YILDIZ TECHNICAL UNIVERSITY
GRADUATE SCHOOL OF SCIENCE AND ENGINEERING
DEPARTMENT OF COMPUTER ENGINEERING

ROBOT NAVIGATION WITH REINFORCEMENT LEARNING

Omer M. T. KAYA, PhD Candidate, Dr. Erkan USLU (Supervisor)
omer.kaya@yildiz.edu.tr, euslu@yildiz.edu.tr

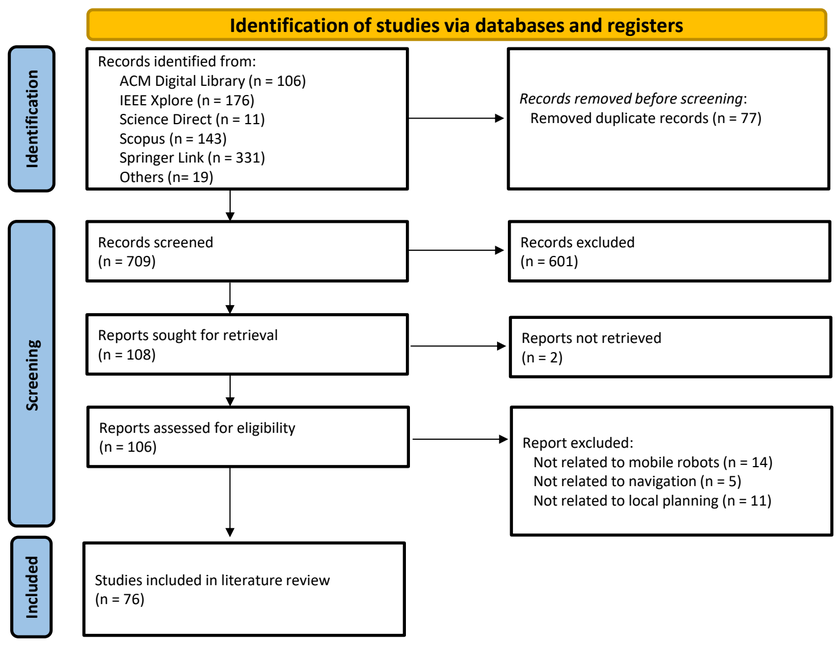
Abstract

With the increasing use of mobile robots, ensuring safe and efficient navigation in complex environments with both stationary and moving obstacles is crucial. This project aims to address this challenge by developing a navigation stack that incorporates a reinforcement learning-based local planner. Unlike previous studies, the project will leverage a large number of diverse parallel training environments arranged in an easy-to-difficult curriculum. Simulation tools that support parallel training will be utilized to enhance the robots' generalization capabilities across varying difficulty levels while significantly reducing training time. Through parallel training and diverse environments, the project aims to achieve a highly generalized and efficient navigation stack within a short time.

I. Introduction

Mobile robots increasingly require more advanced technologies to navigate safely and efficiently in complex environments filled with stationary and moving obstacles. In this context, approximately **709** studies in the literature were reviewed and analyzed using the **PRISMA [1]** method.

Table 1. Research Method



The literature review reveals that three basic approaches stand out in robot navigation:

1. Traditional hierarchical deterministic navigation stacks,
2. Modern end-to-end AI-based navigation stacks, and
3. Hybrid navigation stacks that combine the advantages of these two methods.

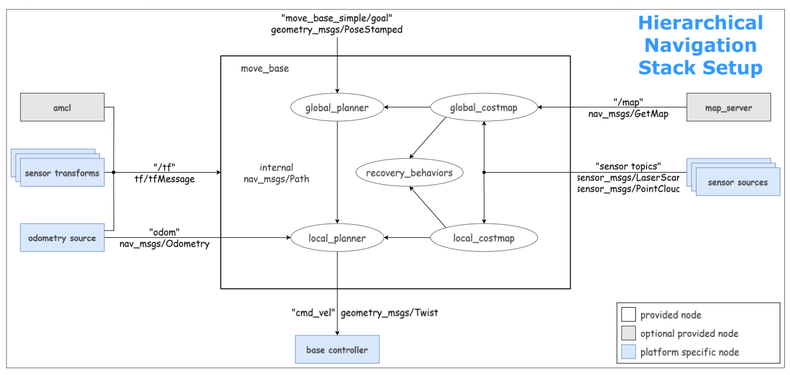


Figure 2. Traditional Hierarchical Navigation Stack Setup [2]

Traditional deterministic structures provide predictable and reliable outputs based on inputs; however, they fall short in handling moving obstacles and random situations.

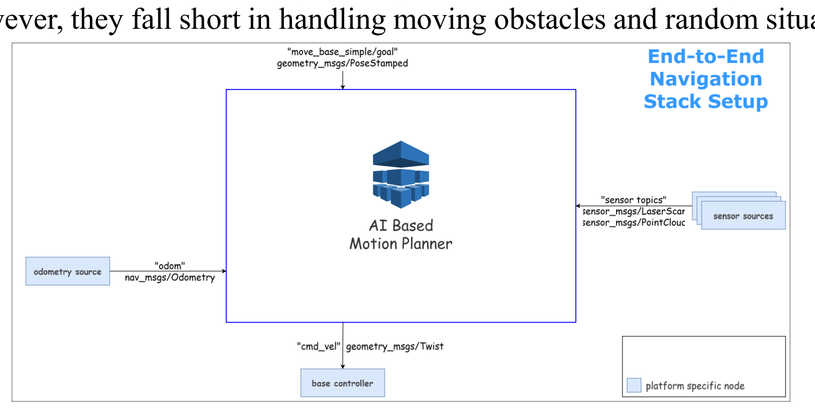


Figure 3. End-to-End Navigation Stack Setup

Modern end-to-end structures excel in high-entropy envs using AI and intensive training but struggle with long-distance navigation and local minima due to limited training diversity and lack of map usage.

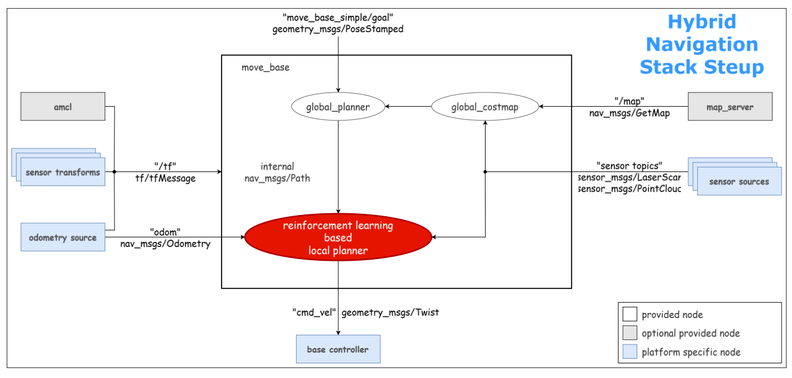


Figure 4. Hybrid Navigation Stack Setup

Hybrid navigation stacks combine the reliability of traditional methods with the flexibility of AI, offering faster solutions to random events. However, training and generalizing learned information to different environments remain key challenges.

A. Research Questions & Hypothessis

The original value of the project is examined under three headings:

1. Generalization
2. Training Time
3. Safety and Efficiency

III. Methods

The primary goal of the project is to develop a reinforcement learning-based local planner with high generalization success that will enable mobile robots to reach their goals safely and efficiently in complex and mobile environments. Secondly, it is aimed to design a parallel training architecture that will enable this local planner to be trained faster.
The project was also shaped by taking inspiration from important sources such as the "Learning to Walk in Minutes Using Massively Parallel Deep Reinforcement Learning" publication [3]. A parallel training scene from the study can be found in the top-right image of Fig. 4.

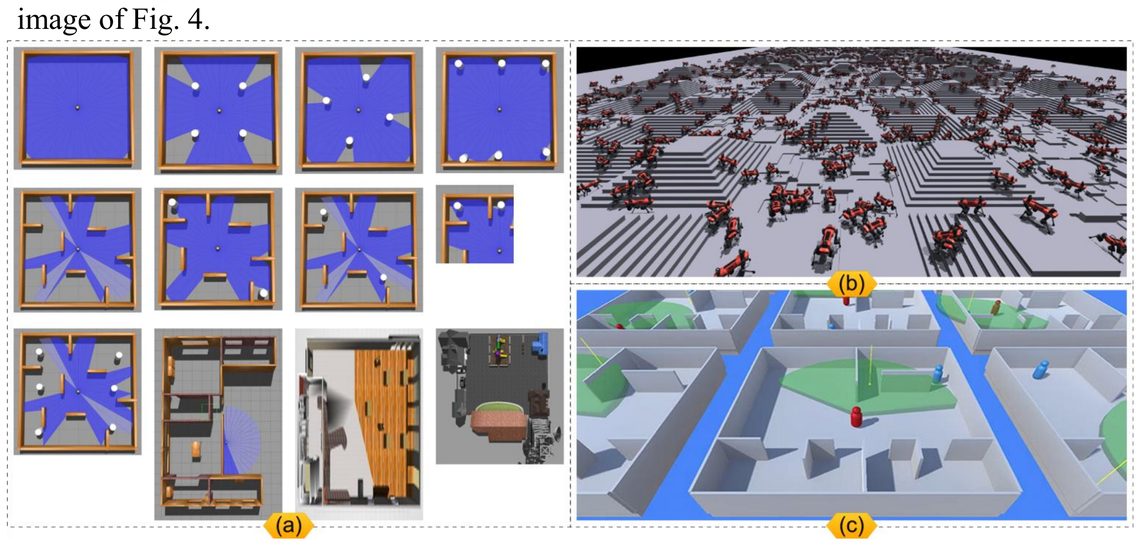


Figure 4. Simulation Environments, **(a)** Gazebo [4], **(b)** Isaac Lab [3], **(c)** Unity [5]

Within the scope of the project, the local planner unit will be developed with modern reinforcement learning algorithms such as **SAC**, **TD3**, **PPO**, **A3C** and **DQN**. In the training processes, a parallel simulation world will be created with a wide variety of environments in a curriculum structure from simple to complex. This approach aims to provide fast learning ability to the proposed navigation stack and to enable the robots to show high generalization success in a wider range.
The created training environments will be divided into four main categories:

- Empty environments
- Static environments
- Dynamic environments
- Hybrid environments with both fixed and moving obstacles.

A differential drive robot will be used in the training and testing processes.

IV. Timeline & Expected Results

Table 2. Project Plan

S	Work Package	Impact on Project Success (%)	MONTH 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Environment setup and baseline model development	%20																
2	Parallelized training and model tuning	%30																
3	Deployment in simulated and real-world scenarios	%40																
4	Publication and dissemination of results	%10																

- Parallel training simulation world
- High generalizaton success
- Low training time
- Robust, safe and efficient navigation ability
- A reinforcement learning-based local planner tested in a real-world environment
- Outperforming traditional and end-to-end approaches in more than half of the metrics

B. Evaluation Metrics

- Success Rate
- Static Collision Occurrence
- Moving Collision Occurrence
- Timeout
- Average Distance
- Average Speed
- Average Time

V. Conclusion

- Robot navigation stacks were examined and divided into three categories.
- It was determined that mixed structures were more advantageous in the current conditions.
- Generalization and training time were determined as the most important problems.
- Various and parallel training environments were suggested.
- It is aimed to increase generalization success.
- It is aimed for mobile robots to gain safe navigation skills in a short time.

VI. References

[1] M. J. Page *et al.*, "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," *J Clin Epidemiol*, vol. 134, pp. 178–189, Jun. 2021, doi: 10.1016/j.jclinepi.2021.03.001.
[2] J. S. Gill, "Setup and Configuration of the Navigation Stack on a Robot." Accessed: Oct. 24, 2024. [Online]. Available: https://wiki.ros.org/navigation/Tutorials/RobotSetup
[3] N. Rudin, D. Hoeller, P. Reist, and M. Hutter, "Learning to Walk in Minutes Using Massively Parallel Deep Reinforcement Learning," Sep. 2021, [Online]. Available: http://arxiv.org/abs/2109.11978
[4] A. Y. Majid, T. van Rietbergen, and R. V. Prasad, "Challenging Conventions Towards Reliable Robot Navigation Using Deep Reinforcement Learning," *Computing&AI Connect*, doi: 10.69709/caic.2024.194188.
[5] "Unity ML-Agents Deep Learning Toolkit Unity China Official Website." Accessed: Jan. 24, 2025. [Online]. Available: https://unity.cn/product/machine-learning-agents