On the Verification and Validation of AI Navigation Algorithms

Ivan Porres*, Sepinoud Azimi*, Sébastien Lafond*, Johan Liljus*, Johanna Salokannel† and Mirva Salokorpi†

*Faculty of Science and Engineering
Åbo Akademi University
Turku, Finland
name.surname@abo.fi
†Novia University of Applied Sciences
Turku, Finland
name.surname@novia.fi

Abstract—This paper explores the state of the art related to the methods to verify and validate navigation algorithms for autonomous surface ships. We perform a systematic mapping study to find research works published in the last 10 years proposing new algorithms for autonomous navigation and collision avoidance and we have extracted what verification and validation approaches have been applied on these algorithms. We observe that most research works use simulations to validate their algorithms. However, these simulations often involve just a few scenarios designed manually. This raises the question if the algorithms have been validated properly. To remedy this, we propose the use of a systematic scenario-based testing approach to validate navigation algorithms extensively.

I. INTRODUCTION

Maritime Autonomous Surface Ships (MASS) of the future will exhibit an increasing range of self-sufficiency. Autonomous capabilities include relieving the vessel operator from constant supervision by taking over certain responsibilities of the vessels using partial or complete remote operation of vessels, or partial or complete unsupervised navigation.

An important motivation for autonomous functions and increased intelligence in ships is to improve safety, efficiency of operations and decrease the environmental footprint. Despite the advances in technologies and constant striving towards improved safety, accidents still happen. In 2017 alone, 3301 accidents were reported by the European Maritime Safety Agency and over 53% of all reported accidents were collisions, contacts or grounding occurrences, all due to navigational error [1]. The development of autonomous navigational capabilities is seen as a possible solution to dramatically reduce the number of accidents due to navigational error.

The use of autonomous navigational functions in vessels raises however the question of what may happen if these autonomous functions have design defects. This question is addressed by Valdez et al. [2], who present a hazard analysis for the design phase of autonomous vessels. In this study, the authors identify AI software failure as a hazard that can lead to many of the identified accidents. Valdez proposes a number of safety controls to eliminate or reduce the likelihood that software hazard appears but this study does not address how to implement these safety controls. If we intend to use AI software components in navigation algorithms, we must ensure that they work as expected and we should be able to analyze and reveal whether these components may contain faults.

Traditionally, navigation algorithms have been based on path planning and optimization and have been designed manually. Programming is a notoriously complex task and developing defect-free programs require the application of correct by construction methods or an extensive verification and validation effort.

An alternative to path planning and optimization algorithms is the use of machine learning (ML), reinforcement learning (RL) and neural networks (NN). Machine learning has shown staggering success in autonomous cars. Machine learning is known to succeed and outperform traditional approaches specially in vaguely defined problem domains, where it is difficult, if not impossible, to create a full formal specification of the phenomenon under study. We consider this to be the case for COLREGs-based navigation and we conjecture that a ML-based navigation approach can outperform existing search-based and optimization algorithms. Still, modern AI software may also contain faults introduced during the learning process of a neural network. As an example, Katz [3] has analyzed the deep neural network implementation of the next-generation airborne collision avoidance system for unmanned aircraft (ACAS Xu) and found that several logical requirements did not hold for the system as well as some adversarial perturbations that could lead to erroneous collision avoidance actions.

This paper explores the state of the art related to the methods used to verify and validate surface ship navigation algorithms. For this, we have performed a systematic mapping study to find research works published in the last 10 years proposing new algorithms and we have extracted what verification and validation approaches have been applied on these algorithms. We have observed that most research works use simulations to validate their algorithms. However, these simulations involve just a few scenarios, often designed manually. Therefore, we propose the use of a systematic scenario-based testing approach to validate navigation algorithms thoroughly.

We proceed as follows. The design of the mapping studied is presented in Section 2, while its main results are presented in
Section 3 and 4. Finally, Section 5 describes the proposal for a method for validation of navigation algorithm using systematic scenario-based testing.

II. STUDY DESIGN

We have adapted and applied the systematic mapping approach described in to the autonomous maritime domain. In this study, we first defined the appropriate research questions, then conducted the search for the relevant papers. Consequently, we filtered the obtained papers based on our predefined inclusion and exclusion criteria. The result of our study, eventually, ended in producing a systematic mapping.

A. Research questions

The first step consists in defining the research question. In this study, we define three main research questions. In order to structure the answer to the main questions, we also defined a few sub-questions. Our research questions (RQs) are as follows.

RQ1 What approaches for navigation or traffic avoidance in autonomous ships have been presented in the research literature?
   (a) When and where have they been published?
   (b) What are the overall approaches?
   (c) Do they involve single ship or a swarm of ships?

RQ2 What are the requirements for these approaches as presented in the research literature?
   (a) How is the safety defined?
   (b) Are the requirements COLREGs compliant?

RQ3 How are these approaches verified and validated in the research literature?

B. Search Strategy

The primary search is done in the Web of Knowledge database, which includes the core Web of Science database as well as several regional databases. The core Web of Science database consists of: Science Citation Index Expanded (1945-present), Social Sciences Citation Index (1956-present), Arts & Humanities Citation Index (1975-present), Conference Proceedings Citation Index- Science (1990-present), Conference Proceedings Citation Index- Social Science & Humanities (1990-present), and Emerging Sources Citation Index (2015-present). We opted for the papers published between 2010 and 2020. We defined the following criteria for our primary search.

\[(\text{maritime} \lor \text{marine} \lor \text{ship} \lor \text{vessel}) \land (\text{autonomous navigation} \lor \text{autonomous traffic avoidance} \lor \text{collision avoidance}) \land (\text{algorithm} \lor \text{AI} \lor \text{artificial intelligence} \lor \text{machine learning} \lor \text{ML} \lor \text{optimization} \lor \text{optimisation}) \land (\text{validation} \lor \text{verification} \lor \text{testing} \lor \text{simulation} \lor \text{quality} \lor \text{safe} \lor \text{safety})\]

This primary search resulted in the collection of 427 papers.

C. Inclusion and Exclusion

At this step, we performed a screening process of the papers, considering only relevant papers based on our inclusion and exclusion criteria. The adopted inclusion criteria are: (1) Only peer-reviewed research papers published in a journal or a conference proceeding; (2) Only papers related to the theme of surface maritime vessel’s in their title or abstract or keywords; (3) Only papers that mentioned machine learning or optimization algorithm in their title or abstract or keywords.

The exclusion criteria were: (1) Papers mentioning “maritime vessel” in their abstract but that cannot be considered as describing research on autonomy; (2) Papers are duplicates (3) Papers containing keywords related to our study but discovered as false positives (e.g. review papers, studies on underwater vessels). The full list of papers was equally divided between the authors to apply the inclusion/exclusion criteria and filter the relevant papers. The final list of papers after applying the inclusion/exclusion criteria consisted of 132 papers.

The identified papers in the screening step were then randomly distributed among four authors for the full reading step. As such, each paper was processed by a second author, to avoid bias. The full list of proceed papers could be found in the Appendix.

III. DATA EXTRACTION AND CLASSIFICATION

For the data extraction we followed the template presented in Table I. We used the extracted data to answer our main research questions. Figure 1 RQ1(a), presents the distribution of the studies between year 2010-2020. As it can be seen from the graphs, the number of publications in the field experienced a dramatic boost in year 2017. The majority of the studies were published as a journal article, followed by conference papers and whole books, 87.5%, 9% and 3.5% respectively, see Figure 2. RQ1(a). This is to be expected as the interest in autonomous vehicles have been piqued over the past few years. As it could be observed from Figure 3 the majority of the papers opted for optimization as their overall approach, RQ1(b). This indicates that the use of AI is still at its infancy when it comes to autonomous navigation for maritime surface vessels. Based on the data analysis results, 82% of the studies involved only one single target ship, whereas the others, focus on a swarm of ships, RQ1(c).

| Data Item                        | Value                        | RQ |
|---------------------------------|------------------------------|----|
| General                         | Integer                      |    |
| Study ID                        |                              |    |
| Paper Title                     | Title of the Paper           |    |
| Authors’ Name                   | List of Authors              |    |
| Year of Publication             | Calendar Year                | RQ1|
| Venue                           | Publication Venue Name       | RQ1|
| Process                         |                              |    |
| Overall Approach                | Algorithmic Approach         | RQ1|
| Single or Swarm                 | Binary                       | RQ1|
| Safety                          | Safety Definition            | RQ2|
| (Non) compliance with Regulations| Binary                      | RQ2|
| Verification & Validation       | Verification V&V Approach    | RQ3|

TABLE I
DATA EXTRACTION FORM
The majority of the articles defined safety based on the values of either Time to Closest Point of Approach (TCPA) or Distance to Closest Point of Approach (DCPA), 82%, RQ2(a). Only 48% of the papers chose to comply with COLREGs in their study design, RQ2(b), see Figure 4.

The majority of the papers (86 out of 132) identified in this study used simulation approaches to validate their results with a small (ranging from 1 to 12) number of scenarios. Three studies used either a real boat or a model boat for the validation [25], [76], [107] and the rest did not use any verification and validation approach, RQ3. The distribution of validation methods is depicted in Figure 5.

IV. CURRENT PRACTICE ON THE VERIFICATION AND VALIDATION OF AI NAVIGATION ALGORITHMS

The verification and validation of navigation algorithms is an important issue since software failures has been identified as a hazard that can lead to many accidents in vessels with autonomous functions. To avoid such hazard, Perera proposes a 3-level approach to validate the behaviour of autonomous vessels, [8]. Level 1 in Perera’s classification requires the use of a software simulation for the motion of all vessels. A level 2 testing system would require that the own ship is a full scale or model vessel that navigates in restricted waters, while the other ships are simulated. In contrast, a level 3 system would require that all involved vessels navigate in open seas.

The mapping study show that most papers use software simulation to validate the proposed results. In these simulations, the simulation starts with a given scenario that describes the initial position and speeds for two or more vessels. The scenario is then animated in the physics-based simulator and the performance of the AI agents under test is evaluated. This corresponds to Level 1 validation in Perera’s classification. However, we have observed that most of these works simulate just some few scenarios and that these scenarios are designed...
manually, often to represent standard situations such as a take over or a crossing. Also, there is a considerable number of research articles that do not contain any verification or validation of their proposed results.

Existing work in the verification and validation in the automotive domain emphasizes the need to use a large number of specially designed scenarios in order to be able to find some faults in autonomous functions. We consider that the same criteria should apply to the maritime domain and that there is a need for domain-specific methods for the systematic verification and validation of autonomous functions in vessels. Therefore, we propose in the next section the use of a systematic scenario-based testing approach to validate navigation algorithms thoroughly.

V. A PROPOSAL FOR NAVIGATION ALGORITHM VALIDATION USING SYSTEMATIC SCENARIO-BASED TESTING

The goal of scenario-based testing is to evaluate a large set scenarios to find those where the AI agents do not perform as expected. In each scenario, the position and the velocity vector of each ship may vary, as well as their destination way-point. An example scenario with two vessels is depicted in Fig. 6.

![Fig. 6. A possible scenario](image)

Testing a single scenario for an autonomous vehicle is computationally expensive since it requires a physics-based simulation in addition to executing the autonomous functions. This includes updating the motion of all the vehicles involved in the scenario as well as simulating the environment sensed by the autonomous functions. Since there is a limited testing budget and we want to maximize the chances to find a defect, it is therefore desirable to select the scenarios that are considered more challenging for the autonomous function. [9]

Several authors have proposed methods to search for challenging scenarios efficiently. [10], [11]. Abdessalem, Nejati, Vuurand and Stifter have proposed a method that uses neural networks as a surrogate model for the scenario fitness functions and then genetic algorithms as a heuristic to search challenging scenarios, [12]. This is presented as a two phase process. First a set of simulations must be executed in order to create the surrogate models of the fitness functions. Once these models have been created, the scenario search is performed.

We have proposed a new approach for scenario-based testing that it is specific to maritime surface vehicles and that avoid the need of training surrogate models. Our approach, presented in [13], is based on the use of a neural network to discriminate and select scenarios that may be challenging for the autonomous system being tested. The selected scenarios are simulated and evaluated and their outcome is used to train the discriminating neural network. Compared to other works such as [12], we combine the training of the discriminator network and the scenario selection in one step, with the intention to reduce the number of necessary simulations. The simulations are evaluated by risk of collision and compliance to COLREGs.

To evaluate our approach, we have tested a collision avoidance algorithm based on a neural network trained using reinforcement learning. The evaluation task was to create 6000 simulation scenarios, each one depicting a different initial situation. Our experimental results show that the proposed testing method generates test suits composed mostly of challenging scenarios. This allows us to validate quickly if the navigation algorithm under test can operate safely while abiding the COLREGs.

VI. CONCLUSIONS

This paper explores the state of the art on the methods to verify and validate navigation algorithms for autonomous surface ships by carrying out a systematic mapping study. The mapping study reveals that most research works use simulations to validate their algorithms. Finally, we have proposed the use of a systematic scenario-based testing approach to validate navigation algorithms extensively.

REFERENCES

[1] EMSA, “Annual overview of marine casualties and incidents 2018.” European Maritime Safety Agency E.M.S. Agency, 2018.

[2] O. A. V. Banda, S. Kannos, F. Goerlandt, P. H. A. J. M. van Gelder, M. Bergström, and P. Kujala, “A systemic hazard analysis and management process for the concept design phase of an autonomous vessel,” Reliab. Eng. Syst. Saf., vol. 191, 2019.

[3] G. Katz, C. W. Barrett, D. L. Dill, K. Julian, and M. J. Kochenderfer, “Reluplex: An efficient SMT solver for verifying deep neural networks,” in Computer Aided Verification - 29th International Conference, CAV 2017, Heidelberg, Germany, July 24-28, 2017, Proceedings, Part I (R. Majumdar and V. Kuncak, eds.), vol. 10426 of Lecture Notes in Computer Science, pp. 97–117, Springer, 2017.

[4] K. Petersen, S. Vakkalanka, and L. Kuzniarz, “Guidelines for conducting systematic mapping studies in software engineering: An update,” Information and Software Technology, vol. 64, pp. 1–18, 2015.
[5] H. Shen, H. Hashimoto, A. Matsuda, Y. Taniguchi, D. Terada, and C. Guo, “Automatic collision avoidance of multiple ships based on deep q-learning,” Applied Ocean Research, vol. 86, pp. 268–288, 2019.

[6] J. Xin, S. Li, J. Sheng, Y. Zhang, and Y. Cui, “Application of improved particle swarm optimization for navigation of unmanned surface vehicles,” Sensors, vol. 19, no. 14, p. 3096, 2019.

[7] J. Han, Y. Cho, J. Kim, N.-s. Son, and S. Y. Kim, “Autonomous collision detection and avoidance for aragon usv: Development and field tests,” Journal of Field Robotics, 2020.

[8] L. P. Perera, “Deep Learning Toward Autonomous Ship Navigation and Possible COLREGs Failures,” Journal of Offshore Mechanics and Arctic Engineering, vol. 142, 12 2019. 031102.

[9] D. Gagliardi, P. Tkachenko, and L. del Re, “Outcome oriented evaluation of autonomous driving functions,” in 57th IEEE Conference on Decision and Control, CDC 2018, Miami, FL, USA, December 17-19, 2018, pp. 6970–6975, IEEE, 2018.

[10] R. B. Abdessalem, S. Nejati, L. C. Briand, and T. Stifter, “Testing vision-based control systems using learnable evolutionary algorithms,” in Proceedings of the 40th International Conference on Software Engineering, ICSE 2018, Gothenburg, Sweden, May 27 - June 03, 2018 (M. Chaudron, I. Crnkovic, M. Chechik, and M. Harman, eds.), pp. 1016–1026, ACM, 2018.

[11] G. E. Mullins, P. G. Stankiewicz, and S. K. Gupta, “Automated generation of diverse and challenging scenarios for test and evaluation of autonomous vehicles,” in 2017 IEEE International Conference on Robotics and Automation, ICRA 2017, Singapore, May 29 - June 3, 2017, pp. 1443-1450, IEEE, 2017.

[12] R. B. Abdessalem, S. Nejati, L. C. Briand, and T. Stifter, “Testing advanced driver assistance systems using multi-objective search and neural networks,” in Proceedings of the 31st IEEE/ACM International Conference on Automated Software Engineering, ASE 2016, Singapore, September 5-7, 2016 (D. Lo, S. Apel, and S. Khursid, eds.), pp. 63–74, ACM, 2016.

[13] I. Forres, S. Azimi, and J. Lilius, “Scenario-based testing of a ship collision avoidance system,” in 46th Euromicro Conference on Software Engineering and Advanced Applications (SEAA), IEEE, 2020.

APPENDIX

ARTICLES INCLUDED IN THE MAPPING STUDY

REFERENCES

[1] Karl Gunnar Aarsæther and Torgeir Moan. Adding the human element to ship manoeuvring simulations. The Journal of Navigation, 63(4):695, 2010.

[2] Mohamed Abdelaal and Axel Hahn. Snmpc-based trajectory tracking and collision avoidance of unmanned surface vessels with rule-based colregs confinement. In 2016 IEEE Conference on Systems, Process and Control (ICSPC), pages 23–28. IEEE, 2016.

[3] Jin-Hyeong Ahn, Key-Pyo Rhee, and Young-Jun You. A study on the collision avoidance of a ship using neural networks and fuzzy logic. Applied Ocean Research, 37:162–173, 2012.

[4] Azeddine Bakdi, Ingrid Kristine Glad, Erik Vanem, and Øystein Engellhardtshin. Ais-based multiple vessel collision and grounding risk identification based on adaptive safety domain. Journal of Marine Science and Engineering, 8(1):5, 2020.

[5] Marco Bibuli, Yogang Singh, Sanjay Sharma, Robert Sutton, Daniel Hatton, and Asiya Khan. A two layered optimal approach towards cooperative motion planning of unmanned surface vehicles in a constrained maritime environment. IFAC-PapersOnLine, 51(29):378–383, 2018.

[6] Morten Breivik et al. Mpc-based mid-level collision avoidance for avs using nonlinear programming. In 2017 IEEE Conference on Control Technology and Applications (CCTA), pages 766–772. IEEE, 2017.

[7] Mauro Candeloro, Anastasios M Lekkas, and Asgeir J Sørensen. A voronoi-diagram-based dynamic path-planning system for underactuated marine vessels. Control Engineering Practice, 61:41–54, 2017.

[8] Wu Chao, Ma Feng, Wu Qing, and Wang Shuwu. A situation awareness approach for usv based on artificial potential fields. In 2017 4th International Conference on Transportation Information and Safety (ICTIS), pages 232–235. IEEE, 2017.

[9] Chen Chen, Xian-Qiao Chen, Feng Ma, Xiao-Jun Zeng, and Jin Wang. A knowledge-free path planning approach for smart ships based on reinforcement learning. Ocean Engineering, 189:106299, 2019.

[10] Siyu Guo, Xiuguo Zhang, Yisong Zheng, and Yiquan Du. An Autonomous Path Planning Model for Unmanned Ships Based on Deep Reinforcement Learning. IEEE Access, 8:2022–2028, JAN 2020.

[11] Lining Chen, Hans Hopman, and Rudy R Negenborn. Distributed model predictive control for vessel train formations of cooperative multi-vessel systems. Transportation Research Part C: Emerging Technologies, 92:101–118, 2018.

[12] PF Chen, PHAqMJ van Gelder, and JM Mou. Integration of elliptical ship domains and velocity obstacles for ship collision candidate detection. TransNav, International Journal on Marine Navigation and Safety of Sea Transportation, 13(4), 2019.

[13] Jinwoo Choi, Jeonghong Park, Jongsaeung Jung, Youngeo Lee, and Hyun-Taek Choi. Development of an autonomous surface vehicle and performance evaluation of autonomous navigation technologies. International Journal of Control, Automation and Systems, 18(3):555–545, 2020.

[14] Shupin Deng, Youyi Zhong, Zhiqin Wu, Min Wang, Lvkai Zhu, and Hongyu Gu. Research on waterborne collision avoidance and early warning algorithm based on location data. Advances in Mechanical Engineering, 12(2):1687814020906079, 2020.

[15] Zaopeng Dong, Tao Bao, Mao Zheng, Xin Yang, Lifei Song, and Yunsheung Mao. Heading control of unmanned marine vehicles based on an improved robust adaptive fuzzy neural network control algorithm. IEEE Access, 7:9704–9713, 2019.

[16] Lei Du, Floris Goerlandt, Osiris A Valdez Banda, Yamin Huang, Yuanqiao Wen, and Pentti Kujala. Improving stand-on ship’s situational awareness by estimating the intention of the give-way ship. Ocean Engineering, 201(107110), 2020.

[17] Armagan Elbolb, Nuno Gracias, and Rafael Garcia. Augmented state–extended kalman filter combined framework for topology estimation in large-area underwater mapping. Journal of Field Robotics, 27(5):656–674, 2010.

[18] Bjørn-Olav H Eriksen, Glenn Bitar, Morten Breivik, and Anastasios M Lekkas. Hybrid collision avoidance for avs compliant with colregs rules 8 and 13–17. Frontiers in Robotics and AI, 7:11, 2020.

[19] Bjørn-Olav H Eriksen, Morten Breivik, Erik F Willth, Andreas L Flaten, and Edmund F Brekke. The branching-course model predictive control algorithm for maritime collision avoidance. Journal of Field Robotics, 36(7):1222–1249, 2019.

[20] R Fiskin, K Kiigi, and E Nasibov. A research on techniques, models and methods proposed for ship collision avoidance path planning problem. International Journal of Maritime Engineering, 160(A2):187–206, 2018.

[21] R Fiskin, E Nasibov, and MO Yardimci. Deterministic-based ship anti-collision route optimization with web-based application. International Journal of Maritime Engineering, 161:A345–A356, 2019.

[22] Ming-yu Fu, Sha-sha Wang, and Yuan-hui Wang. Multi-behavior fusion based potential field method for path planning of unmanned surface vessel. China Ocean Engineering, 33(5):583–592, 2019.

[23] Xiongfei Geng, Yongcai Wang, Ping Wang, and Baochen Zhang. Motion plan of maritime autonomous surface ships by dynamic programming for collision avoidance and speed optimization. Sensors, 19(2):434, 2019.

[24] Siyu Guo, Xiuguo Zhang, Yisong Zheng, and Yiquan Du. An autonomous path planning model for unmanned ships based on deep reinforcement learning. Sensors, 20(2):426, 2020.

[25] Jungwook Han, Yonghoon Cho, Jonghwi Kim, Jinwhan Kim, Namson Sun, and Sun Young Kim. Autonomous collision detection and avoidance for aragon usv: Development and field tests. Journal of Field Robotics, 2020.

[26] Qilong Han, Xiao Yang, Hongtao Song, Shanshan Sui, Hui Zhang, and Zaiqiang Yang. Whale optimization algorithm for ship path optimization in large-scale complex marine environment. IEEE Access, 8:57168–57179, 2020.

[27] Wei He, Shuo Xie, Xinglong Liu, Tao Lu, Tianjiao Luo, Miguel Angel Sotelo, and ZhiXiong Li. A novel image recognition algorithm of target identification for unmanned surface vehicles based on deep learning. Journal of Intelligent & Fuzzy Systems, 37(4):4437–4447, 2019.

[28] Ramdane Hedjar and Messaoud Boukhel. An automatic collision avoidance algorithm for multiple marine surface vehicles. International Journal of Applied Mathematics and Computer Science, 29(4):759–768, 2019.

[29] MA Hinostroza and C Gueudes Soares. Collision avoidance, guidance and control system for autonomous surface vehicles in complex navi
Man-Chun Lee, Chung-Yuan Nieh, Hsin-Chuan Kuo, and Juan-Chen Agnieszka Lazarowska. Research on algorithms for autonomous A Lazarowska. An efficient graph theory-based algorithm for ship collision avoidance. *Ocean Engineering*, 181:212–226, 2019.

Shi-Jie Li, Jialun Liu, and Rudy R Negenborn. Distributed coordination for collision avoidance of multiple ships considering ship maneuverability. *Ocean Engineering*, 191:106511, 2019.

Shi-Jie Li, Jialun Liu, Rudy R Negenborn, and Feng Ma. Optimizing the joint collision avoidance operations of multiple ships from an overall perspective. *Ocean Engineering*, 191:106511, 2019.

Wei-Feng Li and Wenya Ma. Simulation on vessel intelligent collision avoidance based on artificial fish swarm algorithm. *Polish Maritime Research*, 23(1):138–145, 2016.

J. Lisowski. Multi-criteria optimization of multi-step matrix game in collision avoidance of ships. *TransNav: International Journal on Marine Navigation and Safety of Sea Transportation*, 13, 2019.

Józef Lisowski. Computational intelligence methods of a safe ship control. *Procedia computer science*, 35:634–643, 2014.

Deli Liu, Dong Xu, Nan Wang, Ziyeng Zhang, and Pingpeng Tang. Dynamic replanning algorithm of local trajectory for unmanned surface vehicle. In *2016 5th Chinese Control Conference (CCC)*, pages 7120–7125. IEEE, 2016.

Hongdan Liu, Sheng Liu, and Lanyong Zhang. Ship collision avoidance path planning strategy based on quantum bacterial foraging algorithm. In *2015 2nd International Conference on Electrical, Computer Engineering and Electronics*. Atlantis Press, 2015.

Hongdan Liu, Rong Sun, and Qi Liu. The tactics of ship collision avoidance based on quantum-behaved wolf pack algorithm. *Concurrency and Computation: Practice and Experience*, 32(6):e1596, 2020.

Shuchen Liu, Sylvain Roy, Eloy Pairet-Garcia, Jan-Joran Gehrt, Friederike Siemer, Christof Büsskens, Dirk Abel, and René Zweigel. Case study: Networked control for optimal maneuvering of autonomous vessels. *IFAC-PapersOnLine*, 52(8):440–445, 2019.

Xinyu Liu, Yun Li, Jing Zhang, Jian Zheng, and Chunxi Yang. Self-adaptive dynamic obstacle avoidance and path planning for usv under complex maritime environment. *IEEE Access*, 7:114945–114954, 2019.

Yuanchang Liu and Richard Bucknall. Efficient multi-task allocation and path planning for unmanned surface vehicle in support of ocean operations. *Neurocomputing*, 275:1550–1566, 2018.

Yuanchang Liu, Richard Bucknall, and Xinyu Zhang. The fast marching method based intelligent navigation of an unmanned surface vehicle. *Ocean Engineering*, 142:363–376, 2017.

Yuanchang Liu, Rui Song, Richard Bucknall, and Xinyu Zhang. Intelligent multi-task allocation and planning for multiple unmanned surface vehicles (usvs) using self-organising maps and fast marching method. *Information Sciences*, 496:180–197, 2019.

Hongguang Lyu and Yong Yin. Fast path planning for autonomous ships in restricted waters. *Applied Sciences*, 8(12):2592, 2018.

Hongguang Lyu and Yong Yin. Colregs-constrained real-time path planning for autonomous ships using modified artificial potential fields. *The Journal of Navigation*, 72(3):598–608, 2019.

LY MA, Wei Xie, and HB Huang. Convolutional neural network based obstacle detection for unmanned surface vehicle. *Mathematical biosciences and engineering: MBE*, 17(1):845–861, 2019.

Yong Ma, Mengqi Hu, and Xinping Yan. Multi-objective path planning for unmanned surface vehicle with current effects. *ISA transactions*, 85:137–156, 2018.

Mostefa Mohamed-Seghir. Methods based on fuzzy sets to solve problems of safe ship control. In *Novel Algorithms and Techniques in Telecommunications and Networking*, pages 373–377. Springer, 2010.

Wasif Naem, Sable C Henrique, and Liang Hu. A reactive colregs-compliant navigation strategy for autonomous maritime navigation. *IFAC-PapersOnLine*, 49(23):207–213, 2016.

Wasif Naem, George WIrwin, and Aolei Yang. Colregs-based collision avoidance strategies for unmanned surface vehicles. *Mechatronica*, 22(6):669–678, 2012.

Hanlin Niu, Al Savvaris, and Antonios Tsourdos. Usv geometric collision avoidance algorithm for multiple marine vehicles. In *OCEANS 2017-Anchorage*, pages 1–10. IEEE, 2017.

Bartosz O˙zoga and Jakub Montewka. Towards a decision support system for maritime navigation on heavily trafficked basins. *Ocean Engineering*, 159:88–97, 2018.

Madhusmita Panda, Bikramaditya Das, Bidyadhar Subudhi, and Bibhuti Bhusun Pati. A comprehensive review of path planning algorithms for autonomous underwater vehicles. *International Journal of Automation and Computing*, pages 1–32, 2020.

Giulia Pedrelli, Yifan Xing, Jia Hao Peh, Kim Wee Koh, and Szu Hui Ng. A real time simulation optimization framework for vessel collision avoidance conditions. *Progress in Marine Technology and Engineering, pp. Taylor & Francis Group, London, UK*, pages 121–132, 2018.

Liang Hu, Wasif Naem, Eshan Rajabally, Graham Watson, Terry Mills, Zakirul Bhuiyan, Craig Raeburn, Ivor Salter, and Claire Pekean. A multiobjective optimization approach for colregs-compliant path planning of autonomous surface vehicles verified on networked bridge simulators. *IEEE Transactions on Intelligent Transportation Systems*, 21(3):1167–1179, 2019.

Liang Hu, Wasif Naem, Eshan Rajabally, Graham Watson, Terry Mills, Zakirul Bhuiyan, Craig Raeburn, Ivor Salter, and Claire Pekean. A multiobjective optimization approach for autonomous surface vehicles: A multiobjective optimization approach. *IFAC-PapersOnLine*, 50(1):13662–13667, 2017.

Qing Hu, Yi Jiang, Jingbo Zhang, Xiaowen Sun, and Shufang Zhang. Development of an automatic identification system autonomous positioning system. *Sensors*, 15(11):28574–28591, 2015.

Yumin Huang, Lining Chen, Pengfei Chen, Rudy R Negenborn, and PHAJM van Gelder. Ship collision avoidance methods: State-of-the-art. *Safety science*, 121:451–473, 2020.

Yumin Huang, Lining Chen, and PHAJM van Gelder. Generalized velocity obstacle algorithm for preventing ship collisions at sea. *Ocean Engineering*, 173:142–156, 2019.

Yumin Huang, PHAJM van Gelder, and Yuanqiao Wen. Velocity obstacle algorithms for collision prevention at sea. *Ocean Engineering*, 151:308–321, 2018.

Timur Inan and Ahmet Fevzi Baba. Particle swarm optimization-based collision avoidance. *Turkish Journal of Electrical Engineering and Computer Science*, 27(3):2137–2155, 2019.

Min-Gi Jeong, Eun-Bang Lee, and Moonjin Lee. An adaptive route plan technique with risk contour for autonomous navigation of surface vehicles. In *OCEANS 2018 MTS/IEEE Charleston*, pages 1–4. IEEE, 2018.

Min-Gi Jeong, Eun-Bang Lee, Moonjin Lee, and Jung-Yeul Jung. Multi-criteria route planning with risk contour map for smart navigation. *Ocean Engineering*, 172:72–85, 2019.

Yu-Tao Kang, Wei-Jiong Chen, Da-Qi Zhu, Jin-Hui Wang, and Q-Miao Xie. Collision avoidance path planning for ships by particle swarm optimization. *Journal of Marine Science and Technology*, 26(6):777–786, 2019.

Joanna Karbowska-Chilinska, Jolanta Koszelew, Krzysztof Ostrowski, Piotr Kuczyński, Eric Kulbiej, and Piotr Woólezja. Beam search algorithm for ship anti-collision trajectory planning. *Sensors*, 19(24):5338, 2019.

Heesu Kim, Sang-Hyun Kim, Maro Jeon, Jaehak Kim, Sooenseok Song, and Kwang-Jun Paik. A study on path optimization method of an unmanned surface vehicle under environmental loads using genetic algorithm. *Ocean Engineering*, 142:616–624, 2017.

Łukasz Kuczkowski and Roman Śmierszchal. Comparison of single and multi-population evolutionary algorithm for path planning in navigation situation. In *Solid State Phenomena*, volume 210, pages 166–177. Trans Tech Publ, 2014.

Łukasz Kuczkowski and Roman Śmierszchal. Termination functions for evolutionary path planning algorithm. In *2014 19th International Conference on Methods and Models in Automation and Robotics (MMAR)*, pages 636–640. IEEE, 2014.

Yoshiaki Kuwata, Michael T Wolf, Dimitri Zarzhitsky, and Terrance L Huntsberger. Safe maritime navigation with colregs using velocity obstacles. In *2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 4728–4734. IEEE, 2011.

A Lazarowska. An efficient graph theory-based algorithm for ship trajectory planning. *INTERNATIONAL JOURNAL OF MARITIME ENGINEERING*, 161:155–161, 2019.

Agnieszka Lazarowska. Swarm intelligence approach to safe ship control. *Polish Maritime Research*, 22(4):34–40, 2015.

Agnieszka Lazarowska. Research on algorithms for autonomous navigation of ships. *WMU Journal of Maritime Affairs*, 18(2):341–358, 2019.

Man-Chun Lee, Chung-Yuan Nieh, Hsin-Chuan Kuo, and Juan-Chen Huang. An automatic collision avoidance and route generating algorithm for ships based on field model. *Journal of Marine Science and Technology*, 27(2):101–113, 2019.

Jinxin Li, Hongbo Wang, Wei Zhao, and Yuanyuan Xue. Ship’s trajectory planning based on improved multiobjective algorithm for collision avoidance. *Journal of Advanced Transportation*, 2019, 2019.

Shi-Jie Li, Jialun Liu, and Rudy R Negenborn. Distributed coordination for collision avoidance of multiple ships considering ship maneuverability. *Ocean Engineering*, 181:212–226, 2019.
avoidance and the case of singapore strait. *IEEE Transactions on Intelligent Transportation Systems*, 21(3):1204–1215, 2019.

[74] Zihe Qin, Zhuang Lin, Dongmei Yang, and Ping Li. A task-based hierarchical control strategy for autonomous motion of an unmanned surface vehicle swarm. *Applied Ocean Research*, 65:251–261, 2017.

[75] Andrzey Rak and Witold Gierusz. Reinforcement learning in discrete and continuous domains applied to ship trajectory generation. *Polish Maritime Research*, 19(Special):31–36, 2012.

[76] Haqing Shen, Hirota Hashimoto, Akiko Matsuda, Yuuki Taniguchi, Daisuke Terada, and Chen Guo. Automatic collision avoidance of multiple ships based on deep q-learning. *Applied Ocean Research*, 86:268–288, 2019.

[77] Yogang Singh, Sanjay Sharma, Robert Sutton, Daniel Hatton, and Asiya Khan. A constrained a* approach towards optimal path planning for an unmanned surface vehicle in a maritime environment containing dynamic obstacles and ocean currents. *Ocean Engineering*, 169:187–201, 2018.

[78] Yogang Singh, Sanjay Sharma, Robert Sutton, Daniel Hatton, and Asiya Khan. Feasibility study of a constrained dijkstra approach for optimal path planning of an unmanned surface vehicle in a dynamic maritime environment. In 2018 *IEEE International Conference on Autonomous Robots Systems and Competitions (ICARSC)*, pages 117–122. IEEE, 2018.

[79] A Lifei Song, B Yiran Su, C Zaoqeng Dong, D Wei Shen, E Zuquan Xiang, and F Fuxiu Mao. A two-level dynamic obstacle avoidance algorithm for unmanned surface vehicles. *Ocean Engineering*, 170:351–360, 2018.

[80] Lifei Song, Yiran Su, and Richard Bucknall. A multi-layered fast marching method for unmanned surface vehicle path planning in a time-variant maritime environment. *Ocean Engineering*, 129:301–317, 2017.

[81] Xiaojie Sun, Guofeng Wang, Yunsheng Fan, Dongdong Mu, and Bingbing Qiu. An automatic navigation system for unmanned surface vehicles in realistic sea environments. *Applied Sciences*, 8(2):193, 2018.

[82] Xiaojie Sun, Guofeng Wang, Yunsheng Fan, Dongdong Mu, and Bingbing Qiu. Collision avoidance of powered propulsion unmanned surface vehicle with collision compliance and its modeling and identification. *IEEE Access*, 6:55473–55491, 2018.

[83] Rafal Szlapczynski. Evolutionary sets of safe ship trajectories within traffic separation schemes. The *Journal of Navigation*, 66(1):65–81, 2013.

[84] Rafal Szlapczynski. Evolutionary planning of safe ship tracks in restricted visibility. *The Journal of Navigation*, 68(1):39–51, 2015.

[85] Rafal Szlapczynski and Hossein Ghaemi. Framework of an evolutionary multi-objective optimisation method for planning a safe trajectory for a marine autonomous surface ship. *Polish Maritime Research*, 26(4):69–79, 2019.

[86] Rafal Szlapczynski and Joanna Szlapczynska. Evolutionary sets of safe ship trajectories: Problem dedicated operators. In *International Conference on Computational Collective Intelligence*, pages 221–230. Springer, 2011.

[87] CheeKuang Tam and Richard Bucknall. Path-planning algorithm for ships in close-range encounters. *Journal of marine science and technology*, 15(4):395–407, 2010.

[88] Guoge Tan, Jin Zou, Jiayuan Zhuang, Lei Wan, Hanbing Sun, and Zhiyuan Sun. Fast marching square method based intelligent navigation of the unmanned surface vehicle swarm in restricted waters. *Applied Ocean Research*, 95:102018, 2020.

[89] Ming-Cheng Tsou, Sheng-Long Kao, and Chien-Min Su. Decision support from genetic algorithms for ship collision avoidance route planning and alerts. The *Journal of Navigation*, 63(1):167, 2010.

[90] Sebastián Aldo Villar et al. Navigation system for macabot an autonomous surface vehicles using gps aided strapdown inertial navigation system. *IEEE Latin America Transactions*, 17(06):1009–1019, 2019.

[91] C Wang, YS Mao, KJ Du, BQ Hu, and LF Song. Simulation on local obstacle avoidance algorithm for unmanned surface vehicle. *International Journal of Simulation Modelling*, 15(3):460–472, 2016.

[92] Chengbo Wang, Xinyu Zhang, Longze Cong, Junjie Li, and Jiawei Zhang. Research on intelligent collision avoidance decision-making of unmanned ship in unknown environments. *Evolving Systems*, 10(4):649–658, 2019.

[93] Chengbo Wang, Xinyu Zhang, Ruijie Li, and Peifang Dong. Path planning of maritime autonomous surface ships in unknown environment with reinforcement learning. In *International Conference on Cognitive Systems and Signal Processing*, pages 127–137. Springer, 2018.

[94] Hongjian Wang and Xicheng Ban. Research on autonomous collision avoidance method of unmanned surface vessel in the circumstance of moving obstacles. In 2018 *37th Chinese Control Conference (CCC)*, pages 501–506. IEEE, 2018.

[95] Ning Wang, Yuncheng Gao, Zhongjiu Zheng, Hong Zhao, and Jianchuan Yin. A hybrid path-planning scheme for an unmanned surface vehicle. In 2018 *Eighth International Conference on Information Science and Technology (ICIST)*, pages 231–236. IEEE, 2018.

[96] Ning Wang, Xiaoqiao Jin, and Meng Joo Er. A multi-layer path planner for a usv under complex marine environments. *Ocean Engineering*, 184:1–10, 2019.

[97] Ning Wang, Yue Tan, and Shao-Man Liu. Ship domain identification using fast and accurate online self-organizing parsimonious fuzzy neural networks. In *Proceedings of the 50th Chinese Control Conference*, pages 5271–5276. IEEE, 2011.

[98] Zhaokun Wei, Kang Zhao, and Ming Wei. Decision-making in ship collision avoidance based on cat-swarm biological algorithm. In 2015 *International Conference on Computational Science and Engineering*. Atlantis Press, 2015.

[99] Martin S Wiig, Kristin Y Pettersen, and Thomas R Krogstad. A reactive collision avoidance algorithm for vehicles with undereactuated dynamics. In 2017 *IEEE 56th Annual Conference on Decision and Control (CDC)*, pages 1452–1459. IEEE, 2017.

[100] Martin Syre Wiig, Kristin Ytterstad Pettersen, and Thomas Robbek Krogstad. Collision avoidance for undereactuated marine vehicles using the constant avoidance angle algorithm. *IEEE Transactions on Control Systems Technology*, 28(3):951–966, 2019.

[101] Kyle Woerner and Michael Benjamin. Safety and efficiency analysis of autonomous collision avoidance using multi-objective optimization with interval programming. *Naval Engineers Journal*, 126(4):163–168, 2014.

[102] JiooHyun Woo and Nakwan Kim. Collision avoidance for an unmanned surface vehicle using deep reinforcement learning. *Ocean Engineering*, 199:107001, 2020.

[103] R Glenn Wright. Intelligent autonomous ship navigation using multi-sensor modalities. *TransNav: International Journal on Marine Navigation and Safety of Sea Transportation*, 13(3), 2019.

[104] Shuo Xie, Xiumin Chu, Mao Zheng, and Chenguang Liu. Ship proactive collision avoidance method based on an improved beetle antennae search algorithm. *Ocean Engineering*, 192:106542, 2019.

[105] Shuo Xie, Vittorio Garofano, Xiumin Chu, and Rudy R Negenborn. Model predictive ship collision avoidance based on q-learning beetle swarm antenna search and neural networks. *Ocean Engineering*, 193:106609, 2019.

[106] Junfeng Xin, Shixin Li, Jiniu Sheng, Yongbo Zhang, and Ying Cui. Application of improved particle swarm optimization for navigation of unmanned surface vehicles. *Sensors*, 19(14):3096, 2019.

[107] Junfeng Xin, Jiabao Zhong, Fengru Yang, Ying Cui, and Jiniu Sheng. An improved genetic algorithm for path-planning of unmanned surface vehicle. *Sensors*, 19(11):2640, 2019.

[108] Chengke Xiong, Danfeng Chen, Di Lu, Zheng Zeng, and Lian Lian. Path planning of multiple autonomous marine vehicles for adaptive sampling using voronoi-based ant colony optimization. *Robotics and Autonomous Systems*, 115:90–103, 2019.

[109] Haitong Xu, Hao Rong, and C Guedes Soares. Use of ais data for guidance and control of path-following autonomous vessels. *Ocean Engineering*, 194:106635, 2019.

[110] Qingyang Xu. Collision avoidance strategy optimization based on danger immune algorithm. *Computers & Industrial Engineering*, 76:268–279, 2014.

[111] Yan Zhao Xue, Yi Wei, and Yue Qiao. The research on ship intelligence navigation in confined waters. In *Advanced Materials Research*, volume 442, pages 398–401. Trans Tech Publ, 2012.

[112] Yanzhuo Xue, D Clelland, BS Lee, and Duanfeng Han. Automatic simulation of ship navigation. *Ocean Engineering*, 38(17-18):2290–2305, 2011.
[14] Rongjie Yan, Xiangtong Yao, Junjie Yang, and Kai Huang. Formal collision avoidance analysis for rigorous building of autonomous marine vehicles. In National Conference on Embedded System Technology, pages 118–127. Springer, 2017.

[15] Hui Yang, Jie Qi, Yongchun Miao, Haixin Sun, and Jianghui Li. A new robot navigation algorithm based on a double-layer ant algorithm and trajectory optimization. IEEE Transactions on Industrial Electronics, 66(11):8557–8566, 2018.

[16] Rongwu Yang, Jinsong Xu, Xin Wang, and Quan Zhou. Parallel trajectory planning for shipborne autonomous collision avoidance system. Applied Ocean Research, 91:101875, 2019.

[17] Tingting Yang, Chengzhuo Han, Meng Qin, and Chuan Huang. Learning-aided intelligent cooperative collision avoidance mechanism in dynamic vessel networks. IEEE Transactions on Cognitive Communications and Networking, 6(1):74–82, 2019.

[18] Raphael Zaccone and Michele Martelli. A collision avoidance algorithm for ship guidance applications. Journal of Marine Engineering & Technology, 19(sup1):62–75, 2020.

[19] Raphael Zaccone, Michele Martelli, and Massimo Figari. A colreg-compliant ship collision avoidance algorithm. In 2019 18th European Control Conference (ECC), pages 2530–2535. IEEE, 2019.

[20] Zheng Zeng, Karl Sammut, Lian Lian, Andrew Lammas, Fangpo He, and Youhong Tang. Rendezvous path planning for multiple autonomous marine vehicles. IEEE Journal of Oceanic Engineering, 43(3):640–664, 2017.

[21] J Zhang, Q Hu, and B Liao. Ship collision avoidance decision model and simulation based on collision circle. TransNav: International Journal on Marine Navigation and Safety of Sea Transportation, 13(2), 2019.

[22] RL Zhang and M Furusho. Conversion timing of seafarer’s decision-making for unmanned ship navigation. TransNav: International Journal on Marine Navigation and Safety of Sea Transportation, 11(3), 2017.

[23] Xinyu Zhang, Chengbo Wang, Yuanchang Liu, and Xiang Chen. Decision-making for the autonomous navigation of maritime autonomous surface ships based on scene division and deep reinforcement learning. Sensors, 19(18):4055, 2019.

[24] Luman Zhao and Myung-Il Roh. Colregs-compliant multiship collision avoidance based on deep reinforcement learning. Ocean Engineering, 191:106436, 2019.

[25] Luman Zhao, Myung-Il Roh, and Sung-Jun Lee. Control method for path following and collision avoidance of autonomous ship based on deep reinforcement learning. Journal of Marine Science and Technology, 27(4):293–310, 2019.

[26] Yujiao Zhao, Xin Qi, Atilla Incecik, Yong Ma, and Zhixiong Li. Broken lines path following algorithm for a water-jet propulsion usv with disturbance uncertainties. Ocean Engineering, 201:107118, 2020.

[27] Yuxin Zhao, Wang Li, and Peng Shi. A real-time collision avoidance learning system for unmanned surface vessels. Neurocomputing, 182:255–266, 2016.

[28] Huarong Zheng, Rudy R Negenborn, and Gabriel Lodewijks. Fast admm for distributed model predictive control of cooperative waterborne agvs. IEEE Transactions on Control Systems Technology, 25(4):1406–1413, 2016.

[29] Kai Zheng, Yabo Chen, Yi Jiang, and Shuanghu Qiao. A svm based ship collision risk assessment algorithm. Ocean Engineering, 202:107062, 2020.

[30] Xinyuan Zhou, Peng Wu, Haifeng Zhang, Weihong Guo, and Yuanchang Liu. Learn to navigate: cooperative path planning for unmanned surface vehicles using deep reinforcement learning. IEEE Access, 7:165262–165278, 2019.

[31] Jiayuan Zhuang, Lei Zhang, Zihe Qin, Hanbing Sun, Bo Wang, and Jian Cao. Motion control and collision avoidance algorithms for unmanned surface vehicle swarm in practical maritime environment. Polish Maritime Research, 26(1):107–116, 2019.

[32] S Zinchenko, P Nosov, V Mateichuk, P Mamenko, I Popovych, and O Grosheva. Automatic collision avoidance system with many targets, including maneuvering ones. Bulletin of The University of Karaganda-Physics, 4(96):69–79, 2019.