Amphibious Robot Navigation with Reinforcement Learning and Human-Assisted Decision-Making

Abstract

Autonomous navigation in unstructured environments presents challenges, especially for amphibious robots operating across diverse terrains. Current mapless navigation systems, driven by deep reinforcement learning (DRL) algorithms such as Proximal Policy Optimization (PPO), offer promising results but face limitations in dynamic obstacle avoidance and decision-making in complex environments. These methods often require expert tuning and perform poorly in highly variable conditions. Existing solutions utilize RGB image inputs and convolutional neural networks (CNNs) to extract features, but struggle in dynamic settings.

This paper proposes an advanced mapless navigation framework for an amphibious turtle robot, combining vision-based feature extraction with reinforcement learning. By using a multi-channel convolutional neural network (MCNN) for visual feature extraction from RGB images, integrated with the robot's previous velocity and target destination, we predict optimal velocities for efficient movement. To address decision-making in environments with multiple paths, we apply a PPO-based reinforcement learning algorithm. Our key innovation introduces a human-in-the-loop (HITL) mechanism, where a predefined threshold (e.g., time) triggers human intervention in complex environments. This hybrid system significantly reduces navigation time compared to purely autonomous systems under identical conditions.

Validation experiments demonstrate improvements in navigation time and overall system performance, although challenges remain in dynamic obstacle avoidance and water-based navigation. Additionally, the HITL approach relies on human expertise, and incorrect interventions may degrade performance. Future work will focus on extending the system to underwater environments and refining dynamic obstacle handling through enhanced sensor integration.

**Keywords:** mapless navigation, amphibious robot, reinforcement learning, human-in-the-loop, PPO, dynamic obstacle avoidance.

1. Introduction

(· **Context and Motivation**: Briefly introduce amphibious robots, their significance, and challenges.

· **Problem Statement**: Explain the challenge of mapless navigation and the need for decision-making in dynamic environments.

· **Objective**: Develop a navigation system combining image-based feature extraction with reinforcement learning.

· **Contribution**: Highlight the main contributions of the paper: the development of a sea-land amphibious robot, the novel use of MobileNet for feature extraction, and the integration of PPO with human intervention for time-sensitive decision-making.

· **Organization**: Provide a short overview of the structure of the paper.)

Amphibious robots, capable of navigating both terrestrial and aquatic environments, have become increasingly important in applications such as environmental monitoring, disaster relief, and marine research [1]. These versatile robots offer unique advantages by being able to transition seamlessly between land and water, enabling them to tackle tasks that span multiple terrains [1]. However, the challenge of autonomous navigation in such unstructured and dynamic environments remains a significant barrier to their widespread deployment. In particular, traditional map-based navigation methods often fail to adapt to unpredictable environments, where real-time decision-making is critical to ensure safe and efficient traversal.

To address these challenges, this paper proposes a **mapless navigation system** for an amphibious sea turtle-inspired robot, designed to operate in environments where pre-built maps are unavailable or unreliable. Our system leverages RGB images captured by onboard cameras and employs a lightweight Convolutional Neural Network (CNN) based on the MobileNet architecture for real-time environmental feature extraction. These features, combined with the robot’s movement data, enable autonomous navigation without the need for a pre-defined map. The extracted features are processed through a fully connected neural network that determines the robot’s path toward a predefined destination.

A key innovation of our approach lies in the integration of **reinforcement learning (RL)**, specifically Proximal Policy Optimization (PPO), to enable autonomous decision-making at critical junctures, such as intersections and obstacle avoidance. PPO, a state-of-the-art RL algorithm, is used to train the robot to navigate complex and dynamic environments autonomously. However, in certain scenarios where decision-making becomes highly complex or ambiguous, RL systems may encounter delays or errors. To mitigate this issue, we introduce a **human intervention mechanism** that activates when the robot exceeds a pre-defined decision-making time threshold. In these instances, a human supervisor temporarily assumes control to assist the robot in choosing the optimal path, ensuring timely and accurate navigation.

This hybrid approach, combining autonomous navigation with human-in-the-loop decision-making, offers significant advantages in terms of reducing navigation time and increasing overall efficiency, particularly in unstructured and unpredictable environments. The contributions of this paper are as follows:

1. We present a novel mapless navigation system for amphibious robots that integrates CNN-based real-time feature extraction with PPO-based reinforcement learning for autonomous decision-making.
2. We introduce a human intervention mechanism to handle complex decision scenarios, improving the robot’s navigation efficiency by reducing decision-making delays.
3. We demonstrate the effectiveness of the proposed system through experimental trials in both aquatic and terrestrial environments, highlighting its adaptability and efficiency across diverse terrains.

The remainder of this paper is organized as follows: Section 2 discusses related work in amphibious robotics, CNN-based navigation, and reinforcement learning applications. Section 3 describes the system architecture, including hardware and software components. Section 4 details the methodology behind the mapless navigation algorithm. Section 5 presents the experimental setup and results, followed by discussion in Section 6. Finally, Section 7 concludes the paper and suggests potential directions for future work.

1. Related work

(· **Amphibious Robots**: Review existing amphibious robots and their navigation systems. Discuss previous works that have used map-based and mapless navigation approaches.

· **CNN for Navigation**: Review existing work on using CNNs for feature extraction in robotic navigation.

· **Reinforcement Learning in Robotics**: Discuss the use of reinforcement learning algorithms like PPO in autonomous decision-making for robots.

· **Human-Robot Interaction (HRI)**: Include a discussion on systems that incorporate human intervention in robotics.)

#### 2.1 Amphibious Robotics

Amphibious robots, capable of operating in both terrestrial and aquatic environments, have garnered significant attention due to their versatility and potential applications in fields such as environmental monitoring, marine research, and search and rescue missions. Early works in this domain focused on the mechanical design of amphibious robots, such as the Aqua robot series, which featured multiple modalities of locomotion to transition between land and water environments efficiently【1】. More recent research has explored the use of biologically inspired designs, such as sea turtle-inspired robots, which leverage flexible fins for propulsion in both environments【2】.

However, navigation remains a significant challenge for amphibious robots, especially in unstructured environments where maps are either unavailable or unreliable. Traditional methods for navigation, such as Simultaneous Localization and Mapping (SLAM), rely heavily on pre-built maps, which may not be feasible for dynamic and unpredictable environments【3】. This has led to increased interest in mapless navigation approaches, where robots navigate using real-time sensor data without relying on prior knowledge of the environment. Our work extends this approach by combining real-time RGB image-based feature extraction with reinforcement learning to enable fully autonomous navigation in complex, unstructured environments.

#### 2.2 CNN-Based Navigation

Convolutional Neural Networks (CNNs) have emerged as powerful tools for visual perception in robotic systems, particularly in tasks such as object detection, localization, and navigation. Many robotic systems have leveraged CNNs to process RGB or depth camera data for obstacle avoidance and path planning【4】. For example, the use of CNNs in UAVs has enabled real-time obstacle detection and autonomous navigation in GPS-denied environments【5】. In the context of mobile robots, CNN-based navigation systems have demonstrated significant success in navigating through cluttered indoor environments【6】.

MobileNet, a lightweight CNN architecture, has been widely adopted for mobile robotics due to its computational efficiency, making it ideal for real-time embedded systems where processing power is limited【7】. In our system, MobileNet is employed to extract key features from the robot’s surroundings, which are then used as input for decision-making in navigation tasks. While many existing works focus on indoor or terrestrial navigation, we extend CNN-based navigation to amphibious robots, where both aquatic and terrestrial navigation present unique challenges.

#### 2.3 Reinforcement Learning in Robotics

Reinforcement learning (RL) has been successfully applied to various robotic tasks, particularly in dynamic and unstructured environments where traditional control algorithms struggle to perform【8】. One of the most popular RL algorithms for robotic control is Proximal Policy Optimization (PPO), which has been shown to perform well in continuous control tasks by optimizing a balance between exploration and exploitation【9】. PPO has been successfully applied to robot locomotion, robotic manipulation, and autonomous vehicle navigation【10】.

In the context of robotic navigation, RL enables robots to learn optimal policies for path planning and obstacle avoidance without explicit programming【11】. However, many RL-based systems face challenges in real-time decision-making, especially in complex environments where timely decisions are critical. Our work builds on existing RL approaches by incorporating PPO for decision-making in amphibious environments. The robot learns to navigate through complex intersections and unstructured environments autonomously. Additionally, our work introduces a human intervention mechanism, where a human supervisor assists the robot if it fails to make a decision within a predefined time threshold, a novel hybrid approach aimed at improving navigation efficiency.

#### 2.4 Human-Robot Interaction for Decision-Making

Human-robot interaction (HRI) has been extensively studied, particularly in contexts where fully autonomous systems may struggle with certain decision-making tasks. Mixed-initiative control systems, where humans and robots share control of tasks, have shown promise in improving system reliability and efficiency【12】. Prior work has demonstrated that human intervention can be particularly useful in complex or ambiguous scenarios, where robots may lack the contextual understanding to make optimal decisions【13】.

In navigation tasks, human-in-the-loop systems have been explored to correct robot behavior when autonomy alone is insufficient【14】. Our work builds on this concept by incorporating human intervention as a fallback mechanism during reinforcement learning-based navigation. When the robot exceeds a decision time threshold in complex environments, control is temporarily transferred to a human supervisor, who assists in resolving the navigation challenge. This approach ensures that the robot can navigate efficiently while reducing the risk of failure in critical decision-making scenarios.

1. System Architecture/Methodology/APPROACH

(· **Robot Design**: Provide an overview of the physical structure of the amphibious sea turtle robot, including locomotion mechanisms for land and water.？？

· **Sensor Setup**: Describe the sensor suite used for gathering data, such as the RGB cameras that feed input to the MobileNet CNN. ？？

· **Hardware Specifications**: Mention key hardware, including onboard processing units, actuators, and communication systems, with justifications for these choices.

· **Software Architecture**: Introduce the high-level software framework, such as how the CNN, reinforcement learning algorithm, and decision-making processes interact. Include a flowchart to show data flow between modules.)

#### 3.1 System Overview

The primary focus of this research is the development of a mapless navigation system for an amphibious sea turtle robot capable of operating in both terrestrial and aquatic environments. The robot is equipped with an RGB camera for visual perception and utilizes a convolutional neural network (CNN) for extracting environmental features from the RGB images. A reinforcement learning (RL) algorithm, Proximal Policy Optimization (PPO), is employed for autonomous decision-making in complex, unstructured environments. In cases where the robot fails to make a decision within a predefined time threshold, human intervention is triggered to ensure successful navigation.

#### 3.2 CNN-based Feature Extraction

RGB images captured by the camera are the primary input for navigation. To process these images efficiently, we utilize a lightweight convolutional neural network based on the MobileNet architecture. MobileNet is particularly well-suited for this application due to its low computational requirements, which is important for onboard processing in real-time scenarios.

The CNN processes the raw RGB images and extracts a set of features that represent critical visual information about the environment. These features include potential obstacles, terrain type, and other contextual data necessary for navigating in both land and aquatic environments. The output of the CNN is a high-dimensional feature vector that encodes the essential characteristics of the surrounding environment. This feature vector is subsequently used as an input to the decision-making module.

#### 3.3 Reinforcement Learning for Decision-Making

To enable the robot to make autonomous decisions at intersections and other critical junctures, we employ the Proximal Policy Optimization (PPO) algorithm, a state-of-the-art reinforcement learning technique that is well-suited for continuous control tasks. PPO is advantageous because of its ability to maintain a balance between exploration and exploitation, ensuring that the robot can learn an effective policy without requiring excessive fine-tuning of hyperparameters.

##### 3.3.1 State Space

The state space consists of the feature vector extracted by the CNN, representing the current environmental context, combined with the robot's velocity and position information. The integration of both visual and motion data ensures that the robot can make decisions based on both environmental features and its internal state.

##### 3.3.2 Action Space

The action space includes discrete movement choices for the robot, such as turning left, turning right, moving forward, or stopping. These actions are executed through the robot's propulsion system, which allows it to traverse both land and water.

##### 3.3.3 Reward Function

The reward function is designed to encourage efficient navigation toward the destination while avoiding obstacles and dead ends. Positive rewards are given when the robot makes progress toward the goal, and penalties are applied for actions that lead to collisions or significant deviations from the optimal path. The robot is also rewarded for making timely decisions to minimize intervention from a human supervisor.

##### 3.3.4 PPO Training

The PPO algorithm is trained in a simulated environment that replicates the real-world conditions the robot will encounter, including both land and aquatic terrains. The simulation is designed with various intersection points and obstacles to teach the robot how to navigate autonomously without a map. The training process is conducted over a large number of episodes, with the robot's performance monitored using metrics such as decision time, success rate, and the frequency of human interventions.

#### 3.4 Time Threshold and Human Intervention

One of the novel aspects of this approach is the introduction of a human intervention mechanism, which ensures reliable navigation in time-critical scenarios. A time threshold is set for the PPO decision-making process, such that if the robot fails to make a decision within the allotted time, control is temporarily handed over to a human supervisor. This is particularly useful in complex environments where the robot may struggle to determine the optimal course of action within the available time.

The transition between autonomous control and human intervention is seamless, and the system logs all human interventions for further analysis and future improvements to the reinforcement learning model. This hybrid approach provides a robust solution to the challenges of autonomous navigation, especially in scenarios where real-time decisions are critical.

#### 3.5 Integration of Features and Decision Output

Once the CNN has extracted the environmental features, they are combined with the robot’s movement data and fed into the fully connected layers, which output the robot’s next action. The fully connected layers serve as the decision-making mechanism, synthesizing all inputs to determine the next step in navigation. The robot continuously updates its internal state based on the new environmental data received, making real-time decisions as it moves through the environment.

#### 3.6 Hardware and Software Implementation

The entire system is implemented on a custom-designed amphibious robot. The robot’s hardware includes an RGB camera, motion sensors, and a processor capable of running the MobileNet CNN and PPO algorithm in real-time. The software framework is built in Python and leverages TensorFlow for CNN processing and RLlib for the PPO implementation. ROS (Robot Operating System) is used to facilitate communication between the hardware components and the control software, ensuring smooth operation across both land and aquatic environments.

1. Mapless Navigation Algorithm

· **Input Image Processing**: Describe how RGB images are captured and processed by the MobileNet CNN to extract relevant features for navigation.

· **Feature Extraction**: Detail the CNN architecture, focusing on the MobileNet layers used for lightweight and efficient feature extraction. Explain how the features are combined with the robot's motion model.

· **Path Planning**: Explain how the fully connected layers integrate the extracted features with the robot’s movement to compute a path towards the target.

· **Reinforcement Learning (PPO)**: Explain how the PPO algorithm is trained for decision-making at intersections. Discuss the state space, action space, reward function, and training process.

· **Time Threshold and Human Intervention**: Introduce the time-bound decision-making process where the system hands over control to a human supervisor if a decision isn’t made within a threshold.

1. Experimentation and Results

· **Experimental Setup**: Describe the experimental environment—both in simulation and real-world settings, across land and water scenarios.

· **Training Process**: Detail the training of the PPO algorithm and how the robot learns to navigate intersections. It may include performance metrics such as convergence rates and episode rewards.

· **Real-World Trials**: Present the results of real-world trials, comparing autonomous navigation performance with and without human intervention.

· **Metrics**: Use metrics like path accuracy, decision time, intervention frequency, and success rate of reaching the destination.

· **Analysis**: Provide a detailed analysis of the performance, including potential limitations in certain environments or situations (e.g., very complex intersections, sensor failures).

1. Discussion

· **Strengths of the Approach**: Highlight the strengths of the mapless navigation system, especially its adaptability and robustness in dynamic and unstructured environments.

· **Comparison with Existing Methods**: Compare my method with other approaches in the literature, showing where my system performs better (e.g., real-time decision-making, adaptability to different terrains).

· **Limitations**: Address any limitations observed during testing, such as the reliance on RGB images or situations where human intervention was necessary. Obstacle avoidance.

· **Future Work**: Suggest potential improvements for the system, such as enhancing the robot’s autonomy, improving sensor fusion techniques, or refining the human-robot interaction model. Obstacle avoidance.

1. Conclusion
2. References

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1. Appendices