

AI-Based Path Planning for Multidirectional Mobile Robots in Dynamic Warehouse Environment

Graduate



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Introduction: Autonomous mobile robots are playing an increasingly important role in logistics and warehouse automation. They must be able to navigate cluttered and dynamic environments safely and efficiently. Path planning—the ability to generate, follow, and adapt collision-free paths and trajectories in the presence of static and moving obstacles—is a core technology enabling such transportation systems.

The goal of this work is to develop an AI-based path planner that can be executed locally on a robot. As a robot platform, an omnidirectional robot called MuFa (Multifunktionelle Fahreinheit) is used (see Fig. 1). It was developed at OST and is intended as a logistics robot capable of transporting small crates or components. For this work, as shown in Fig. 1, the robot is equipped with an experimental setup consisting of sensors (IMU, LiDAR) and a Raspberry Pi 5 with an attached Neural Processing Unit (NPU). An NPU is specialized hardware designed to execute neural networks locally. However, deploying neural networks on an NPU imposes certain restrictions, such as quantized inference or the inability to use recurrent layers.

Approach: The final solution is inspired by Globally Guided Reinforcement Learning (G2RL), a system that operates on local 2D maps. These maps contain static and dynamic obstacles, the robot's collision box, and a global path generated using the A* algorithm.

The original G2RL system is designed for a discrete environment with discrete actions (up, down, left, right, stop). To apply this approach to a continuous environment, several adaptations were required. First, the output actions were changed to continuous velocity commands in the x and y directions, as well as in the angular velocity. This required a reinforcement learning algorithm that is suitable for continuous action spaces. In this work, the Soft Actor-Critic (SAC) algorithm was selected. It was implemented using the reinforcement learning framework Stable Baselines3 (SB3). Webots was used as the simulation environment (see Fig. 2). After training, the model was quantized to enable deployment on the NPU.

Result: Training time proved to be a significant challenge. Due to limitations of Webots, however, switching to a high-performance computing cluster was not possible. Additionally, SB3 restricts training to a single robot instance at a time. To still incorporate dynamic obstacles during training, moving boxes were used.

Because of these constraints, a sub-optimal model had to be deployed on the NPU. Quantization resulted in a sharp decline in performance when the model was executed on the NPU. In contrast, the non-quantized model demonstrated strong performance, achieving an overall success rate of

over 95% in navigating to the goal. Fig. 3 shows the debugging view of the demo system. Despite the limitations, this work lays a solid foundation for further research and development of AI-based path planning systems in logistics and dynamic warehouse environments.

Fig. 1. MuFa robot platform serving as experimental setup, including sensors and a Raspberry Pi 5 with NPU.
Own presentation

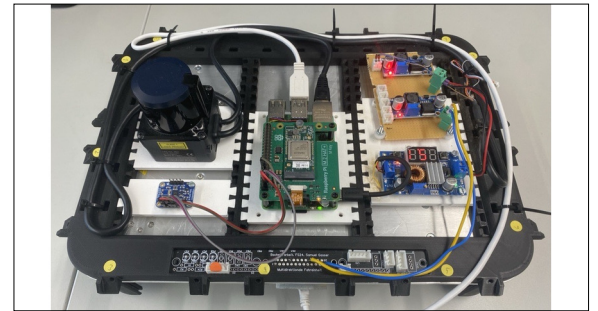


Fig. 2. Webots simulation environment used for training and testing. The blue box is a model of the MuFa robot platform.
Own presentation

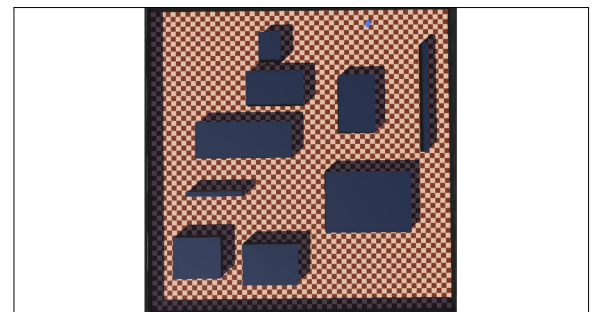
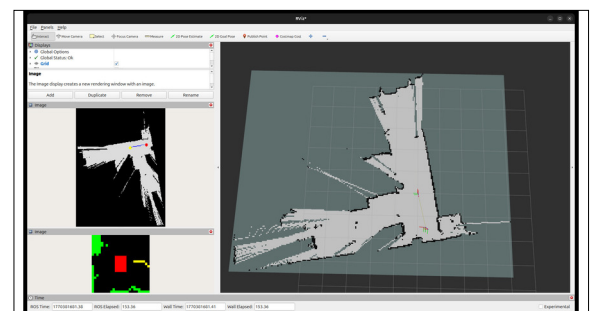


Fig. 3. View of the demo system. Bottom left: robot's collision box (red), obstacles (green), and path (yellow).
Own presentation



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Subject Area

Electrical Engineering