Agent Intelligent Urban Navigation

DANIEL ALEJANDRO PRESIGA

PROFESSOR: CARLOS A. SIERRA

UNIVERSIDAD DISTRITAL FRANCISCO JOSE DE CALDAS

2. Motivation / Problem Statement

Urban mobility is increasingly challenging due to unpredictable traffic behaviors, congestion, and the need for safe and efficient navigation.

Traditional rule-based systems often fail to adapt in real time to chaotic environments.

Reinforcement learning offers a promising approach by enabling agents to learn optimal behavior from experience.

3. Project Objective

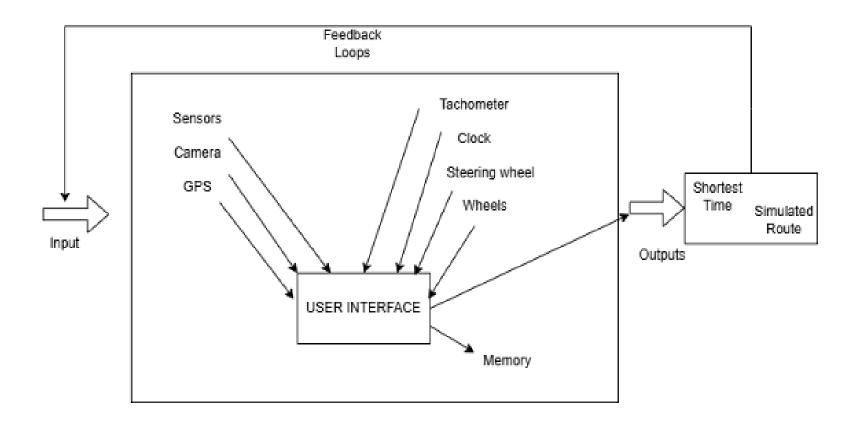
General Objective:

To implement an intelligent autonomous agent for urban navigation.

Specific Objectives:

- Design a modular agent capable of perceiving and acting in a simulated environment.
- Apply reinforcement learning.
- Evaluate performance under in a simulated urban scenary.

4. System Architecture



5.Experiment

- A simulated urban environment was built with obstacles and moderately complex routes.
- ► The agent was trained directly within this environment using the Gymnasium library and Deep Q-Learning principles.
- The reward function was designed to encourage efficient and legal navigation while penalizing collisions and inefficient behavior.
- Several experiments were conducted by varying the number of training episodes (repetitions) to observe how the agent's learning and performance evolved over time.

6. Results

- When trained with a low number of episodes, the agent tended to get stuck or loop repeatedly in the same area.
- ► However, when trained with a high number of repetitions such as 30,000 or more— the agent showed a clear ability to navigate more intelligently and reach the destination more reliably.
- More training led to better movement, orientation, and goalseeking behavior.

7. Conclusions

Ithough the final system lacks a polished interface and still requires improvements, it successfully fulfills its core function:

- The agent learns from its virtual environment and improves over time.
- This project provides a solid foundation for future work on advanced visualization, richer interactions, and real-world deployment.

8. Future Work

Although the core functionality of the agent has been validated, several enhancements are needed to bring the system closer to real-world application:

Interface Improvements:

The current visual interface is basic and limited. A more interactive and user-friendly interface would help in visualizing the agent's decision-making process and improve usability for both testing and demonstrations.

Transition to Real-World Scenarios:

Future iterations of this project may explore the integration of the trained agent into real environments using real sensors and robotics platforms. This would require adapting the simulation outputs to control physical actuators, allowing the agent to operate in smart city environments or robotic navigation tasks.

Multi-Agent Interaction:

Expanding the environment to include other agents (e.g., other vehicles or pedestrians) would challenge the decision-making process and lead to more robust strategies.

9. Questions

Thank you for your attention.