I-BOAT: An autonomous sailboat to monitor the state of the seas*

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Abstract

I-Boat is a low-cost and open system of sensors that monitor and digitize our coastal- marine ecosystems to understand their state, ecological health and functioning, with the concept of any sensor, anytime, anywhere. It is made of solitary and sustainable autonomous sailboats that perceive and reason about atmospheric and underwater abiotic and biotic conditions of our critical natural resources by building a digital sea world that understands the considered ecosystems conditions and forecast their evolutions. The I-Boat infrastructure will address knowledge gaps for cross sea-basins information exchange as well as integrating innovative control technology into autonomous sailboats, leading the world with many sustainable and environmental monitoring devices for the well-being of the seas.

Keywords

Unmanned Surface Vehicle, Autonomous Sailboat, water quality monitoring, Deep Reinforcement learning, Artificial Potential Fields.

1. Introduction

Aquatic ecosystems provide essential goods and services enabling life on Earth. The impact of human activities may severely compromise the functioning of aquatic ecosystems, thus severely affecting marine life and damaging the integrity of the marine food chain, with severe impacts on food security, tourism, and all the other provisioning, regulating, cultural, and supporting services the marine and coastal ecosystems provide. Human-induced pressures strongly impact the marine ecosystems with direct and indirect effects on the stability of the natural environment [1]. It is widely recognised that a systemic (holistic) approach should developed by including all the relevant pressures and ecosystem components at different temporal and spatial scales, to achieve good environmental status for marine ecosystems. Conventional monitoring systems targeting relevant ecosystem indicators (e.g., MSFD indicators) are typically manually performed based on time-consuming and labour-intensive on-site sampling and data collection. Onboard research vessels, experts collect water samples, identify the position and then send them to laboratories for analysis. In this case, real-time data that enable swift decision-making for public health protection cannot be obtained. In addition, weather and other uncertain factors can affect the deployment of the measuring equipment, and complex lab analysis significantly reduces the efficiency of getting measurements and results. Therefore, there is a need for a more efficient method of monitoring water quality, and several solutions for innovative marine robotics have been proposed. Marine robotics allow for pervasive real-time water monitoring by implementing onboard analysis and new digital representation of the physical world, improving marine research, resource management,

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system performance, and managing delicate engineering operations at sea. Exploring and monitoring the oceans with autonomous platforms can provide researchers and decision-makers valuable data, trends, and insights into Earth's largest ecosystem. Although several autonomous and robotic solutions have been recently developed to complement routine marine and coastal monitoring, their design and development tailored to European seas still need to be improved. In particular, cost-effectiveness, energy efficiency, control and robustness are important issues with implications regarding autonomy and sustainability, which strongly limit the area's coverage, incurring high costs for labour, operations and equipment [2].

Research on marine robotics and automation has so far aimed at developing and testing surface and underwater vehicles powered by batteries or diesel [3]. These vehicles have severe limitations in range and durability, depending on the capacity of the battery or fuel on board for propulsion, making them unfit for long-term operations in rea-world settings [4]. Wind-powered crafts, a time-tested innovation used by humans since ancient times, offer a compelling solution for ocean monitoring, overcoming the limitations of battery and diesel-powered vehicles. By harnessing energy from the environment for propulsion, these crafts eliminate the need for transporting fuel, making them highly efficient. Here we want to combine autonomous sailing vessels with traditional and innovative sensing devices to perform optimised long-term ocean monitoring in European seas. The platform is being developed toghether with innovative sensing methodologies in the current I-Boat project in order to acquire data for water quality monitoring. The autonomous sailing drone is connected to a digital twin for a virtual representation of the explored marine environments with real-time collected data, to allow biodiversity characterization and better forecasting trend of species. The key features of the I-Boat infrastructure are:

- Wind is the only source of propulsion.
- Fully autonomous – the entire control system is on board and, therefore, performa planning and navigation manoeuvres automatically and without human assistance;
- completely self-sufficient from an energy point of view, opening up to a wider range of applications.

Figure 1: The I-Boat autonomous sailboat with navigational and environmental sensors.

2. Autonomous Navigation

Local path planning is essential for autonomous sailboat safety in complex environments [5]. Unlike global path planning, which focuses on long-term optimized routes, local path planning manages immediate challenges such as initial detection, dynamic obstacles, changing weather conditions, and rapid environmental responses. Over time, various strategies have been introduced to enhance its effectiveness and operational reliability. Traditional methods, such as artificial potential fields, employ repulsive potentials like exo-potentials centered at obstacle locations and attractive potentials at the goal, along with endo-potentials that adapt based on wind conditions and sailboat kinematics [6]. These methods enable responsive and efficient obstacle avoidance, contributing to safer autonomous navigation even in the presence of marine currents. Their real-time applicability and low computational demands support embedded systems, but reliance on constant communication and susceptibility to local minima reduce their reliability in remote or unpredictable environments. To address these issues, potential field methods have been enhanced with vector field histograms to better avoid both static and dynamic obstacles, regardless of whether their positions are known [7], improving robustness in complex scenarios. The goal of obstacle avoidance is to navigate around objects and plan a path that avoids them altogether, ensuring smooth and efficient movement toward a goal. Over the past few decades, advances in sensor technology, computational capacity, and intelligent algorithms have significantly improved obstacle avoidance for autonomous sailboats. Adaptive potential control methods, such as transforming kinematic constraints into virtual obstacles, enable real-time collision risk assessment and hybrid propulsion-based avoidance using sailboat safety zones (SSZ), especially for vessels like OceanVoy that have low mobility and limited maneuverability. However, classical algorithms like A* [8, 7] may fall into local optima, prompting new developments such as evidential-theory-based real-time risk evaluation systems for collision avoidance in unmanned surface vehicles (USVs), and Optimal Reciprocal Collision Avoidance (ORCA) methods grounded in COLREGs [9]. While Ant Colony Optimization (ACO) has been considered, its sensitivity to local minima and limited modeling of wind fields has led to improved ACO variants [10]. Alternative techniques such as velocity obstacles [11] and dynamic windows have also been explored, though they require refinement to handle complex environments effectively. In response, model-free deep reinforcement learning (DRL) has emerged as a powerful solution due to its superior perception and decision-making capabilities. Novel two-stage DRL approaches have been proposed: a coarse stage for approximate localization and a fine stage for precise maneuvering, resulting in success rates of over 83 [12]. Other integrated methods include A*-based path planning combined with PID tracking using line-of-sight (LOS) guidance for collision avoidance [13], and Q-learning implementations for static obstacle navigation [14]. Platforms like *Pigame* have further tested Q-learning strategies under complex conditions [15]. In windless simulation environments, PPO-based algorithms have proven effective in navigating dense obstacle fields [16], while deep Q-learning has been applied for obstacle avoidance in calm scenarios with external disturbances [17]. Expanding on this, studies like [18] have modeled full digital environments with static and dynamic obstacles using PPO and integrated COLREGs-based behaviors. Comparative research using digital twins has evaluated PPO, SAC, Behavior Cloning (BC), and Generative Adversarial Imitation Learning (GAIL), with SAC+BC+GAIL showing potential for further improvement despite its current limitations [19].

In terms of performance optimization, planners like RRT have been applied to efficiently explore feasible paths in cluttered environments [20]. However, due to suboptimality in some cases, classical graph-based algorithms such as A* and D* have also been explored for identifying shorter and cost-efficient paths. Yet, their limited responsiveness to environmental changes makes them less ideal for real-time use. To address this, hybrid methods integrating Model Predictive Control (MPC) and artificial potential fields have been developed to model the sailboat's interaction with multiple dynamic obstacles, accounting for environmental forces through stability analyses such as Lyapunov functions and zero-pole mapping [21]. While these approaches enhance predictive accuracy and safety, their high computational overhead can impede real-time deployment. Consequently, recent research has shifted toward reinforcement learning (RL) due to its ability to learn optimal policies in uncertain and dynamic settings. These advanced RL methods—such as PPO, Soft Actor-Critic (SAC), and MPC-based hybrids—not only enhance the system's capacity for autonomous decision-making but also improve adaptability to diverse environments. These techniques directly impact local path planning by enabling sailboats to make robust and informed decisions, reducing reliance on human control, and increasing operational safety and efficiency. Over the past decade, these innovations have reshaped the trajectory of local planning systems, making them more resilient, intelligent, and capable of functioning in real-time, with ongoing validation in simulated and semi-real-world environments.

Considering the challenges of local path planning, hybrid approaches appear particularly promising. Drawing from our analysis of the literature and our own research, we propose the integration of a local occupancy grid map for real-time updates in the local path planning layer. This local grid periodically updates the global path planner, enabling responsive adaptation to environmental changes. Our approach involves storing time-series data of obstacle positions and sailboat location, using this to construct dynamic local maps. Autonomous sailboat navigation presents several technical challenges when relying solely on either reinforcement learning (RL) or traditional path planning. RL, while powerful, suffers from a large and complex state space, making it computationally expensive to train. Additionally, designing an appropriate reward function is often difficult, especially in dynamic and unpredictable environments like the open sea. On the other hand, classical path planning algorithms face issues such as getting stuck in local minima, producing oscillatory trajectories, and exhibiting sensitivity to initial conditions. These methods also struggle to incorporate dynamic constraints effectively, which limits their responsiveness in real-time scenarios. To address these limitations, hybrid methods have emerged as a promising solution. By combining potential field-based planning for coarse trajectory generation with RL for fine-tuned, adaptive decision-making, hybrid approaches leverage the strengths of both paradigms. This integration leads to improved overall performance, increased robustness, and enhanced adaptability to changing conditions. Moreover, hybrid systems can reduce computational overhead by offloading simpler tasks to low-cost algorithms while reserving RL for high-impact decisions. As a result, hybrid approaches represent a strategic advancement in autonomous sailboat control, offering scalable, efficient, and resilient solutions for complex maritime environments.

Initially, we implemented A* for local navigation, but our findings suggest that APF, when combined with learning-based global planners, offers superior responsiveness and adaptability. This has led us to focus on hybrid approaches where APF handles localized obstacle avoidance, and global planning is guided by learning-based methods such as PPO.

Autonomous sailboat navigation presents significant challenges due to the dynamic nature of maritime environments, where factors such as wind direction, tides, and currents play a crucial role. Traditional path planning techniques like A* combined with PI controllers have been effective in structured environments where obstacles and environmental conditions are relatively static. However, these methods often struggle with adaptability in dynamic environments, leading to inefficiencies in trajectory planning and obstacle avoidance.

As technology continues to evolve—especially with the rise of renewable energy sources for autonomous vehicles—the integration of adaptive algorithms becomes increasingly essential. Energy constraints demand not only efficient path planning but also optimized control strategies to minimize energy usage. The combination of DRL and APF enables more nuanced navigation by dynamically responding to wind variability and obstacle proximity in real time. These methods complement static techniques like A*, which are reliable for predefined routes but less effective in unpredictable environments. Thus, a hybrid approach offers an effective balance for long-term autonomous operations.

The integration of reinforcement learning, specifically Proximal Policy Optimization (PPO), has been shown to significantly improve real-time decision-making by allowing sailboats to adapt their trajectories based on environmental variables such as wind direction and obstacle positions [22]. Unlike static planners, PPO-based approaches adapt through feedback, making them well-suited for dynamic maritime settings.

In this study, we evaluate and compare the performance of DRL with Artificial Potential Fields (APF) and A* with PI control in an autonomous sailboat navigation context using a realistic Gazebo simulation environment. This section describes the simulation setup, the implementation of each algorithm, and the evaluation metrics used to assess performance[23].

The simulation environment was built using Gazebo [24], a physics-based platform ideal for testing autonomous systems under realistic conditions. For this study, we customized the environment to reflect maritime conditions, including wind, ocean currents, and both static and dynamic obstacles. Particular attention was given to the modeling of wind and current forces, as these are crucial for sailboat navigation, as shown in Figure 2.

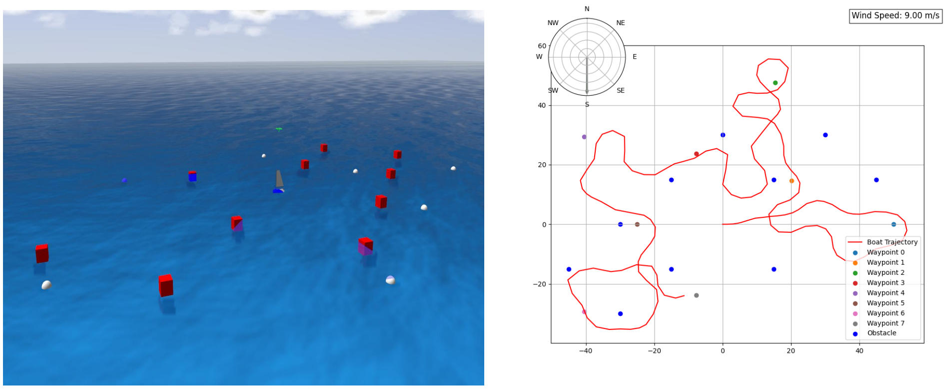

Figure 2: Sailboat model in the Gazebo simulation environment with wind and obstacles, and boat trajectory using DRL with Potential Fields.

3. Conclusions

We are currently focusing on the implementation of a local occupancy grid map system, wherein the APF governs local decision-making and obstacle avoidance, while PPO manages global route optimization. This division of responsibility leverages the real-time reactivity of APF and the strategic foresight of PPO, forming a cohesive framework suitable for dynamic and uncertain environments.

While validating autonomous navigation algorithms remains challenging due to performance variability and environmental complexity, both reinforcement learning and traditional path planning offer valuable solutions. Path planning algorithms demonstrate strength in generating optimal trajectories in structured environments, whereas reinforcement learning—especially with advancements in computational efficiency and Markov decision processes—enables adaptability in dynamic scenarios such as upwind sailing. The integration of both approaches through hybrid systems provides a compelling balance between precision and flexibility, making them highly suitable for autonomous sailboat navigation. Ultimately, this research highlights the importance of leveraging simulation environments to iteratively train, validate, and refine these algorithms, paving the way for reliable deployment in real-world maritime applications.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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