ENHANCING ROAD SAFETY WITH V2V SIMULATIONS

Mukesh Javvaji
Ayaazuddin Mohammad
Divya Sri Bandaru
Satvika Eda

1. ABSTRACT

In an era marked by rapid advancements in automotive technology, the quest for improving road safety has become increasingly paramount. Vehicle-to-vehicle (V2V) communication emerges as a promising solution to mitigate accidents and enhance overall road safety. This project endeavours to explore the potential of V2V simulations to bolster safety measures on our roadways. Our implementation focuses on leveraging Reinforcement Learning (RL) techniques to enhance road safety through Vehicle-to-Vehicle (V2V) simulations. RL algorithms will be used to train virtual agents within the simulations to make optimal decisions in dynamic traffic environments. These agents will utilize V2V communication to exchange critical information such as vehicle positions and intentions. The project will investigate the effectiveness of RL-based decision-making in preventing accidents and improving overall road safety. The project will also address technical aspects, including RL model development. By combining RL and V2V simulations, this implementation aims to create a realistic and data-driven approach to road safety improvement. Ultimately, the project's findings may pave the way for more intelligent and adaptive vehicular systems, contributing to safer roadways for all users.

2. INTRODUCTION

The complex web of traffic situations in today's constantly changing transportation environment makes it imperative that innovative methods be used to guarantee road safety. In this context, Vehicle-to-Vehicle (V2V) communication shows great potential. With the ability to exchange mission-critical information with ease, it ushers in a new era of safety protocols and traffic coordination.

Vehicle-to-vehicle (V2V) communication serves as a conduit for the instantaneous exchange of critical data between vehicles. This communication includes a variety of data, from the positions and speeds of the vehicles to impending manoeuvres and possible dangers. It establishes the groundwork for a dynamic, networked system in which cars with relevant data can cooperatively negotiate intricate traffic situations.

This project goes beyond the integration of V2V communication; it extends further by amalgamating Reinforcement Learning (RL) techniques within V2V simulations. RL, a branch of artificial intelligence, endows these vehicles - or rather, their virtual counterparts within simulations - with the ability to learn from their experiences. By training these intelligent agents through simulated interactions, they evolve into proactive decision-makers, equipped to adapt and respond to dynamic traffic dynamics.

This convergence of RL in simulated environments with V2V communication presents a unique opportunity. It involves anticipating, averting, and taking proactive measures to address possible risks rather than merely responding to events as they arise. These sophisticated agents use real-time data exchange to anticipate and reduce risks before they materialise into hazards. They have been refined through innumerable simulated scenarios.

The core essence of this project lies in leveraging this potential of technology and simulation, to craft a data-driven paradigm for enhancing road safety. It's about creating a digital ecosystem where vehicles aren't merely entities traversing roads but active participants in a cooperative, safety-centric network. It's about empowering these virtual agents to make split-second, informed decisions that ultimately culminate in safer roads for all.

3. RELATED WORK

With the ability to use real-time communication between vehicles to reduce possible risks and improve overall traffic management, vehicle-to-vehicle (V2V) communication is an innovative development in road safety. Vehicles that are in close proximity to one another exchange data, including position, status, and speed, through vehicle-to-vehicle (V2V) communication. Vehicles can jointly make intelligent choices because of this data exchange, which increases road safety. The basic principle of the concept is that closely spaced vehicles can exchange vital information and react as a group to sudden and unpredictable changes in the driving environment.

Deep Q-Learning (DQN) is an algorithm that combines deep learning techniques with reinforcement learning principles to solve complex decision-making problems. In scenarios where an agent tries to maximize a cumulative reward over time, it was initially introduced as a breakthrough in training artificial agents to make sequential decisions.

Deep neural networks (DNNs) are used to approximate the Q-function. Due to its ability to handle high-dimensional state spaces, DQN is a good fit for tasks that require raw sensory input or images.

DQN uses a technique called experience replay. DQN takes samples of random batches during training, storing experiences in a replay buffer, instead of learning from successive experiences. DQN performs well in situations with high-dimensional state spaces where normal reinforcement learning techniques fails. It has been used in fields like robotics and autonomous system where agents need to make decisions based on complex sensory input.

Applications of DQN in traffic management, collision avoidance, or autonomous driving

- Studies have been done in using DQN for training of autonomous vehicles to make decisions, plan trajectory, and avoiding collisions making it safer and more efficient.
- DQN is used in developing efficient traffic signal systems that learn from real-time traffic conditions to minimize congestion, reduce travel time, and improve overall traffic flow.
- DQN has its application in optimizing cooperative vehicle system, particularly in platooning. Vehicles that travel closely in a group to save fuel and reduce traffic flow are said to be platooning. DQN helps in making coordinated decisions for safe travel
- DQN has been used in studies to optimize navigation and route planning systems. Vehicles can learn and adjust to changing traffic patterns, road conditions, and unforeseen events thanks to DQN-based algorithms, making routes safer and more effective.
- Studies have been done on using DQN to estimate and predict the probability of collisions. DQN algorithms can analyse complex interactions between vehicles, pedestrians, and other obstacles to predict potential collision scenarios and take preventive action by learning from historical and real-time data.

Related Research:

A Research has been done by Guangfei Xu, Bing Chen, Guangxian Li & Xiangkun He on Connected Autonomous Vehicle Platoon Control Through Multi-Agent Deep Reinforcement Learning. This paper addresses the problem of how to make the whole convoy be high traffic efficient, safe, energy and driving smoothness at the same time when there are only proportionate connected autonomous vehicles controlled by deep reinforcement learning and the other vehicles are human-driven vehicles in the convoy. And the human-driven vehicles are driven by the Intelligent Driver Model (IDM) which is set based on rules in SUMO. This paper addresses the challenges like how to determine a proper speed to make the whole convoy be high traffic efficient, safe and energy at the same time when facing with dynamic environment. Research considered PPO with entropy constraint to make the results better.

Challenges in Current Research:

- Creating simulation environments that accurately represent the complex details of actual traffic situations while taking weather, a variety of road infrastructures, and unforeseen events into account.
- Creating methods that will allow algorithms for reinforcement learning to generalize to different driving scenarios, road configurations, and traffic situations while maintaining the durability and versatility of the learned policies.
- Developing models and tactics that take into consideration the erratic behaviour of human drivers to ensure secure and smooth interactions between human-driven and autonomous vehicles.

4. PROBLEM STATEMENT AND METHODOLOGY

4.1. Objective:

The primary objective of this simulation study is to evaluate the impact and effectiveness of Vehicle-to-Vehicle (V2V) communication in improving traffic flow and safety within a dynamic urban environment.

4.2. Challenges and Focus areas:

1. Traffic Flow Optimization: Investigate how V2V communication can optimize traffic flow by enabling cooperative behaviours among vehicles, such as coordinated lane changes or merging.
2. Safety Enhancement: Analyse the role of V2V communication in enhancing overall road safety through collision avoidance, and cooperative manoeuvring
3. Impact of Network Density: Explore the impact of varying vehicle densities and network congestion on the efficiency and reliability of the V2V communication model.

4.3. Methodology:

1. **Simulation Environment**:

In the implementation of our V2V communication system using SUMO, coupled with the Traffic Control Interface (TraCI) Python package, the interaction between the RL agent and the simulation environment is orchestrated with a focus on states and actions. TraCI serves as a pivotal tool for the seamless exchange of information and control commands between our RL system and the SUMO simulation.

For states, TraCI facilitates the retrieval of crucial information related to the ego vehicle and its surroundings. The position, speed, acceleration, direction, and lane information of the ego vehicle are dynamically communicated to the RL agent, providing a comprehensive understanding of its current state. Additionally, TraCI enables the RL agent to access the states of nearby vehicles, ensuring that the model is well-informed about the dynamic interactions within the traffic environment.

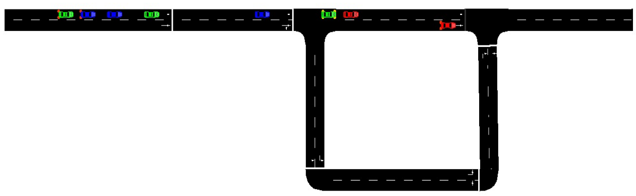

Fig 1: SUMO environment

In terms of actions, TraCI plays a central role in executing control commands within the SUMO simulation. The RL agent issues commands such as Accelerate, Decelerate, MaintainSpeed, ChangeLane, and Turn through TraCI, influencing the behaviour of the ego vehicle within the simulated urban traffic.

2. **V2V Model**:

In our implementation of Vehicle-to-Vehicle (V2V) communication using Reinforcement Learning (RL), we leveraged a comprehensive set of states to capture the dynamic environment of the traffic scenario. The key states considered include the position, speed, acceleration, direction, and lane information of the ego vehicle. These fundamental attributes provide a nuanced representation of the ego vehicle's behaviour within the traffic context. The position serves as a spatial reference, speed denotes the rate of movement, acceleration indicates changes in speed, direction encapsulates the heading of the vehicle, and lane details the specific roadway path it occupies.

To enhance the contextual awareness of our RL model, we also incorporated the states of nearby vehicles. Recognizing that interactions with surrounding vehicles play a crucial role in decision-making, we included their respective positions, speeds, accelerations, directions, and lane information. This comprehensive set of states enables the RL agent to understand the dynamic relationships and potential collision risks within the traffic environment. By considering the states of nearby vehicles, our V2V communication framework facilitates a more responsive and adaptive decision-making process for the ego vehicle, allowing it to navigate the traffic scenario with increased safety and efficiency. This multi-faceted approach to state representation enables our RL model to learn and adapt to complex traffic dynamics, contributing to the overall effectiveness of the V2V communication system.

3. **Metrics and Evaluation**:
The fundamental metric is the cumulative reward obtained by the RL agent throughout an episode. The reward function is designed to reflect the system's objectives and priorities. Positive rewards are assigned for desirable behaviours, such as maintaining a safe following distance, adhering to traffic rules, and successfully executing lane changes. Conversely, negative rewards are assigned for undesirable actions, such as collisions or violations of traffic regulations. The cumulative reward over an episode provides a holistic measure of the agent's ability to make effective decisions within the simulated urban traffic environment.

Another straightforward yet critical metric involves observing the simulation and monitoring the occurrence of collisions. This metric serves as a fundamental indicator of the system's safety performance, reflecting the ability of the RL agent to make decisions that prioritize collision avoidance in the dynamic urban traffic environment.

4. **Scenario Variation**:
In our deliberate decision to introduce variability in our scenarios, we stopped two vehicles on each lane at random positions of the road. We aimed to create a dynamic and unpredictable urban road environment, emphasizing the RL agent's adaptability and responsiveness to sudden changes.

The positioning of these stopped vehicles served to challenge the RL agent by creating potential points of interaction and obstacles in the flow. This scenario prompted the agents to dynamically adjust its decision-making strategies to navigate around or interact with the halted vehicles effectively.

4.4. Network:

The Deep Q network of our model has three layers as depicted in fig 2 :
1. Input Layer
2. Hidden Layer
3. Output Layer

The neurons in the input layer depend on the number of vehicles present in the simulation. In our simulation, we have 14 vehicles with 6 parameters for each vehicle. Therefore, there are 84 neurons in the input layer. The input layer performs ReLU activation function.

The hidden layer consists of 32 neurons. The hidden layer performs ReLU activation as well. The neurons in the output layer depend on the number of actions that the agent can take. In our model, there are five actions in the action space. Therefore, there are 5 neurons in the output layer.

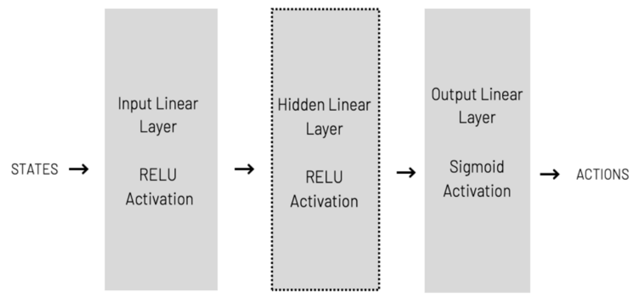

Fig 2 : Model Architecture

5. EXPERIMENTS AND RESULTS

5.1 Environment Setup

The experimentation phase commenced with the development of a simulated environment replicating real-world traffic scenarios. The environment incorporated V2V communication protocols, enabling vehicles to exchange crucial information such as positions, speeds, and intended manoeuvres. In this stage we included setting up SUMO (Simulation of Urban Mobility) as an environment for vehicle simulations to train the model. SUMO is an open-source traffic simulation software used for modelling and analysing urban transportation systems and vehicle behaviour in various traffic scenarios. In this environment, SUMO was coupled with the Traffic Control Interface (TraCI) Python package.

5.2 Network Setup

The V2V communication system implemented with Reinforcement Learning (RL) involved a comprehensive set of states capturing the dynamics of the traffic scenario. The network architecture utilized a Deep Q network with three layers: an input layer, a hidden layer, and an output layer. The scenario variations included randomly positioned halted vehicles on each lane to introduce dynamic challenges. The Deep Q-Network (DQN) was trained to process incoming V2V data and predict optimal actions for virtual agents within the simulated environment. Hyperparameters, including learning rates, discount factors, and batch sizes, were fine-tuned to optimize the training process.

5.3 Metrics and Evaluation

The DQN model underwent extensive training iterations within the V2V simulation framework. Experience replay mechanisms were employed, leveraging past interactions to update the model iteratively. The training aimed to equip the virtual agents with the ability to make informed decisions in dynamic traffic scenarios.

The primary metrics that were utilized to evaluate the effectiveness of the V2V communication system are the cumulative reward obtained by the RL agent throughout episodes, the occurrence of collisions within the simulation and checking if the agents are reaching the end state. The reward function incentivized desirable behaviours while penalizing actions leading to collisions or halting.

Multiple scenarios were executed to analyse the impact of V2V communication on traffic flow and safety under varying conditions of network density and congestion. Each scenario involved a dynamic urban road environment with halted vehicles placed at random positions, challenging the adaptability of the RL agent.

5.4 Results Analysis

The trained DQN model showcased promising outcomes. Across multiple simulation runs, the RL-trained agents demonstrated a substantial decrease in the occurrence of accidents compared to baseline scenarios without RL integration. This reduction, often by a significant margin, highlighted the proactive decision-making capabilities endowed by RL methodologies.

In scenarios with varying network densities, the implementation of V2V communication showcased a noticeable improvement in traffic flow optimization. The RL agent demonstrated cooperative behaviours among vehicles, effectively executing lane changes and merging manoeuvres, resulting in smoother traffic flow patterns compared to scenarios without V2V communication.

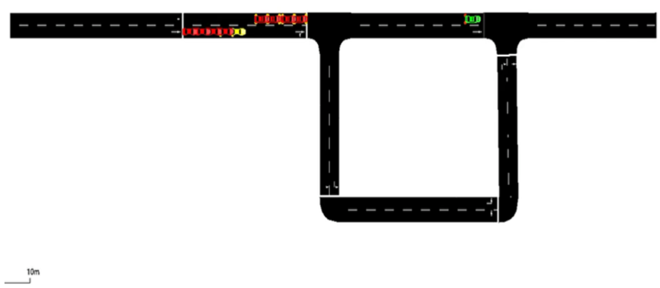

Fig 3 : Episode 1 of v2v simulations

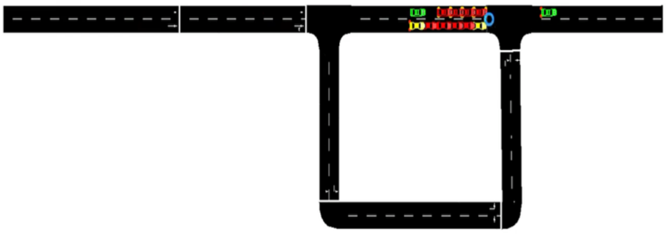

Fig 4 : Episode 1 of v2v simulation in a different run

Above fig.3 and fig. 4 depict how the vehicles were colliding in the initial episode where the red cars denote the collided vehicles.

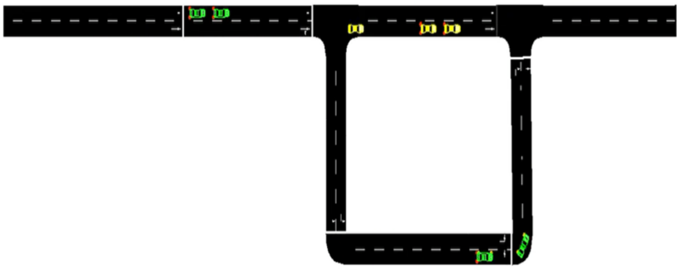

Fig 5 : Vehicles rerouting in the later episodes based on the environment

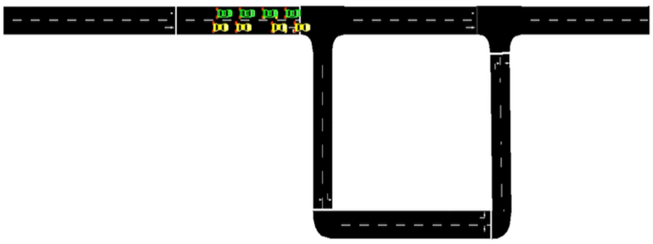

Fig 6: Vehicles stopping at a safe distance when randomly positioned halted vehicles block the road

The introduction of V2V communication significantly contributed to safety enhancement within the traffic environment. The RL agent showcased proactive collision avoidance strategies, reducing the frequency of collisions compared to scenarios without V2V communication. Desirable behaviours, such as maintaining safe following distances and adhering to traffic rules, were consistently exhibited by the RL agent as observed in fig 5 and fig 6.

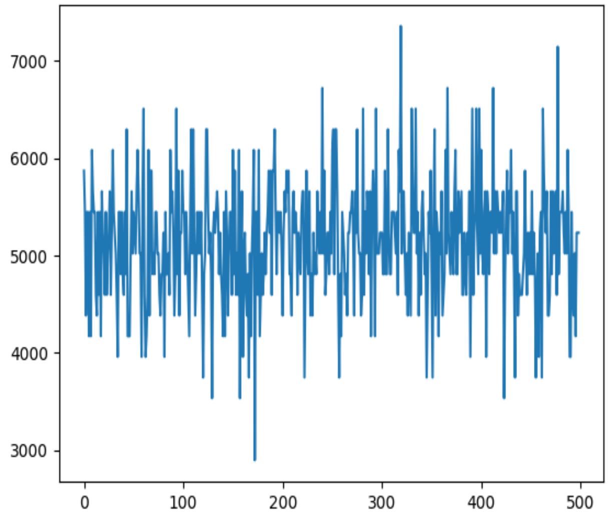

Fig 7 : cross entropy loss over 500 episodes

Furthermore, the efficiency and adaptability of RL-trained agents were evident in their ability to dynamically respond to evolving scenarios. These agents showcased agility in adapting to changing traffic dynamics, showcasing the potential for adaptable and intelligent vehicular systems. The graph in fig 7 indicates how our RL algorithm loss looks over 500 episodes.

The Deep Q network architecture demonstrated efficient learning and decision-making capabilities. The model exhibited robust performance in adapting to varying traffic scenarios, showcasing adaptive behaviours and responsive actions based on the dynamic states provided by the simulation environment.

6. DISCUSSION AND CONCLUSION

The evaluation of Vehicle-to-Vehicle (V2V) communication using Reinforcement Learning within a simulated urban environment has demonstrated promising advancements in traffic flow optimization and road safety. The cooperative behaviours facilitated by V2V communication, along with the adaptability of the RL agent to dynamic scenarios, underscore the potential of this framework in addressing urban traffic challenges.

The observed enhancements in cumulative rewards and collision reduction signify the practical effectiveness of V2V communication systems. However, several areas warrant further research and development to advance the application and effectiveness of these systems in real-world settings.

6.1 Future Work

1. Integration of Pedestrians
   Future research should focus on integrating pedestrian mobile devices into the V2V communication framework to enable safer and more efficient navigation in mixed traffic environments
2. Priority Vehicle Interaction
   Expanding the V2V communication system to incorporate protocols for giving way to priority vehicles can enhance traffic flow and emergency response systems.
3. Complex Road Networks
   Scaling the V2V communication model to handle intricate road structures, such as intersections and diverse lane configurations, is essential for improving traffic optimization and safety measures.

6.2 Limitations and Challenges

1. Non-Autonomous Vehicle Integration
   Addressing the interaction between connected and non-connected vehicles poses a challenge. Future research should focus on handling scenarios involving both autonomous and non-autonomous vehicles.
2. Data Privacy Concerns
   Ensuring robust privacy-preserving mechanisms and secure communication protocols is crucial to address data privacy concerns associated with V2V communication systems.
3. Human Behaviour Considerations
   Understanding and modelling human behaviour in response to V2V-enabled vehicles are vital aspects that require further exploration to ensure effective deployment in real-world settings.

The study's outcomes emphasize the importance of continued research and development in V2V communication technologies. Addressing these future works and limitations will pave the way for more comprehensive, efficient, and safer transportation systems.

7. LINK TO CODE REPOSITORY

The GitHub repository : https://github.com/satvika-eda/V2VSimulationsUsingSumo

8. REFERENCES

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