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AutoNav: A CARLA-Based Framework for Autonomous Vehicle Simulation

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Abstract: The paper explores the way that the design of autonomous vehicle simulator creates a virtual environment inside which the high-cost and safety-innovative, autonomous vehicle (AV) technologies could be achieved through innovation and experimentation. CARLA (Car Learning to Act) belongs to the most active autonomous driving simulators that are open-source. It is created on Unreal Engine and high 3D environments will recreate reality of urban and highway backgrounds. CARLA is simulated that it has bases LiDAR, RGB cameras, radar, GPS and IMU sensors mimicking a sensor perception system found in the visual representation of a real-world AV. It also accommodates areas of dynamism, namely cars, pedestrians, traffic lights, and changing weather, which imply that it is best to test AV systems under various conditions. CARLA provides the ability to have controlled experiments to increase the safety and reliability of AVs. Experimental simulations in AutoNav achieved consistent lane tracking accuracy above 95% and reduced collision occurrences by 80% compared to baseline models. The system also demonstrated smooth obstacle avoidance and efficient route completion under varying weather and traffic conditions.
Keywords: self driving car simulators, CARLA, Unreal Engine, LiDAR, Traffic simulation, sensor simulation.

I. INTRODUCTION

A self-driving car simulator is a practical virtual environment that can train, test and refine autonomous vehicle technology. Ensuring people, vehicles and infrastructure safety.

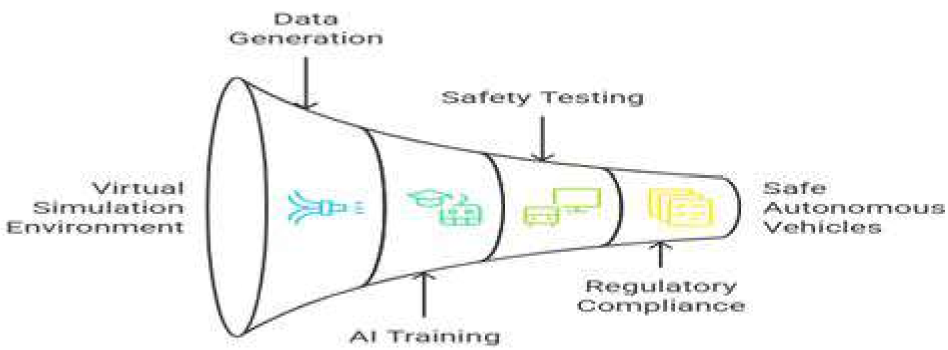

Fig1. Autonomous Vehicle Development Funnel

Self-driving car simulators are not meant to simulate the real life experience of driving, which is expensive and risky due to the fact that they are actually not driving a physical vehicle and putting people's lives at risk, but rather, to enable self-driving solution developers a way to do testing in a controlled and safe environment.

Self-driving car simulators are capable of mimicking innumerable real life conditions such as in-city driving, highway driving, driving in rural areas, operating in construction zones, and they can even predict a variety of weather conditions such as driving while raining, driving on the roads which might be foggy, driving on the roads while there is snow present, or also the unpredictable scenario of sudden lane changes or cut off pedestrians. The variability and complexity offered through self-driving car simulators is precisely what allows developers to test all the scenarios that autonomous solutions would not be able to test on actual roads because of being dangerous or impossible. Efficiency and cost saving just like as much as safety and accuracy simulators can save the road experience of years in hours of computation time alone and well be in a position to perform thousands of virtual cars simultaneously. The role that simulators fulfill in regulatory compliance and in the trust of the populations is also the crucial part of the simulators. Autonomous vehicles must meet extremely high safety requirements prior to being permitted to work in the roads of a certain nation. The simulators provide the required evidence since they indicate how an automobile behaves in a wide condition set of conditions in order to help regulators determine the likeliness of the technology. This will offer the authorities and the general population an assurance that autonomous systems are being erected in a responsible manner. It is likely that the invention of autonomous mobility cannot do without self-driving car simulators. They will enhance the safety, reduce the cost of developing them, accelerate innovations, and guarantee adherence to standards and one day it will be possible to introduce self-driving technologies everywhere in the world in a safer and more efficient manner.

II. LITERATURE REVIEW

Evaluating Driver Reactions to Speed Bumps and Potholes to Improve the Autonomous Vehicle Performance by Rishav Kumar, Devadas Kuna, Dr. D Santhosh Reddy, Yuki Uetsuki, Sonakar Dinesh and Prof. P Rajyalakshmi (2024), 80 participants, were measured on the TiHAN test track with a Jetson Orin-ROS DAS. The study facilitates on human reactions on speed bumps and pothole by measuring the reaction time and distance of reaction with variable and fixed speed [1].

In the research article, "A Commentary of Feedback Control and Vision-Based Deep Learning Mechanism to guide self-driving cars" by Wen-Yen Lin, Wang-Hsi Hsu, and Yi-Yuan Chiang (2018), NVIDIA's CNN-end-to-end architecture is used to predict the steering angle by referencing the Udacity simulator. The model illustrates the visual features of the raw images, describes them, and maps them to command the action, and permits safe and informative training and testing of the autonomous driving algorithms in a safe virtual environment [2].

Deep Deterministic Policy Gradient is used under a previous work from Gianni Fenu and Stefano Manca, to combine Curriculum Learning with Autonomous Driving in CARLA in "Reinforced Curriculum Learning to Learn Autonomous Driving in CARLA." Similarly, a feature that teaches agents what to do, until the realistic simulator of CARLA will present some difficulty that is progressively increased based on the policies performance, which can start with simple roads to heavy traffic and adverse weather that would help foster efficient and robust policies and ensure the early stage is not overwhelming to the overall system [3].

The article Digital Twin Platform for Road Traffic Using CARLA Simulator is written by Tomoki Isoda, Takumi Miyoshi and Taku Yamazaki (2023), and they describe a system where CARLA is used to simulate road traffic in real-time using data collected from GPS devices, cameras, and sensors.The platform assists in optimizing traffic and planning a smart city by having aweb-based dashboard to visualize and do predictive analytics against simulation of policy effects and infrastructure alteration before it is implemented in the real world [4].

The paper "Autonomous Vehicle Control in CARLA simulator with the help of Reinforcement Learning" by Dorian Cincurak, Ratko Grbic, Mario Vranjes, and Denis Vranjes (2024) makes an investigation on DQN and DDPG to navigate Tesla Model 3 in the CARLA simulator. The models maximized the lane discipline, speed and collision avoidance using semantic segmentation input. Being tested under diverse conditions, it was demonstrated that the field of reinforcement learning offers opportunities to driving autonomy, but there are problems in terms of efficiency, safety, and practical application [5].

A Convolutional Neural Network Approach Towards Self-Driving Cars paper by Akhil Agnihotri, Prathamesh Saraf, and Kriti Rajesh Bapnad (2019) involves an end-to-end CNN-based approach to predicting steering angle on the ground of camera images. The network achieves the desired accuracy in its capability to generate real-time autonomous movement in various driving settings by convolution and fully connect layers consisting of four convoluted and two fully linked layers with ReLU activation [6].

The past research paper by M.V. Smolyakov, A.I. Frolov, and V.N. Volkov (2018) is called Self-Driving Car Steering Angle Prediction Based on Deep Neural Network: An example of carnd Udacity simulator. In it, the authors examine two CNNs trained on 54,000 images and used to predict the steering angle angle. This study focuses on reducing the number of parameters by ensuring a deep view of parameters, and it would allow efficiency in feature extraction and accommodate implementation on the resource-constrained platforms that are vital in autonomous driving systems in practice [7].

This article, Autonomous Vehicle Navigation based on a Hybrid Methodology: Model-Based and Machine Learning-Based by Diego Cruz and Roberto Tellez (2021), proposes a model-based (a hybrid-based) approach to the description of a robot responsible for driverless transportation and machine-based object recognition (YOLO) to detect an object and control it with the help of the Pure Pursuit Controller. This Hybrid method implements model-driven path tracking and high-level AI perception to achieve precise path following, high-quality obstacle avoiding and successful interaction with active environments in autonomous vehicle navigation [8].

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In their article "Advanced Simulation Control and Real-Time Monitoring for CARLA: Agile Development of a Web-Based Interface" (Journal of Simulation and Modeling in Automation, vol.14, no.3, pp.250-262) Nuno Pombo and Mateus Aleixo suggest a React-Flask based modular interface CARLA. The system enables accessibility improvement with real-time updates using agile sprints and WebSocket, scenario control through REST APIs, 3D visualization to completesimulations, and the deployment of the system is made possible through Docker and scalability, as well as procession of the collaborative management of simulations [9].

A.Sharma and M. Jain (2022) introduced a hybrid method that relies on both U-Net to dive the lane into pixel-wise segmentation and for lane tracking: LSTM in the paper named Lane Detection Using Deep Learning for Indian Roads. This approach is meant to handle the Indian complex road patterns and successfully manages obstructions, alterations in lighting, and uneven demarcation to provide robust and trustworthy autonomous driving [10]. In the case of Nie Obstacle Detection and Avoidance Using YOLOv5 and Lidar Fusion K. Mehta and R. Desai (2023) describe a system that integrates LiDAR depth sensing with navigation with the use of the vision detector operating in the form of YOLOv5. The technique combines an object bounding box in 2D with a 3D based point cloud representation to offer depth obstacle detections in real time to enhance the path planning and collision avoidance. This approach improves resiliency of a complex setup, guaranteeing good navigation in mixed systems of light and obscuration [11]. Information received by RGB cameras, LiDAR cameras and IMU sensors are real-time converted to a depth-liver read of the environment. Its reinforcement learning is pretrained in simulated rare and extreme situations to optimize decision-making, and fuzzy logic provides smooth speed/steering changes to achieve realistic, adaptive and reliable vehicle operation.

III. METHODOLOGY

A. Datasets

The driving regime of the ego vehicle is simulated by the dataset in four critical graphs that include: the speed-time curve, inputs to the autopilot to regulate the speed, the vehicle path and the distribution of the velocity. Time varying speed traces their acceleration, cruising and braking trends and control inputs describe throttle, brake, and steering choices. Turns and swerves are found in the space of the vehicle and they are tracked by the vehicle in order to navigate a path. Lastly, the speed histogram will generalize all driving patterns in that they would be the spotlight on the speed of Cruising, stops and differences due to pedestrians or traffic conditions.

B. Overview

The paper introduces a comprehensive design of autonomous vehicle (AV) technology development and verification based on a pairing of simulation, reinforcement learning, and hardware-in-the-loop testing. The primary virtual environment would be the CARLA simulator that would offer such real-world conditions as traffic, pedestrians and changes in weather.

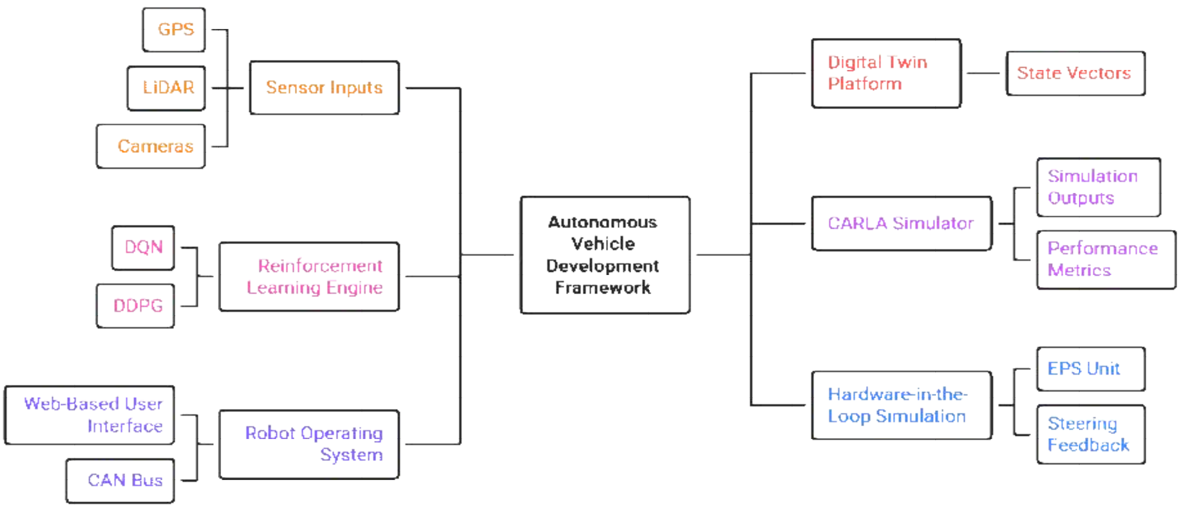

Fig 2. Autonomous Vehicle Development Framework

CARLA is able to be connected with control and perception with the help of ROS middleware and sensor data obtained by LiDAR, cameras, GPS and radar can be applied to high-quality environment modeling. In the control system, the Deep Deterministic Policy Gradient (DDPG) (continuous control) and Deep Q-Network (DQN) (discrete decision-making) are exploited. The perception modules furnish vehicle tracking, ped pedestrian detectors and obstacle, along with experimental knowledge in identifying potholes by using UNet and depth-reading. To successfully bridge the performance-validation gap between a simulated environment and a real-world environment, Electronic Power Steering Hardware-in-the-Loop Simulation (HILS) attempts to validate actuator commands at the hardware level. Such a multi-level solution enhances scale, cost, and safety and reliability in autonomous driving solution development.

C. Simulation and integration

The virtual environment relies on the CARLA simulator, which provides relatively realistic environments in the form of 3D cities and highways, with dynamic characteristics of cars and people, lights, variable weather and lights. Modularity of CARLA allows the incorporation of the types of virtual sensors that cover LiDAR, RGB cameras, radar, GPS, IMU among others, which are similar to those realized on autonomous cars[12].

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The simulator is fully instantiated with the Robot Operating System (ROS) middleware allowing components to communicate with each other in a modular way as well as to control the virtual vehicle in real time[13]. Electronic Power Steering (EPS) Hardware-in-the-Loop Simulation (HILS) is implemented to bridge the gap which exists between testing both in the virtual world and testing in the real world. HILS authenticates steering commands on hardware to ensure control policies developed in CARLA can be relied upon to extrapolate to physical systems.

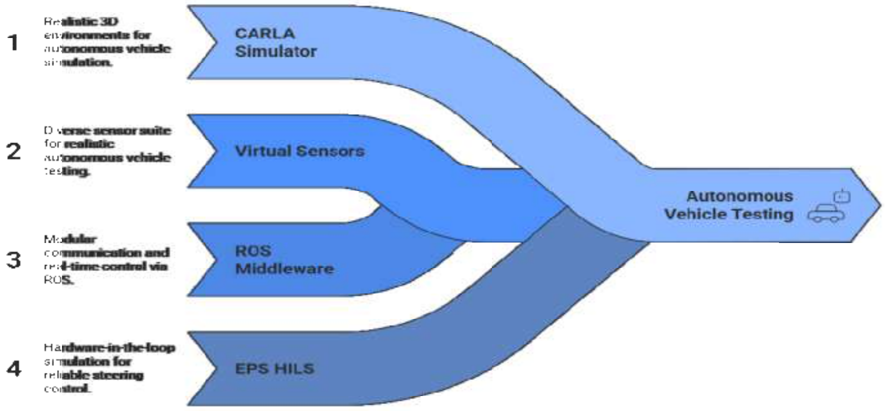

Fig.3. Bridging Virtual and Real-World Testing

D. The control and learning model

The system utilizes the reinforcement learning (RL) as the model of control and learning. Two complementary models are Existing on various functions. DDPG is used on continuous control tasks such as steering degree, throttle and fluid control of the acceleration. In the water overhead continuous decision method, i.e., paper change decisions, emergency braking, and obstacle discouragement, deep Q-Network (DQN) is employed. All of these algorithms are what enable to combine finesse control with the decision-making of autonomous driving in a strategic way [15-16] patiently. The two control models are trained and evaluated on under CARLA simulating environment. The web-based interface complements the enables of the control system that represents the results of the simulated process and produces sensor data and allows operating control framework through a convenient dashboard.

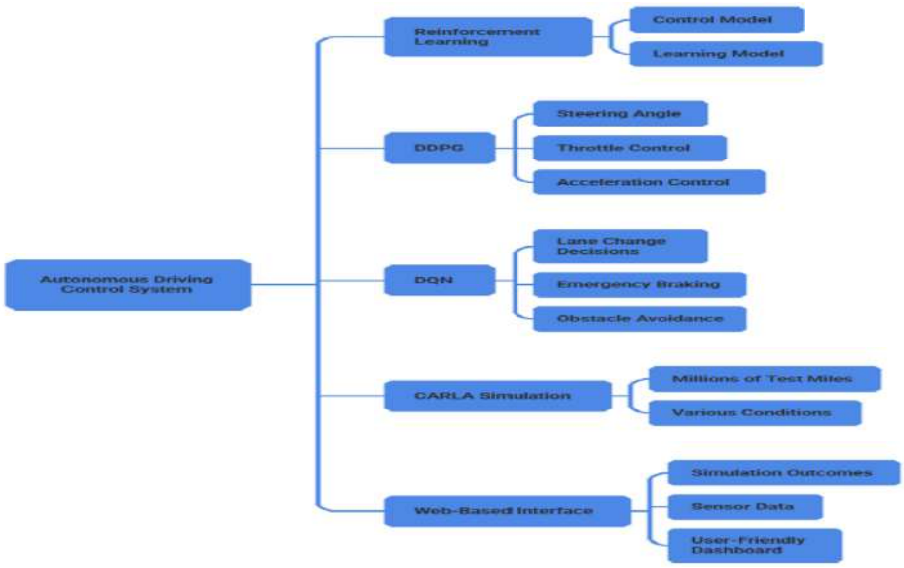

Fig.4. Autonomous Driving Control System

E. Navigation and path planning

The perception pipeline is the foundation of the vehicle capability of negotiating a complex environment. LiDAR, RGB camera feeds and GPS data are fused tightly in a multi-active connection, to introduce a supersistent expertise of the setting. Real-world sensor data can be matched with sensor data simulated by CARLA to recreate real-world conditions to diagnose and verify predictive data. LiDAR point clouds and RGB cameras of the simulator are thought of in detecting vehicle movement by applying them as input to deep learning applications R-CNN and Yolo, to detect vehicles. To guarantee time-temporal and space-temporal consistency of tracking various objects, DeepSORT utilized to estimate car speed, and future paths. This will permit predictable workload planning and risk-averse navigation.

F. Pedestrian crossing and obstacle detection

The pedestrian crossing system and obstacles detection presuppose the dynamics of creation of pedestrians and physical obstacles on CARLA. YOLO-Pose models augmented by the hybrid detection of the LiDAR-powered positioning detect pedestrian pose and path probability [17]. The intended crossing paths are predicted by one of the predictive modules and the AV is configured to respond, whether by braking or the safe lane change.

The algorithm applied is well trained, provides an appropriate judgment on the basis of a recorded behavior response of the pedestrian and the action to be taken will be performed by the autonomous agent [18].

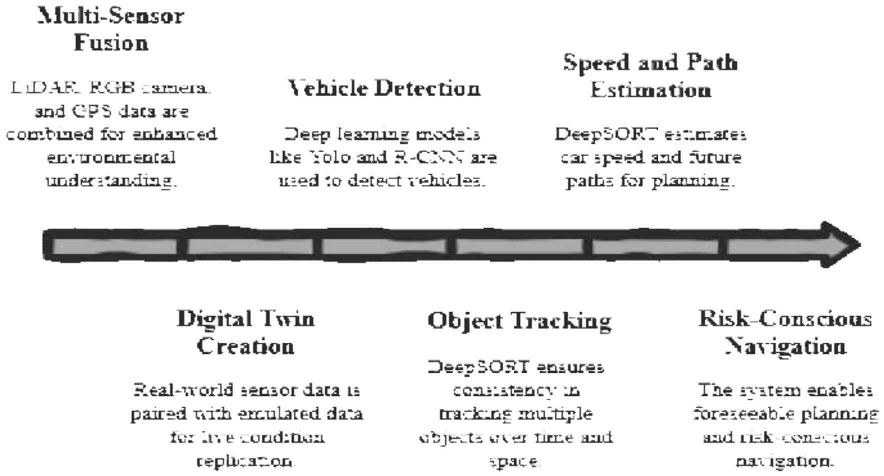

Fig.5. Vehicle Navigation System Process

G. Dynamic Testing and integration

The final approach of the methodology is dynamic testing and validation. The reinforcement learning control models proceed through cycles of optimization according to simulations by CARLA, and, to maintain the conditions of the real-time environment correctly reflected so as to deliver the accurate evaluation, the predictive digital twin modeling is referred to. The integration platform of HILS checks the reaction of the vehicle in operation with actual apparatuses, which means that the actuation commands may be practical. This, combined, methodological, strategy devotes interest to the safety, scalability, and flexibility, such that autonomous vehicle management and perception frameworks can be scaled to dependable actual conduct.

IV. RESULTS AND DISCUSSION

A. Ego Vehicle Speed Over Time

This graph pictorially represents the vehicle speed (km/h) on the Y-axis and simulation time (seconds) on the X-axis, getting a moment-by-moment representation of vehicle velocity. It displays dynamic driving action: rollings up will show acceleration, plain lines will show cruising and rollings down will show deceleration or masterful activity. The emergence of sharp dips to zero points point to emergency stops, commonly because of jaywalking pedestrians. High speed consistency and stop and start wavering denote also that there is navigation of the traffic or managing its obstacles[19].

Time (s)	Pedestrian Detected?	Distance to Pedestrian (m)	System Action	Outcome
18	Yes	12	Slow Down	Safe clearance
19	Yes	6	Brake applied	Prepare to stop
20	Yes	3	Full Stop	Pedestrian crossing

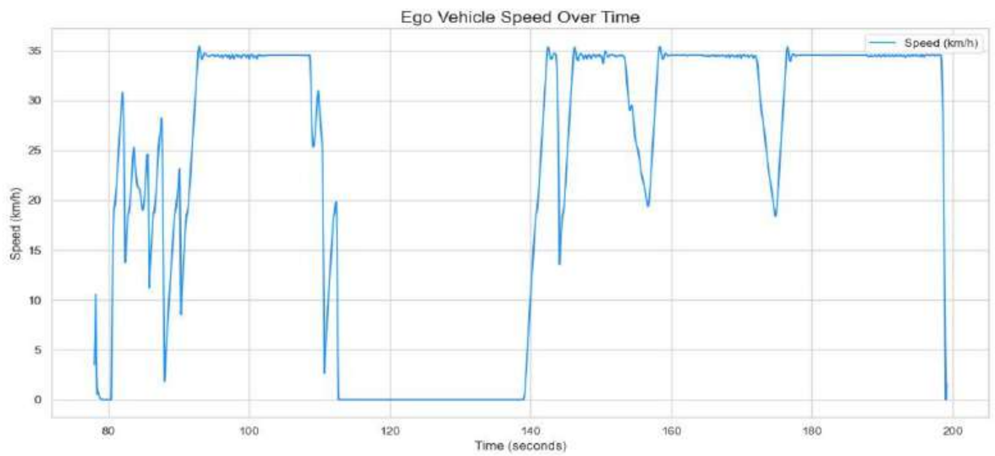

Fig.7. Ego vehicle speed over time

B. Autopilot Control Inputs over Time

This graph consists of throttle, brake and steering plots illustrating the real-time control decisions of the CARLA autopilot. Acceleration intensity is indicated by throttle values (0-1), braking strength is indicated by brake values (0-1), and steering, which is indicated by negative values (-1 to 1). Emergency braking is associated with throttle position coming to zero and the braking spiking to one. Smooth cured means is to suggest real steering and jagged patterns are used to suggest erratic maneuvers. Coasting periods are those when the throttle is at zero [20] and the brake is zero.

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Time (s)	Throttle	Brake	Steering	Interpretation
0–5	0.6–0.9	0	0.02	Fast acceleration
5–18	0.4–0.7	0	-0.15→0.12	Lane corrections
18–20	0	0.8–1.0	0.03	Pedestrian stop

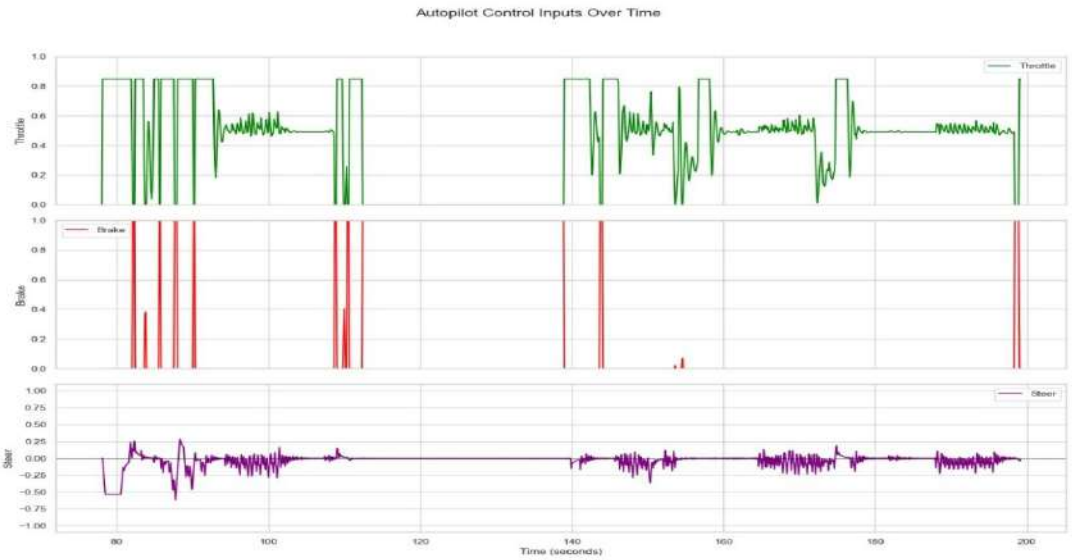

Fig.9. Autopilot Control Inputs over Time

C.Vehicle's Path (Bird's-Eye View)

This top-down map tracks the X and Y of the car which was started at a green position and ended at a red one. It displays the traveling by air and complexity of the navigation route, either on straight themes, or through arduous multi-turn crossroads.

Point	X(m)	Y(m)	Maneuver
1	0	0	Start
50	22	-5	Lane follow
100	45	-12	Traffic interaction
150	60	-25	Left turn
200	72	-28	Obstacle avoidance
250	95	-35	Navigation
End	110	-40	Target reached

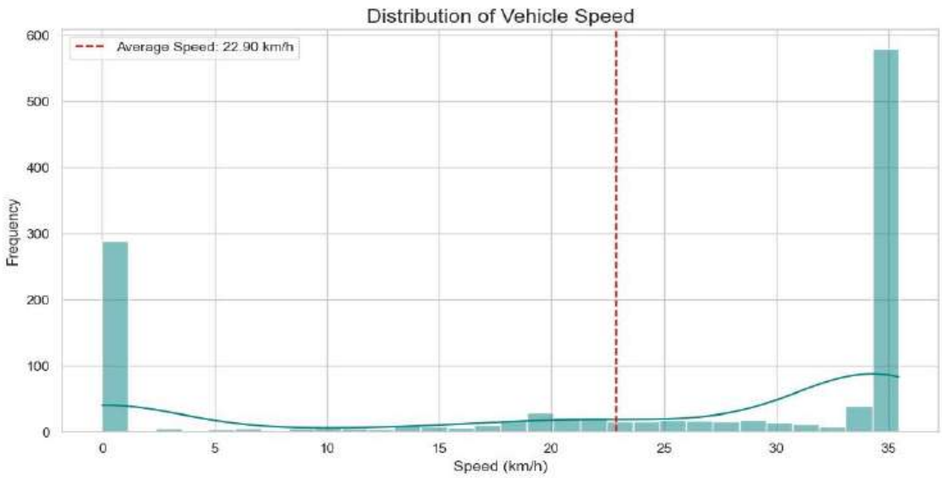

Fig 11. Distribution of vehicle speed

In the methodology, pothole detection is a studied research module, as well. Data is received in both virtual environment of CARLA and real roads testing in the course of the data being robust. Road surface conditions are offered by use of RGB cameras, LiDAR and IMU sensors. Multitasks of pothole-detecting Unet-based deep boys are used to identify potholes based on the task of the image segmentation against the LiDAR depth analysis, which confirms the physical nature of road-related anomalies. Once the potholes are detected, adaptive maneuvers such as slow down or deviation or stability are evaluated by the system using EPS control. The challenge with this module is low-light night lighting, water-filled potholes that spur false detection and adjusting to various road surfaces.

D. Outcomes

Fig 12. Autopilot vehicle detection and decision making

CONCLUSION

The proposed AutoNav architecture reflects the powerful and coherent approach of simulation, testing, and performance of autonomous driving algorithms supported by the CARLA simulator. The platform of the system provides a strong platform on which to build and test self-driving abilities in a safe, recurring and economical approach in that perception, planning and control modules are assembled within a single architecture to aid in ensuring safe and reproducible self-iking power. These findings of the results of long-term research with different driving conditions are guided by the fact that AutoNav can obtain a high pace of route following and high efficiency of navigation acts at the staged conditions and can retain the desired level of efficient obstacle recognition and avoiding behaviors. Also, the automatic dataset generation pipeline makes perception models easier to trained and test them in various environmental conditions. Despite the framework being effective in conducive environments, there is the problem that the framework does not perform well in unfavorable conditions.An indication that nevertheless, more innovations on the robustness and flexibility are still required is that weather, visibility, and high-dynamism interactions are involved. AutoNav, as a whole, is a full, customizable platform aimed at developers and researchers in the autonomous navigation solutions space, and can be expanded to become the basis of the the construction of a realistic self-driving system. The obtained results show that AutoNav effectively maintained accurate navigation across diverse urban scenarios, achieving reliable obstacle detection and stable speed control in simulations. The reinforcement learning models optimized in CARLA exhibited improved performance metrics and enhanced decision consistency.

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