



HAL
open science

Path planning for a maritime surface ship based on Deep Reinforcement Learning and weather forecast

Eva Artusi, Fabien Chaillan, Aldo Napoli

► To cite this version:

Eva Artusi, Fabien Chaillan, Aldo Napoli. Path planning for a maritime surface ship based on Deep Reinforcement Learning and weather forecast. IEEE/MTS OCEANS 2021, Sep 2021, San Diego, CA, United States. hal-03726769

HAL Id: hal-03726769

<https://hal.science/hal-03726769v1>

Submitted on 18 Jul 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Path planning for a maritime surface ship based on Deep Reinforcement Learning and weather forecast

Eva ARTUSI^{1,2}Fabien CHAILLAN²Aldo NAPOLI¹¹MINES ParisTech – PSL Research University – Sophia Antipolis, France²NAVAL GROUP - Naval Research - Ollioules, France

Abstract—Artificial Intelligence (AI) algorithms as decision support assist operators to choose appropriate decisions in naval missions. This article offers a decision support model to predict the path of a Maritime Surface Ship (MSS) in a dynamic environment by using Deep Reinforcement Learning (DRL). In this way, we suggest taking into account weather forecast and simplified static and mobile obstacles.

Keywords—Path planning, Maritime Surface Ship, Deep Reinforcement Learning, Weather forecast

1. INTRODUCTION

To reach as soon as possible a known goal location, the travel time must be minimized and will depend on changing environmental conditions, essentially wind and waves, on the maritime vehicle's ability to take these evolutions into account and on static and mobile obstacles.

2. STATE OF THE ART

2.1. Path planning for MSS

Path planning is a topic where A*, dynamic A* and other algorithms have been studied for many years. Currently, the development of AI especially DRL has opened new possibilities of solving path planning problems [1]. For example Cheng and al [2] employ DQN [3] strategy for Unmanned Surface Vehicle path planning and obstacle avoidance.

2.2. DRL notions

RL [4] is modeled as a Markov Decision Process, where an agent has its state updated at every time, taking an action and then receiving a reward provided by the environment. The agent's goal is to learn a policy to maximize its expected sum of rewards. DRL algorithms incorporate neural networks to represent the policy.

3. MARITIME SURFACE SHIP MODEL FOR DRL TRAINING

3.1. The MSS kinematic motion and environmental forces

In this study, a simplified three-degree-of-freedom vessel kinematic model is used to describe the MSS motions in the horizontal plane. **Fig 1** illustrates the ship kinematic variables where β_{wind} , β_{wave} are wind and wave direction in an earth-fixed reference, $\alpha_{r_{wind}}$, $\alpha_{r_{wave}}$ are the relative wind and wave direction in vessel-fixed frame. x, y, ψ are the earth-fixed position and heading angle, u, v, r the vessel-fixed velocities with r constant in our case.

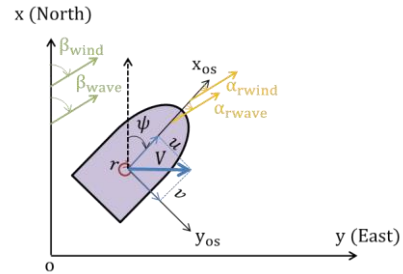


Fig 1 : The ship kinematic variables

3.2. Resistance to forward movement

It will be assumed that optimizing the MSS travel time is equivalent to minimizing its resistance to forward movement (RFM) depending on weather conditions.

$$\text{RFM}(V, \alpha_{r_{wave}}, H, V_{wind}, \alpha_{r_{wind}}) = R_o(V) + v(V, \alpha_{r_{wave}}, H)R_w + F_{x_{wind}}(V_{wind}, \alpha_{r_{wind}})$$

With R_o , the resistance to forward movement without wind and swell, v , wave angle correction factor, H the wave height, R_w , the resistance to forward motion for a given swell in front of the ship, $F_{x_{wind}}$ wind force along the ship's longitudinal axis and V the MSS speed assumed to be equal to the surge speed.

3.3. DRL framework definition

The DRL framework is illustrated on **Fig 2**, where the environment, the state space, the action space and reward functions are defined. The MSS has only one control input, the heading angle ψ in degrees.

The Deep-Q-learning algorithm (DQN) was chosen to train our agent. DQN is well suited for discrete actions and utilizes experience replay to enhance the learning process and to overcome the issue of correlated data.

4. EXPERIMENTS AND RESULTS

4.1. Assumptions and weather forecast

For this first study mobile obstacles are simplified and their paths are generated pseudo-randomly. Besides, Convention on the International Regulations for Preventing Collisions at Sea (COLREGs) [5] are not taken into account.

The ERA5 reanalysis-dataset from ECMWF was used [6] as weather forecast with a regular Lat-Lon grid with a spatial resolution of 0.25 degrees (about 28 km).

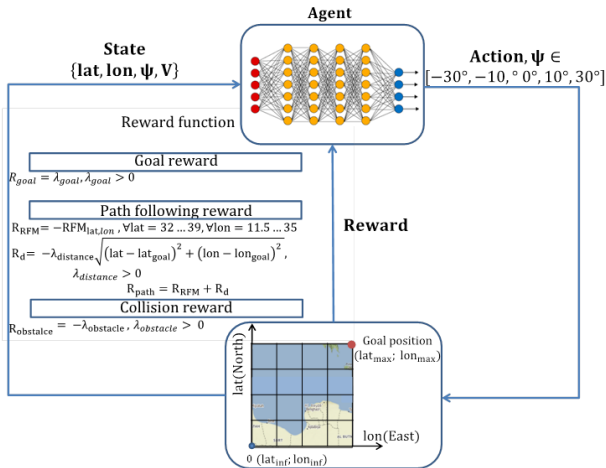


Fig 2 : The DRL framework

4.2. Tools, libraries and training

The implementation uses the RL framework provided by the Python library **OpenAI Gym** [7] and DQN is extracted from **Stable Baselines** [8]. The DQN algorithm was trained on 100,000 episodes with a buffer size of 50,000. The policy used is a multi layer perceptron, the discount factor is 0.99 and the learning rate 0.0005.

4.3. Simulation results

Fig 3 illustrates a MSS predicted path predicted controlled by the DQN policy. The colorbar represents

RFM values. The starting point is initialized by the operator and the goal area is always the same. The MSS is able to reach the goal area choosing heading angles and avoiding static obstacles in white. All along its path the MSS tries to minimize its RFM.

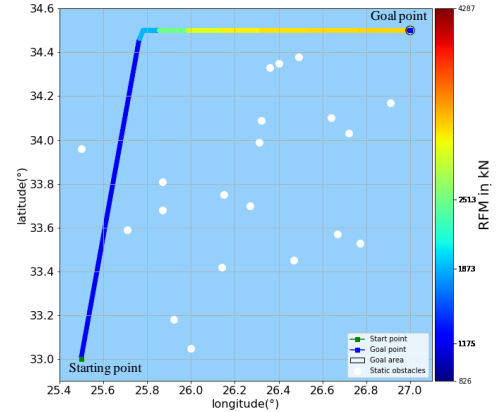


Fig 3 : A predicted path based on DQN and RFM

5. CONCLUSION

This research offers a decision support model to assist operators to predict the optimal path situation-appropriate taking into account weather forecast. Based on the DQN algorithm, a MSS path prediction model was realized providing heading angles recommendation to operators. The agent was trained with different geographical areas in the Mediterranean Sea with pseudo-random starting points and pseudo-random mobile obstacles. The MSS behavior and mobile obstacles are simplified in this simulation. Next step is to make the ship behavior more realistic where vessel dynamic model will be added with smart mobile obstacles.

REFERENCES

- [1] Zhou, Zhang, W. Guo, and Liu, « Learn to Navigate: Cooperative Path Planning for Unmanned Surface Vehicles Using Deep Reinforcement Learning », *IEEE Access*, vol. 7, p. 165262-165278, 2019,
- [2] Cheng and Zhang, « Concise Deep Reinforcement Learning Obstacle Avoidance for Underactuated Unmanned Marine Vessels », *Neurocomput.*, vol. 272, n° C, p. 63–73, 2018,
- [3] V. Mnih *et al.*, « Playing Atari with Deep Reinforcement Learning », 2013.
- [4] Sutton and Barto, *Reinforcement learning: an introduction*, Second edition. Cambridge, Massachusetts: The MIT Press, 2018.
- [5] Luman and Roh, « COLREGs-compliant multiship collision avoidance based on deep reinforcement learning », *Ocean Eng.*, vol. 191, 2019,
- [6] Meteorological dataset: <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-monthly-means?tab=form>
- [7] Brockman, Cheung, Pettersson, Schneider, Schulman, Tang, and Zaremba, « OpenAI gym, » CoRR, vol. abs/1606.01540, 2016.
- [8] Hill, Raffin, Ernestus, Gleave, Kanervisto, Traore, Dhariwal, Hesse, Klimov, Nichol, Plappert, Radford, Schulman, Sidor, and Wu. (2018). Stable baselines.