STATE-OF-THE-ART ANALYSIS OF ARTIFICIAL INTELLIGENCE APPROACHES IN THE MARITIME INDUSTRY

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ABSTRACT

The beginning of 2020 finds Artificial Intelligence and Big Data in the forefront of digital transformation. The maritime industry is embracing them wholeheartedly due to their true potential to meet the ever-increasing and complex traffic and shipping demand for safety, performance, energy efficiency, automation, and environmental impact. The implementation of AI approaches in maritime stems from the need to effectively process and analyse the extremely large amounts of data that are being generated by maritime vessels. The key to addressing these challenges lies in research and innovation, especially in novel algorithms, tools, and platforms within the areas of AI and Big Data to unlock the new possibilities of a diverse range of current maritime applications. Under this context, the current publication aims at showcasing AI approaches and research initiatives in the maritime industry by performing an indicative landscape analysis of research publications in the aforementioned domains, between the period 2016-2022. The various AI initiatives uncovered from the research are grouped and presented in three representative categories to provide a clear picture of the research effort of integrating AI in maritime processes.

KEYWORDS

Artificial Intelligence, Landscape Analysis, Maritime Industry, Operation Monitoring, Fuel Consumption, Canal Passage

1. INTRODUCTION

The beginning of 2020 finds Artificial Intelligence and Big Data in the forefront of digital transformation. The maritime industry is embracing them wholeheartedly due to their true potential to meet the ever-increasing and complex traffic and shipping demand for safety, performance, energy efficiency, automation, and environmental impact. The implementation of AI approaches in maritime stems from the need to effectively process and analyse the extremely large amounts of data that are being generated by maritime vessels. The key to addressing these challenges lies in research and innovation, especially in novel algorithms, tools, and platforms within the areas of AI and Big Data to unlock the new possibilities of a diverse range of current maritime applications for vessel traffic monitoring and management, ship energy system design and operation, autonomous shipping, fleet intelligence and route optimisation, and so on. While digital transformation is progressing rapidly in all aspects of the society, it is now the right time to unlock the potential of extreme-scale data and advanced technologies to address the high computational, modelling and data processing demands required for accurate modelling, estimation and optimization of design and operation of ships and fleets under various dynamic conditions in a timely manner. Under this context, the current publication aims at showcasing AI approaches and research initiatives in the maritime industry by performing an indicative landscape analysis of research publications in the aforementioned domains, between the period of 2016-2022. This specific time period was chosen to assess the latest AI initiatives that are being developed in the maritime industry. All in all, 18 distinct AI initiatives were uncovered from the analysis, which were in turn grouped and presented in three representative categories to provide a clear picture of the research effort of integrating AI in maritime processes, while also identifying shortcomings, challenges, and future directions. This paper was written under the context of the EU funded project, VesselAI that aims to develop, validate and demonstrate a novel holistic framework based on a combination of the state-of-the-art HPC, Big Data and AI technologies, capable of performing extreme-scale and distributed analytics for fuelling the next generation digital twins in maritime applications and beyond, including vessel motion and behaviour modelling, analysis and prediction, ship energy system design and optimisation, unmanned vessels, route optimisation and fleet intelligence.

2. ANALYSIS OF ARTIFICIAL INTELLIGENCE APPROACHES IN THE MARITIME INDUSTRY

This section consists of the main body of research of this paper and breaks down the identified research papers in three main groups based on the area of implementation of the research approach: operations monitoring, fuel consumption and canal passage. While other papers were also found in categories such as crew management, maritime policy and quality management, the volume of papers was not enough to generate solid conclusions.

2.1 Operations Monitoring

Managing vessels and ensuring their smooth operation is a decisive factor for the successful transport of any cargo and thus for maximizing the profit of the ship-owner/company. Trajectory prediction is one of the kernel problems that must be addressed to realize proactive information service. Qi and Zheng (Qi and Zheng 2016) proposed an intelligent model to solve the issue of the trajectory prediction of vessels based on data mining and machine learning methods. The spatial clustering algorithm of data mining is used to cluster the historical trajectories of vessels, and the cluster results represent the distribution patterns of these historical trajectories. The support vector machine algorithm of machine learning is used to train the classifiers and the classifiers define the pattern of the new trajectory of the vessel, which must be predicted. De Arijit (De Arijit et al. 2017) presented a mixed integer non-linear programming model considering various scheduling and routing constraints, loading/unloading constraints and vessel capacity constraints. Several time window constraints are inculcated in the mathematical model to enhance the service level at each port. Owing to the inherent complexity of the aforementioned problem, an effective search heuristic named Particle Swarm Optimization for Composite Particle (PSO-CP) is employed. Another research paper (Fadilah et al. 2021), created a website-based management system by using the programming language PHP with MySQL database and CodeIgniter framework. The result of this research was that the Cilacap Nusantara Maritime Academy's administrative system can increase the efficiency of time for filing permits and writing letters. Furthermore, Chen et al. (Chen et al. 2022), tested synthetic data to classify boat activities into three categories: random walk, following and chasing, and the proposed AI-based system evaluated an efficient method of detecting boat activities and maritime threats. Hongchu Yu et al. (Yu et al. 2022), wrote a paper, in which they aimed to integrate ship movement behaviour, geographical features, and the International Regulations for Avoiding Collisions at Sea. The proposed methods sought to reduce the human error associated with maritime accidents. The proposed AI method was a path optimisation model which evaluated economic efficiency and safety-driven unmanned ship path planning that will promote the future growth of intelligent port development. Miguel A. Salido (Salido, Rodriguez-Mollins and Barber 2022), tested two AI based techniques; the first was a planning technique in order to solve the container tracking problem and the second was an optimised algorithm to solve the berth allocation problem. The result was that a terminal operator was conducted and could decide which algorithm was the most appropriate to solve both problems together. Giovanni Soldi (Soldi et al. 2021), reviewed space-based technologies for Maritime Surveillance. The used methodology was a combination of Bayesian and statistical fusion techniques with AIS data, and the results showed that to track multiple targets, heterogeneous space-based and terrestrial sensors had to be used. Rizk (Rizk, Khater and Abdelwahab, 2011) wrote a paper, in which he described the use of Neural Networks for object classification using collected RCS real data from radar system in order to classify vessels according to RCS signals that are important for many maritime applications. The study indicated that the NN based classification scheme provides excellent performance in targets classification, especially when 72 equally distributed RCS values from the whole RCS polar plot are used by model NN1 for classification. Masoud Abedi (Abedi and Pourkiani 2020), proposed an artificial intelligence-based task distribution algorithm (AITDA) which aimed to reduce the response time and the internet traffic by distribution of the tasks between fog and cloud services. The result of the AITDA algorithm shows that this method reduces the response time and internet traffic compared to the cloud-fog-based approaches. In another paper (Theodoropoulos et al. 2021), the examined methodology is based on 1 D Convolutional Neural Network (CNN) using time series data in order to harmonise data collected by sensors onboard, and to implement an artificial intelligent framework to recognise patterns that indicate early signs of defective behaviour in the operational state of the vessel. (Liu et al. 2021), proposed the development of a Convolutional Neural Network to improve ship detection under different weather conditions. The proposed methodology is capable to create CNN-based detection results, which are more reliable and robust under adverse weather conditions. This learning method shows superior performance in terms of accuracy and efficiency than the other methods (SSD, Faster R-CNN, YOLOv2 and YOLOv3).

2.2 Fuel Consumption

Fuel and energy in general make up the highest cost in every journey. As diesel prices continue to rise, plenty of research has been conducted to find a more efficient way to predict fuel consumption and asset health during sea voyages. Wenshuo Tang (Tang, Flynn and Valentin, 2016), explored the feasibility of data-driven methods to evaluate Remaining Useful Life (RUL) of the system assets to inform a preventative and cost-efficient management system. The paper's resulting model is based on a state-of-the-art machine learning technique, Relevance Vector Machine (RVM), which is a powerful tool for resolving uncertainty in large data sets, and more specifically in a public battery life cycle testing dataset, provided from NASA Ames Research Centre. Ugo Campora (Campora, Cravero and Zaccone 2018) described a simulation based monitoring and diagnostic method to overcome the lack of data. A MATLAB-SIMULINK® model of the frigate propulsion system was used to generate a database of different faulty conditions of the plant. A monitoring and diagnostic system, based on Mahalanobis distance and artificial neural networks have been developed. Experimental data measured during the sea trials have been used for model calibration and validation. Finally, Zhe Xiao (Xiao et al. 2020), proposed machine learning methods to improve the quality of data passed to emission models in order to be applied not only to improve emission consumption but also to other GPS and time-series problems. The results showed that the methodology can improve the default methods proposed to cover missing data. Also, the proposed methodology can boost the detection otherwise undetectable emissions.

2.3 Port Canal – Canal Passage

Movement in ports or canals can lead to great delays in a naval journey and thus increase the travel cost and lower efficiency. In this category, Enrico Alderini (Anderlini, Parker and Thomas 2019) used reinforcement learning strategies to control the docking of an AUV onto a fixed platform in a simulation environment. Two reinforcement learning schemes were investigated: one with continuous state and action spaces, deep deterministic policy gradient (DDPG), and one with continuous state but discrete action spaces, deep Q network (DQN). Adding to this, Shaoning Pang (Pang et al. 2016) proposed a cognitive background modelling method for land and water composition scenes (CBM-lw) to interpret the traffic of boats passing across boat ramps. An adaptive learning rate was computed to account for changes on land and water composition scenes, in which a geometrical model is integrated with pixel classification to determine the portion of water changes caused by tidal dynamics and other environmental influences. Experimental comparative tests and quantitative performance evaluations of real-world boat-flow monitoring traffic sequences demonstrated the benefits of the proposed algorithm. As Beatriz Molina Serrano mentions in (Serrano et al. 2017), Bayesian networks are a useful tool to make an efficient planning because they facilitate the knowledge of relationships between variables, even when there is a large number of them. Finally, Maria Inês Pereira (Pereira et al. 2021), proposed a lightweight volumetric Convolutional Neural Network (vCNN) which can recognise different docking-based structures using 3D data in real time. The used methodology demonstrated a 90% accuracy in the recognition of different docking structures using low resolution sensors. Results were obtained by using a real autonomous surface vehicle trained on vCNN, which showed that the synthetic-to-real domain adaptation approach was suitable for maritime mobile robots.

3. CONCLUSION

The scope of this publication was to perform a landscape analysis to assess the most popular categories of maritime processes, in which AI applications are being implemented according to the research bibliography. The analysis showed that in recent years, operations monitoring, fuel consumption and canal passage are three categories that gather the interest of the research community. Operations monitoring is an umbrella term that includes various maritime processes. Fuel consumption optimisation is a category of growing interest although there are challenges that are being reported and concern the willingness of maritime companies to share the data produced from naval journeys. Such data is integral for any AI model training and this challenge concerns the entirety of maritime research. Finally, canal passage is a very specific challenge for naval journeys that requires very specific solutions that consider the parameters of a given vessel, journey, body of water etc. Other categories that were uncovered include crew safety and management, maritime policy, and quality assurance but could not be reported in this paper due to space limitations. Future steps of the current research would focus in extending the results of the landscape analysis and identifying more categories of AI research in maritime.

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