Reinforcement Learning for Real-Time Decision-Making in Autonomous Vehicles

Muhammad Hamza Rao
Student ID: mur5582

Scientific Seminar – Summer 2025

June 11, 2025

Introduction

- Autonomous Vehicles (AVs) face challenges in real-time decision-making in urban environments.
- Traditional methods lack adaptability in complex, unpredictable scenarios.
- Reinforcement Learning (RL) enables learning from interaction via rewards/penalties.

Research Question

How do different RL techniques compare in predicting and adapting to human driver behavior using real-time sensor data?

- Evaluate safety, efficiency, and adaptability.
- Focus on urban traffic scenarios.

Literature Review

Traditional Methods

- Rule-Based Systems
- Finite State Machines (FSM)
- Behavior Trees
- Model Predictive Control (MPC)

Limitations

- Poor generalization
- No learning ability
- High computational cost

Fundamentals of Reinforcement Learning

- Agent interacts with environment to maximize cumulative rewards.
- Key components: States, Actions, Rewards, Policies.
- Algorithms: DQN, PPO, SAC.
- Trained using platforms like CARLA, SUMO.

Key RL Algorithms

- **DQN:** Discrete control, fast but limited precision.
- **DDPG:** Continuous control, sample efficient.
- **PPO:** Stable, on-policy, good for urban tasks.
- **SAC:** Robust, entropy-based, adaptable.
- **TD3:** Improved DDPG, stable under noise.

Evaluation Criteria

- Prediction Accuracy
- Safety
- Adaptability
- Policy Stability
- Efficiency

Scenario-Based Algorithm Comparison

Scenario	Top Algorithms
Lane Keeping	TD3, SAC
Intersection Handling	PPO, SAC
Lane Changing	TD3, SAC
Obstacle Avoidance	SAC, TD3

Challenges and Limitations

- Sample inefficiency in real-world.
- Poor generalization across diverse environments.
- Safety and interpretability issues.
- Sim-to-real transfer bottlenecks.
- Computational constraints in real-time.

Conclusion and Future Work

- SAC and TD3 are top-performing RL methods for AVs.
- Real-world deployment needs safe RL and sim-to-real strategies.
- Future work: hybrid systems, policy transfer, and lifelong learning.

Thank You!

Questions?