Abstract

This thesis addresses a key challenge in service robotics: enabling autonomous mobile robots to navigate unpredictable environments with unexpected changes. Effective generalization is essential for advancing robot autonomy, as robots must be capable of handling unseen situations. Traditional approaches often focus on training with numerous fixed scenarios, but this research demonstrates that improving generalization through varied start and goal points can significantly improve adaptability. The primary objective of this research is to develop a deep reinforcement learning approach that enhances the generalization and transferability of mobile robot navigation in unseen environments. This is achieved by extending the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm. The proposed solution integrates randomization at start and end points, dynamic obstacles, and variable robot orientations to foster robust exploration and adaptability. The research methodology integrates the Noetic ROS framework with a skid-steered robot simulation in Gazebo and a custom OpenAI Gym environment. Training is carried out using the TD3 algorithm with LiDAR sensor data for decision-making. The model parameters are continuously updated on the basis of interactions, and extensive randomization is introduced during training to maximize generalization capabilities. The solution is tested in various custom environments designed with diverse object configurations. Experimental results demonstrate that the extended model significantly outperforms non-extended models in navigating complex and unfamiliar environments. Key metrics such as success rate, collision rate, and distance traveled reveal enhanced performance, with the extended model achieving superior efficiency and adaptability compared to models trained in more constrained scenarios. The findings contribute to the field of autonomous service robotics by providing a scalable approach to achieve robust generalization. This research highlights that training with diverse start and goal points, rather than simply increasing the number of static scenarios, is more effective for improving adaptability and flexibility.