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Editorial

Risk Assessment and Traffic Behaviour Evaluation of Ships

Juan-Chen Huang * and Shuen-Tai Ung

Department of Merchant Marine, National Taiwan Ocean University, Keelung 202301, Taiwan; shuentai@mail.ntou.edu.tw
* Correspondence: jchuang@ntou.edu.tw

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Recent advancements in information technology and ship equipment have led to massive data collection on maritime traffic, particularly through automatic identification systems (AIS). Such ship navigation data offer vital insights into the current and historical statuses of vessels, thereby becoming an indispensable asset in the investigation of ship behaviors. The combination of human expertise-based tools including navigation protocols, collision regulations, and artificial intelligence techniques such as optimization theory, machine learning, and deep learning, has provided a fresh perspective on understanding ship behavior and detecting anomalies. This integrative suite of tools has empowered scholars to undertake comprehensive studies and devise methodologies for risk evaluations in maritime traffic and the effective oversight of navigation safety.

AIS were developed to monitor ship behavior to avert atypical maritime casualties. They can provide informative parameters relating to vessels, including static and dynamic attributes, such as ship type, dimensions (length, width, draft), spatial coordinates (longitude and latitude), heading, course over ground, and speed over ground. Notably, AIS facilitate real-time, high-frequency data transmission, delivering a continuous stream of information, thereby enabling seamless, online ship-to-ship and ship-to-shore communication channels.

The analysis of AIS data has catalyzed a heightened emphasis on technological domains like the detection of anomalies in ship behavior, and trajectory predictions, with particular significance attributed to confined and constrained maritime areas, including ports, channels, and straits. These advancements hold pivotal importance in the realm of averting collisions and mitigating potential hazards, making it essential to systematically conduct analyses and studies to enhance maritime safety in diverse scenarios. Such scholarly pursuits are indispensable in advancing the cause of maritime safety. AIS data afford stakeholders the capacity to track ship trajectories and conduct quantitative analyses concerning statistical analysis of traffic and cargo flow. The application of artificial intelligence methodologies, including machine learning and deep learning, to AIS data facilitates the discernment of patterns in ship behavior, which, in turn, supports the advancement of key maritime technologies including ship categorization, trajectory grouping, anomaly detection, collision avoidance, and the optimization of maneuvering strategies, etc. This research is crucial for guiding ship operations, maritime supervision, and the shipping trade, rendering it a prominent subject of investigation and challenge within the maritime research domain (Yang et al., 2019) [1]. Notably, this research area has been prominently featured in works by Tu et al., 2017 [2], Le Tixerant et al., 2018 [3], and Svanberg et al., 2019 [4]. The following review is dedicated to an exploration of ship behavior characteristics and investigations related to anomaly detection.

The exploration of AIS data has attracted great interest, given its capacity to unveil the intricate behavioral patterns exhibited by vessels. This, in turn, serves as robust foundational support for further research on anomaly detection, trajectory prediction, and route planning. An anomalous ship is discerned through the manifestation of behavior patterns markedly deviating from conventional navigational practices, identified based on alterations in vessel position and movement characteristics. Davenport, 2008 [5], delineated

16 categories of abnormal ship behaviors, covering positional and kinematic irregularities, encompassing all general abnormal behaviors. In a recent study concentrating on the analysis of ship behavior, Dogancay et al., 2021 [6], implemented Davenport's classification methodology in their examination of ship behavior, including aspects such as deviations in speed and course, ingress into restricted zones, peculiar ship maneuvering, and the intentional or unintentional hiding of messages or sending of incorrect messages, etc. Mazzarella et al., 2014 [7], used machine learning techniques and AIS data for the identification of fishing zones. In recent years, scholarly investigations have prominently centered around the domains of information processing, feature extraction, and the practical utilization of acquired knowledge. Wei et al., 2020 [8], developed an AIS trajectory compression algorithm that takes into account ship behavior by integrating the Douglas–Peucker (DP) and sliding window algorithms. Their algorithm achieves the compression of AIS trajectories in accordance with the distinctive behavioral attributes of the ships under consideration. However, it is afflicted by certain limitations, namely, the absence of adaptive threshold determination and long runtime durations. Chen et al., 2020 [9], introduced a ship behavior classification algorithm based on convolutional neural networks (CNNs) and AIS data. This algorithm exhibits competence in effectively extracting intricate behavioral details but has limitations in parameter configuration and stringent quality requirements for sample data. Li et al., 2022 [10], introduced an innovative visual analysis approach that integrates multiple views to explore ship behavior patterns. This methodology incorporates the fast dynamic time-warping similarity measurement algorithm by Salvador et al., 2007 [11], and an ordering points-based density clustering algorithm as proposed by Lei et al., 2021 [12]. The method clusters ship trajectories to show the differences and similarities between ship traffic flows. Additionally, it integrates the Electronic Chart System (ECS) to visualize and replay ship trajectories, thereby facilitating the depiction of evolving ship density trends. Zhou et al., 2023 [13], conducted a comprehensive analysis of ship behavior within spatiotemporal contexts, aiming to automatically identify ship behaviors during encounters, obviating the reliance on distance or risk level assumptions.

Due to the real-time characteristics inherent in AIS data, their application in collision avoidance has become widespread. Ozoga et al., 2018 [14], Nguyen et al., 2018 [15], and Rong et al., 2022 [16], utilized AIS data to integrate the temporal parameters of the Time to Closest Point of Approach (TCPA) and the spatial aspects encapsulated by the Distance to Closest Point of Approach (DCPA) for the purpose of formulating collision risk indices. This approach enables the precise identification and analysis of vessel collision behaviors, and the determination of safe temporal intervals for vessel maneuvering, consequently mitigating collision risks in ship encounters. Rong et al., 2022 [15], have notably introduced an innovative methodology for the automated identification of ship behaviors under the collision avoidance process from vessel trajectories. These behaviors can be accurately discerned based on the trajectory data. In a related vein, Tritsarolis et al., 2022 [17], have devised a framework rooted in a multi-layer perceptron (MLP) model and AIS data to investigate the vessel collision risk assessment (VCRA) problem from the perspective of machine learning. In comparison to alternative methods, such as support vector machines (Gang et al., 2016) [18], adaptive fuzzy neural networks (Li et al., 2018) [19], and relevance vector machines (Park & Jeong, 2021) [20], their approach not only reduces processing time but also affords researchers the exploration of more intricate machine learning architectures, thereby yielding higher accuracy while sustaining framework responsiveness. Furthermore, Yu et al., 2023 [21], undertook an exhaustive review of scholarly publications spanning the past decade in three principal research domains: vessel collision risk assessment, the detection and prediction of vessel traffic hotspots, and collision-avoidance-based vessel path optimization. This comprehensive review not only serves to explicate the focus of research within the field but also illuminates its connections to interdisciplinary studies. Moreover, it aids in the identification of shortcomings and charts the course for future research endeavors. These findings are poised to offer invaluable insights to scholars and the shipping industry.

AIS data are categorized as spatiotemporal information, and this has garnered extensive attention in the field of ship trajectory clustering. Zhen et al., 2017 [22], Wang et al., 2021 [23], Zhao et al., 2019 [24], and Wang et al., 2023 [25], have adopted machine learning methodologies to propose novel techniques for quantifying spatiotemporal trajectory distances and assessing trajectory similarities. These methodologies incorporate the integration of dynamic time warping (DTW) and the Douglas–Peucker algorithm (DP), strategically employed to address issues associated with the direction of spatiotemporal trajectories and the elimination of superfluous data, thereby facilitating the efficient clustering of trajectories. In a congruent vein, Wang et al., 2023 [24], have integrated the DP algorithm, DTW, and spatial clustering based on hierarchical density to effectuate the clustering of ship trajectories while considering the behavioral disparities across various ship categories. The resultant clustered routes offer the capability to forecast the routes most likely to be traversed by a given vessel. Deep learning, involving the construction of a nonlinear network to approximate the desired function, negates the necessity for intricate mathematical models, thereby enabling the near-optimal approximation of functions and the facilitation of feature acquisition from data. Li et al., 2023 [26], have undertaken a comparative analysis of the latest ship trajectory prediction algorithms predicated on both machine learning and deep learning techniques. This analysis reveals the distinctive attributes characterizing various prediction strategies, affording invaluable insights to diverse stakeholders, and guiding their selection of the most appropriate methodologies as tailored solutions under specific contextual conditions. In a related study, Yu et al., 2022 [27], conducted a comprehensive examination of ship trajectories predicated on dynamic AIS data, encompassing geospatial parameters such as longitude, latitude, course over ground (COG), and speed over ground (SOG). Harnessing the advantages conferred by long short-term memory (LSTM), they proceeded to conduct predictive modeling of ship trajectories. The outcomes demonstrate the superior performance of the LSTM algorithm, both in an overarching context and with regard to detailed performance aspects.

In addition to their applications in collision risk assessment and the prediction of ship routes or trajectories, ship classification methods based on AIS data serve the purpose of identifying specific vessel types, thereby making valuable contributions to the realm of maritime navigation safety and regulations. One approach to feature extraction in ship classification involves directly extracting geometric characteristics of ship shapes and the kinematic of vessel behavior from AIS static and dynamic data, all without the need for conversion into graphical representations. These features are subsequently employed as the training data for ship classification models. Sánchez et al., 2020 [28], extracted ship trajectory features from AIS spatiotemporal data, including trajectory statistics such as ship speed, heading, and voyage distance. They applied support vector machines (SVM) and decision trees to delineate the categorization of sailboats into fishing vessels and non-fishing vessels. While the test results demonstrated the utility of the classification outcomes, the effectiveness of the feature extraction process remains an area warranting further refinement. In a related vein, Wang et al., 2021 [29], utilized the random forest methodology to discriminate among five distinct categories of vessels, including passenger ships, tugboats, oil tankers, fishing vessels, and cargo ships, yielding an accuracy rate of 86.14%. The outcomes underscored that certain vessel types, such as cargo ships and cruise liners, may exhibit resemblances in their static trajectories and vessel configurations. The mere extraction of static attributes may prove insufficient for the construction of a classification model with the capacity to effectively differentiate among these five vessel types. The combination of static data derived from AIS records with the dynamic behaviors of vessels stands as a pivotal step to enhance ship type classification performance. Yan et al., 2022 [30], harnessed the advantages associated with satellite-based AIS data, including broad geographic coverage, extended data acquisition intervals, and the representation of a diverse spectrum of vessel types. The researchers extracted both static and dynamic attributes pertaining to ship behavior, with dynamic behaviors including attributes such as ship positions, voyage distances, and vessel speeds, among others. Using a machine learning random forest algorithm and integrating these two distinct categories of features, a ship classification model was trained to categorize cargo ships, oil tankers, fishing vessels, passenger ships, and tugboats, achieving an impressive accuracy rate of 92.7%. The model test results demonstrated a significant improvement in accuracy through the integration of geometric and dynamic behavior features.

To demonstrate the application of risk assessment and ship behavior anomaly detection, we have launched a Special Issue that showcases six papers on this topic. A brief overview of all the contributions, emphasizing the main investigation topics and the outcomes of the analyses, follows below.

First, the research on abnormal ship behavior detection is based on maritime automatic identification system (AIS) data. AIS messages are broadcast to nearby vessels and contain information about the sending ship's identification, position, speed, and course. An AIS serves as a tool for collision avoidance and enhancing onboard situational awareness. Recently, there has been significant growth in the number and range of applications of AIS toward enhancing maritime traffic safety. Wolsing et al. highlighted the significance of AIS-based ship behavior anomaly detection. AIS can monitor almost any large ship globally and has the potential to greatly support ship traffic services and collision risk assessment. Ship behavior anomaly detection also assists in spotting potential risks and unusual maritime activities, such as illegal fishing or potential security threats. The authors review various methods and techniques recently developed used for anomaly detection in AIS data. This encompasses conventional statistics, machine learning methods, and deep learning models, among others. The paper examines the advantages and limitations of these methods by reviewing 44 research articles on AIS-based ship behavior anomaly detection. It identifies the tackled AIS anomaly types, assesses their potential use cases, and closely examines the landscape of recent AIS anomaly research as well as their limitations. The authors specifically address challenges in processing AIS data, like data quality, missing data, scalability issues, and how researchers can tackle these challenges. They also emphasize the crucial role of feature engineering in AIS data analysis, as selecting appropriate features can enhance the performance of anomaly detection algorithms. Lastly, the paper explores potential future directions in AIS anomaly detection research, encompassing real-time data integration, enhancing model interpretability, and resolving privacy concerns.

Regarding risk assessment, there are two papers on this topic. One of them focuses on ship grounding. Ship grounding accounts for approximately one third of commercial groundings in the global maritime industry. Grounding is an accident in which the ship's hull strikes the seabed resulting in hull damage, water ingress, and the potential pollution of the marine environment through fuel or cargo leakage. Galić et al. conducted a chronological examination of models used to estimate ship grounding frequency, encompassing both early methodologies and recent developments.

In essence, most research on grounding risk assessment builds upon Macduff and Fuji's original concepts. Mcduff's model provides grounding probability, while Fuji's model estimates the number of grounded ships. Ship grounding probability is typically calculated by multiplying geometric probability (the likelihood of a ship being a grounding candidate, i.e., sailing in a grounding-prone area) and causing probability (the likelihood of a ship failing to avoid grounding due to internal or external factors). Following the Macduff and Fuji models, Pedersen and Simonsen introduced their own grounding models. The Pedersen/Simonsen models offer a notable advantage by utilizing traffic distribution instead of traffic volume and density. To ensure accuracy, a comprehensive AIS traffic database is essential. Without complete ship distribution data for a specific area, the method tends to provide estimations rather than precise results. Recent scientific articles on grounding frequency models indicate a growing preference for simulation models like Bayesian networks. These models are gaining popularity due to their capacity to represent complex and uncertain relationships when modeling grounding probability. When data are insufficient for a given area, these models shine in their ability to blend existing data with expert knowledge, allowing for updates as more evidence becomes available, thus enhancing the model's practicality. Nevertheless, with increased model complexity comes a greater challenge in determining numerous probability parameters. Different approaches can be used to build models like statistical techniques, probabilistic models, machine learning, and more. Finally, the paper discusses the directions for future research. All these approaches aim to provide guidance for future research on the frequency of grounding. This research will contribute to the development of new models that will enhance safety at sea.

Another study in risk assessment examines the hazards linked to the unloading of oil tankers, which is a high-risk, labor-intensive activity. Minor operational mistakes can lead to severe incidents like fires and explosions. Given that over 70% of industrial accidents stem from human error, accident prevention is paramount. Given that human error is influenced by various performance shaping factors (PSFs), identifying critical PSFs is crucial for ensuring safe oil tanker unloading operations.

The objective of Zhang et al., 2022 [31], is straightforward: to mitigate human errors by investigating crucial performance-shaping factors during oil tanker unloading operations. This is of significant practical importance due to the high-risk nature of tanker offloading, necessitating a strong focus on safety and reliability. The study employs gray relational analysis (GRA) to handle incomplete data, defines "risk" as a rational basis for ranking PSFs, and utilizes hierarchical task analysis (HTA) to account for PSF variations across task stages. The proposed method underwent testing in a real-world case involving an oil tanker unloading at an offshore terminal, identifying key performance-shaping factors such as work environment, personnel training, communication processes, and equipment reliability. The results demonstrate the method's capability to pinpoint critical PSFs, offering recommendations for averting human errors and enhancing safety both on ships and at docks.

Lastly, there are three papers that focus on optimizing methods in maritime. One pertains to maritime search and rescue (SAR), which is crucial in emergencies stemming from maritime accidents with severe potential for casualties and property damage. Sun et al., 2022 [32] holds substantial practical value. It employs an enhanced particle swarm optimization approach to investigate the most effective resource allocation strategy for deploying limited SAR resources at navigation-constrained coastal islands. The paper transforms the SAR resource allocation challenge in coastal regions into a nonlinear optimization model. Using the enhanced particle swarm optimization (EPSO) model, incorporating parameter adjustments and novel heuristic strategies, the study explores optimal solutions for SAR resource allocation under varying ship and aircraft base station configurations. Experimental results demonstrate that the proposed EPSO model can efficiently allocate maritime rescue resources, offering extensive coverage with minimal time requirements. This method has the potential to enhance search and rescue mission effectiveness and positively impact the maritime rescue field. The research outcomes can guide maritime traffic regulatory authorities in making informed decisions regarding SAR base station construction.

The Container Ship Stowage Planning Problem (CSPP) is a complex logistical challenge aimed at optimizing transportation efficiency and cost reduction, significantly impacting shipping companies and ports. Typically, CSPP involves multi-objective optimization, considering conflicting goals such as maximizing profit, minimizing transportation time, and ensuring cargo safety. Wang et al. devised a multi-objective CSPP solution that enhances ship stability and reduces the number of shifts over the whole route while adhering to real-world constraints like ship structure and container yard layout. Ship stability is assessed using initial metacentric height (GM), heel, and trim. Meanwhile, it uses the total amount of relocation in the container terminal yard, the voluntary shift in the container ship's bay, and the necessary shift in the future unloading port to measure the number of shifts on the whole route. The proposed approach incorporates a modified version of the nondominated sorting genetic algorithm III (NSGA-III) with a local search component to tackle this problem. The algorithm yields a set of non-dominated solutions, offering flexibility for decision makers to choose the most practical implementation based on their expertise and preferences. Extensive experimentation with 48 examples confirmed the algorithm's effectiveness, particularly in solving multi-objective CSPP scenarios. Navigating ships in ice-covered waters is a complex task due to the increased risks involved, and planning routes requires balancing the trade-off between time or fuel expenditure and navigation risk. In a recent study conducted by Zvyagina et al., 2022 [33], they examined the process of identifying Pareto-optimal routes that minimize both risk and cost in ice-covered waters.

Routing ships in ice-covered waters poses a formidable challenge due to increased navigation risks and the need to balance time or fuel costs with safety concerns. Zvyagina et al., 2022 [33], investigated the characteristics of identifying Pareto-optimal routes considering both risk and cost in ice-covered waters. The paper introduces a multi-objective model for optimizing ship routes using ice charts and vessel specifications. Ship risk is linked to ice thickness and concentration values from ice charts in the navigation area. The model employs an extended wave algorithm to generate a set of potential paths, from which a Pareto-optimal solution can be selected based on objective functions such as route length, maximum ice thickness, and maximum ice concentration. The paper holds practical significance as it addresses the challenge of finding routes that strike a balance between risk and cost in ice-covered waters. It draws from various disciplines, including multi-objective optimization, ice intelligence, and route planning, offering the potential for safer and more cost-efficient navigation solutions in polar and ice-covered regions. The computational example in the paper focuses on the Gulf of Finland's ice chart, and the developed method can be readily applied to assist specific ships in independent ice navigation when a relevant ice chart is available.

Conflicts of Interest: The authors declare no conflict of interest.

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