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Enhancing Autonomous Surface Vehicle Navigation: Dual-Objective Control using Deep Reinforcement Learning

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ABSTRACT

In this article, we delve into the practicality of using a cutting-edge deep reinforcement learning technique called proximal policy optimization. This technique is designed for tasks involving continuous control and shows promise for a specific challenge: guiding an autonomous surface vehicle that has limited control capabilities. The objective is to make the vehicle follow a predetermined path while also ensuring it avoids collisions with stationary obstacles it encounters along the route. To tackle this dual challenge, an artificial intelligence agent is employed. This agent is equipped with multiple rangefinder sensors that help it detect obstacles in its vicinity. The agent's training and performance assessment take place within a complex simulation environment, which poses various challenges. The simulation environment is generated with stochastic elements, adding an element of unpredictability to the scenarios the agent faces. The foundation of this environment is the OpenAI gym Python toolkit, which provides a platform for creating and testing AI algorithms in diverse scenarios. An interesting aspect of this approach is that the AI agent is given real-time access to its own reward mechanism. This means that as the agent operates, it can understand how its actions align with the overarching goals. Consequently, the agent has the ability to dynamically adjust its decision-making strategy. Depending on the situation, the agent can shift its focus between strictly adhering to the intended path and prioritizing obstacle avoidance to a greater extent. Upon thorough training and refining its strategies, the AI agent manages to achieve an impressively high success rate in completing its tasks. In episodic scenarios, where the agent has to follow the path and avoid obstacles, it approaches a success rate of nearly 100%. This accomplishment highlights the potential of applying advanced deep reinforcement learning techniques to complex real-world challenges in autonomous navigation and control.

Keywords: Proximal policy optimization, Deep reinforcement learning, Autonomous surface vehicle, Obstacle avoidance, Continuous control, Simulation environment

1. INTRODUCTION

Autonomy offers surface vehicles the opportunity to improve the efficiency of transportation while still cutting down on greenhouse emissions. However, for safe and reliable autonomous surface vehicles (ASV), effective path planning is a pre-requisite which should cater to the two important tasks of path following and collision avoidance (COLAV). In the literature, a distinction is typically made

between reactive and deliberate COLAV methods. In short, reactive approaches, most notably artificial potentiated methods, dynamic window methods , velocity obstacle methods and optimal control-based methods , base their guidance decisions on sensor readings from the local environment, whereas deliberate methods, among them popular graph-search algorithms such as A* and Voronoi graphs as well as randomized approaches such as rapidly-exploring random tree and probabilistic

roadmap, exploit a priori known characteristics of the global environment in order to construct an optimal path in advance, which is to be followed using allow-level steering controller.

2. LITERATURE SURVEY

2.1 The vector field histogram - fast obstacle avoidance for mobile robots, Robotics and Automation

AUTHORS: J. Borenstein and Y. Koren

A real-time obstacle avoidance method for mobile robots which has been developed and implemented is described. This method, named the vector field histogram (VFH), permits the detection of unknown obstacles and avoids collisions while simultaneously steering the mobile robot toward the target. The VFH method uses a two-dimensional Cartesian histogram grid as a world model. This world model is updated continuously with range data sampled by onboard range sensors. The VFH method subsequently uses a two-stage data-reduction process to compute the desired control commands for the vehicle. Experimental results from a mobile robot traversing densely cluttered obstacle courses in smooth and continuous motion and at an average speed of 0.6-0.7 m/s are shown. A comparison of the VFH method to earlier methods is given.

2.2 Motion planning and collision avoidance using navigation vector fields

AUTHORS: D. Panagou

This paper presents a novel feedback method on the motion planning for unicycle robots in environments with static obstacles, along with an extension to the distributed planning and coordination in multi-robot systems. The method employs a family of 2-dimensional analytic vector fields, whose integral curves exhibit various patterns depending on the value of a parameter λ . More specifically, for an a priori known value of λ , the vector field has a unique singular point of dipole type

and can be used to steer the unicycle to a goal configuration. Furthermore, for the unique value of λ that the vector field has a continuum of singular points, the integral curves are used to define flows around obstacles. An almost global feedback motion plan can then be constructed by suitably blending attractive and repulsive vector fields in a static obstacle environment. The method does not suffer from the appearance of sinks (stable nodes) away from goal point. Compared to other similar methods which are free of local minima, the proposed approach does not require any parameter tuning to render the desired convergence properties. The paper also addresses the extension of the method to the distributed coordination and control of multiple robots, where each robot needs to navigate to a goal configuration while avoiding collisions with the remaining robots, and while using local information only. More specifically, based on the results which apply to the single-robot case, a motion coordination protocol is presented which guarantees the safety of the multi-robot system and the almost global convergence of the robots to their goal configurations. The efficacy of the proposed methodology is demonstrated via simulation results in static and dynamic environments.

2.3 High-speed navigation using the global dynamic window approach

AUTHORS: O. Brock and O. Khatib

Many applications in mobile robotics require the safe execution of a collision-free motion to a goal position. Planning approaches are well suited for achieving a goal position in known static environments, while real-time obstacle avoidance methods allow reactive motion behavior in dynamic and unknown environments. This paper proposes the global dynamic window approach as a generalization of the dynamic window approach. It combines methods from motion planning and real-time obstacle avoidance to result in a framework that allows robust execution of high-velocity, goal-

directed reactive motion for a mobile robot in unknown and dynamic environments. The global dynamic window approach is applicable to nonholonomic and holonomic mobile robots.

2.4 A modified dynamic window algorithm for horizontal collision avoidance for auvs

AUTHORS: B. H. Eriksen, M. Breivik, K. Y. Pettersen

Much research has been done on the subject of collision avoidance (COLAV). However, few results are presented that consider vehicles with second-order nonholonomic constraints, such as autonomous underwater vehicles (AUVs). This paper considers the dynamic window (DW) algorithm for reactive horizontal COLAV for AUVs, and uses the HUGIN 1000 AUV in a case study. The DW algorithm is originally developed for vehicles with first-order nonholonomic constraints and is hence not directly applicable for AUVs without resulting in degraded performance. This paper suggests further developments of the DW algorithm to make it better suited for use with AUVs. In particular, a new method for predicting AUV trajectories using a linear approximation which accounts for second-order nonholonomic constraints is developed. The new prediction method, together with a modified search space, reduces the mean square prediction error to about one percent of the original algorithm. The performance and robustness of the modified DW algorithm is evaluated through simulations using a nonlinear model of the HUGIN 1000 AUV.

2.5 Proactive collision avoidance for asvs using a dynamic reciprocal velocity obstacles method

AUTHORS: D. Kufoalor, E. Brekke, and T. Johansen

We propose a collision avoidance method that incorporates the interactive behavior of agents and is proactive in dealing with the uncertainty of the future behavior of obstacles. The

proposed method considers interactions that will be experienced by an autonomous surface vessel (ASV) in an environment governed by the international regulations for preventing collisions at sea (COLREGs). Our approach aims at encouraging dynamic obstacles to cooperate according to COLREGs. Therefore, we propose a strategy for assessing the cooperative behavior of obstacles, and the result of the assessment is used to adapt collision avoidance decisions within the Reciprocal Velocity Obstacles (RVO) framework. Moreover, we propose a predictive approach to solving known limitations of the RVO framework, and we present computationally feasible extensions that enable the use of complex dynamic models and objectives suitable for ASVs. We demonstrate the performance and potentials of our method through a simulation study, and the results show that the proposed method leads to proactive and more predictable ASV behavior compared with both Velocity Obstacles (VO) and RVO, especially when obstacles cooperate by following COLREGs.

3. PROPOSED SYSTEM

We propose three approaches for transforming the sensor readings into a reduced observation space from which a satisfactory policy mapping should be easier to achieve. Applying proximal policy optimization, a state-of-the-art deep reinforcement learning algorithm for continuous control tasks, on the dual-objective problem of controlling an under actuated autonomous surface vehicle to follow an a priori known path while avoiding collisions with non-moving obstacles along the way. The AI agent, which is equipped with multiple range sensors for obstacle detection, is trained and evaluated in a challenging, stochastically generated simulation environment based on the OpenAI gym Python toolkit.

3.1 System design

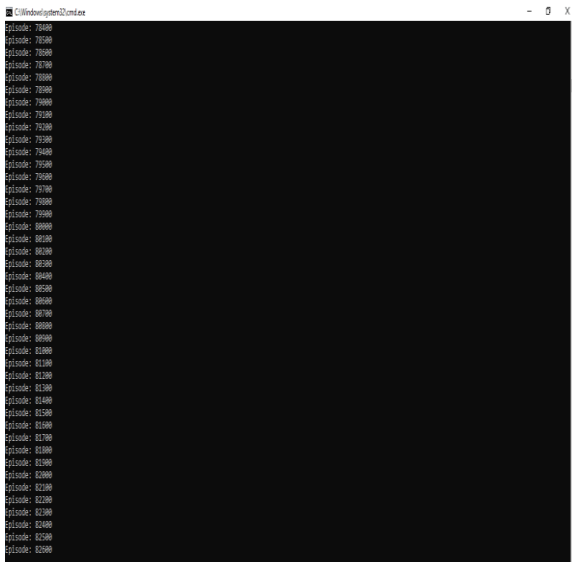
In System Design has separated into three sorts like GUI Designing, UML Designing with

benefits being developed of venture in effortless manner with various entertainer and its utilizer case by utilize case outline, stream of the task using arrangement, Class chart gives data about various class in the undertaking with techniques that must be used in the venture if goes to our task our UML Will utilizable in this manner The third and post import for the undertaking in framework configuration is Data base plan where we attempt to plan information base predicated on the quantity of modules in our task.

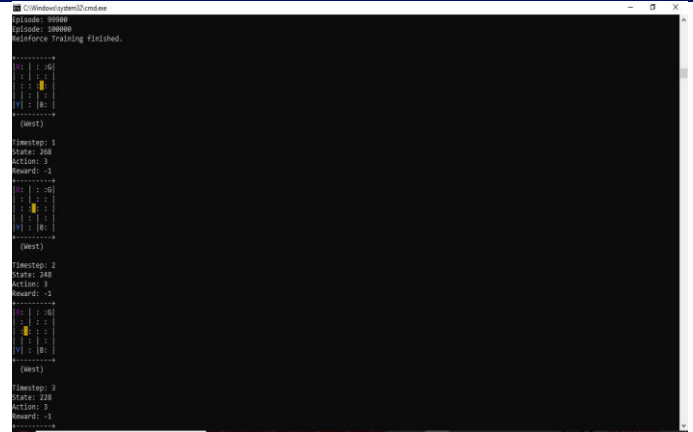
4. RESULTS



In above screen vehicle simulation displayed and then reinforcement learning will start training to get optimal path by avoiding obstacle to reach destination



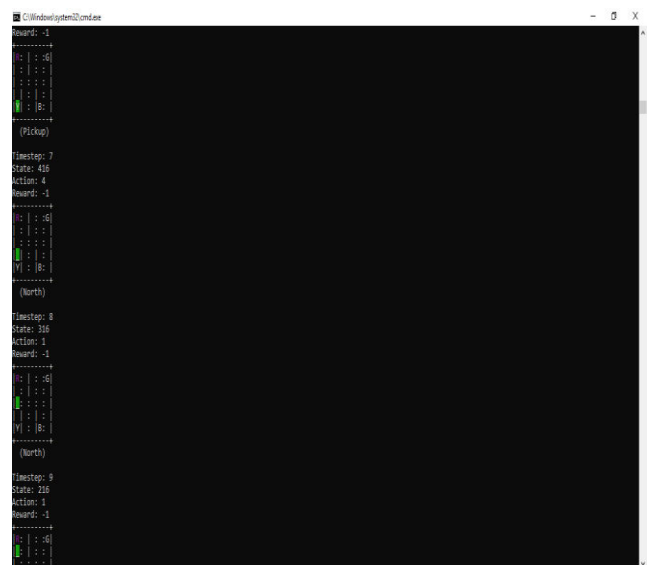
In above screen reinforcement algorithm start iterating or running episode to predict or to take action to find optimal path



In above screen you can see yellow vehicle start moving towards Y or B

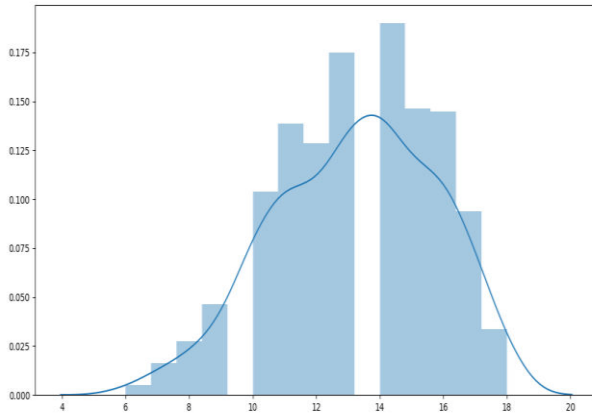


In above screen we can see vehicle reached to source Y or B location as both are in same row and see below screen where vehicle changed to green colour after reaching to source Y



In above screen in first diagram vehicle changed to green and mark simulation as

PICKUP and then start moving towards destination R



In above graph x-axis represents rewards and y-axis represents probability of correct decision and the lower the probability the better is the action or decision. In above graph at 20th reward the decision was accurate.

5. CONCLUSION

In this work, we have demonstrated that RL is a viable approach to the challenging dual-objective problem of controlling a vessel to follow a path given by a priori known waypoints while avoiding obstacles along the way without relying on a map. More specifically, we have shown that the state-of-the-art PPO algorithm converges to a policy that yields intelligent guidance behavior under the presence of non-moving obstacles surrounding and blocking the desired path.

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