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Editorial

Artificial Intelligence in Marine Science and Engineering

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1. Introduction

This Special Issue covers research in Artificial Intelligence in Marine Science and Engineering and shows how to apply it to many different professional areas, e.g., engineering, economics, and management. Each paper of this Special Issue is contributed by a different author from across the world and covers a different area of Artificial Intelligence applied to Marine Science. This Special Issue connects analytic principles with business practice and provides an interface between the main disciplines of engineering/technology and the organizational, administrative, economic, and planning abilities of management in Marine Science and Engineering. It also refers to other disciplines such as finance, marketing, behavioral economics, and risk analysis. This Special Issue is of particular interest to researchers, engineers, and economists who are developing new advances in analytics but also to practitioners working on this subject.

2. Artificial Intelligence in Marine Science and Engineering

In order to improve the horizontal transportation efficiency of the terminal Automated Guided Vehicles (AGVs), it is necessary to focus on coordinating the time and space synchronization operation of the loading and unloading of equipment, the transportation of equipment during the operation, and the reduction in the completion time of the task. Traditional scheduling methods limited dynamic response capabilities and were not suitable for handling dynamic terminal operating environments. Therefore, the paper [1] discusses how to use delivery task information and AGVs' spatiotemporal information to dynamically schedule AGVs, minimizes the delay time of tasks and AGVs travel time, and proposes a deep reinforcement learning algorithm framework. The framework combines the benefits of real-time response and flexibility of the Convolutional Neural Network (CNN) and the Deep Deterministic Policy Gradient (DDPG) algorithms and can dynamically adjust AGVs scheduling strategies according to the input spatiotemporal state information. In the framework, firstly, the AGVs scheduling process is defined as a Markov decision process, which analyzes the system's spatiotemporal state information in detail, introduces assignment heuristic rules, and rewards the reshaping mechanism in order to realize the decoupling of the model and the AGVs dynamic scheduling problem. Then, a multi-channel matrix is built to characterize space–time state information, the CNN is used to generalize and approximate the action value functions of different state information, and the DDPG algorithm is used to achieve the best AGV and container matching in the decision stage. The proposed model and algorithm frame are applied to experiments with different cases. The scheduling performance of the adaptive genetic algorithm and rolling horizon approach are compared. The results show that, compared with a single scheduling rule, the proposed algorithm improves the average performance of task completion time, task delay time, AGVs travel time and task delay rate by 15.63%, 56.16%, 16.36% and 30.22%,

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respectively; compared with AGA and RHPA, it reduces the tasks completion time by approximately 3.10% and 2.40%.

Tuna fish school detection provides information on the fishing decisions of purse seine fleets. In the manuscript [2], the authors present a recognition system that included fish shoal image acquisition, point extraction, point matching, and data storage. Points are a crucial characteristic for images of free-swimming tuna schools and point algorithm analysis and point matching were studied for their applications in fish shoal recognition. The feature points were obtained by using one of the best point algorithms (scale invariant feature transform, speeded up robust features, oriented fast and rotated brief). The k-nearest neighbors (KNN) algorithm uses 'feature similarity' to predict the values of new points, which means that new data points will be assigned a value based on how closely they match the points that exist in the database. Finally, the authors tested the model, and the experimental results showed that the proposed method can accurately and effectively recognize tuna free-swimming schools.

Unmanned Surface Vehicle (USV) has a broad application prospect and autonomous path planning as its crucial technology has developed into a hot research direction in the field of USV research [3,4]. Paper [5] proposes an Improved Dueling Deep Double-Q Network Based on Prioritized Experience Replay (IPD3QN) to address the slow and unstable convergence of traditional Deep Q Network (DQN) algorithms in the autonomous path planning of USV. Firstly, the authors used the deep double Q-Network to decouple the selection and calculation of the target Q value action to eliminate overestimation. The prioritized experience replay method was adopted to extract experience samples from the experience replay unit, increase the utilization rate of actual samples, and accelerate the training speed of the neural network. Then, the neural network was optimized by introducing a dueling network structure. Finally, the soft update method was used to improve the stability of the algorithm, and the dynamic ϵ—greedy method was used to find the optimal strategy. The experiments are first conducted in the Open AI Gym test platform to pre-validate the algorithm for two classical control problems: the Cart pole and Mountain Car problems. The impact of algorithm hyperparameters on the model performance was analyzed in detail. The algorithm was then validated in the Maze environment. The comparative analysis of simulation experiments showed that IPD3QN had a significant improvement in learning performance regarding convergence speed and convergence stability compared with DQN, D3QN, PD2QN, PDQN, PD3QN. Also, USV can plan the optimal path according to the actual navigation environment with the IPD3QN algorithm.

Nearshore wave forecasting is susceptible to changes in regional wind fields and environments. However, surface wind field changes are difficult to determine due to the lack of in situ observational data. Therefore, accurate wind and coastal wave forecasts during typhoon periods are necessary. The purpose of the paper [6] was to develop artificial intelligence (AI)-based techniques [7] for forecasting wind–wave processes near coastal areas during typhoons. The proposed integrated models employed combined a numerical weather prediction (NWP) model and AI techniques, namely numerical (NUM)-AI-based wind–wave prediction models. This hybrid model comprising VGGNNet and High-Resolution Network (HRNet) was integrated with recurrent-based gated recurrent unit (GRU). Termed mVHR_GRU, this model was constructed using a convolutional layer for extracting features from spatial images with high-to-low resolution and a recurrent GRU model for time series prediction. To investigate the potential of mVHR_GRU for wind–wave prediction, VGGNet, HRNet, and Two-Step Wind-Wave Prediction (TSWP) were selected as benchmark models. The coastal waters in northeast Taiwan were the study area. The length of the forecast horizon was from 1 to 6 h. The mVHR_GRU model outperformed the HR_GRU, VGGNet, and TSWP models according to the error indicators. The coefficient of mVHR_GRU efficiency improved by 13% to 18% and by 13% to 15% at the Longdong and Guishandao buoys, respectively. In addition, in a comparison of the NUM–AI-based model and a numerical model simulating waves nearshore (SWAN), the SWAN model generated greater errors than the NUM–AI-based model. The results of the NUM–AI-based wind–wave prediction model were in favorable accordance with the observed results, indicating the feasibility of the established model in processing spatial data.

Vessel recognition plays important role in ensuring navigation safety. However, existing methods are mainly based on a single sensor, such as automatic identification system (AIS), marine radar, closed-circuit television (CCTV), etc. [8]. To this end, paper [9] proposed a coarse-to-fine recognition method by fusing CCTV and marine radar, called multi-scale matching vessel recognition (MSM-VR). This method first proposes a novel calibration method that does not use any additional calibration target. The calibration is transformed to solve an N point registration model. Furthermore, marine radar image is used for coarse detection. A region of interest (ROI) area is computed for coarse detection results. Lastly, the authors designed a novel convolutional neural network (CNN) called VesNet and transformed the recognition into feature extraction. The VesNet was used to extract the vessel features. As a result, the MVM-VR method has been validated by using actual datasets collected along different waterways such as the Nanjing waterway and Wuhan waterway, China, covering different times and weather conditions. Experimental results show that the MSM-VR method can adapt to different times, different weather conditions, and different waterways with good detection stability. The recognition accuracy was no less than 96%. Compared to other methods, the proposed method has high accuracy and great robustness.

Aimed to improve the efficiency of port operations, Shanghai Zhenhua Heavy Industries Co., Ltd. (ZPMC) (Shanghai, China) proposed a new U-shape trafficked automated terminal in paper [10]. The new U-shape trafficked automated terminal brings a new hybrid scheduling problem. A hybrid scheduling model for yard crane (YC), AGV and ET in the U-shape trafficked automated terminal yard was established to solve the problem. The AGV and ET yard lanes were assumed to be one-way lane, taking the YC, AGV and ET scheduling results (the container transportation sequences) as variables and the minimization of the maximum completion time as the objective function. A scheduling model architecture with hierarchical abstraction of scheduling objects was proposed to refine the problem. The total completion time was solved based on a static and dynamic mixed scheduling strategy. A chaotic particle swarm optimization algorithm with speed control (CCPSO) was proposed, which include a chaotic particle strategy, a particle iterative speed control strategy, and a particle mapping space for hybrid scheduling. The presented model and algorithm were applied to experiments with different numbers of containers and AGVs. The parameters of simulation part refer to Qinzhou Port. The simulation results showed that CCPSO can obtain a near-optimal solution in a shorter time and find a better solution when the solution time is sufficient, comparing with the traditional particle swarm optimization algorithm, the adaptive particle swarm optimization algorithm, and the random position particle swarm optimization algorithm.

In order for the detection ability of floating small targets in sea clutter to be improved, on the basis of the complete ensemble empirical mode decomposition (CEEMD) algorithm, the high-frequency parts and low-frequency parts are determined by the energy proportion of the intrinsic mode function (IMF); the high-frequency part is denoised by wavelet packet transform (WPT), whereas the denoised high-frequency IMFs and low-frequency IMFs reconstruct the pure sea clutter signal together. According to the chaotic characteristics of sea clutter, authors in [11] proposed an adaptive training timesteps strategy. The training timesteps of network were determined by the width of embedded window, and the chaotic long short-term memory network detection was designed. The sea clutter signals after denoising were predicted by chaotic long short-term memory (LSTM) network, and small target signals were detected from the prediction errors. The experimental results showed that the CEEMD-WPT algorithm was consistent with the target distribution characteristics of sea clutter, and the denoising performance was improved by 33.6% on average. The proposed chaotic long- and short-term memory network, which determines the training step length according to the width of embedded window, is a new detection method that can accurately detect small targets submerged in the background of sea clutter.

In paper [12], authors proposed a novel deep generative inpainting network (GIN) trained under the framework of generative adversarial learning, which is optimized for the restoration of cloud-disturbed satellite sea surface temperature (SST) imagery. The proposed GIN architecture can achieve accurate and fast restoration results. The proposed GIN consists of rough and fine reconstruction stages to promote the details and textures of missing (clouded) regions in SST images. The authors also proposed a novel preprocessing strategy that replaces the land areas with the average value of daily oceanic surface temperatures for improving restoration accuracy. To learn the proposed GIN, the authors developed a novel approach that combines multiple loss functions well-suited for improving the restoration quality over missing SST information. The results showed that the difference in temperature between restored and actual satellite image data was no larger than 0.7 °C in monthly average values, which suggests excellent resilience against the missing sea surface temperature data. The proposed GIN has a faster restoration time and is feasible for real-time ocean-related applications. Furthermore, the computational cost of restoring SST images is much lower than the popular interpolation methods.

Submarine inspections and surveys require underwater vehicles to operate in deep waters efficiently, safely and reliably [13]. Autonomous Underwater Vehicles employing advanced navigation and control systems present several advantages [14]. Robust control algorithms and novel improvements in positioning and navigation are needed to optimize underwater operations [15]. Paper [13] proposed a new general formulation of this problem together with a basic approach for the management of deep underwater operations. This approach considers the field of view and the operational requirements as a fundamental input in the development of the trajectory in the autonomous guidance system. The constraints and involved variables are also defined, providing more accurate modelling compared with traditional formulations of the positioning system. Different case studies are presented based on commercial underwater cameras/sonars, analyzing the influence of the main variables in the measurement process to obtain optimal resolution results. The application of this approach in autonomous underwater operations ensures suitable data acquisition processes according to the payload installed onboard.

3. Future Works

Despite the closure of this Special Issue, a thorough investigation on the issues related to artificial intelligence in marine science and engineering is expected in the near future. Thereby, achievements relating to advances in artificial intelligence in marine science and engineering pose ongoing challenges to the research community.

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