

A METHOD FOR TIME-EFFICIENT NEGOTIATION FOR AUTONOMOUS DRIVING

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering

By

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**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
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SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

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APRIL - 2024



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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **SHEETHAL S (40111194)** and **SUSHELA R M (40111298)** who carried out the project entitled "**A METHOD FOR TIME-EFFICIENT NEGOTIATION FOR AUTONOMOUS DRIVING**" under my supervision from January 2024 to April 2024.

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ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to **The Board of Management of SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY** for their encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr. T. Sasikala M.E., Ph.D., Dean**, School of Computing and **Dr. L. Lakshmanan M.E., Ph.D., Head of the Department**, Department of Computer Science and Engineering for providing me necessary support during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my Project Guide **Dr. J. Jabez M.E., Ph.D.**, for his valuable guidance, suggestions and constant encouragement paved way for the successful completion of my project work.

I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

ABSTRACT

Autonomous cars are the future smart cars anticipated to be driver less, efficient and crash avoiding ideal urban car of the future. To reach this goal automakers have started working in this area to realize the potential and solve the challenges currently in this area to reach the expected outcome. This work is aimed to develop and deploy automatic negotiation protocols that autonomous cars may use to communicate with one another through unexpected road conditions. This work supports by simulations performed with the well-known robot simulation platform Gazebo. Road traffic may thus be modelled as a multi-robot system with each robot acting as an autonomous car. We'll create a few distinct, unexpected road conditions, such a road with obstructed lines, a crossroads without traffic lights, or completely stopped traffic. The goal of the project is to research negotiation procedures that will allow robots to communicate with one another and clear traffic congestion without human involvement. To assess the efficacy and efficiency of several negotiating methods, we will develop them and put them to use. The idea of road graph, a revolutionary technique we recently presented for modelling roads and traffic, will serve as the foundation for negotiating process. Using the idea of a road graph, we can then discuss numerous aspects of traffic, including traffic flow, traffic-control procedures, vehicle data, and vehicle management techniques. By utilising Gazebo's resources, we can create a variety of road conditions in a 3D model. Robots can move quickly on any of these types of roads. Robot Operating System, a Linux-based system, will form the foundation for robot programming. Python is used. We pick Python because it is easier to use and has more pre-existing libraries. In addition to Gazebo simulations, we can test traffic conditions with only two cars by using our existing TuttleBot robots.

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LIST OF ABBREVIATIONS

ABBREVIATIONS

AV

FCFS

ROS

LiDAR

DRL

EXPANSIONS

Autonomous Vehicle

First Come First Serve

Robot Operating System

Light Detection and Ranging

Deep Reinforcement Learning

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION OF AUTONOMOUS CARS

The development of autonomous driving technology has the potential to completely revolutionize how we commute and transport goods. The use of autonomous vehicles has the potential to increase traffic efficiency, reduce congestion, and improve road safety. The complexity of interaction and negotiation between these various entities must be addressed as we advance toward a day where a mix of human-driven and autonomous cars use our roads. Enabling vehicles to successfully negotiate with one another and with conventional human-driven vehicles is one of the key obstacles for completely fulfilling the potential of autonomous driving. When dealing with complex traffic situations, handling unpredictable road conditions, and maximizing traffic flow without human involvement, cars must communicate and work together in order to negotiate.

The goal of this project "A Method for Time-Efficient Negotiation for Autonomous Driving," is to address this important problem by creating novel strategies and protocols that will allow autonomous vehicles to negotiate on the road efficiently and successfully. The main goal is to develop a framework that enables autonomous cars to reduce traffic jams, improve safety, and maximize the usage of road infrastructure in real-time, ultimately delivering a smooth and effective commuting experience. The project will investigate cutting-edge methods from robotics, distributed systems, and artificial intelligence in order to accomplish these objectives.

These approaches will make it possible for autonomous vehicles to negotiate agreements, make wise choices, and quickly adjust to shifting traffic conditions, all while minimizing disruptions and delays. The idea of decentralized decision-making, in which autonomous cars function as intelligent entities capable of evaluating their environment, anticipating the intentions of other vehicles, and

cooperatively optimizing their routes and behaviors, will serve as the foundation for this research. The project will also make use of sophisticated communication protocols, data sharing frameworks, and machine learning algorithms to enable effective negotiation in challenging mixed-traffic environments.

This project's importance goes beyond just the field of driverless vehicles. Its achievements could herald in a new era of intelligent, self-regulating road networks, having a considerable impact on traffic management, transportation infrastructure, and urban planning. Additionally, this research supports broader sustainability objectives by potentially lowering fuel consumption and greenhouse gas emissions by easing traffic congestion and enhancing traffic flow.

1.2 ROLE OF AI AND MACHINE LEARNING ON AUTONOMOUS CARS

The AI and machine learning algorithms that power autonomous vehicles rely on large amounts of data collected from various sources, such as LiDAR (Light Detection and Ranging) sensors, radar, and GPS. This data is used to build a detailed map of the vehicle's environment and to train the vehicle's algorithms to recognize and respond to different scenarios.

Computer vision technology is used to help autonomous vehicles perceive their surroundings in real-time. Cameras mounted on the vehicle capture images of the road, other vehicles, and pedestrians, which are then analyzed by the vehicle's AI algorithms to identify and track objects and obstacles. Overall, the principles behind autonomous self-driving vehicles involve complex technologies and algorithms that allow them to navigate roads and make decisions in a way that is safe and efficient.

In the realm of autonomous vehicle (AV) technology, efficient and safe transportation systems are paramount. Two fundamental concepts that contribute significantly to achieving these goals are First-Come-First-Serve (FCFS) scheduling and vehicle platooning algorithms. FCFS, a simple yet effective scheduling policy, prioritizes tasks based on their arrival times, ensuring fairness and minimizing wait times. On the other hand, vehicle platooning

algorithms enable a group of vehicles to travel closely together, leveraging cooperative behaviors to enhance traffic flow, safety, and fuel efficiency.

Both FCFS and vehicle platooning algorithms play pivotal roles in shaping the future of transportation systems, offering solutions to various challenges associated with autonomous vehicle deployment and management. This explores the significance of these concepts in the context of AV technology and their implications for creating smarter, more sustainable transportation networks.

In the landscape of autonomous vehicle (AV) technology, optimizing traffic management and resource allocation are crucial for ensuring smooth and efficient transportation networks. First-Come-First-Serve (FCFS) scheduling stands as a foundational principle in task management, ensuring fairness and minimizing latency by prioritizing tasks based on their arrival times.

Complementing FCFS, vehicle platooning algorithms orchestrate groups of AVs to travel in close proximity, capitalizing on coordinated movements to improve traffic flow, reduce congestion, and enhance fuel efficiency. Together, these concepts form the backbone of modern transportation systems, promising a future where AVs navigate seamlessly through urban landscapes, revolutionizing the way we commute and interact with our surroundings.

CHAPTER 2

LITERATURE SURVEY

The main problem raised is the requirement for autonomous vehicles to handle complicated and unexpected social interactions on the road. Despite significant advancements in the technical aspects of driving, autonomous vehicle technology still has work to do when it comes to dealing with situations that call for negotiation, communication, and cooperation between vehicles, such as blocked roads, unsupervised junctions, or traffic jams.

Cooperative automated lane merge with role-based negotiation [1] by Lucas Eiermann; Oliver Sawade; Sebastian Bunk; Gabi Breuel; Ilja Radusch in 2020 proposed that recent years have witnessed significant progress in automated vehicle research, with a focus on enhancing vehicle-to-vehicle communication. Despite impressive advancements, autonomous vehicles still face challenges in executing basic maneuvers like intersections and lane merges, demanding high levels of safety, security, and robustness. Cooperative approaches using wireless communication can address these challenges by improving perception, prediction, and planning. The survey centers on a cooperative automated lane merge function, especially addressing complex on-ramp merge scenarios. The research employs a 3D simulation environment to implement and test the function, evaluating its performance and network load. The study explores tradeoffs in function and network protocol design and sets the stage for further research to advance the capabilities of autonomous vehicles.

Basic research on the driving performance of an autonomous rescue robot with obstacles [2] by N. Suzuki; Y. Yamazaki in 2015 proposed the challenges in Disaster Environments. Disaster areas, especially after earthquakes, present hurdles such as debris, slopes, and stairs. Remote-controlled robots face communication delays. It introduces the use of acceleration sensors to enable robots to autonomously negotiate slopes and stairs. These sensors provide real-time data for immediate adjustments. States that the experimental results demonstrate the effectiveness of acceleration

sensor-based navigation in disaster-stricken areas. Acceleration sensors have the potential to significantly improve the autonomy and effectiveness of search-and-rescue robots, expediting response times and increasing the chances of successful disaster response. Future research may involve further optimization of acceleration sensor use and the development of advanced control algorithms, expanding applications beyond earthquakes.

A Review of Motion Planning for Highway Autonomous Driving [3] by Laurène Claussmann; Marc Revilloud; Dominique Gruyer; Sébastien Glaser in 2020 proposed the Autonomous Vehicle Era. Self-driving vehicles are on the horizon, despite controversies due to recent accidents. Their appeal lies in safer, quicker, more accessible, comfortable, convenient, and eco-friendly transportation. The survey reviews motion planning techniques, specifically in the context of highway driving, where high speed, small curvature roads, and constrained environments are the norm. It addresses lane changes, obstacle avoidance, car following, and merging. It outlines the challenging conditions that define motion planning in highway settings. It explores existing challenges and open research issues, paving the way for future advancements in autonomous highway driving. This paper offers a comprehensive view of motion planning in the context of autonomous highway driving, underlining the promise and challenges of self-driving vehicles in transforming transportation.

Deep Learning for Image and Point Cloud Fusion in Autonomous Driving [4] by Yaodong Cui; Ren Chen; Wenbo Chu; Long Chen; Daxin Tian; Ying Li; Dongpu Cao in 2020 proposed that autonomous vehicles have made rapid progress, but achieving full autonomy in complex, dynamic environments remain challenging. Autonomous vehicles rely on sensor fusion for robust environmental perception, with camera-LiDAR fusion emerging as a key research focus. The lack of critical reviews on deep-learning-based camera-LiDAR fusion methods, covering depth completion, object detection, semantic segmentation, tracking, and online cross-sensor calibration. These methods are compared using publicly available datasets, offering insights into their relative strengths and weaknesses.

Efficient Speed Planning for Autonomous Driving in Dynamic Environment With Interaction Point Model [5] Yingbing Chen; Ren Xin; Jie Cheng; Qingwen Zhang; Xiaodong Mei; Ming Liu; Lujia Wang in 2020 proposed a Safe interaction with other traffic participants is vital for autonomous driving, especially in complex scenarios like intersections and occlusions. Many methods require extensive manual parameter tuning. Used Interaction Point Model (IPM). The survey introduces the IPM, a learning-based model that unifies interaction representation by considering protection time and interaction priority. The IPM is integrated into a novel planning framework, enhancing its practical applicability. Comprehensive simulations in highly dynamic environments validate the IPM's effectiveness and robustness. IPM hold promise for improving safety and reliability in autonomous driving systems, particularly in complex traffic scenarios.

Multi-Input Autonomous Driving Based on Deep Reinforcement Learning with Double Bias Experience Replay [6] by Jianping Cui; Liang Yuan; Li He; Wendong Xiao; Teng Ran; Jianbo Zhang in 2023 proposed a system on achieving both safety and speed in autonomous driving through deep reinforcement learning (DRL) is a formidable challenge. It introduces the Double-Bias Experience Replay (DBER) method, enabling autonomous agents to influence their own learning tendencies, effectively balancing safety and speed. A new loss function is proposed to better balance the relationship between negative and positive losses in training, significantly impacting the learning process. The DBER approach is tested across three prominent DRL algorithms, showcasing its advantages and improved performance compared to existing methods. The DBER approach has the potential to advance the development of autonomous driving technologies by addressing the challenges of safety and speed in DRL.

A Decision Control Method for Autonomous Driving Based on Multi-Task Reinforcement Learning [7] by Yingfeng Cai; Shaoqing Yang; Hai Wang; Chenglong Teng; Long Chen in 2021 proposed the application of multi-task reinforcement learning to enhance autonomous driving. Traditional rule-based

control methods have limitations in complex traffic conditions. The proposed approach divides driving tasks into subtasks, reducing training time and improving efficiency in complex multi-lane traffic. An adaptive noise exploration method ensures agent robustness. Simulation results confirm the approach's effectiveness in autonomous driving control. This method holds potential for improving autonomous driving under challenging traffic scenarios.

An Autonomous Driving System for Unknown Environments Using a Unified Map [8] by Inwook Shim; Jongwon Choi; Seunghak Shin; Tae-Hyun Oh; Unghui Lee; Byungtae Ahn; Dong-Geol Choi; David Hyunchul Shim; In-So Kweon in 2015 proposed Autonomous Vehicle Path Planning. It has many challenges and limitations of traditional map-based approaches. Integration of Unified Maps for efficient collision-free route generation. Real-world deployment and validation in diverse environments. The potential of Unified Maps in shaping the future of autonomous transportation.

An Online Multiobject Tracking Network for Autonomous Driving in Areas Facing Epidemic [9] by Mianzhao Wang; Fan Shi; Meng Zhao; Chen Jia; Weiwei Tian; Tian He; Yu Fu; Xu Cheng in 2022 proposed the Significance of multi-object tracking in autonomous driving and challenges in epidemic-affected areas. The challenges faced are Complex motion blur, frequent occlusions, and appearance deformations in epidemic-affected regions.

TSAEN Approach: Components, including TACM and SAEM, to gather and aggregate appearance cues from previous frames.

TACM: Learning temporal homogeneity features for understanding correlated appearance cues.

SAEM: Adjusting spatial deformations and aggregating features for re-identification embedding learning.

Confirmation of TSAEN's effectiveness in improving multi-object tracking performance in epidemic-affected areas. The importance of addressing multi-object tracking challenges in epidemic-stricken areas and the potential of the TSAEN method.

Improving Efficiency of Autonomous Vehicles by V2V Communication [10] by Changliu Liu, Chung-Wei Lin, Shinichi Shiraishi, Masayoshi Tomizuka in 2018 highlighted the significance of addressing efficiency issues with driverless cars, presents V2V communication as a remedy, and admits the difficulties in putting the plan into practice. In addition to increasing efficiency, the suggested method advances current conversations about the smooth incorporation of autonomous cars into contemporary transportation networks.

2.1 INFERENCES FROM LITERATURE SURVEY

[1] The survey underscores the growing significance of vehicle-to-vehicle communication in autonomous vehicle research. It acknowledges ongoing progress but highlights challenges in basic driving maneuvers. The study focuses on a cooperative lane merge function for on-ramp scenarios, using simulation for testing. Cooperative communication shows promise in addressing these challenges, and future research aims to refine and expand such approaches for safer and more efficient autonomous driving.

[2] Acceleration sensors provide a promising solution for autonomous search-and-rescue robots in disaster scenarios. They enable real-time navigation of challenging terrain, overcoming communication delays. This technology can expedite response times and improve rescue efforts in complex environments. Future research will likely refine this approach and explore broader disaster applications.

[3] Self-driving vehicles are rapidly approaching, despite concerns about recent accidents. Their appeal lies in the transformative potential of safer, quicker, and more efficient transportation. The survey is centered on motion planning for highway driving, addressing specific challenges and algorithms. It serves as a roadmap for future research and development in this field.

[4] The survey explores the dynamic field of autonomous vehicles, focusing on the fusion of camera and LiDAR data using deep learning. It addresses a critical gap in research, providing a comprehensive review of fusion methods for depth

completion, object detection, semantic segmentation, tracking, and online cross-sensor calibration. The evaluation of these methods highlights their relative strengths and weaknesses. Moreover, the survey identifies the gap between academic research and practical applications, offering valuable insights and promising directions for future research in this area.

[5] The survey highlights the critical need for safe interactions in autonomous driving, especially in complex scenarios. Existing approaches often require manual tuning and are scenario-specific. To address this, the survey introduces the Interaction Point Model (IPM), a learning-based approach unifying interaction representation. The IPM is seamlessly integrated into a planning framework, demonstrating its effectiveness through simulations in dynamic environments. This approach has significant potential to enhance the safety and reliability of autonomous driving in complex traffic scenarios.

[6] The survey addresses the challenge of safe and efficient autonomous driving through deep reinforcement learning (DRL). It introduces the innovative Double-Bias Experience Replay (DBER) approach, allowing autonomous agents to influence their learning tendencies, balancing safety and speed. A new loss function is proposed to enhance learning. DBER is tested on three DRL algorithms and consistently outperforms existing methods in a driving simulator, offering higher rewards, faster speeds, reduced lane changes, and more efficient learning within the same training time. This approach has significant potential to advance the development of safer and more efficient autonomous driving technologies.

[7] The survey explores the application of multi-task reinforcement learning to enhance autonomous driving. Traditional rule-based control methods have limitations in complex traffic conditions. The proposed approach divides driving tasks into subtasks, reducing training time and improving efficiency in complex multi-lane traffic. An adaptive noise exploration method ensures agent robustness. Simulation results confirm the approach's effectiveness in autonomous driving control. This method holds potential for improving autonomous driving under challenging traffic scenarios.

[8] The importance of self-driving cars in future transportation systems, the benefits of Unified Maps for collision-free navigation, successful implementation in commercial vehicles, and rigorous validation in diverse environments, indicating their potential to shape the future of autonomous transportation. The study also suggests future research directions to further enhance this technology.

[9] The vital role of multi-object tracking in autonomous driving, especially in epidemic-affected regions like during the COVID-19 pandemic. It introduces the Temporal-Spatial Aggregation Embedding Network (TSAEN) as a solution to address challenges such as motion blur, occlusions, and appearance changes. TSAEN comprises the Temporal-Aware Correlation Module (TACM) and Spatial-Aggregate Embedding Module (SAEM) to improve tracking by integrating appearance cues from previous frames. The survey's experimental results confirm TSAEN's strong overall performance, making it a valuable tool for multi-object tracking, particularly in epidemic-affected areas. Future research directions are also suggested.

[10] The pressing need to address efficiency challenges in autonomous vehicles. The authors propose V2V communication as a crucial solution, emphasizing its potential to enhance efficiency. The acknowledgment of challenges indicates a realistic awareness of implementation hurdles. Importantly, the proposed approach not only addresses efficiency concerns but also actively contributes to the broader discourse on seamlessly integrating autonomous vehicles into contemporary transportation systems. This suggests a holistic perspective that goes beyond individual vehicle efficiency, considering the larger context of transportation infrastructure and technology integration.

2.2 OPEN PROBLEMS IN EXISTING SYSTEM

The challenge is primarily attributed to conflicts of interest between human-driven and cutting-in autonomous vehicles. These conflicts become more severe as traffic density increases. Additionally, current cut-in algorithms for autonomous vehicles face a challenging trade-off between safety and cut-in performance. In

essence, the primary problem is the need to find a solution that can effectively handle these conflicts and optimize the cut-in process while ensuring safety, especially in high-traffic situations.

Lane merging scenarios are particularly problematic for autonomous vehicles due to conflicts of interest between human-driven vehicles and autonomous vehicles attempting to merge into traffic. These conflicts stem from differences in behavior, decision-making, and expectations between human drivers and autonomous systems.

The conflicts mentioned above become more severe as traffic density increases. In high-traffic situations, the challenges and risks associated with lane merging become more pronounced. This is likely due to the need for more frequent and complex maneuvers to navigate safely through traffic.

Current autonomous vehicle cut-in algorithms face a challenging trade-off. On one hand, there is a desire to optimize cut-in performance, ensuring smooth and efficient lane changes. On the other hand, safety is paramount, and compromising safety for the sake of performance is not acceptable. This trade-off makes it difficult to design algorithms that can perform both optimally and safely.

CHAPTER 3

REQUIREMENT ANALYSIS

3.1 RISK ANALYSIS OF THE PROJECT

1. Technical Risks:

There is a chance that the negotiation algorithms won't perform as planned, which could result in poor choices or inefficiencies. Rigorous testing and validation are required for mitigation.

Gazebo, the simulation environment, might not accurately reflect actual conditions, which could produce unreal outcomes. To guarantee the simulation is as precise as feasible, efforts should be done.

2. Safety Risks:

If negotiating protocol testing in real-world circumstances doesn't go as planned, there can be brief traffic jams or accidents. Prior to implementation in the real world, these risks can be reduced by thorough testing in controlled situations.

Safety concerns could arise from interactions between autonomous cars and human-driven vehicles or pedestrians. The negotiating protocols must take this into account.

3. Regulatory and Legal Risks:

Creating and implementing negotiation protocols might include adhering to complicated and ever-changing rules and laws. Involving legal professionals will help ensure compliance.

Liability determination can be difficult in cases of accidents or disputes involving autonomous cars. There should be clear legal frameworks and insurance methods in place.

4. Security Risks:

The vulnerability of autonomous vehicles to cyberattacks. To avoid hostile interference, communication channels and negotiation mechanisms must be secure.

Sensitive information may be used in the negotiation process. To safeguard the information sent between vehicles, privacy threats should be addressed.

5. Adoption and Social Risks:

The general public might be wary of autonomous vehicles, particularly if they think of them as unpredictable or dangerous in social situations. To solve these issues, effective communication and public relations are essential.

Obstacles may arise from opposition from traditional transportation stakeholders or industry. It's crucial to interact with these regulators and stakeholders.

6. Performance and Scalability Risks:

As there are more autonomous vehicles on the road, the negotiation mechanisms should operate effectively. Scalability testing and adaptation of the processes are essential.

Even in instances with heavy traffic, the negotiating system ought to function smoothly. To evaluate performance under varied conditions, stress testing is crucial.

7. Ethical and Moral Risks:

The morality of autonomous cars' decisions in complex social situations may be questioned. Transparency in decision-making and ethical standards are crucial.

8. Budget and Resource Risks:

Due to unforeseen difficulties or delays, the project can cost more than expected. Regular cost monitoring and efficient project management are crucial.

9. Environmental Impact Risks:

Interactions between autonomous cars may have an impact on their energy use and emissions. Optimizing driving habits can help mitigate damage to the environment.

10. External Factors:

The project may be impacted by quick changes in the autonomous car market, technology, or legislation. Being flexible and up to date is essential.

3.2 USE CASE ANALYSIS

In the envisioned autonomous vehicle system, several critical use cases drive the functionality and interactions of the vehicles. One fundamental scenario is vehicle platooning, where autonomous vehicles synchronize their speed and maintain

close distances to each other, thereby reducing aerodynamic drag and improving fuel efficiency. In this use case, vehicles equipped with platooning capabilities detect nearby platoon-enabled vehicles, with a designated leader adjusting speed and trajectory based on traffic conditions. Follower vehicles then emulate these adjustments, ensuring a safe and efficient platoon formation. In case of a vehicle leaving the platoon, nearby vehicles dynamically adapt their speed and position to fill the gap and maintain the integrity of the platoon.

Emergency braking represents another pivotal use case, demonstrating the system's ability to respond to unforeseen obstacles or pedestrian presence. When sensors detect an obstacle or pedestrian in the vehicle's path, the onboard AI system calculates the necessary braking distance and severity of action. The vehicle then initiates emergency braking protocols to avoid collisions, prioritizing the safety of both occupants and pedestrians. In situations where braking alone may not suffice, the vehicle may employ evasive maneuvers to steer clear of potential hazards and ensure a safe outcome.

Autonomous parking is also a crucial use case, showcasing the system's capabilities in navigating to available parking spaces and executing parking maneuvers without human intervention. Utilizing sensor data and mapping information, vehicles scan for suitable parking spots based on size, proximity, and availability. Once a suitable space is identified, the vehicle autonomously navigates to the spot, employing precision maneuvers to align itself within the designated area. In cases where the selected space becomes occupied or inaccessible, the vehicle dynamically reevaluates its options and selects an alternative parking spot to fulfill the parking task efficiently.

Finally, vehicle-to-vehicle communication emerges as a cornerstone use case, enabling seamless information exchange and coordination among autonomous vehicles. Through real-time data sharing regarding speed, location, and traffic conditions, vehicles collaborate to optimize traffic flow, enhance safety, and minimize congestion. In the event of communication disruptions, vehicles rely on onboard sensors and sophisticated AI algorithms to maintain safe distances and make informed decisions, ensuring continued functionality and adaptability in

dynamic traffic environments. These use cases collectively underscore the comprehensive capabilities of autonomous vehicles in revolutionizing transportation by prioritizing safety, efficiency, and convenience in diverse scenarios.

3.3 SOFTWARE REQUIREMENTS SPECIFICATION DOCUMENT

1. Simulation Environment:

Gazebo is a popular robot simulation system. It's necessary for simulating autonomous vehicles' interactions and testing negotiation protocols.

2. Programming Languages:

C++ or Python are the languages that are commonly used for developing software in robotics and autonomous systems. The choice may depend on the specific tools and libraries you plan to use.

3. Robotics Frameworks:

ROS (Robotic Operating System) is widely used in robotics research. It provides a framework for building robotic systems and is compatible with Gazebo.

4. Machine Learning and AI Libraries:

TensorFlow or PyTorch are the libraries that can be used for machine learning aspects of the project, such as training and implementing algorithms for autonomous decision-making.

5. Sensor Simulation:

Depending on the sensors used in the autonomous vehicles, we use software for simulating lidar, radar, and cameras.

6. Communication Protocols:

The software should facilitate communication between autonomous vehicles, allowing them to negotiate. This may involve using standard TCP/IP protocols or ROS for inter-robot communication.

7. Algorithm Development:

Using an IDE like Visual Studio Code, Eclipse, or PyCharm for coding and debugging the negotiation algorithms.

8. Data Visualization:

Matplotlib, Rviz are the tools can be used for visualizing the simulation data and the negotiation processes.

9. Database Management:

If the project requires storing and retrieving negotiation data or historical information, you may need a database system.

10. Simulation Data Management:

Software for recording and analyzing simulation data is crucial for testing and improving negotiation protocols.

11. Security Software:

If the project involves securing communication between autonomous vehicles, consider security libraries for data encryption and protection against cyber threats.

12. Project Management Tools:

Tools like JIRA, Trello, or Microsoft Project can help with project planning, scheduling, and tracking.

13. Documentation Tools:

For creating project documentation and reports, consider using markdown editors like MarkdownPad or Typora.

14. Networking and Communication Tools:

Wireshark or tcpdump are the tools that can help monitor and analyze network traffic and communication between autonomous vehicles.

CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

Research on autonomous vehicles has made remarkable progress in the last decade, offering hope for safer, more convenient, and efficient transportation solutions. Autonomous vehicle systems involve the integration of various technologies, including computer vision, graphical processing, navigation systems, sensor technologies, and more. Recent advancements in machine learning technologies have enabled self-driving cars to learn from millions of driving hours, surpassing the experience of human drivers in handling complex road situations.

Driving isn't just a technical task; it also involves complex social interactions. For example, in situations where two cars meet in a narrow road or on a bridge, decisions need to be made about which car should yield the right of way. These situations require communication and cooperation among vehicles, infrastructures, and authorities. While machine learning has made great strides, research into communication, negotiation, and cooperation among autonomous vehicles is lacking.

The primary goal of the project mentioned in the passage is to design and implement automated negotiation protocols for autonomous vehicles. These protocols would enable vehicles to negotiate with each other when they encounter unexpected road situations, such as blocked roads, uncontrolled junctions, or traffic jams. The research project will utilize simulation using the Gazebo robot simulation system. Each robot in the simulation represents an autonomous vehicle, and the scenarios mimic real-world traffic situations.

The project aims to investigate how these robots can interact and negotiate with each other to resolve traffic issues without external intervention. The project will design and implement various negotiation protocols, and the effectiveness and efficiency of these protocols will be compared.

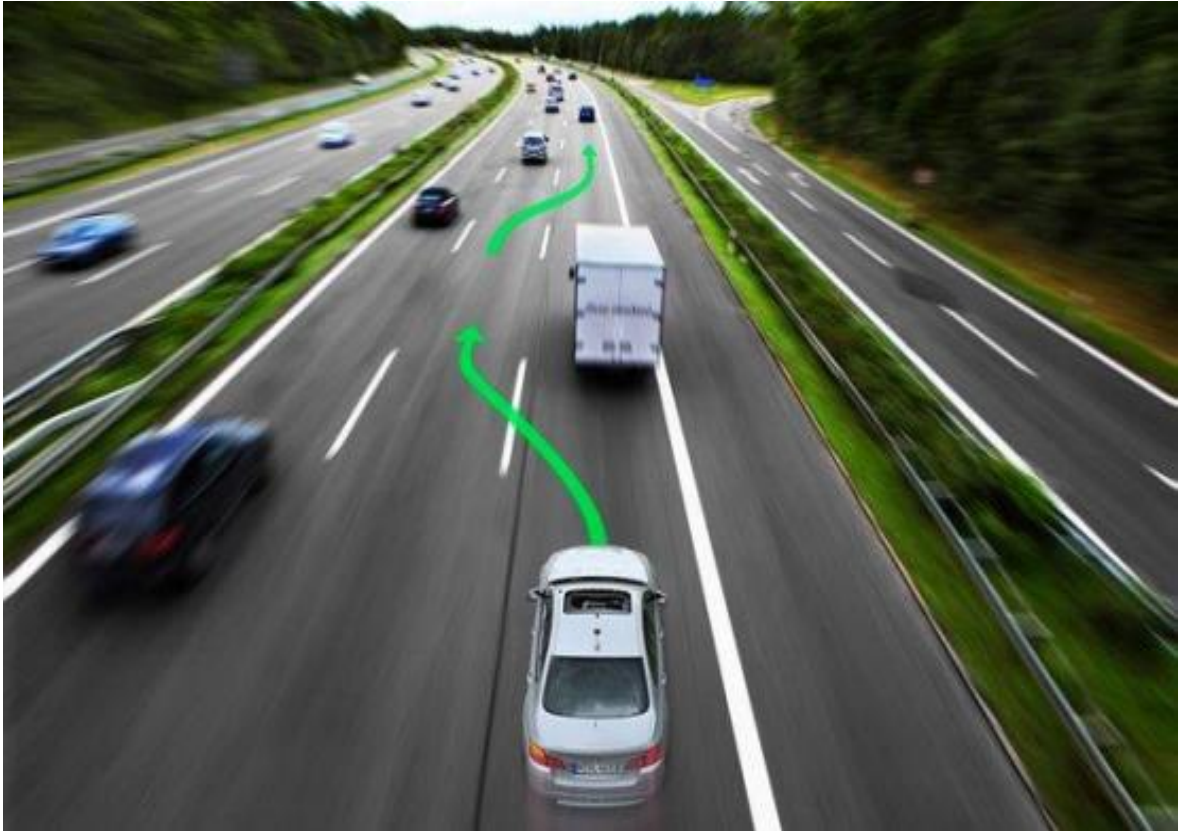


Fig 4.1: A Representation of an Autonomous Vehicle

4.1 PROCESS MODEL

Spiral Model for Autonomous Vehicle Negotiation Protocol Development:

1. Planning:

Develop negotiation protocols for autonomous vehicles. Risks include technological challenges, safety concerns, regulatory compliance, and uncertainties related to social interactions.

2. Risk Analysis:

Focus on risks associated with the effectiveness and safety of negotiation protocols and potential challenges in handling complex social interactions. Plan to address these risks as the project progresses.

3. Requirements and Concept Development:

Define the essential requirements for the negotiation protocols, considering scenarios like blocked roads, uncontrolled junctions, and traffic jams. Create a

conceptual design for the negotiation protocols, outlining how they will address social interactions.

4. Prototype Development:

Develop an initial version of the negotiation protocols that addresses one or more specific social interaction scenarios. Use the prototype to verify its feasibility within the simulation environment (Gazebo).

5. Risk Mitigation and Review:

Assess the prototype's performance and feasibility. Address high-priority risks identified during prototype testing.

6. Design and Development:

Based on feedback from the prototype, improve the architecture and design of the negotiation protocols. Create a more detailed and refined version of the protocols.

7. Testing and Validation:

Test the negotiation protocols in a variety of simulation scenarios, including blocked roads, uncontrolled junctions, and traffic jams. Ensure the protocols effectively handle complex social interactions in a safe and efficient manner.

8. Risk Management:

Continue to analyze risks at each iteration and make necessary adjustments to the risk management plan. Address newly identified risks as the project progresses.

9. Evaluation and Feedback:

Assess the performance of the negotiation protocols based on simulation results and stakeholder feedback. Continuously improve the protocols based on the feedback received.

4.2 ARCHITECTURE / OVERALL DESIGN OF PROPOSED SYSTEM

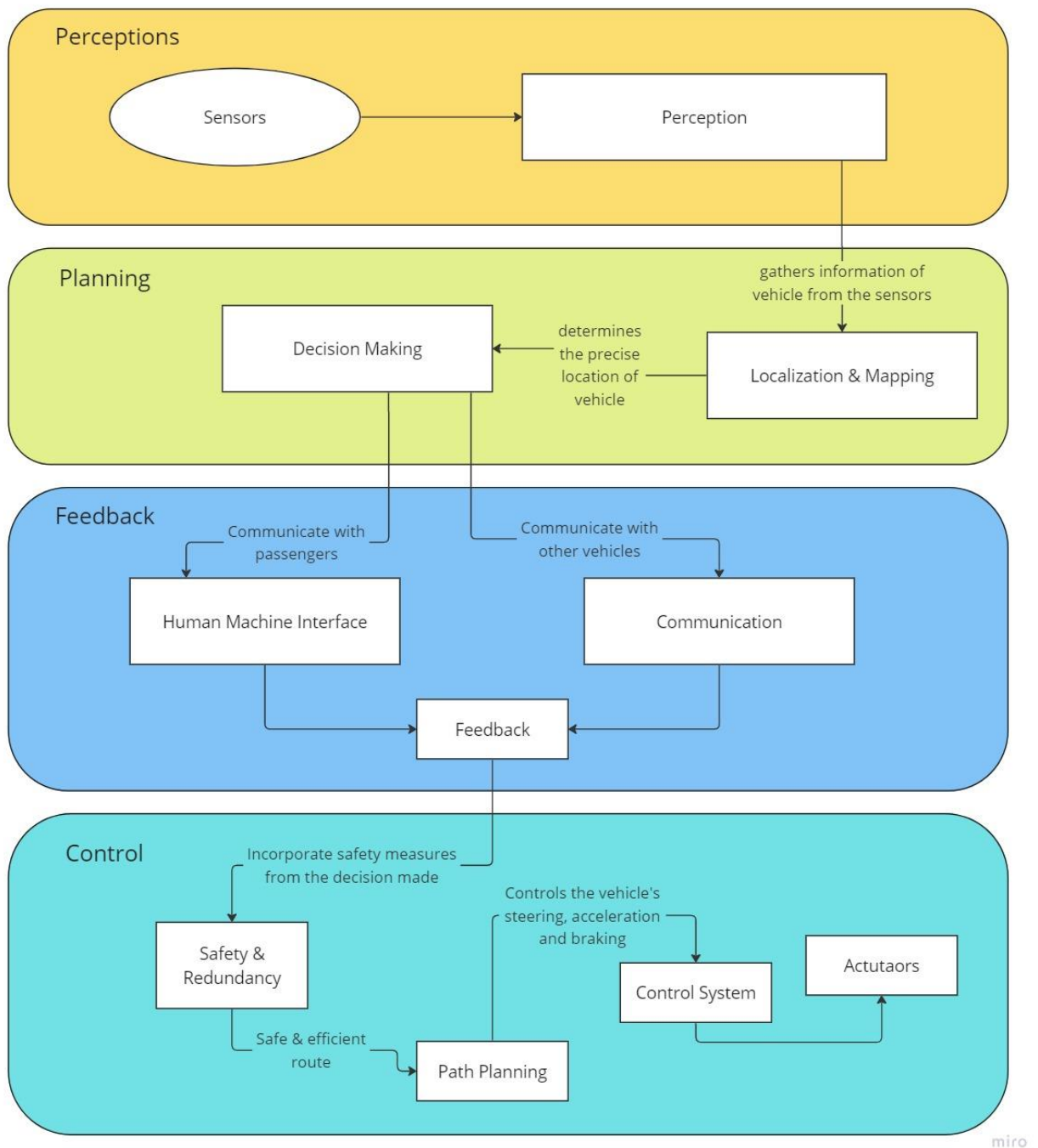


Fig 4.2: System Architecture

The block diagram of the proposed system has been shown in the above figures.

The architecture for "the method of time-efficient autonomous driving" consist of several key blocks or components:

1. Perception System: This block involves sensors (e.g., LiDAR, cameras, radar) that gather information from the vehicle's surroundings to understand the environment,

identify objects, and detect obstacles.

2. Localization and Mapping: This block is responsible for determining the precise location of the vehicle in the environment and creating a high-definition map of the surroundings for navigation.

3. Path Planning: The path planning block generates a safe and efficient route for the autonomous vehicle to follow, taking into account real-time traffic conditions and obstacles.

4. Control System: The control block utilizes the generated path to control the vehicle's steering, acceleration, and braking, ensuring smooth and safe maneuvers.

5. Decision-Making System: This block integrates data from perception, mapping, and path planning to make real-time decisions, such as lane changes, overtaking, and reacting to unexpected situations on the road.

6. Human-Machine Interface (HMI): The HMI block enables communication between the autonomous vehicle and passengers, providing feedback and ensuring passenger safety and comfort.

7. Communication: Autonomous vehicles often need to communicate with other vehicles, infrastructure, and cloud services to share information and enhance overall traffic efficiency.

8. Safety and Redundancy: Incorporating safety measures and redundancy in the architecture is crucial to ensure the vehicle can handle unexpected failures or emergencies.

These blocks work together to create a comprehensive system that enables time-efficient autonomous driving while ensuring safety and reliability. The actual implementation and complexity of each block may vary depending on the specific autonomous driving system and its objectives.

4.3 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION AND TESTING PLAN OF THE PROPOSED MODEL/SYSTEM

4.3.1 Software for Implementation:

1. Robot Simulation Environment (Gazebo):

Use Gazebo to simulate the autonomous vehicles and their interactions in a realistic 3D environment. It allows you to create and model the negotiation scenarios.

2. Robot Operating System (ROS):

ROS provides a framework for developing robotic software. It helps manage robot behavior, hardware integration, and communication between components.

3. Programming Languages:

Utilize languages like C++ and Python for developing the negotiation protocols and related software.

4. Machine Learning Libraries:

If machine learning is part of your negotiation protocols, consider using libraries like TensorFlow or PyTorch for developing and training machine learning models.

5. Simulation Data Management:

Use tools and software for data logging and management. This includes storing data from simulations for analysis and further improvement.

6. Sensor Simulation:

If your autonomous vehicles use lidar, radar, or cameras, you may need sensor simulation tools to replicate their functionality within Gazebo.

7. Networking and Communication Tools:

Implement communication protocols and tools that enable autonomous vehicles to exchange information and negotiate. This includes software for inter-vehicle communication.

8. Security Software:

Ensure that communication and data are secured. Implement security measures and encryption to protect against potential cyber threats.

4.3.2. Testing Plan:

1. Unit Testing:

Begin with unit testing to validate the functionality of individual components of the negotiation protocols, such as decision-making modules and communication systems.

2. Integration Testing:

Test the integration of various modules and components to ensure they work cohesively. This includes the integration of decision-making modules, communication systems, and sensor inputs.

3. Scenario-Based Testing:

Design specific scenarios that replicate real-world situations, such as blocked roads, uncontrolled junctions, or traffic jams. Test the negotiation protocols in these scenarios to assess their effectiveness.

4. Stress Testing:

Evaluate how the negotiation protocols perform under extreme conditions, such as high traffic volumes or complex scenarios involving multiple autonomous vehicles.

5. Security and Resilience Testing:

Test the security measures in place to protect against cyber threats. Verify the resilience of the negotiation protocols to malicious attacks or interference.

6. Scalability Testing:

Assess how well the negotiation protocols scale as the number of autonomous vehicles in the simulation environment increases. This helps ensure they work efficiently in various traffic conditions.

7. Regulatory Compliance Testing:

Verify that the negotiation protocols adhere to relevant regulations and standards in the autonomous vehicle industry. Ensure compliance with safety and ethical guidelines.

8. Human Interaction Testing:

Simulate interactions between autonomous vehicles and human-driven vehicles or pedestrians to assess safety and effective communication.

9. Data Analysis and Evaluation:

Analyze the data collected during simulations to evaluate the negotiation protocols' performance, efficiency, and safety. Identify areas for improvement.

10. Feedback and Iteration:

Based on testing results and feedback, iterate on the negotiation protocols, making necessary adjustments to enhance their effectiveness and safety.

11. Documentation and Reporting:

Document the testing process, results, and any modifications made to the negotiation protocols. Maintain comprehensive records for future reference and reporting.

12. Peer Review and Validation:

Subject the negotiation protocols and research findings to peer review within the research and autonomous vehicle community to validate their effectiveness and contributions to the field.

13. Publication and Dissemination:

Share research findings and testing outcomes through publications and presentations at conferences to contribute to the body of research in the field.

This testing plan ensures that the negotiation protocols are thoroughly evaluated

for their effectiveness, safety, and compliance with industry standards and regulations. It also allows for continuous improvement as the project progresses.

4.4 PROJECT MANAGEMENT PLAN

1. Project Initiation:

The primary goal is to design and implement automated negotiation protocols for autonomous vehicles to handle complex social interactions and unexpected road situations. Assemble a multidisciplinary team, including researchers, simulation experts, software developers, and domain experts, to collaborate on the project.

2. Scope Definition:

The project focuses on developing negotiation protocols for handling complex social interactions among autonomous vehicles. Expected deliverables include the negotiation protocols, simulation scenarios, research reports, and any software tools developed.

3. Risk Assessment and Management:

Identify potential risks, including technological challenges, safety concerns, regulatory compliance, and uncertainties in social interactions. Prioritize risks based on their impact and likelihood, with a focus on safety and effectiveness. Develop strategies to mitigate and manage high-priority risks, especially those related to safety and regulatory compliance.

4. Software and Tool Selection:

Utilize a suitable robot simulation environment, such as Gazebo, to model autonomous vehicle interactions. Choose programming languages and tools for developing the negotiation protocols and related software. If machine learning is involved, select appropriate frameworks for model development.

5. Software Development:

Develop initial prototypes of the negotiation protocols and test their functionality. Integrate the protocols with the simulation environment and other components. Implement unit and integration testing to ensure software reliability and

effectiveness.

6. Scenario Design and Simulation:

Design specific simulation scenarios that mirror real-world situations, such as blocked roads, uncontrolled junctions, and traffic jams. Conduct tests within these scenarios to evaluate the negotiation protocols' performance and effectiveness.

7. Data Management and Analysis:

Set up data logging tools to capture simulation data. Analyze simulation results to evaluate protocol performance, identify areas for improvement, and meet safety and compliance standards.

8. Quality Assurance and Compliance:

Implement quality assurance procedures to ensure that negotiation protocols meet desired standards for safety and effectiveness. Ensure that the project complies with ethical guidelines, data privacy regulations, and any legal requirements related to autonomous vehicle testing.

9. Continuous Improvement and Iteration:

Establish a continuous improvement process that allows for adjustments to the negotiation protocols and other project components based on insights and feedback.

4.5 TRANSITION / SOFTWARE TO OPERATIONS PLAN

1. Transition Phase:

Preparing the automated negotiation protocols and associated software for operational use.

2. System Deployment:

Deploying the negotiation protocols in a production environment suitable for autonomous vehicle testing, ensuring access to appropriate simulation and testing resources. Ensuring the necessary hardware, including autonomous vehicles and communication infrastructure, is in place to support operational use.

3. Configuration and Calibration:

Configuring the negotiation protocols to adapt to real-world operational conditions, considering factors like vehicle types and infrastructure. Fine-tuning the negotiation protocols to optimize performance, safety, and compliance in real-world scenarios.

4. Testing and Validation:

Conducting extensive testing in operational scenarios to validate the performance and safety of the negotiation protocols, with a focus on scenarios like blocked roads, uncontrolled junctions, and traffic jams. Ensuring that the protocols comply with safety standards and regulatory requirements for autonomous vehicles.

5. Monitoring and Control:

Implementing real-time monitoring of the negotiation protocols and autonomous vehicles to detect and respond to operational issues promptly. Developing control mechanisms to intervene when necessary for safety and compliance, including protocols for vehicle interactions and decision-making.

6. Data Handling and Analysis:

Setting up data management procedures to handle operational data efficiently and securely, ensuring data privacy and integrity. Continue data analysis for ongoing performance evaluation and improvement of the negotiation protocols.

7. Maintenance and Updates:

Establishing a maintenance schedule to address software updates, hardware maintenance, and configuration changes. Implementing version control to track changes to the negotiation protocols and ensure backward compatibility.

8. Incident Response:

Develop an incident response plan to handle unexpected events, accidents, system failures, and potential cyber threats.

9. Reporting and Documentation:

Regular reporting on the operational performance of the negotiation protocols, including safety and efficiency metrics. Comprehensive documentation on operational procedures, configurations, and updates for compliance and transparency.

10. Continuous Improvement:

Establishing a feedback mechanism to collect user and operator feedback for continuous improvement of the negotiation protocols and operational processes. Using insights from operational use to make iterative updates to the protocols to enhance safety and efficiency.

11. Security Measures:

Implementing security measures to protect the system from potential cyber threats and unauthorized access, safeguarding sensitive operational data. Ensuring data privacy measures are in place to protect the privacy of autonomous vehicle users and sensitive information.

12. Scalability and Adaptability:

Planning for the system to accommodate a growing number of autonomous vehicles and increasing complexity of road situations. Being prepared to adapt to evolving technologies and regulations as the autonomous vehicle landscape evolves.

13. End-of-Life Planning:

Develop a strategy for the eventual retirement or replacement of the negotiation protocols, considering technological advancements and changing needs in the field of autonomous vehicles.

4.6 SIMULATION RULES FOR AUTONOMOUS VEHICLE INTERACTION

1. State Management: The vehicles maintain different states (e.g., MOVING, ENTER_INTERSECTION, PASS_INTERSECTION, STOP) based on their current actions and environmental conditions. These states dictate the vehicle's behavior

and interactions with other vehicles.

2. Collision Avoidance: Vehicles incorporate collision avoidance mechanisms to prevent accidents and maintain safe distances from obstacles and other vehicles. They adjust their speed and trajectory dynamically to avoid collisions.

3. Negotiation Protocols: Vehicles use negotiation protocols to interact with each other when encountering unexpected road situations or conflicts, such as entering intersections or passing through narrow passages. Negotiation involves communication, decision-making, and coordination among vehicles to resolve conflicts and ensure smooth traffic flow.

4. Priority Handling: Certain vehicles may have priority over others based on predefined rules or negotiation outcomes. For example, vehicles already within an intersection might have the right of way over approaching vehicles.

5. Communication: Vehicles communicate with each other using standardized protocols to exchange information about their current state, intentions, and negotiation proposals. Communication facilitates cooperative decision-making and coordination among vehicles.

6. Dynamic Path Planning: Vehicles employ dynamic path planning algorithms to generate optimal trajectories while considering factors such as traffic conditions, negotiation agreements, and safety constraints. Path planning aims to minimize travel time and optimize route efficiency.

7. Speed and Trajectory Control: Vehicles control their speed and trajectory based on negotiation outcomes, traffic conditions, and safety considerations. Smooth acceleration and deceleration profiles are enforced to ensure passenger comfort and traffic efficiency.

8. Fallback Strategies: Vehicles have fallback strategies in place to handle communication failures or unforeseen events. These strategies include default

behavior presets or predefined safety maneuvers to prevent accidents and maintain safe operation.

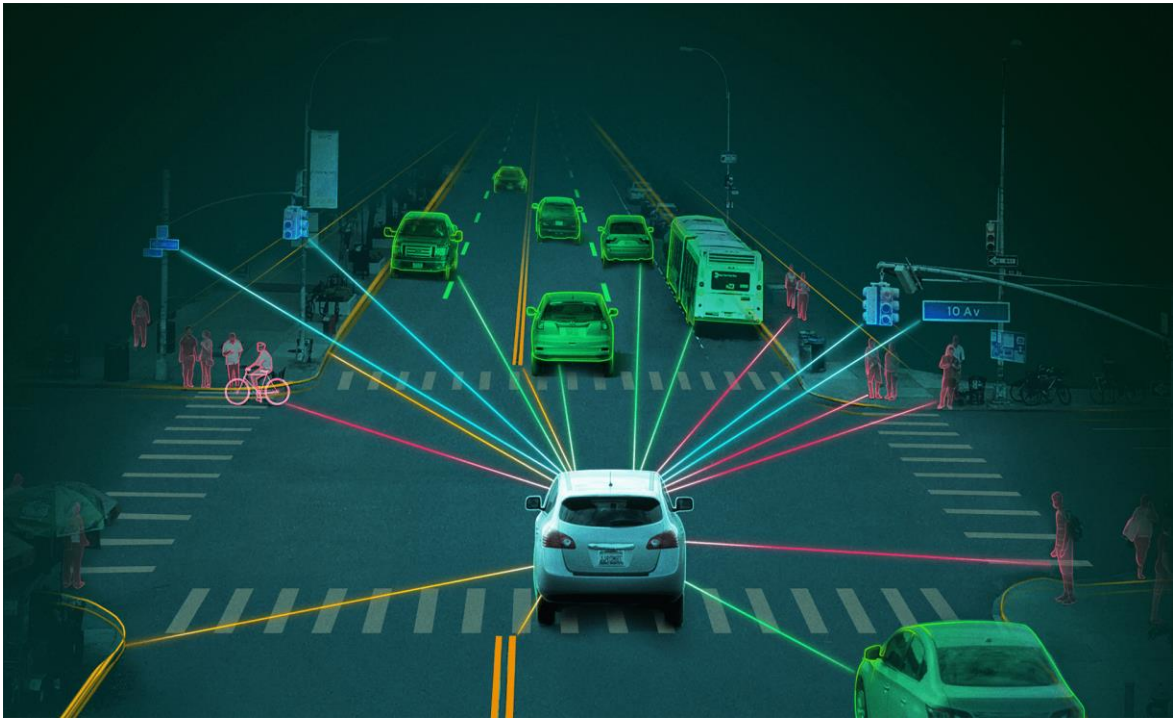


Fig 4.3: Bibliometric View of Autonomous Driving

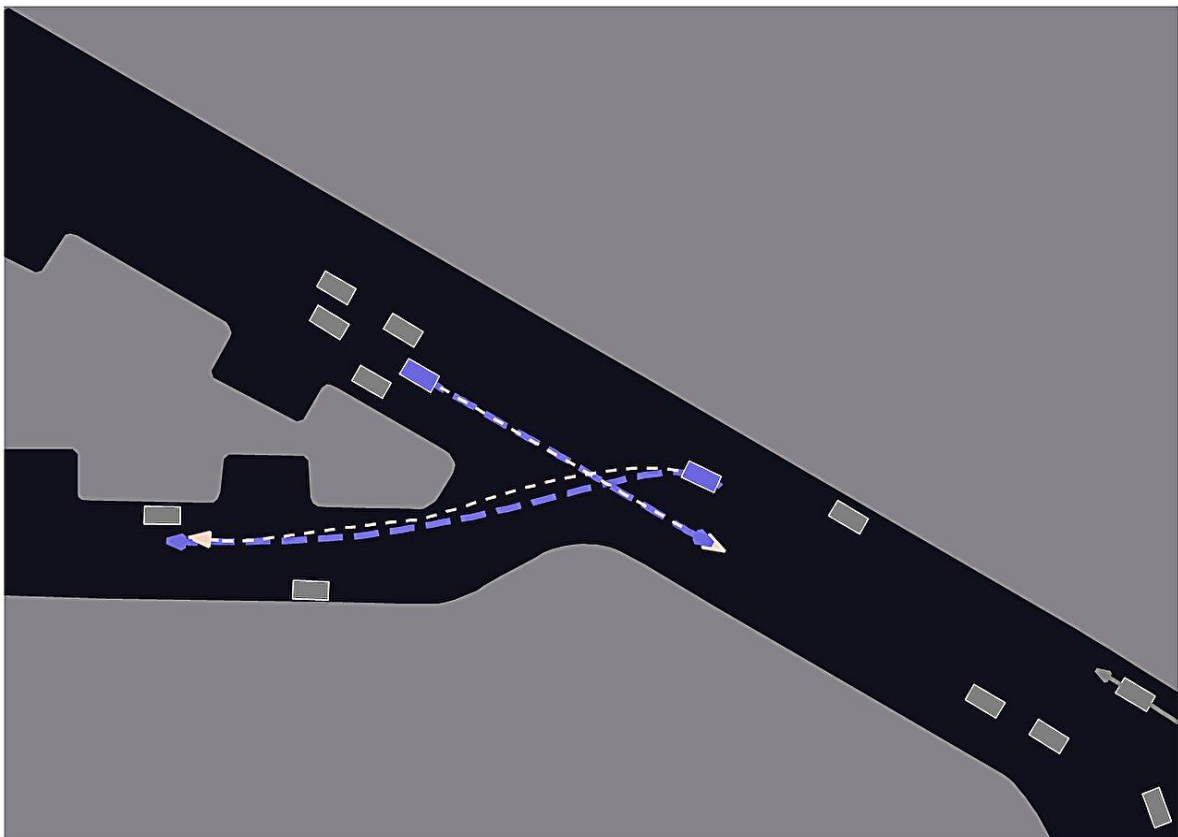


Fig 4.4: Predictive Accuracy of Autonomous Driving

CHAPTER 5

IMPLEMENTATION DETAILS

5.1 ALGORITHMS

In this project, we employ two fundamental algorithms to enhance the efficiency and effectiveness of autonomous vehicle systems:

First Come, First Served (FCFS) and Vehicle Platooning. FCFS, a straightforward scheduling algorithm, prioritizes tasks based on their arrival time. When applied to autonomous vehicles, FCFS manages queues of vehicles approaching intersections or navigating through traffic, assigning priority based on arrival time or position in the queue. This ensures fairness and minimizes wait times by processing vehicles in the order they arrive, optimizing traffic flow.

On the other hand, vehicle platooning involves a cooperative driving strategy where multiple vehicles travel closely together in a convoy-like formation. Controlled by a lead vehicle or a centralized system, platooning offers benefits such as reduced aerodynamic drag, improved fuel efficiency, and increased safety through synchronized movements and braking. By integrating FCFS for intersection management and vehicle platooning for traffic coordination, the project aims to enhance safety, efficiency, and sustainability in urban autonomous vehicle operations. These algorithms play vital roles in optimizing vehicle movements, reducing congestion, and facilitating smooth interactions among autonomous vehicles and other road users, ultimately improving the overall transportation experience.

5.2 IMPLEMENTATION OF SENSORS

The implementation of sensors in autonomous vehicles is crucial for gathering real-time data about the vehicle's surroundings, enabling it to perceive and navigate its environment safely and effectively. Various types of sensors are integrated into the vehicle's hardware and software systems to provide comprehensive environmental awareness. These sensors typically include:

1. LiDAR (Light Detection and Ranging): LiDAR sensors emit laser pulses and measure the time it takes for the light to bounce back, creating a 3D map of the vehicle's surroundings. This high-resolution mapping allows the vehicle to detect obstacles, pedestrians, and other vehicles with precision.

2. Radar: Radar sensors use radio waves to detect objects in the vehicle's vicinity. They are particularly useful for detecting moving objects and assessing their speed and trajectory, enhancing the vehicle's ability to anticipate and respond to dynamic traffic conditions.

3. Cameras: Vision-based cameras capture images and videos of the vehicle's surroundings, providing visual data for object recognition, lane detection, traffic sign recognition, and pedestrian detection. Deep learning algorithms analyze the camera feeds to identify and classify objects in the environment.

4. Ultrasonic Sensors: Ultrasonic sensors emit high-frequency sound waves and measure the time it takes for the waves to bounce back, enabling the vehicle to detect nearby objects and obstacles, especially at close range. Ultrasonic sensors are commonly used for parking assistance and obstacle detection at low speeds.

5. GPS (Global Positioning System): GPS receivers provide accurate positioning and navigation information to the vehicle, enabling it to determine its location, plan routes, and navigate to predefined destinations. GPS data is integrated with other sensor inputs to ensure precise localization and navigation.

6. IMU (Inertial Measurement Unit): IMU sensors measure the vehicle's acceleration, angular velocity, and orientation relative to the Earth's frame of reference. By tracking the vehicle's motion and orientation in real-time, IMU sensors contribute to navigation, motion planning, and stabilization.

7. Environmental Sensors: Environmental sensors measure various environmental factors such as temperature, humidity, air quality, and road surface conditions. These sensors provide valuable information for adaptive control systems, predictive maintenance, and optimizing vehicle performance in different

weather and road conditions.

The integration and fusion of these sensor technologies enable autonomous vehicles to perceive and interpret their surroundings accurately, make informed decisions in real-time, and navigate safely and efficiently in diverse driving environments. Advanced sensor fusion algorithms combine data from multiple sensors to enhance perception reliability, reduce sensor noise, and mitigate environmental uncertainties, ensuring robust and resilient autonomous driving capabilities.

5.3 TESTING METHODOLOGIES

Testing methodologies such as white-box testing and black-box testing are essential components of the testing process for autonomous vehicles (AVs). These methodologies help ensure the reliability, functionality, and safety of AVs by systematically evaluating their software and hardware components. Here's how white-box and black-box testing are applied in the context of AV development:

1. White-Box Testing:

White-box testing, also known as structural testing or code-based testing, involves examining the internal structure and logic of the software code to validate its correctness. In the context of AVs, white-box testing focuses on verifying the functionality of individual software modules, algorithms, and subsystems that govern the vehicle's behavior. Key aspects of white-box testing for AVs include:

- **Code Coverage:** Assessing the extent to which the code has been executed during testing, including statement coverage, branch coverage, and path coverage metrics.
- **Control Flow Analysis:** Analyzing the flow of control within the software code to identify potential execution paths, loops, and decision points.
- **Data Flow Analysis:** Evaluating the flow of data through the software modules to detect data dependencies, variable assignments, and data manipulation operations.
- **Static Analysis:** Using automated tools to analyze the source code statically for potential defects, vulnerabilities, and coding errors without executing the code.

2. Black-Box Testing:

Black-box testing, also known as functional testing or specification-based testing, focuses on validating the behavior of the AV system based on its external inputs and outputs, without examining the internal implementation details. Black-box testing simulates real-world scenarios and user interactions to assess the system's functionality, performance, and usability. Key aspects of black-box testing for AVs include:

- **Functional Testing:** Verifying that the AV system behaves according to its specified functional requirements, including navigation, object detection, decision-making, and vehicle control.
- **Scenario-based Testing:** Designing test scenarios that represent typical driving situations, edge cases, and failure modes to evaluate the system's responses and performance under various conditions.
- **Simulation Testing:** Using virtual environments and simulators to replicate real-world driving scenarios and assess the AV's behavior, sensor fusion, decision-making algorithms, and interaction with other road users.
- **User Experience Testing:** Evaluating the user interface, human-machine interaction, voice commands, feedback mechanisms, and overall user experience to ensure usability, comfort, and safety for passengers and operators.

By combining white-box and black-box testing methodologies, AV developers can comprehensively evaluate the functionality, safety, and performance of autonomous vehicles, addressing both internal logic and external behavior to deliver reliable and robust AV systems for deployment on public roads.

CHAPTER 6

RESULTS AND DISCUSSIONS

The project creates automated negotiating methods for autonomous vehicle communication under unforeseen road situations, improving traffic flow without the need for human intervention. The simulation-based experimentation tool Gazebo is used to mimic road traffic as a multi-robot system. The suggested protocols successfully allow autonomous vehicles to work together, which eases traffic. Testing in the real world using TurtleBot robots verifies practical applicability. The research provides insights into cooperative communication and cutting-edge modelling tools for traffic management, advancing autonomous driving technology and smart urban mobility. Overall, it opens the door for more effective and safe driverless urban vehicles.

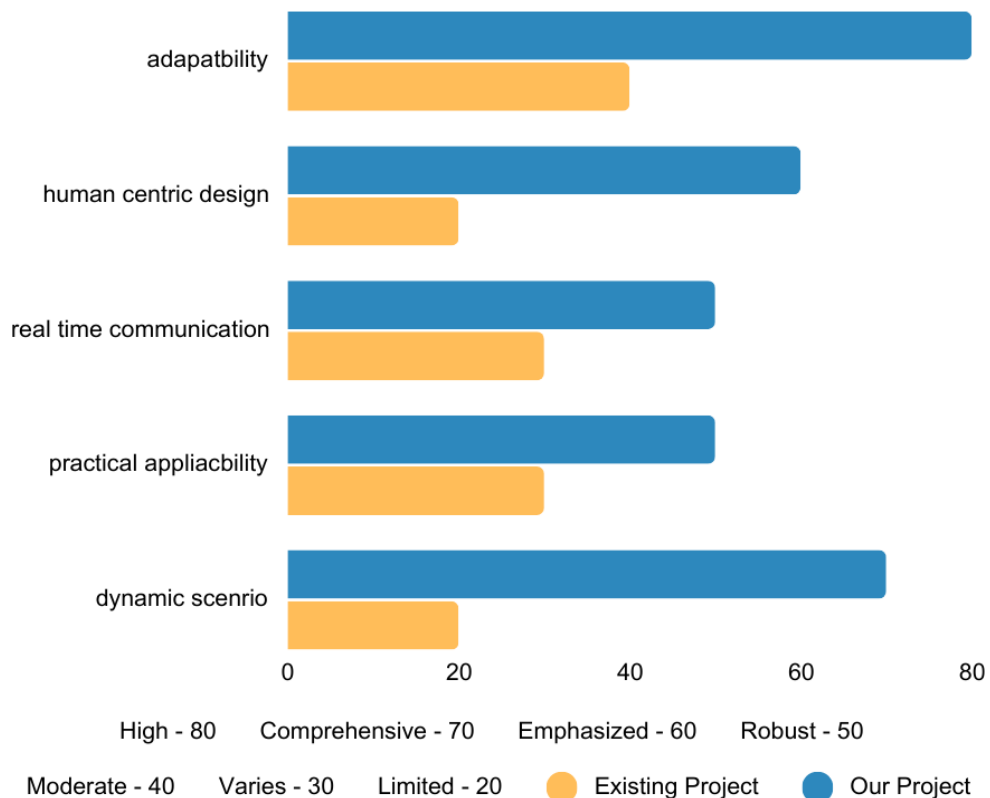


Fig 5.1: Urban Traffic Control Using Autonomous Systems

CHAPTER 7

CONCLUSION

Our research project has reshaped the field of adaptive urban traffic management in addition to pushing the boundaries of autonomous vehicle negotiation. Our research has successfully tackled issues that have never been investigated before by using a comprehensive paradigm that goes beyond traditional algorithmic advancements. By combining state-of-the-art sensing technologies, human-centered design concepts, dynamic scenario modeling, and reliable communication protocols, our system stands out as a trailblazer that goes beyond what is possible with current technologies. Our solution provides a complete and nuanced approach by embracing interdisciplinary collaboration, taking into account many viewpoints and demonstrating its effectiveness in real-world situations. Our project is at the forefront of innovation due to its proven practical application and viability, which are supported by dynamic simulations, comprehensive traffic modeling, real-world testing, and user-friendly programming. The initiative represents an evolutionary shift as well as a technology advance, setting the stage for autonomous car negotiating systems that are cooperative, flexible, and extensively used in the future to completely alter the dynamics of urban transportation.

7.1 FUTURE WORKS

Future work for the project could focus on several key areas to further enhance the effectiveness and scalability of the proposed system. Firstly, refining negotiation protocols used by autonomous vehicles could ensure efficient decision-making and coordination in complex traffic scenarios. Exploring adaptive algorithms that dynamically adjust negotiation strategies based on real-time traffic conditions and environmental factors could optimize system performance. Leveraging high-resolution sensor data could improve decision-making accuracy and enable better anticipation of potential hazards or obstacles on the road.

Another crucial aspect of future work involves scalability and robustness testing to evaluate system performance under varying traffic densities, network conditions,

and environmental factors. Conducting comprehensive tests to validate the system's ability to handle large-scale deployments and ensure robustness against cyberattacks or communication disruptions is essential. Furthermore, transitioning from simulation-based testing to real-world deployment in controlled environments could provide valuable insights and empirical data. Gathering feedback from real-world scenarios and validating system effectiveness and safety in practical driving conditions would be pivotal for advancing the project's objectives and contributing to the development of autonomous vehicle technology.

7.2 RESEARCH AND IMPLEMENTATION ISSUES

Research and implementation of negotiation protocols for autonomous vehicles present several challenges and considerations. Firstly, developing effective negotiation algorithms requires a deep understanding of human driving behavior, traffic regulations, and social norms. Incorporating these elements into autonomous vehicle decision-making processes is complex and may require interdisciplinary research involving psychology, sociology, and transportation engineering.

Furthermore, ensuring interoperability and compatibility between different autonomous vehicle systems is essential for seamless communication and negotiation on the road. Standardization efforts and protocols for communication and data exchange need to be established to facilitate collaboration among vehicles from different manufacturers.

Another challenge is the real-time nature of negotiation and decision-making in dynamic traffic environments. Autonomous vehicles must process large volumes of sensor data, assess various negotiation options, and make decisions rapidly to ensure safe and efficient navigation. This necessitates the development of efficient algorithms and computational techniques for real-time decision-making.

Moreover, the deployment of negotiation protocols in real-world settings requires rigorous testing and validation to assess their effectiveness, safety, and scalability. Conducting extensive simulation-based testing and validation in controlled

environments is essential before transitioning to real-world deployments. Additionally, addressing privacy and security concerns related to vehicle-to-vehicle communication and data exchange is crucial to prevent potential cyber threats and ensure user trust and acceptance.

Overall, addressing these research and implementation challenges is critical for the successful development and deployment of negotiation protocols for autonomous vehicles, ultimately contributing to safer and more efficient transportation systems.

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APPENDIX

A. SOURCE CODE

```
#!/usr/bin/env python
import rospy
from geometry_msgs.msg import Point, Quaternion, Twist
from std_msgs.msg import Int32, String
from nav_msgs.msg import Odometry
import ActionType as types
from rocon_std_msgs.msg._StringArray import StringArray
from Directed_Graph import *

class IntersectionAgent:
    def __init__(self, total_robots):
        rospy.init_node('centercontrol', anonymous=True, disable_signals=True)
        self.total_robots = total_robots

        # we can have a function to calculate these value
        self.add_to_queue_distance = 4.0
        self.collision_region = 1.0
        self.safe_region = 0.5

        # initialize attribute related to vehicles
        self.pos_x = [0.0] * self.total_robots
        self.pos_y = [0.0] * self.total_robots
        # self.pos_z = [0.0] * self.total_robots
        self.direction = [''] * self.total_robots
        self.command = [None] * self.total_robots
        self.position = [None] * self.total_robots
        self.received_state = [None] * self.total_robots
        self.odom = [None] * self.total_robots
        self.cmd_vel = [None] * self.total_robots
```

```

# init centralize
rospy.loginfo('Center Control Available')
self.rate = rospy.Rate(10)
self.online = rospy.Publisher('online', String, queue_size=100)
online_str = "Hello everyone, the Center Control Server is online."
self.online.publish(online_str)

self.ready = rospy.Publisher('ready', String, queue_size=100)
self.ready.publish(types.NOT_READY)

self.total = rospy.Publisher('total_direction', StringArray, queue_size=15)

self.vertices = []
self.directed_graph = Graph()

# position and speed of robots
for i in range(self.total_robots):
    self.odom[i] = rospy.Subscriber('/tb3_' + str(i) + '/odom', Odometry,
self.callback_odom, (i))
    self.position[i] = rospy.wait_for_message('/tb3_' + str(i) + '/direction', String)
    self.direction[i] = self.position[i].data
    self.command[i] = rospy.Publisher('tb3_' + str(i) + '_command', String,
queue_size=15)
    self.received_state[i] = rospy.Subscriber('tb3_' + str(i) + '/self_command',
String, self.callback_state, (i))
    self.vertices.append(i)

for i in self.vertices:
    self.directed_graph.add_vertex(Vertex(i))

# store current distance
self.current_dist = [0.0] * self.total_robots

```

```

# check whether added to queue or not
self.added_to_queue = [False] * self.total_robots
self.added_to_graph = [False] * len(self.vertices)

# active queue represent the priority order
self.active_queue = []

output_file =
open("../catkin_ws/src/turtlebot3_simulations/turtlebot3_gazebo/info.txt", "w+")

self.ready.publish(types.READY)

# represent the state of centralize model (init state is moving for all robots)
self.state = [types.MOVING] * self.total_robots
print(self.direction)

while not rospy.is_shutdown():
    self.total.publish(self.direction)
    for i in range(self.total_robots):
        # get the current distance to target
        self.current_dist[i] = self.pos_x[i] if self.direction[i] == types.DIR_LEFT or
self.direction[i] == types.DIR_RIGHT else self.pos_y[i]

        print("Robot {}: {} with {}".format(i, abs(self.current_dist[i]),
self.direction[i]))

        # if a robot is just outside collision region -> add to queue
        if abs(self.current_dist[i]) <= self.add_to_queue_distance and not
self.added_to_queue[i] and self.current_dist[i] != 0:
            self.added_to_queue[i] = True
            # active queue will hold the id of robots which serve FCFS
            self.active_queue.append(i)
    print(self.active_queue)

```

```

# handle queue
if self.active_queue:
    if abs(self.current_dist[self.active_queue[0]]) <= (self.collision_region +
0.05):

        self.state[self.active_queue[0]] = types.ENTER_INTERSECTION
        if self.added_to_graph[self.active_queue[0]] == False:
            self.added_to_graph[self.active_queue[0]] = True
            for i in self.vertices:
                if i != self.active_queue[0]:

self.directed_graph.add_edges(self.vertices[self.vertices.index(self.active_queue[0
]]), i)

                self.vertices.pop(self.vertices.index(self.active_queue[0]))
                output_file.write(self.directed_graph.print_graph() + '\n')

            if len(self.vertices) == 0:
                output_file.close()

        if self.active_queue[1:]:
            for i in self.active_queue[1:]:
                if abs(self.current_dist[i]) <= self.collision_region:
                    self.state[i] = types.STOP

# check if the first vehicle from the queue has passed the threshold yet
self.check_passed(self.active_queue[0])

# public commands to robots
for i in range(self.total_robots):
    self.command[i].publish(self.state[i])

print(self.state)

if self.all_same(self.state):
    rospy.signal_shutdown('No Vehicles Available in the Intersection!')

```

```

        rospy.on_shutdown(self.myhook)
    else:
        self.rate.sleep()

def all_same(self, x):
    return all(a == x[0] and a == types.PASS_INTERSECTION for a in x)

def check_passed(self, first):
    if self.direction[first] == types.DIR_LEFT or self.direction[first] ==
types.DIR_DOWN:
        if self.current_dist[first] <= -self.safe_region:
            self.state[first] = types.PASS_INTERSECTION
            self.active_queue.pop(0)
        else:
            if self.current_dist[first] >= self.safe_region:
                self.state[first] = types.PASS_INTERSECTION
                self.active_queue.pop(0)

def myhook(self):
    print("shutdown time!")

def callback_odom(self, msg, args):
    self.pos_x[args] = msg.pose.pose.position.x
    self.pos_y[args] = msg.pose.pose.position.y
    # self.pos_z[args] = msg.pose.pose.position.z

def callback_state(self, msg, args):
    self.state[args] = msg.data

if __name__ == "__main__":
    IntersectionAgent(total_robots=8)

```

B. SCREENSHOTS

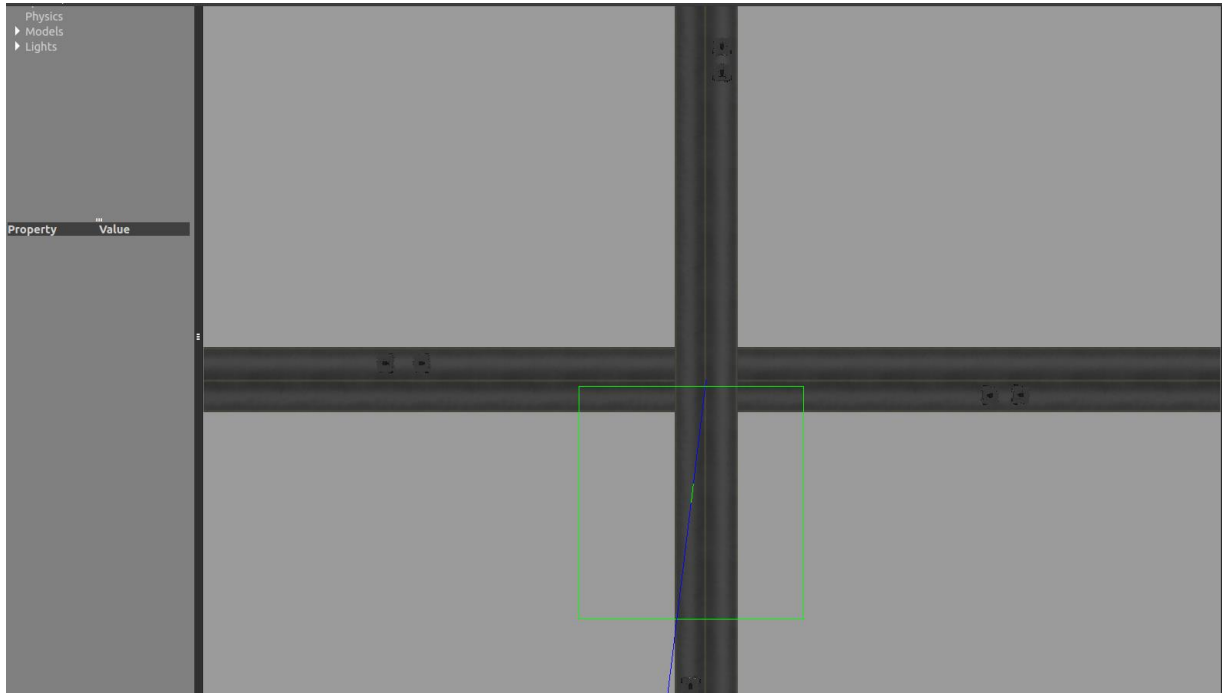


Fig B.1: Traffic flow simulation in gazebo

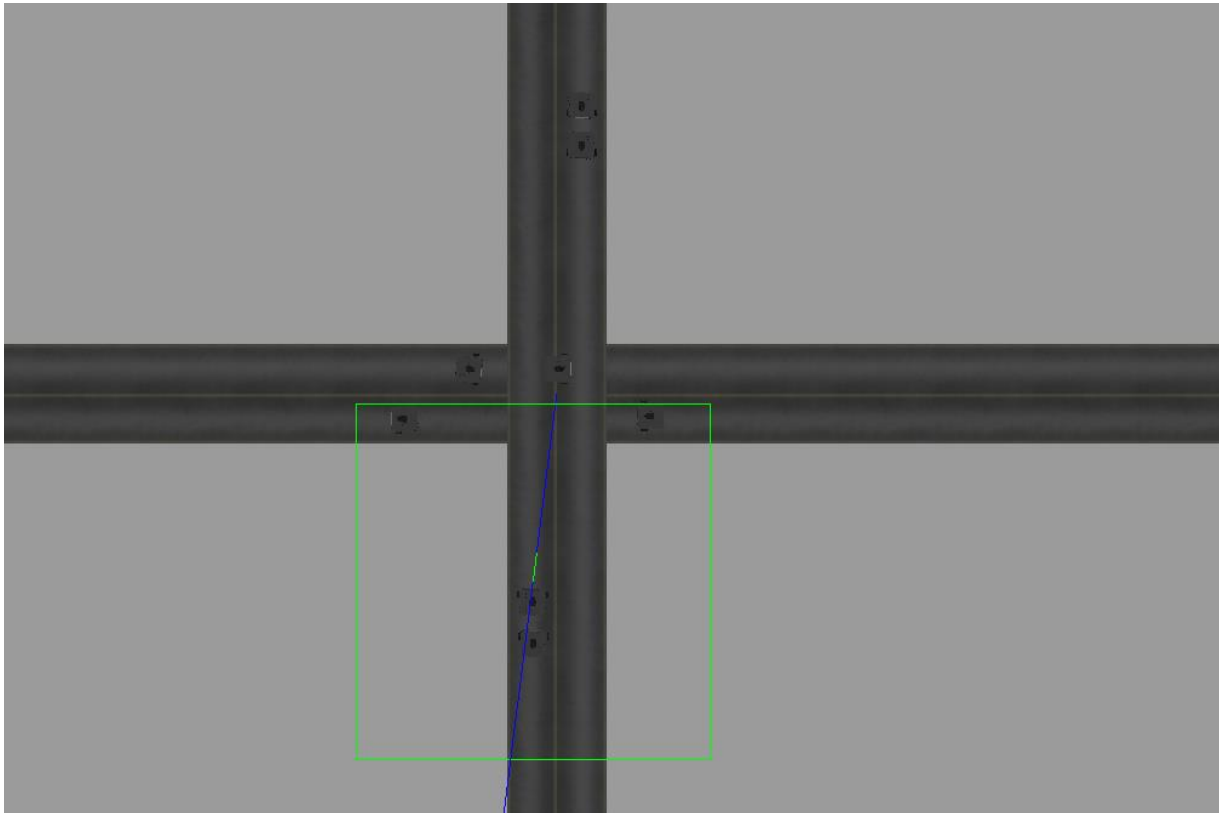


Fig B.2: Coordinated robot movement at intersection

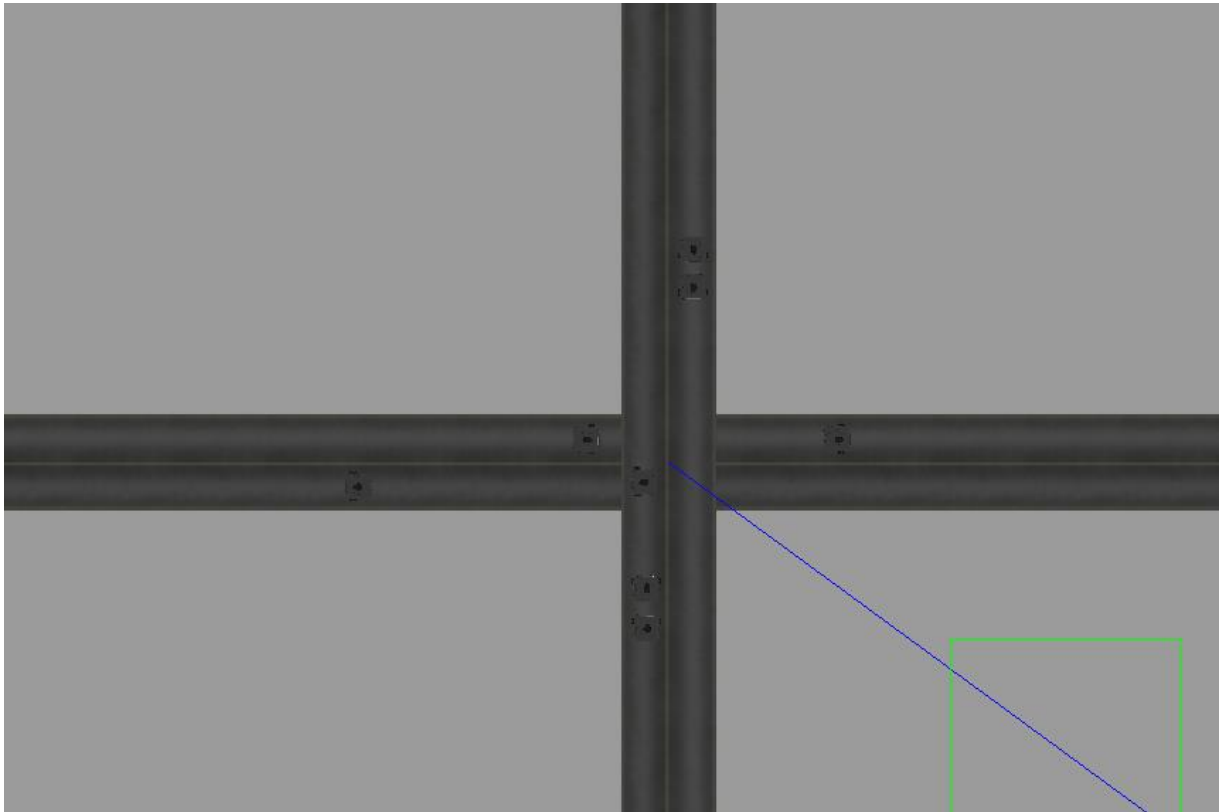


Fig B.3: Multi-robot traffic management at intersection

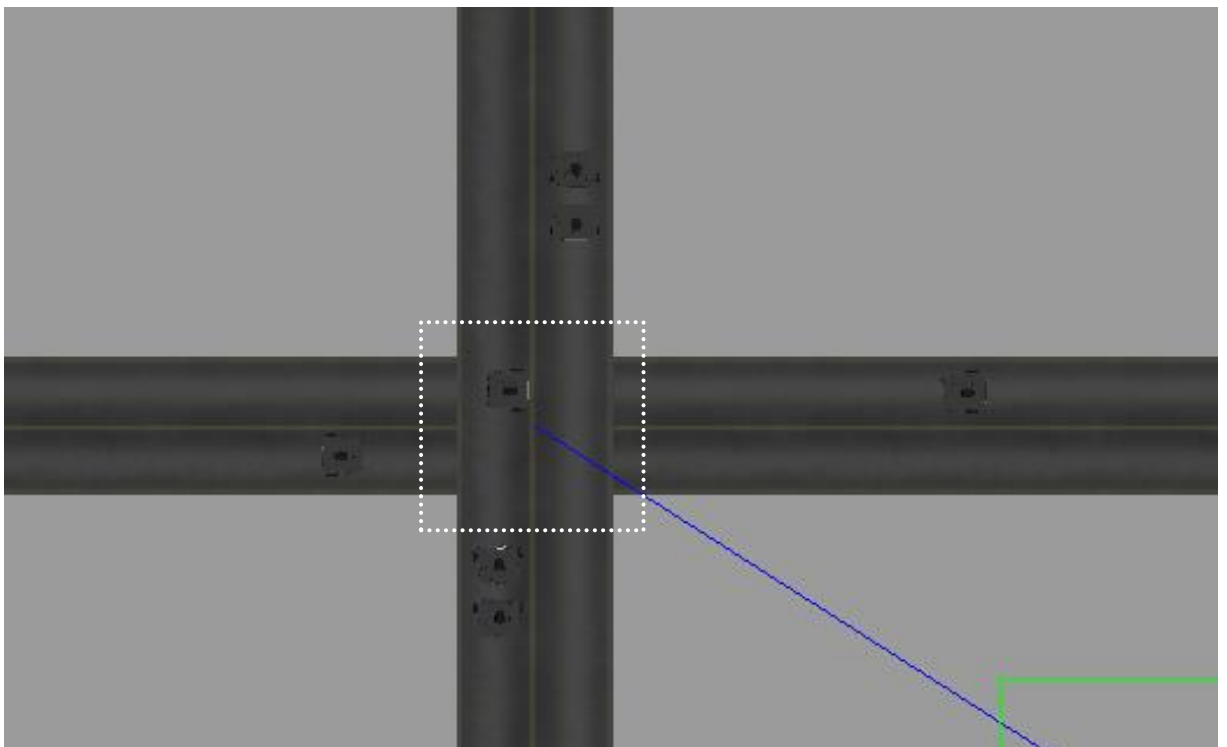


Fig B.4: Simulation of multiple robots navigating an intersection

C.RESEARCH PAPER

A METHOD FOR TIME-EFFICIENT NEGOTIATION FOR AUTONOMOUS DRIVING

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Abstract: Coordination and decision-making in complicated contexts are severely hindered by robust robot navigation. In this study, we offer a multi-robot system that uses the Gazebo simulator and Robot Operating System (ROS) to simulate and evaluate traffic flow at a junction. Three sets of Python scripts make up the system: one for controlling the actions of each robot, one for managing intersections centrally, and one for representing robot interactions as a directed graph. Every robot obeys traffic laws and navigates to its destination using preprogrammed actions and odometry data. Good intersection traversal and smooth traffic flow are guaranteed since the motions of the robots are coordinated by a central controller. For efficient routing and collision avoidance, the directed graph dynamically updates to reflect changes in the robot's position. Our simulation can be used to assess how different intersection management techniques affect traffic efficiency, scalability, and safety. We show how well our method works to simulate real-world traffic situations and validate intersection management algorithms for autonomous robot systems through trial and analysis.

I. INTRODUCTION

This study tells that the automatic negotiation mechanism which is used in autonomous automobiles, primarily focuses on handling the challenges put forth by unpredictable traffic conditions. This strategy uses the combination of FCFS and vehicle platooning algorithms to increase and enhance communication among self-driving vehicles. As the automotive industry gets closer to fully autonomous driving, it is more

important now than ever to have efficient safety mechanisms in place for countering unexpected road events.

FCFS algorithms keep in place a balanced and systematic flow of negotiating techniques among self-driving vehicles ensuring equal accessibility to shared resources. With a combination of several algorithms, this method strives to create the fundamental groundwork for traffic management. During close-quarters driving the vehicle platooning strategy increases safety, productivity, and the optimization of traffic flow.

Gazebo simulations and road graph models provide strong testing conditions which is used to provide validation for our method. To demonstrate the efficiency of the suggested negotiation techniques with the help of ROS and practical testing with Python programming. This work substantially increases the possibility of autonomous vehicles to function in unpredictable environments and to help build a safer and more effective urban transportation system.

Our study adds to the innovative infrastructure that helps self-driving cars handle erratic road conditions. We offer a complete method to improve coordination and communication among self-driving cars. Adaptive urban traffic management has benefited greatly from this research, which addresses the problems caused by chaotic traffic conditions and paves the way for a safer and more effective transportation system.

With the automotive sector moving closer to complete autonomy, the capacity to handle dynamic and unpredictable traffic situations becomes essential. What drives us is creating

efficient planning for autonomous vehicles; we want to ensure that they can handle unforeseen challenges and contribute to the establishment of a dependable and secure urban transportation system. The idea is to assist the greater goal of a seamless and efficient ecosystem for autonomous vehicles while simultaneously building a robust structure that can survive the unpredictable nature of the roadways.

II. LITERATURE SURVEY

The main problem raised is the requirement for autonomous vehicles to handle complicated and unexpected social interactions on the road. Despite significant advancements in the technical aspects of driving, autonomous vehicle technology still has work to do when it comes to dealing with situations that call for negotiation, communication, and cooperation between vehicles, such as blocked roads, unsupervised junctions, or traffic jams.

[1] Proposed that recent years have witnessed significant progress in automated vehicle research, with a focus on enhancing vehicle-to-vehicle communication. Despite impressive advancements, autonomous vehicles still face challenges in executing basic maneuvers like intersections and lane merges, demanding high levels of safety, security, and robustness. Cooperative approaches using wireless communication can address these challenges by improving perception, prediction, and planning.

The survey centers on a cooperative automated lane merge function, especially addressing complex on-ramp merge scenarios. The research employs a 3D simulation environment to implement and test the function, evaluating its network load and performance. The study explores network protocol design and tradeoffs in function and sets the stage for further research to advance the capabilities of autonomous vehicles.

[2] Proposed the challenges in Disaster Environments. Disaster areas, especially after earthquakes, present hurdles such as debris, slopes, and stairs. Remote-controlled robots face communication delays. It introduces the use of acceleration sensors to enable robots to autonomously negotiate slopes and stairs. These sensors provide real-time data for immediate adjustments. States that the experimental results

demonstrate the effectiveness of acceleration sensor-based navigation in disaster-stricken areas. Acceleration sensors have the potential to significantly improve the autonomy and effectiveness of search-and-rescue robots, expediting response times and increasing the chances of successful disaster response. Future research may involve further optimization of acceleration sensor use and the development of advanced control algorithms, expanding applications beyond earthquakes.

[3] Proposed the Autonomous Vehicle Era. Self-driving vehicles are on the horizon, despite controversies due to recent accidents. Their appeal lies in safer, quicker, more accessible, comfortable, convenient, and eco-friendly transportation. The survey reviews motion planning techniques, specifically in the context of highway driving, where high speed, small curvature roads, and constrained environments are the norm. It addresses lane changes, obstacle avoidance, car following, and merging.

It Outlines the challenging conditions that define motion planning in highway settings. It explores existing challenges and open research issues, paving the way for future advancements in autonomous highway driving.

This paper offers a comprehensive view of motion planning with regards to autonomous driving in highway, underlining the promise and challenges of self-driving vehicles in transforming transportation.

[4] Proposed that autonomous vehicles have made rapid progress, but achieving full autonomy in complex, dynamic environments remain challenging. Autonomous vehicles rely on sensor fusion for robust environmental perception, with camera-LiDAR fusion emerging as a key research focus. The lack of critical reviews on deep-learning-based camera-LiDAR fusion methods, covering depth completion, object detection, semantic segmentation, tracking, and online cross-sensor calibration. These methods are compared using publicly available datasets, offering insights into their relative strengths and weaknesses.

[5] Proposed a Safe interaction with other traffic participants is vital for autonomous driving, especially in complex scenarios like intersections

and occlusions. Many methods require extensive manual parameter tuning. Used Interaction Point Model (IPM).

The survey introduces the IPM, a learning-based model that unifies interaction representation by considering protection time and interaction priority. The IPM is integrated into an innovative planning structure, enhancing its practical applicability.

Realistic simulation in an extremely dynamic setting that validate the IPM's effectiveness and robustness. IPM holds promise for improving reliability and safety in autonomous vehicles, particularly in complex traffic scenarios.

[6] Proposed a system for achieving both safety and speed in driving autonomously by means of deep reinforcement learning (DRL) is a formidable challenge. It introduces the Double-Bias Experience Replay (DBER) method, enabling autonomous agents to influence their learning tendencies, effectively balancing safety and speed. With a substantial impact on learning, a novel loss function is suggested to better balance the interaction between positive and negative losses in training. The DBER approach is tested across three prominent DRL algorithms, showcasing its advantages and improved performance compared to existing methods. The DBER approach has the potential to advance the development of autonomous driving technologies by addressing the challenges of safety and speed in DRL.

[7] Proposed the usage of multitask reinforcement learning to improve self-driving cars. Traditional rule-based control methods have limitations in complex traffic conditions. The proposed approach divides driving tasks into subtasks, cutting down the training time and increasing productivity in intricate multi-lane traffic. An adaptive noise exploration method ensures agent robustness. Simulation results confirm the approach's effectiveness in autonomous driving control. This method holds the potential for improving autonomous driving under challenging traffic scenarios.

[8] Proposed Autonomous Vehicle Path Planning. It has many challenges and limitations of traditional map-based approaches. Integration of Unified Maps for efficient collision-free route

generation. Real-world deployment and validation in diverse environments. The potential of Unified Maps in shaping the future of autonomous transportation.

[9] Proposed the importance of multi-object monitoring in autonomous vehicles and the difficulties faced in places impacted by epidemics. The challenges faced are frequent occlusions, appearance deformations, and Complex motion blur in epidemic-affected regions.

TSAEN Approach: Components, including TACM and SAEM, together and aggregate appearance cues from previous frames.

TACM: Learning temporal homogeneity features for understanding correlated appearance cues.

SAEM: Adjusting spatial deformations and aggregating features for re-identification embedding learning.

Confirmation of TSAEN's effectiveness in improving multi-object tracking performance in epidemic-affected areas. The importance of addressing multi-object tracking challenges in epidemic-stricken areas and the potential of the TSAEN method.

[10] Proposed the importance of mitigating efficiency concerns in autonomous vehicles, introduced V2V communication as a solution, and acknowledged the challenges for successful implementation. The proposed approach not only improves efficiency but also contributes to ongoing discussions on the seamless integration of autonomous vehicles into modern transportation systems.

[11] Highlighted the thriving field of MAPF research, pointed out current standardization issues, and praised Stern and associates' efforts in creating a useful tool. Unifying terminology and benchmarks have been created, which has greatly advanced the area, improved communication, and allowed for more advancement in the difficult field of Multi-Agent Pathfinding.

[12] Addressed the need for a cohesive structure, using AMOP and SAOP as models. The practical significance of the protocols is enhanced by empirical evaluations and real-world implementations, which also set the path for

future developments in multilateral negotiation protocols.

III. MATERIALS AND METHODS

The objective of this research is to develop and put into practice automated negotiating methods that will enable autonomous vehicles (AVs) to deal with unforeseen traffic conditions.

Simulation Environment

A framework for building and simulating different road scenarios is offered by the Gazebo simulation environment. Within the simulation environment, unusual road conditions like blocked lanes, junctions without traffic control, and traffic jams are constructed and put into action.

Autonomous Vehicle Representation

In the simulation, a robot with the ability to navigate and make decisions on its own is used to represent each autonomous vehicle. Within the ROS (Robot Operating System) framework, Python scripts are used to mimic the behaviour of individual robots.

Negotiation Procedures

To allow robots to communicate and independently clear traffic congestion, various negotiation procedures are developed and put into use. When robots come into unforeseen road conditions, these rules control how they interact, compromise, and work together.

Evaluation of Effectiveness

Through comparative analysis, the efficiency and effectiveness of the developed negotiating protocols are assessed. Different protocols are evaluated based on a range of parameters, such as negotiation success rate, traffic flow improvement, and traffic jam resolution time.

Experimental Setup

Various scenarios and iterations of negotiation procedures are used in the simulation tests. Adjusting parameters like vehicle count, road layouts, and traffic density allows for the simulation of various road conditions and assesses the negotiation protocols' resilience and scalability.

Data Gathering and Analysis

During simulation runs, information is gathered on the results of negotiations, the dynamics of

traffic flow, and protocol performance indicators. The gathered data is analysed using statistical analysis and visualisation tools in order to provide insights into the efficacy of the negotiation processes that were created.

Framework of Implementation

ROS libraries and the Python programming language are used to construct negotiation protocols and simulation scenarios. The simulation environment is provided by Gazebo, while the coordination and communication amongst autonomous cars is facilitated via ROS.

Experimental Validation

In-depth simulation studies are used to verify the efficacy of the designed negotiation procedures. These investigations compare and evaluate various protocol variants and evaluate how well they function in a range of traffic scenarios and road conditions.

Ethical Aspects

During the development and assessment of negotiation procedures, ethical issues pertaining to safety, justice, and the social impact of autonomous vehicle encounters are taken into account. In simulated road situations, safety protocols are put in place to guarantee that autonomous vehicles behave responsibly.

Data Visualisation and Data Logging

Detailed data logging techniques are used in the simulation studies to capture a range of parameters and events, such as vehicle trajectories, messages exchanged during negotiations, and traffic flow dynamics. A deeper comprehension of the negotiating process and its influence on traffic management is made possible by the analysis and interpretation of the gathered data using sophisticated visualisation tools.

Evaluation with Humans in the Loop

To gauge the efficacy and user acceptability of the developed negotiation protocols, evaluation sessions with humans in the loop are carried out in addition to fully automated simulations. The proposed protocols are refined and validated with the help of human participants who function as traffic controllers or observers. They offer qualitative input on the effectiveness of the autonomous vehicle system and the authenticity of negotiation contacts.

IV. ARCHITECTURE

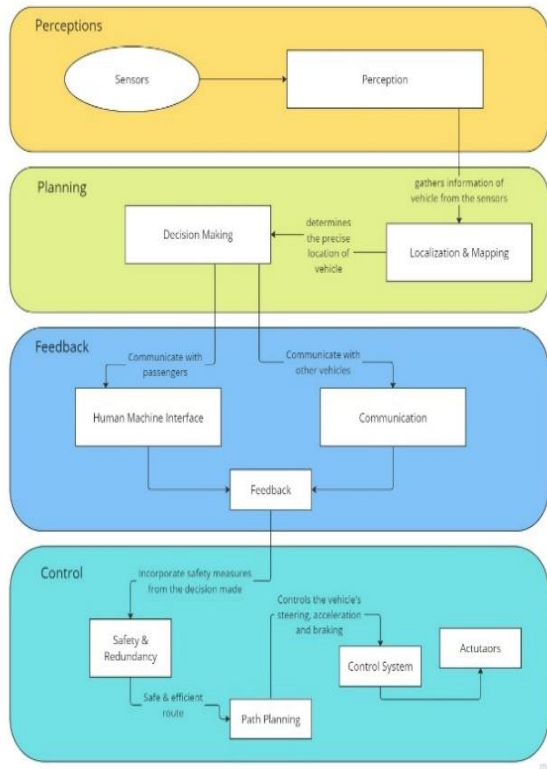


FIGURE 1. Block Diagram of the System Proposed

The following are the main building blocks or elements that make up "the method of time-efficient autonomous driving" architecture:

1.Perception System: A number of sensors equipped (such as Lidar, cameras, and radar). The Lidar system helps to identify objects and detect all the environmental structures around the vehicle. This gives a height-tend sense for the vehicle and gives an almost precise environmental context.

2.Localization and Mapping: This sets up a safe route by profiling the environment and determining the precise location of the vehicle with respect to its surroundings.

3.Path Planning: Path planning is done by considering the traffic conditions and hurdles along the entire route. So that the self-driving vehicles will follow a safe and efficient route.

4.Control System: The control system is equipped with the created path which has control over the vehicle's brakes, speed, and steering. So that there is safety and security.

5.Decision-Making System: This system has

information from the combination of mapping, path planning, recognition, real-time decision-making, overtaking, changing course, and safely responding to unpredictable circumstances on the road.

6.Human-Machine Interface (HMI): This interface establishes communication between the passenger and the self-driving vehicle. Thus this helps the passenger to provide input and give them control of the autonomous vehicle.

7.Communication: Self-driving vehicles need communication with businesses cloud administrators and other vehicles to provide feedback so that the makers can improve upon it.

8.Redundancy and Safety: Safety measures and redundancy are very important and should be integrated into the architecture of the car to avoid mishaps, emergencies, and unanticipated breakdowns.

V. RESULT AND DISCUSSION

Our study addresses unsolved problems and equips very necessary technologies to apply in the real world which is a revolutionizing task management and autonomous vehicle planning. This framework builds on top of the previous efforts to equip human-centric plan concepts, energetic scenario modeling, modern detecting improvements, and trustworthy communication systems. The system feasibility is increased by the focus on engaging corporations in practical applications by guaranteeing a configuration that helps to consider numerous viewpoints. This project has a realistic approach stems from its broad importance, which is done by user-friendly programming, extensive activity modeling, real-world testing, and active simulations.

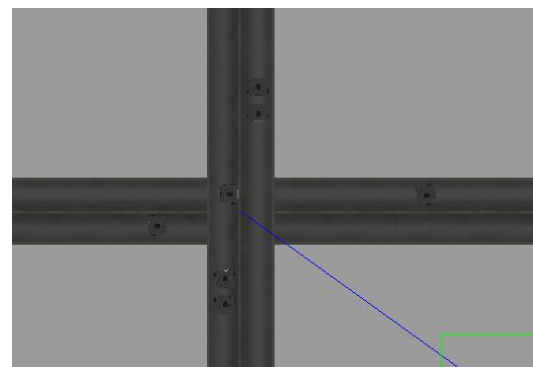


FIGURE 2. Simulation of multiple robots navigating an intersection

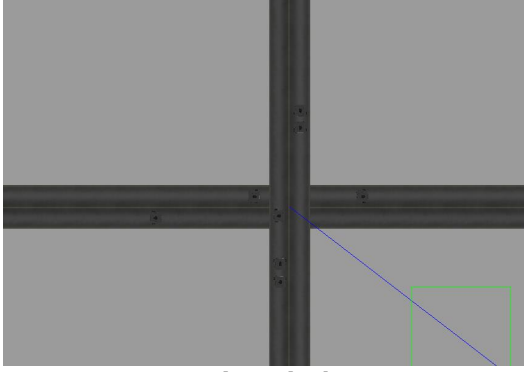


FIGURE 3. Coordinated robot movement at intersection

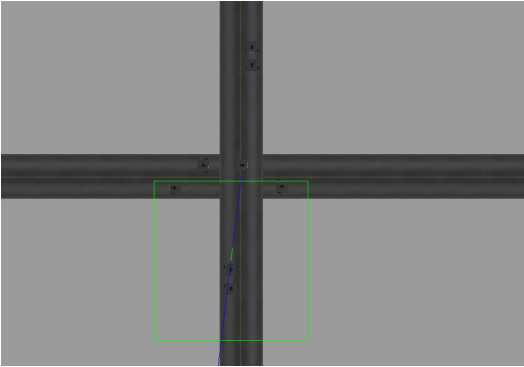


FIGURE 4. Multi-robot traffic management at intersection



FIGURE 5. Traffic flow simulation in gazebo

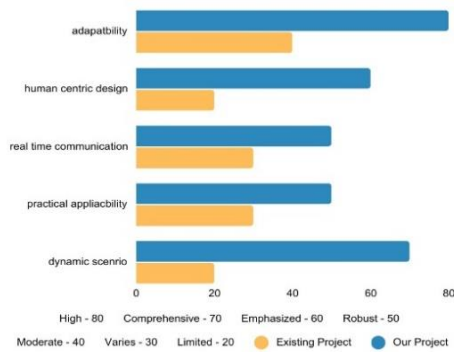


FIGURE 6. Urban traffic control using autonomous systems

VI. CONCLUSION

This study has shifted the field of adaptive urban traffic management on top of pushing the envelope in conversations about self-driving vehicles. This work surpasses traditional algorithmic advancements by thoroughly simulating problems that are yet to be studied. This special system has an incorporation of modern sensor technologies, human-centered design concepts, dynamic scenario modeling, and reliable communication protocols. These features surpass the existing technology. In real-world circumstances, our system provides a comprehensive and sophisticated approach by encouraging interdisciplinary collaboration with the help of multiple points of view. With the support of comprehensive traffic modeling, dynamic simulations, user-friendly programming, and real-world testing, our project are at the forefront of innovation because of their practical ability and viability.

VII. FUTURE ENHANCEMENT

A part of our approach to system development is strategic planning for future developments. With machine learning algorithms, the system will be able to make changes based on historical data and real-time feedback. The ability to adapt to changing traffic patterns will be improved by the dynamic learning of human behavior. Modern sensor technologies like LiDAR and radar can be employed to enhance the system's perception for smooth navigation in complex urban environments. Comprehensive testing is ensured by expanding simulation scenarios to include a variety of situations, such as bad weather. Real-time traffic optimization and broader communication between vehicles are expected benefits of cloud-based collaboration. The easy-to-use AI-human interface will promote better cooperation between human drivers and self-driving cars. Our technology will be integrated into infrastructure sensors through collaboration with smart city projects, helping to optimize traffic flows. Robust cybersecurity protocols are essential for the safe operation of autonomous vehicles. Multiple field trials, conducted in collaboration with local authorities, will evaluate the system's performance in different urban contexts. Finally, standardized methods for smooth integration into existing traffic regulations

will be established through cooperation with regulatory agencies. Together, these innovations make our system more flexible, safer, and more efficient in the ever-changing world of urban mobility.

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D. CERTIFICATE



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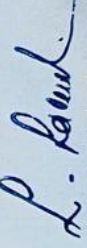
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Department of Computer Science and Engineering

Certificate of Presentation

This is to certify that
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in the
International Conference on Cognitive Computing and Artificial Intelligence (ICCCAI-2024) in association with
Taylor's University, Malaysia held on 7th & 8th March 2024.



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