For the last term in Eq. (3-4) that represents the ship prediction position errors added to the nominal trajectory, it is given in detail below.

$$R(\varphi_A(T)) \cdot \vec{Q}_A(T) = \begin{bmatrix} sin(\varphi_A(T)) & -cos(\varphi_A(T)) \\ cos(\varphi_A(T)) & sin(\varphi_A(T)) \end{bmatrix} \begin{bmatrix} Q_{A,x}(T) \\ Q_{A,y}(T) \end{bmatrix} \tag{A4}$$

where $Q_{A,x}(T)$ and $Q_{A,y}(T)$ refer to the heading and lateral ship position prediction error components, which are considered to be positive if they are toward to the front and left side, respectively. The nominal heading of ship A at time T can be computed based on the successive waypoint coordinates, as follows:

$$\varphi_A(T) = arctan\left(\frac{y_{A,d_i} - y_{A,o_i}}{x_{A,d_i} - x_{A,o_i}}\right) \quad T \in [t_{A,o_i}, t_{A,d_i}] \tag{A5}$$

where (x_{A,o_i}, y_{A,o_i}) and (x_{A,d_i}, y_{A,d_i}) denote the positions of the origin and destination waypoints of segment *i*, with the exception of the case $x_{A,d_i} = x_{A,o_i}$, where $\varphi_A(T)$=0/π.

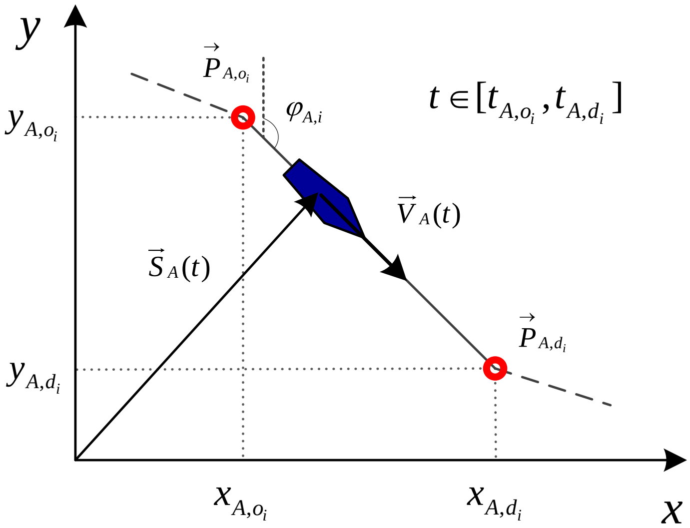

Figure A1. Absolute motion of ship *A* in segment *i*.

Appendix B. Calculation of Minimum Passing Distance

Suppose the navigation plan trajectories of ships A and B comprise N_A and N_B segments, respectively. Then the nominal relative positions between the ship A sailing in segments i = 1, 2, ..., N_A and the ship B sailing in segments j = 1, 2, ..., N_B at time t can be formulated as follows:

$$\vec{S}^{N}_{AB,ij}(t) = \vec{S}^{N}_{A,i}(t) - \vec{S}^{N}_{B,j}(t) = \vec{S}^{N}_{0,AB,ij} + \vec{V}_{AB,ij} \cdot t \qquad t \in [t_{A,o_i}, t_{A,d_i}] \cap [t_{B,o_j}, t_{B,d_j}] \quad \text{(B1)}$$

where $\vec{S}^{N}_{A,i}(t)$ and $\vec{S}^{N}_{B,j}(t)$ are the nominal prediction positions of ships A and B at time t, $\vec{V}_{AB,ij}$ represents the relative speed of ship A over ship B at time t, and $\vec{S}^{N}_{0,AB,ij}$ represents the derived relative initial positions of the two ships with the assumption of ship linear motion, which can be expressed as:

$$\vec{S}^{N}_{0,AB,ij} = \vec{P}_{A,o_i} - \vec{P}_{B,o_j} - (\vec{V}_{A,i} \cdot t_{A,o_i} - \vec{V}_{B,j} \cdot t_{B,o_j}) \quad \text{(B2)}$$

The distance between the two ships at time t is given by making use of Eq. (B1), as follows:

$$Dist^{N}_{AB,ij}(t) = \sqrt{||\vec{S}^{N}_{0,AB,ij}||^2 + 2\vec{S}^{N}_{0,AB,ij} \cdot \vec{V}_{AB,ij} \cdot t + ||\vec{V}_{AB,ij}||^2 \cdot t^2} \quad \text{(B3)}$$

Since Eq. (B3) is a function with respect to t, the minimum distance between the ships for each pair of segments i and j is determined by t, as follows:

$$Dist^{N}_{min,\,AB,ij} = \sqrt{||\vec{S}^{N}_{0,AB,ij}||^2 + 2\vec{S}^{N}_{0,AB,ij} \cdot \vec{V}_{AB,ij} \cdot t_{d_{min},AB,ij} + ||\vec{V}_{AB,ij}||^2 \cdot {t_{d_{min},AB,ij}}^2} \quad \text{(B4)}$$

where $t_{d_{min},AB,ij}$ denotes the time of the closest approach for the pair of segments i and j, which has the following three possibilities:

$$t_{d_{min},AB,ij} = \begin{cases} max\{t_{A,o_i}, t_{B,o_j}\} & t^{*}_{AB,ij} < max\{t_{A,o_i}, t_{B,o_j}\} \\ -\vec{S}^{N}_{0,AB,ij} \cdot \vec{V}_{AB,ij} / {V_{AB,ij}}^2 & t^{*}_{AB,ij} \in [t_{A,o_i}, t_{A,d_i}] \cap [t_{B,o_j}, t_{B,d_j}] \\ min\{t_{A,d_i}, t_{B,d_j}\} & t^{*}_{AB,ij} > min\{t_{A,d_i}, t_{B,d_j}\} \end{cases} \quad \text{(B5)}$$

After that, the minimum distance between the two ships over the prediction time horizon can be given as follows:

$$CPA^{*}_{AB} = \min_{i,j}\{Dist^{N}_{min,\,AB,ij}\} \qquad i = 1, 2, \ldots, NA \text{ and } j = 1, 2, \ldots, NB \quad \text{(B6)}$$

Appendix C: Operation Procedure of AIS Pre-Processing

Figure C1 presents the main process of AIS data pre-processing. The detailed procedure is given as follows.

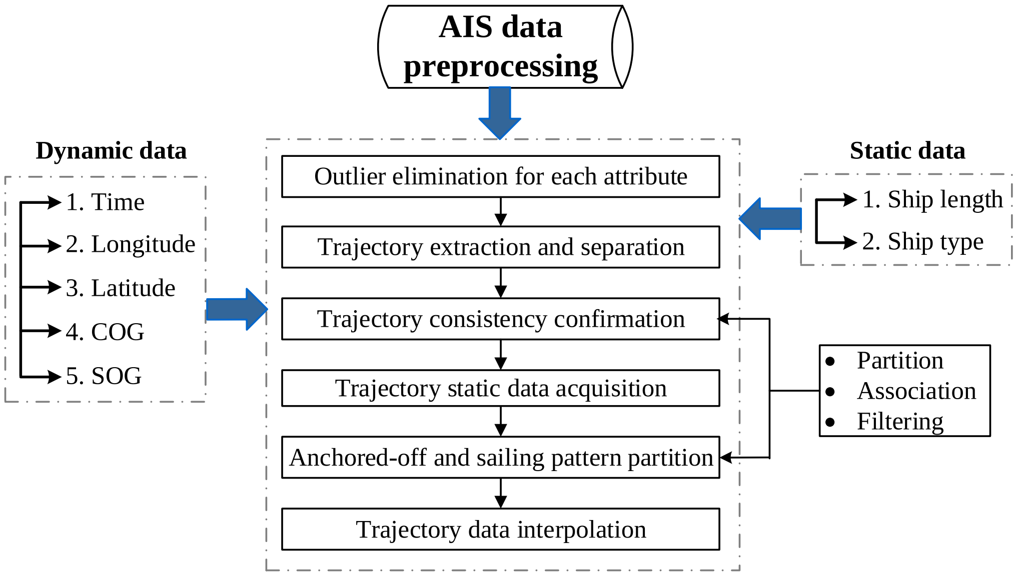

Figure C1. The procedure of AIS data pre-processing.

1. **Outlier elimination for each attribute.** For each attribute, the values that are not in the normal range can be regarded as noises and need to be eliminated. For example, if ship ID < 000000000 or ship ID > 999999999, and SOG < 0 or SOG > 35, and COG < 0 or COG >360, the corresponding records will be removed.

2. **Trajectory extraction and separation.** Each ship's data records are extracted based on their MMSI number since it is a unique number given for ship identity verification. Then sort each ship's data records by time and split them into trajectories according to the time interval (*e.g.* larger than 6 min) between consecutive data records.

3. **Trajectory consistency confirmation.** During the data processing, it can be found that some MMSI numbers are shared by more than one ship, which may be caused by crews' improper use of MMSI numbers. As a result, the different ship trajectories with the same MMSI numbers may be mixed if they appear in the research waters at the same time. To deal with this issue as well as eliminate the abnormal speed or position records which need

to be identified according to the sequential set of trajectory points, the spatial logical integrity method presented in (Zhao et al., 2018) is referred to confirm the consistency of trajectories. The method mainly includes three steps, which are partition, association and filtering. The partition between consecutive points is executed if Eq. (C2) cannot be satisfied.

$$v_i^{t_j} = \frac{\sqrt{(x_i^{t_{j+1}} - x_i^{t_j})^2 + (y_i^{t_{j+1}} - y_i^{t_j})^2}}{t_{j+1} - t_j} \tag{C1}$$

$$\left\|\vec{v}_i^{t_j}\right\| - d_i \cdot (t_{j+1} - t_j) \leq v_i^{t_j} \leq \left\|\vec{v}_i^{t_j}\right\| + a_i \cdot (t_{j+1} - t_j) \tag{C2}$$

where $(x_i^{t_j}, y_i^{t_j})$ represents the position of ship i at time t_j, $v_i^{t_j}$ is the average speed of ship i from time t_j to t_{j+1}, $\left\|\vec{v}_i^{t_j}\right\|$ is the recorded speed at time t_j, a_i and d_i are the maximum acceleration and deceleration for ships, respectively. Then, the association for all the obtained sub-trajectories will be implemented if the relationship between the last point of the former sub-trajectories and the first point of the latter sub-trajectories satisfy both Eq. (C2) and the time interval threshold (*e.g.* less than 6 min). Finally, the sub-trajectories that lack completeness will be discarded.

4. **Trajectory static data acquisition.** Obtain the static messages of ship trajectories in terms of the corresponding MMSI numbers.

5. **Anchored-off and sailing pattern partition.** After matching static messages for all trajectories, they are further split into anchored-off and sailing patterns. The procedure of trajectory pattern partition is given below. First, the points in the trajectories with speed less than the speed threshold (*e.g.* 2 knots) are marked as 0, whereas the rest are marked as 1. Then, the association for the points with the same markers are conducted according to the time interval threshold (*e.g.* less than 6 min). Finally, the sub-trajectories that do not satisfy the completeness are discarded. The sub-trajectories with marker 0 are regarded as anchored-off patterns, while the rest are considered as sailing patterns.

6. **Trajectory data interpolation.** As the AIS data is transmitted at varying frequencies, the trajectories need to be interpolated to obtain the snapshot of ship state at the same time. In

this study, the position and speed are interpolated by the following formulas.

$$x_i^t = x_i^{t_j} + \left\| \vec{v}_{i,x}^{t_j} \right\| \cdot (t_{j+1} - t_j) \tag{C3}$$

$$y_i^t = y_i^{t_j} + \left\| \vec{v}_{i,y}^{t_j} \right\| \cdot (t_{j+1} - t_j) \tag{C4}$$

where $\left\| \vec{v}_{i,x}^t \right\|$ and $\left\| \vec{v}_{i,y}^t \right\|$ are the speeds in the longitude and latitude directions at time *t*, respectively.

It should be noted that the above trajectory completeness is determined based on the number of points, the time duration and whether the trajectories have static information. The trajectories whose number of points (*e.g.* less than 60) or time duration (*e.g.* shorter than 10 min) is too small, or lacking static information will be discarded since they cannot fully reflect the ship motion features of interest. More details about the above procedure are presented in the related references (Kang et al., 2018; Zhang et al., 2019; Zhao et al., 2018).

Appendix D. Pseudocode for Static Maritime Traffic Partition Procedure

Algorithm D.1 presents the pseudocode of the static maritime traffic partition. It involves two important modules: similarity measure and SNMF implementation. The similarity measure takes both conflict criticality and spatial distance as the similarity of ship pairs (step 3). Further, the Newton-like algorithm is used to optimize the SNMF framework (step 7).

Algorithm D.1: Static maritime traffic partition

Input: The set of ships associated with their attributes $\{x_a\}_{a=1:N}$, and the desired number of clusters k.
Output: The set of clusters $\{C_1, C_2, \cdots C_k\}$.
// **A.** Similarity measure
1. Initialize similarity matrix as $W_{ij} \leftarrow \mathbf{0}_{[N\times N]}$.
2. **For** $\forall\, x_i, x_j \in \{x_a\}_{a=1:N}$ **do**
3. $W_{ij} = W_{ij}^c \cdot \alpha + W_{ij}^d \cdot (1-\alpha)$
4. **End**
// **B.** SNMF implementation
5. $D = diag(d_i)$, where $d_i = \sum_{j=1}^{N} W_{ij}$.
6. $\widetilde{W} = D^{-1/2} W D^{-1/2}$
7. $H^* = \arg\min \left\| \widetilde{W} - HH^T \right\|^2$, where $H \in \mathbb{R}_+^{N\times NS}$.
8. **For** $i = 1:N$ **do**
9. $j^* = \arg\max_{\{j=1,2,\cdots,NS\}} H_{ij}$
10. $x_i \in C_{j^*}$
11. **End**

Appendix E: Detailed Illustration of the FCI approach

The operation details of the FCI approach are depicted as follows.

Suppose there are n assessment samples and each sample records m indices as $A_j = (a_{1j}, a_{2j}, \ldots, a_{mj})$. Then the sample data set is expressed as matrix $A = (a_{ij})_{m\times n}$, where a_{ij} represents the ith index of sample j.

As each index has different orders of magnitude, the elements in A should be standardized to eliminate the dimensionality influence, using the following equation:

$$r_{ij} = (a_{ij} - a_{i,min})/(a_{i,max} - a_{i,min}) \tag{E.1}$$

where $a_{i,min}$ and $a_{i,max}$ represent the minimum and maximum values in the ith row in A, respectively. Hence, matrix A can be transformed into a normalised matrix R.

After that, assume that the n samples with m attributes are clustered with c classes/patterns, the fuzzy membership matrix and class centre matrix can be defined as $U = (u_{kj})_{c\times n}$ and $S = (s_{ik})_{m\times c}$, where u_{kj} represents the membership value of sample j assigning to class k, subject to $0 \leq u_{kj} \leq 1$ and $\sum_{k=1}^{c} u_{kj} = 1$, and s_{ik} denotes the centre of index i in class k, satisfying $0 \leq s_{ik} \leq 1$.

To gain the optimal U and S, the objective function that minimizes the square sum of the weighted Euclidean distance from samples 1-n to class centres 1-c is constructed as follows:

$$\min\left[F\left(w_i, u_{kj}, s_{ik}\right)\right] = \min\left\{\sum_{j=1}^{n}\sum_{k=1}^{c}\left({u_{kj}}^2\sum_{i=1}^{m}(w_i(r_{ij} - s_{ik}))^2\right)\right\} \tag{E.2}$$

where w_i represents the weight of different indices, subject to $0 \leq w_i \leq 1$ and $\sum_{i=1}^{m} w_i = 1$.

According to the objective function in Eq. (A.2), the w, U, and S can be iteratively optimized by the Lagrange multiplier method, using the following equations:

$$w_i = \left[\sum_{i=1}^{m}\frac{\sum_{j=1}^{n}\sum_{k=1}^{c}[u_{kj}(r_{ij} - s_{ik})]^2}{\sum_{j=1}^{n}\sum_{k=1}^{c}[u_{kj}(r_{ij} - s_{ik})]^2}\right]^{-1} \tag{E.3}$$

$$u_{kj} = \left[\sum_{h=1}^{c} \frac{\sum_{i=1}^{m} [w_i (r_{ij} - s_{ik})]^2}{\sum_{i=1}^{m} [w_i (r_{ij} - s_{ih})]^2} \right]^{-1} \tag{E.4}$$

$$s_{ik} = \sum_{j=1}^{n} u_{kj}{}^2 \, w_i{}^2 r_{ij} / \sum_{j=1}^{n} u_{kj}{}^2 \, w_i{}^2 \tag{E.5}$$

The specific update process comprises the following steps.

1) Initialize the precision parameters ε_1, ε_2, and ε_3 used for w_i, u_{kj}, and s_{ik}.

2) Let $l = 0$ and generate the original w^l and U^l which satisfy the constraints mentioned above.

3) Calculate the original S^l by inputting the original w^l and U^l into Eq. (A.5) and $l = l+1$.

4) Update w^l, U^l, and S^l via Eq. (A.3)–(A.5), respectively.

5) Identify whether all the following constraints are satisfied

$$\max_i |w_i^{l+1} - w_i^l| \leq \varepsilon_1$$

$$\max_{kj} |u_{kj}^{l+1} - u_{kj}^l| \leq \varepsilon_2$$

$$\max_{ik} |s_{ik}^{l+1} - s_{ik}^l| \leq \varepsilon_3$$

If not, $l = l+1$ and repeat step 4 until the above termination conditions are held.

6) Output the optimal w, U and S.

Appendix F: Research Papers Arising from this Thesis

Finally, this part lists the researcher's key publications arising from this research.

Published journal papers:

[1] **Xin X**, K Liu, S Loughney, J Wang, Z Yang. Maritime traffic clustering to capture high-risk multi-ship encounters in complex waters[J]. Reliability Engineering & System Safety, 2023, 230: 108936.

[2] **Xin X**, Z Yang, K Liu, J Zhang, X Wu. Multi-stage and multi-topology analysis of ship traffic complexity for probabilistic collision detection[J]. Expert Systems with Applications, 2023, 213: 118890.

[3] **Xin X**, K Liu, Z Yang, J Zhang, X Wu. A probabilistic risk approach for the collision detection of multi-ships under spatiotemporal movement uncertainty[J]. Reliability Engineering & System Safety, 2021, 215: 107772.

Journal papers under review:

[4] **Xin X**, Liu K, Loughney S, J Wang, Z Yang. Graph-based ship traffic partitioning for intelligent maritime surveillance in complex port waters[J]. Expert Systems with Applications, 2023. (Under review)

[5] **Xin X**, Liu K, Loughney S, J Wang, N Ekere, Z Yang. Multi-scale collision risk evaluation for maritime transportation system in complex port waters[J]. Reliability Engineering & System Safety, 2023. (Under review)