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Editorial

Data/Knowledge-Driven Behaviour Analysis for Maritime Autonomous Surface Ships

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This Special Issue, "Data-/Knowledge-Driven Behavior Analysis of Maritime Autonomous Surface Ships", includes twelve contributions [1–12] published during 2021–2022. Maritime traffic data (e.g., radar data, AIS data, and CCTV data) provide designers, officers on watch, and traffic operators with extensive information about the states of ships at present and in history, representing a treasure trove for behavior analysis. Additionally, navigation rules and regulations (i.e., knowledge) offer valuable prior knowledge about ship manners at sea. Combining multisource heterogeneous big data and artificial intelligence techniques inspires innovative and important means for the development of MASS. Thus, this Special Issue aimed to collect studies that provide new views on data-/knowledge-driven analytical tools for maritime autonomous surface ships, including data-driven behavior modeling, knowledge-driven behavior modeling, multisource heterogeneous traffic data fusion, risk analysis and management of MASS, etc. A brief overview of all the contributions, emphasizing the main investigation topics and the outcomes of the analyses, follows below.

Data-driven behavior modelling methods are powerful tools that can be used to discover ship manners from large amounts of data. Guo et al. [5] developed a deep convolutional neural network (CNN) for ship trajectory classification. The improved QuickBundle clustering algorithm was used to preprocess the trajectory data, the trajectory data were further converted into image data, and then a deep CNN-based trajectory classification model was developed. Based on the proposed model, the manually annotated dataset was set as the input for model training. By comparison with the traditional connected neural network model and SVM model, the proposed method can effectively distinguish ship trajectories in different waterways. Xu et al. [9] developed a prediction model for ship traffic flow in wind farms area. Instead of using time series data, a spatiotemporal dependence feature matrix was developed to predict the ship traffic flow, and a Gated Recurrent Unit (GRU) of a Recurrent Neural Network (RNN) was used to identify multiple traffic flow sections from complex waters. By comparison with traditional methods using traffic data from wind farms in Yancheng City (China), e.g., the Autoregressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM), the proposed method, based on spatiotemporal dependence, performs better than the current traffic flow prediction methods.

Knowledge-driven methods offer tools that teach the machine to understand a ship's behaviors. Zhong et al. [12] proposed an ontological ship behavior model based on COLREGs, which is expected to automatically perform reasoning based on the knowledge derived from COLREGs. Knowledge graph techniques were employed. The ship behavior

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was viewed as the changes in temporal–spatial attributes of the ship, as described using the Resource Description Framework (RDF), function mapping, and set expression methods. Rule 9 (Narrow Channel Article) from COLREGs was inputted into the proposed method to demonstrate the feasibility of the proposed method. The results show its potential for the complete machine reasoning of ship behavior knowledge in the future. Song et al. [6] proposed a semantic model of ship behavior based on the ontology model, which aims to help the machine to understand ship behavior from ship trajectory data. Multi-scale features of ship behavior are observed, and the behaviors are divided into four sub-scales in cognitive space, namely, action, activity, process, and event. As demonstrated in case studies, some typical behaviors are deduced using a reasoner, such as Pellet, based on defined axioms and semantic web rule language (SWRL). The proposed model shows potential for smart maritime management.

Multisource heterogeneous traffic data fusion broadens the range of sources for the observation of ship behavior, and vision-based sensors have become an important means. Chen et al. [2] studied ship intention detection and prediction methods based on observed ship behaviors using radar, cameras, and Automatic Identification Systems and proposed a vision and Bayesian framework. Traditionally, radar and AIS data have been used for ship behavior analysis and intention detection, whereas it is still difficult to detect real-time ship intention due to low data frequency. Thus, the authors proposed the addition of a vision-based sensor for intention detection and prediction and argued that it could be used for real-time intention detection and prediction in intersection waters. Specifically, an algorithm based on the fusion of image sequences and radar information was proposed. The RANSAC method was used to fit radar and image detection information, and the YOLOv5 detector was used to track ship motions in the image sequence. Wu et al. [8] developed a multi-sensor hierarchical detection and tracking method for inland waterway ship chimneys which can be used to monitor the emission behavior of ships in inland waters. A convolutional neural network was developed to extract the ships from visible images. Then, the Ostu binarization algorithm and image morphology operation were employed to obtain the chimney target from the ship image, and an improved DeepSORT algorithm was developed for ship chimney tracking.

Safety is an important issue for the development of MASS and is also an ultimate goal of behavior analysis. Five contributions focused on the safety of MASS in the design phase and operation phase, and one contribution overviewed recent achievements regarding intelligent algorithms for MASS.

To investigate the safety of MASS in the design phase, Zhang et al. [10] proposed a hybrid causal logic method for the preliminary hazard analysis of maritime autonomous surface ships, which is expected to provide a reference for the MASS design and safety assessment process. Due to limited historical data, it is difficult to conduct comprehensive hazard analysis of MASS. To overcome this limitation, the authors developed a hybrid causal logic (HCL). Specifically, the event sequence diagram (ESD) was used for hazardous scenarios, the fault tree (FT) method was utilized to analyze mechanical events in ESD, the Bayesian Belief Network (BBN) was applied to analyze the human factors in MASS, and conventional ship operation data and MASS experiments data were used to determine the accident probability. As the authors demonstrated, the proposed method can be used to identify the key influential factors and accident-causing event chains for MASS in the case of autonomy level III.

To enhance the safety of MASS in the operation phase, Du et al. [3] developed the onboard available-maneuvering-margin (AMM)-based ship collision alert system (CAS) that supports the evasive behavior of ships. The AMM is an important factor for avoiding the types of collisions experienced by human navigators in ship real encounters, and it can reflect the risk perceived by the navigators. Thus, it can be used for ship collision alerts. Some typical encounter scenarios from historical AIS data were selected for the demonstration of the AMM-based CAS, and the results show that the proposed method can be used for two-ship and multi-ship encounters, providing timing alerts to autonomous systems or navigators onboard ships. Gu et al. [4] developed a motion-planning algorithm for unmanned surface vehicles that considers wind and currents and is based on regularization trajectory cells. A regularization trajectory cell library incorporating the influences of wind and current was developed, and the search cost was updated. Through simulation experiments, the authors showed that the proposed method can offer a trackable trajectory for a USV in some complex environments. Song [1] proposed a collision avoidance algorithm for USVs based on obstacle classification and fuzzy rules. Specifically, the time to the closest point of approach (TCPA) was used to determine the priorities of collision avoidance; the velocity obstacle algorithm was used to determine the safety avoidance strategy; fuzzy rules were designed to understand the multi-encounter scenario; and the particle swarm optimization (PSO) algorithm was introduced to identify the optimal solution. The simulation verified and validated the proposed method's effectiveness in complex scenarios. Zhang et al. [11] developed a novel decision support method for ship collision avoidance based on the deduction of the maneuvering process. A fuzzy-based collision risk indicator, modified velocity obstacle algorithm, and fuzzy adaptive PID method were proposed to determine the time required for collision avoidance, identify evasive decisions, execute the selected evasive decision, and resume sailing operations. The simulation results show that the proposed method can support ship collision avoidance in some complex encounter environments.

Tang et al. [7] analyzed and summarized the intelligent algorithms for MASS related to risk perception, decision making, and execution that have been published in the last five years. By reviewing the existing achievements, the authors concluded that the establishment of a risk perception system with digital and visual integration would improve the quality of risk identification. MASS strongly relies on intelligent algorithms to achieve both safe and efficient collision avoidance goals in a high-complexity manner, and the speed and accuracy of ship motion control still require improvement. Lastly, the authors also discussed the roles of humans and machines based on different autonomy levels.

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

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