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**B. Eng AVE SCIENTIFIC SEMINAR PAPER [Summer 2025]**

**TOPIC: Reinforcement Learning for Real-Time Decision-Making in Autonomous Vehicles.**

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**Main Research Question:** "How do different reinforcement learning techniques compare in predicting and adapting to unpredictable human driver behavior in urban traffic environments using real-time sensor data, and which method provides the best balance between safety and efficiency in decision-making?"

**Description:** Reinforcement learning (RL) enables autonomous vehicles (AVs) to learn the best driving policies through trial and error. RL helps AVs anticipate and react to human driver behavior during real-time traffic using sensor information. This research investigates various RL techniques for improving decision-making in urban traffic. The aim is to maximize safety and efficiency simultaneously in AV systems.

**Abbreviations:**

1. AV - Autonomous Vehicle
2. RL - Reinforcement Learning
3. DQN - Deep Q-Network
4. PPO - Proximal Policy Optimization
5. REINFORCE - A Policy Gradient Algorithm
6. DDPG - Deep Deterministic Policy Gradient
7. TD3 - Twin Delayed Deep Deterministic Policy Gradient
8. SAC - Soft Actor-Critic
9. CARLA - Car Learning to Act
10. SUMO - Simulation of Urban Mobility
11. V2X - Vehicle-to-Everything
12. SAE - Society of Automotive Engineers

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**1.1 Motivation for Autonomous Vehicles**

The creation of autonomous vehicles (AVs) is one of the most remarkable technological advancements in modern transportation. AVs promise to revolutionize the transportation of people and goods by reducing traffic accidents, making traffic flow smoother, lowering emissions, and improving mobility for the disabled. According to the World Health Organization, approximately 1.3 million people die annually in road traffic crashes, and over 90% of these crashes are the result of human error. Autonomous vehicle technology, driven by advanced artificial intelligence (AI) and machine learning (ML) processes, promises to mitigate these problems by eliminating the unpredictability of human decision-making and enhancing road safety.

Besides safety, AVs will revolutionize urban mobility. In congested, overpopulated cities plagued by inefficiencies and congestion, AVs could help facilitate smoother traffic flow, dynamic ride-sharing platforms, and optimal fuel usage. Technology companies and automakers are investing billions in AV development and research, and the industry is progressing well in areas of perception, localization, path planning, and control. Even with these advancements, numerous hurdles remain to enable fully autonomous vehicles to be deployed safely and reliably on complicated city streets.

**1.2 Challenges in Urban Driving Environments**

Urban traffic environments are stochastic and dynamic. Unlike the controlled conditions on freeways, urban roads consist of numerous more difficulties like dense traffic, regular pedestrian crossings, arbitrary pedestrian behavior, cyclists, fluctuating road conditions, and diverse human-driven vehicles with different driving patterns. The stochasticity of these environments makes decision-making for AVs more challenging by incorporating relevant uncertainty.

The largest challenge is foresaying and responding to human drivers' behavior. The driving pattern by humans could be erratic and determined by several factors in their immediate context such as impatience, distraction, or a willing violation of the rules. Such variability in AVs needs to be assessed to make live, real-time judgments without causing accidents or hindrance to performance. This gets compounded in scenarios with mixed traffic levels where AVs must live among human-traffic vehicles.

Additionally, decision-making processes in AVs must integrate high-dimensional, real-time data from heterogeneous sensors like cameras, LiDAR, radar, and GPS. Processing all this information, making decisions, and executing safe control actions within milliseconds is extremely computationally and algorithmically intensive. Rule-based and model-based approaches fail to work in such uncertain, dynamic environments, and more adaptive and intelligent approaches are needed.