Integrating Occupancy Grids with Spatial-Temporal Reinforcement Learning for Enhanced Control

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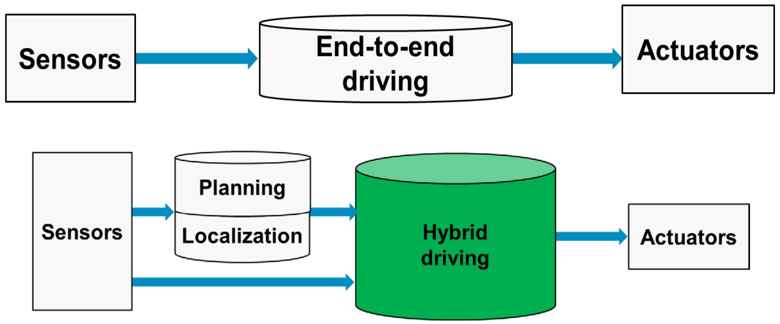
Integrating Occupancy Grids with Spatial-Temporal Reinforcement Learning for Enhanced Control – Project Goals

- Enhance the capability and efficiency of a deep reinforcement learning-based vehicle control framework to interpret and navigate spatially and temporally complex dynamic driving environments.
- Improve vehicle safety with an innovative planning and control strategy utilizing attention mechanisms.
- Combine the strengths of reinforcement learning and transformer-based architectures.
- Increase the interpretability of reinforcement learning-based behavior generation across spatial and temporal dimensions.

Integrating Occupancy Grids with Spatial-Temporal Reinforcement Learning for Enhanced Control – Motivation

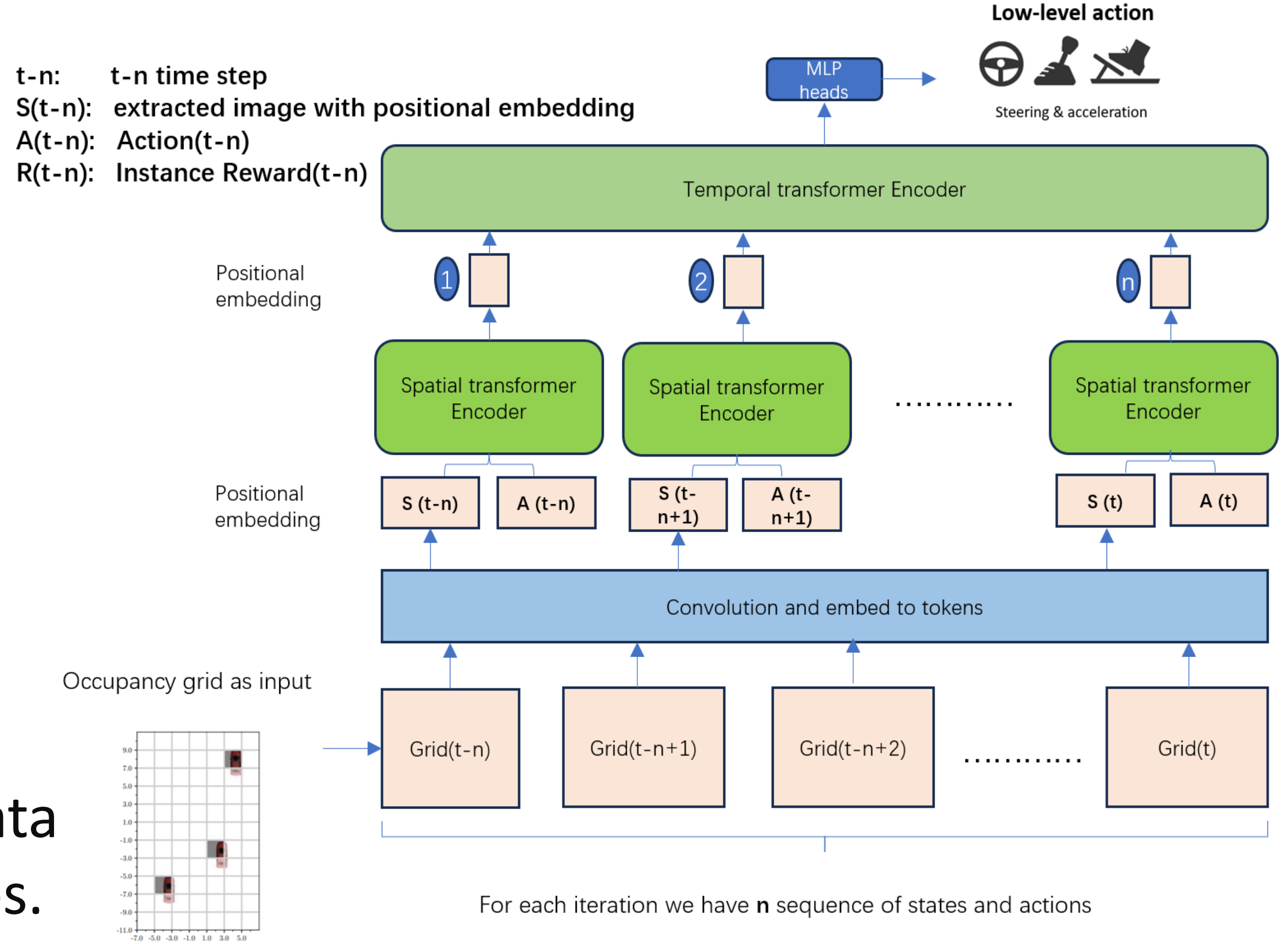
- **Automated driving can be structured as**
  - End-to-end: machine learning representation- not explainable, unclear safety measures and constraints.
  - Modular: decomposed into subproblems, complex, lacks generalization.
  - General reinforcement learning: operates under the Markov assumption that current behavior solely depends on the current action and state. Focused on the immediate transition.



- **End-to-end training using both spatial and temporal attention.**
  - The combination of the occupancy grid representation, CNNs, and spatial attention mechanisms provides a structured way to represent complex spatial information.
  - The incorporation of temporal embedding and temporal transformers allows the model to make informed decisions based on a series of actions and states over time.

Integrating Occupancy Grids with Spatial-Temporal Reinforcement Learning for Enhanced Control – Approach

This research represents an advancement in spatial-temporal understanding within autonomous driving systems. By leveraging transformers, which are renowned for their effectiveness in sequence-to-sequence tasks, in combination with occupancy grids and spatial attention mechanisms, the model is expected to demonstrate superior performance in interpreting complex environmental data and navigating intricate traffic scenarios.

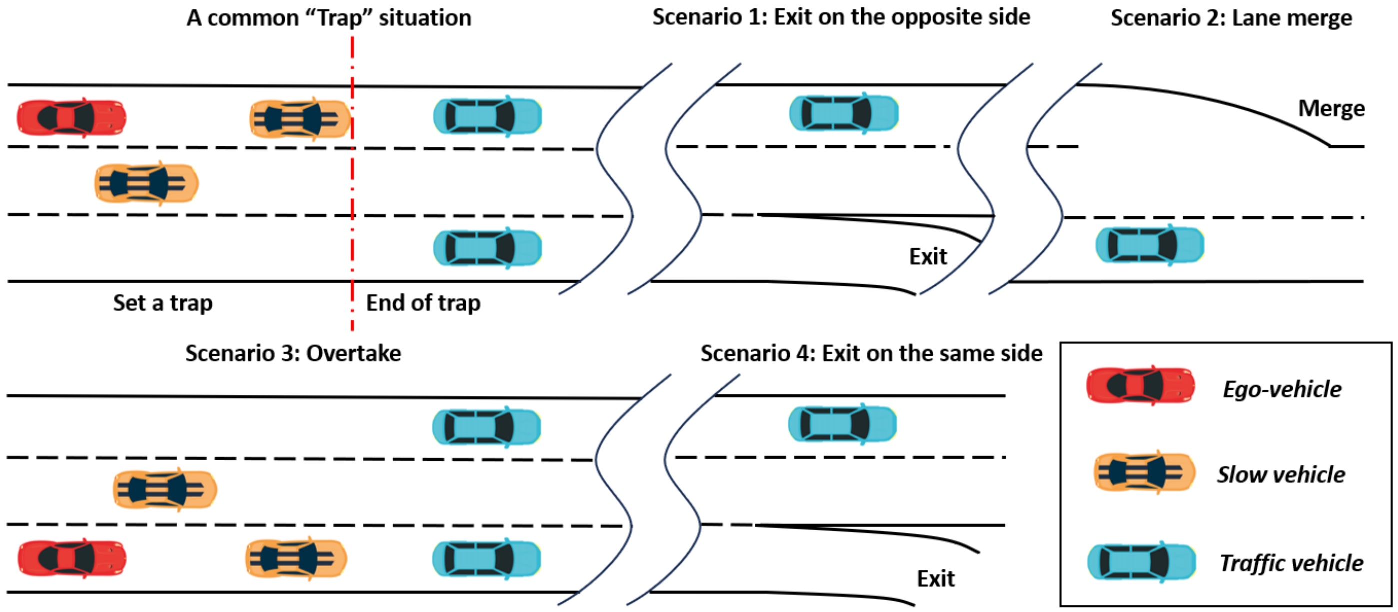


A Hierarchical Deep Reinforcement Learning Framework to control vehicles for Highway Driving Environment

Integrating Occupancy Grids with Spatial-Temporal Reinforcement Learning for Enhanced Control – Expected Outcomes

We will present case studies and demonstrations of the model in various scenarios, including simulations of autonomous navigation, obstacle avoidance, and planning and decision-making, and evaluate quantitatively and qualitatively:

- Navigation success
- Accuracy and efficiency
- Improvements in traffic safety



Highway driving scenarios to test the feasibility of this spatial and temporal framework