**Project Description:**

The project is a daring endeavour at the intersection of robotics and artificial intelligence. In more context, its goal is to equip machines such as service robots as mentioned in the specification report to autonomously navigate through complex indoor environments, just as humans do. The project scope leaps forward in the field of advanced machine learning for applications ranging from smart homes, defence to industrial automation.

The project leverages a paradigm, reinforcement learning (RL) that inspires from biological psychology where an agent maximizes the sum of reward signal by making actions in an environment. This is achieved through the simulation of sensor measurements where the agent can factor in real time environmental data, enabling it to make intelligent navigational decisions similar to human spatial awareness.

The key contribution of this project is the comprehensive navigation system which merges RL and Localisation techniques to autonomously navigate indoor spaces. The Proximal Policy Optimisation (PPO) algorithm implemented by the PyTorch framework, optimizes policies to make informed movements depending on the environment’s feedback making it well suited for the control required in indoor navigation.

The project effectively leveraged a combination of technologies and top-level libraries such as:

* **AI2-THOR Framework:** Integrating of AI2THOR enabled the creation of a highly realistic 3D environment which is crucial for training the agent for real-world deployment.
* **OpenAI Gym:** Utilising the Gym toolkit for solving the navigation problem as an RL task enhanced compatibility with RL by providing a standardized environment.
* **PyTorch:** Implementing the Proximal Policy Optimization (PPO) agent using PyTorch offered flexibility and efficient computational capabilities.
* **Matplotlib:** Including Matplotlib for visualization enhanced accessibility to analyse and optimize navigation performance.

The technologies and libraries used provided the tools and sources to create a simulated environment within Python, implement reinforcement learning, simulate the sensor measurements, visualize navigation, transform and manage data. These tools contributed to tackle the complex task of intelligent navigation efficiently.

**Aims and Objectives:**

The objective of this project is to implement a robust algorithm to navigate the robot efficiently using a deep learning model where it uses the simulation environment to overcome the gap between virtual and real world under a low-cost budget without compromising the ethical considerations and safety of the user (key objective from specification report).

**Achieved Objectives**

* Implemented AI2-THOR and Gym, two extensively prominent tools in the field of visual AI and RL, for simulating the environments and creating the reinforcement learning setup for indoor environments.
* Developed a Proximal Policy Optimization module using PyTorch for control policy.
* Captured sensor measurements and estimated the agent’s pose to enhance robust decisions made by the system.
* Monitored the agent’s poses in different frames and planned paths during training for optimization.
* Demonstrated the functionality of the navigation system in simulated indoor environments, aligning with the primary object of the project “Reinforcement learning for intelligent navigation”.

**Unachieved Objectives**

* To explore enhancements that could potentially lead to more efficient navigation techniques.
* To fine-tune the algorithm to achieve optimal navigational strategies.

Overall, the project achieved its primary aims and objectives by creating a functional RL-based navigation system in simulated environments.

**Outputs:**

* The principal output is a trained autonomous navigation agent capable of moving through simulated indoor environments. The agent gains the capacity to plan and execute pathways to predetermined goals. The PPO-based agent learns effective policies for navigating in the environment.
* During training, the visualisation tools generate paths that show intended pathways, agent trajectories, and current poses. These visualisations provide useful information about the agent's behaviour and performance. The implementation of particle filter localization allows the agent to estimate its pose accurately, contributing to robust navigation.
* The software's simulation of sensor readings, particle weight computation, and posture estimation all contribute to navigation robustness. These outputs are critical for navigating in complex contexts with confidence. A path planning module ensures effective and obstacle-free navigation towards predefined goals.

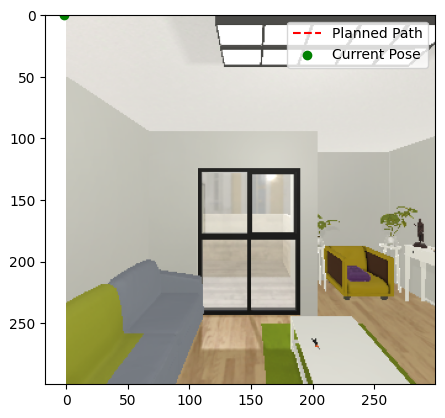


Figure 1: FloorPlan 221 (Iteration)

**Evaluation:**

While assessing the project's progress and successes in reinforcement learning and localization for intelligent navigation, it is clear that numerous key milestones have been accomplished.

The successful integration and use of AI2-THOR, a robust AI platform, for modelling intelligent navigation settings is a noteworthy accomplishment. This platform simulates and tests reinforcement learning agents in a realistic and dynamic environment.

The development of a Proximal Policy Optimization (PPO) agent demonstrates the project's potential to generate advanced machine learning models for navigation problems. This agent is capable of learning and optimizing strategies for complex navigation settings.

Particle Filter Localization: The development of a particle filter localization system is a significant accomplishment. This system enables the agent to estimate its pose (position and orientation) in the environment, which is essential for intelligent navigation.

**Shortfalls and Areas for Improvement**

The project has integrated several components, there is room for performance optimization. PPO agent and localization system fine-tuning could possibly lead to more effective navigation.

The navigation system could valuably benefit from improved optimization strategies when dealing with noisy sensor data.

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