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Editorial

Application of Artificial Intelligence in Maritime Transportation

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Maritime logistics and supply chain management have become more complicated due to economic globalization development. It is urgent to improve maritime transportation efficiency to enhance maritime logistics and supply chain management efficacy. Artificial intelligence (AI) technology has become more sophisticated via the support of varied real-world application scenarios, large-scale training samples, affordable, yet powerful, computational powers, etc. AI usage and its success in the maritime field has been significantly enhanced due to widely deployed sensors on ships, coastal buildings, etc. (i.e., the AI models can be trained with sufficient maritime data samples). In this way, the maritime and computer science communities have attempted to improve the maritime transportation efficiency by introducing varied cutting-edge AI techniques. The maritime transportation industry has anticipated more demanding AI methods for the purpose of maritime safety and environmental protection. In other words, the newly developed AI techniques can help avoid maritime traffic accidents and environ-mental pollution and improve the safety and greenness of navigation through the ship's autopilot, intelligent navigation, real-time monitoring, etc.

Artificial intelligence can perceive and predict maritime transportation situations by analyzing the ship's position, speed, and heading direction by integrating meteorology and sea current data [1,2]. These data can be used in ship automatic control and ship–port–vehicle cooperation-related activities. The ship automation control procedure can be used for autonomous driving, real-time navigation, automatic collision avoidance, automatous ship berthing, etc. Ships can be aware of potential traffic accidents with the help of computer vision and deep learning models, which can be further integrated to improve maritime traffic safety and efficiency [3]. Ship–shore–vehicle collaboration can achieve the efficient docking between ships and land vehicles using real-time data exchange and intelligent scheduling algorithms, which improves the cargo transportation efficiency and reduces congestion.

Ship trajectory optimization deserves the community's attentions by considering factors such as the ship's speed, fuel consumption, sailing time, etc. In this way, the crew can optimize their trajectory with less energy consumption, higher transportation efficiency, and on safer travelling routes [4]. The AI technique can be applied to maritime monitoring and management systems, which can realize the monitoring and early warning of maritime violations using varied maritime data sources (historical ship trajectory data, navigation data, and satellite imagery) [5]. Ship berthing and disembarking information, the port traffic condition, and the quay (yard) crane schedule can be further integrated to optimize the container terminal productivity. In this way, the cargo loading/unloading efficiency can be significantly improved, and the waiting time can be reduced as well [6]. AI techniques can also enable multi-ship collaboration to fulfill the task of cargo transportation via ship fleets. Based on the above-mentioned analysis, AI techniques can enhance the maritime transportation efficiency in a more intelligent, automatic, and environmentally friendly

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manner. The primary goal of the Special Issue is to explore typical AI applications and solutions in the maritime transportation field, which can be described in terms of the following aspects.

Ship trajectory planning and optimization using automatic identification system (AIS) data has attracted attention in the maritime field. Sedaghat et al. (Contribution 1) proposed a novel system to monitor maritime traffic, which can be further used to predict ship positions in a real-time manner. Zhao et al. (Contribution 2) proposed an encoder–decoder-based deep learning model to predict long-range ship trajectories. Lee et al. (Contribution 3) introduced a Dijkstra-based model to efficiently find the shortest ship travelling path using country-wide AIS data. Zheng et al. (Contribution 4) identified spoofing ship trajectories using large-scale AIS data with an isolation forest based framework. Zhen et al. (Contribution 5) analyzed the varied influence of environment factors on maritime traffic safety, which included the current, water depth, traffic volume, etc. A-star related conventional machine learning models were introduced to optimize ship trajectory planning and optimization tasks (Contributions 6 and 7). Li et al. (Contribution 8) tried to explore spatial–temporal relationships between ports via the help of a graph neural network. More specifically, the proposed framework employed a graph attention network to identify the traffic patterns, which aimed to determine the potential, yet intrinsic, relationship between two neighboring feature dimensions. Chen et al. (Contribution 9) explored the ship maneuvering performance in polar waters by considering both the static and kinematic ship information. Arbabkhah et al. (Contribution 10) employed a traditional XGBoost model to predict the time of arrival to enhance the port operation productivity.

Ship detection, tracking, and identification using maritime surveillance images has also become a hot topic in the community to fulfill ship visual navigation and intelligent navigation needs. Chen et al. (Contribution 11) employed a contextual encoder to enhance the maritime image restoration performance, and a weighted bidirectional feature pyramid network was further proposed to accurately detect ships in rain and fog-interference video clips. Zhou et al. (Contribution 12) developed a novel multiple feature fusion-guided deep learning model to enhance the resolutions of maritime images captured under adverse weather conditions. The maritime community attempts to obtain ship kinematic information (i.e., speed and distance) using varied visual sensory data sources. Zhao et al. (Contribution 13) proposed a novel you only look once (YOLO)-based ship speed extraction model under hazy weather situations. The framework employed a lightweight convolutional neural network to suppress the haze interference from maritime images, and the YOLO V5 model was introduced to detect ships in the haze-free image sequences. The ship speeds were further exploited by mapping ship imaging displacement in the real world. In addition, Zhao et al. (Contribution 14) proposed an improved U-Net pixel segmentation model to identify the shoreline in a pixel-wise manner. Ye et al. (Contribution 15) proposed an enhanced attention mechanism based a YOLO model to implement a ship detection task in real time.

Attention has also been given to ship fleet management optimization, ship–port cooperation, ship energy consumption reduction, autonomous port management, etc. Cheng et al. (Contribution 16) developed a novel cooperative unmanned surface vehicle (USV) unmanned autonomous vehicle system for the purpose of enhancing the USV perception capability in an underwater environment. Chen et al. (Contribution 17) proposed an ensemble farmwork to simulate ship autonomous berthing and controlling with a linear quadratic regulator and a covariance matrix adaptation evolution module. The study aimed to tackle ship autonomous berthing challenges, which involved with ship route planning, speed controlling, etc. Yan et al. (Contribution 18) developed a novel framework to analyze maritime traffic safety in wind farm water areas using a complex network theory. Li et al. (Contribution 19) proposed a magnetic focusing-related model to quantify the ship main engine crankshaft angle using inductive angular displacement sensory data. Bai et al. (Contribution 20) proposed a ship-controlling algorithm by integrating a composite sliding mode observer and a modified feed-forward phase-locked loop. Yang et al.

(Contribution 21) tried to optimize a double-cantilevered rail crane schedule in a U-shaped automated container terminal.

Maritime transportation will emit low levels of carbon in the future, and artificial intelligence techniques will play an increasingly important role in the smart maritime shipping era. The Special Issue aimed to enhance the maritime transportation efficiency via artificial intelligence techniques, while typical maritime traffic situations were exploited. Overall, the AIS data are commonly used for intelligent navigation, and must attention is paid to suppressing the AIS data outliers, optimizing the ship travelling trajectories, ship speed control, etc. In addition, intelligent maritime traffic situation awareness was also exploited via the support of maritime monitoring videos. Ships' trajectories and speeds were accurately estimated from the maritime videos via cutting-edge computer vision models. Moreover, maritime traffic efficiency and safety were further investigated via the help of varied maritime data sources and AI techniques.

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List of Contributions

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