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Longitudinal and Lateral Control of Autonomous Vehicles

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***Abstract* - The research concentrates on the design and assessment of longitudinal and lateral control frameworks for autonomous vehicles using the CARLA simulation platform. The primary goal is to enhance autonomous driving performance under realistic traffic conditions by implementing and evaluating control approaches such as Proportional-Integral-Derivative, Pure Pursuit, and GPS-based steering methods. Longitudinal control is responsible for precise velocity regulation and maintaining safe inter-vehicle distances, whereas lateral control governs steering actions to ensure lane keeping and smooth turning maneuvers. The proposed controllers are validated across multiple driving scenarios, including lane transitions and curved road navigation, using performance indicators such as path-tracking precision, response speed, and system stability. CARLA's high-fidelity simulation environment enables safe experimentation with critical situations such as emergency braking and obstacle avoidance**.

***Keywords* - Reinforcement learning, Suspension system, Vehicle dynamics, Ride comfort, PID, Quarter-car model.**

I. INTRODUCTION

Autonomous vehicles, commonly known as self-driving cars, are transforming modern transportation by minimizing human involvement and enhancing road safety. These systems depend on advanced longitudinal and lateral control mechanisms to achieve reliable vehicle motion. Longitudinal control regulates vehicle speed through acceleration and braking actions, while lateral control manages steering operations to ensure accurate lane keeping. In this work, the CARLA simulator, an open-source and high-fidelity simulation platform, is employed to design and assess these control strategies within a realistic virtual driving environment. Autonomous vehicles rely on perception sensors such as LiDAR to understand their surroundings. Within the CARLA simulation framework, LiDAR enables the virtual vehicle to perceive and interpret the environment in a manner similar to real-world driving conditions [1]. The project utilizes virtual sensor models along with realistic driving scenarios, including braking and turning maneuvers, to evaluate the effectiveness of vehicle control strategies. Longitudinal control governs forward and backward vehicle motion by controlling acceleration and deceleration, enabling smooth speed variations and safe stopping behavior. Lateral control, in contrast, is responsible for steering the vehicle to maintain lane alignment and execute directional changes [2]. Both control mechanisms operate in coordination to ensure stable, smooth, and safe vehicle operation. During cornering maneuvers, the vehicle must reduce speed using longitudinal control while simultaneously adjusting steering inputs through lateral control to follow the desired trajectory.

Control approaches such as Proportional-Integral-Derivative (PID) and Pure Pursuit are evaluated using performance metrics that include path-following accuracy, smoothness of control actions, response time, and robustness under uncertain or dynamically changing conditions. These conditions include roads with varying geometries, different traffic densities, moving pedestrians, and changing weather environments [4]. The simulation setup incorporates virtual LiDAR, GPS, and camera sensors to closely replicate real-world vehicle perception, enabling comprehensive testing of the interaction between control algorithms and sensor data.

Scenario-based evaluations are conducted for straight-road driving, lane-change maneuvers, sharp turns, and emergency braking events, with each scenario designed to assess specific aspects of controller performance. The simulator further enables detailed analysis of autonomous vehicle responses across diverse driving situations such as curves, interseLctions, and traffic signal.

II. LITERATURE SURVEY

When compared with traditional passive suspension mechanisms, active suspension systems have gained increasing importance for enhancing vehicle ride comfort and overall stability. The authors demonstrated that passive suspensions lack the adaptability required to respond effectively to irregular road surfaces and unpredictable driving conditions faced by modern vehicles. Their study emphasized that embedding intelligent control strategies within suspension systems provides an effective solution for balancing passenger comfort and vehicle stability. This contribution established a

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strong foundation for continued research into intelligent suspension systems aimed at real-world automotive applications [1].

The researchers illustrated the capability of active suspension systems to significantly improve ride comfort and safety in modern vehicles. While passive suspension designs remain cost-efficient, the authors highlighted their limitations in adapting to varying road conditions and high-performance driving requirements. By positioning active suspension as a key technological advancement, the study reinforced its importance in enhancing vehicle dynamic behavior. Furthermore, suspension systems were identified as essential components in future transportation systems, particularly for intelligent and autonomous vehicle development [2].

Howell *et al.* (1997) offered some of the earliest perspectives on applying advanced control concepts to vehicle suspension systems. Their research exposed the deficiencies of conventional suspension designs in maintaining road contact and passenger comfort, motivating the shift toward more adaptive and flexible control solutions. Despite its early publication, the work remains influential as it marked a transition from classical mechanical design approaches to computationally driven control methodologies. This study paved the way for subsequent progress in adaptive and active suspension system development [3].

A detailed review of advancements in intelligent automotive suspension systems was presented, with particular focus on how modern control and optimization techniques enhance vehicle dynamic performance. The authors emphasized that increasing expectations for safety and ride quality have driven greater reliance on computational intelligence within vehicle engineering. Their analysis underscored the significant role of suspension systems in shaping the driving experience under diverse operating conditions and reflected the industry's broader transition toward AI-enabled vehicle subsystems [4].

Wu et al. (2024) highlighted recent progress in active suspension technologies, placing strong emphasis on the integration of advanced computational tools and intelligent algorithms. The authors observed that modern control approaches provide improved adaptability under challenging driving conditions while simultaneously addressing passenger comfort and vehicle stability objectives. Their findings indicated that safe, reliable, and comfortable transportation increasingly depends on sophisticated suspension systems. The study also stressed the importance of active suspension in supporting future autonomous driving technologies [5].

Wang et al. (2023) focused on the evolution of active suspension systems within connected and intelligent vehicle frameworks. The authors noted that suspension technologies now contribute to higher-level vehicle intelligence and system integration beyond basic vibration isolation. As vehicle automation advances, suspension systems must deliver comfort, safety, and adaptability across varying scenarios. The study offered valuable insights into how suspension control supports next-generation smart mobility in alignment with global transportation trends. advancements in suspension technology are facilitating higher-level vehicle intelligence and system integration, going beyond straightforward vibration reduction. Their research made clear that suspension systems need to provide comfort, safety, and adaptability in a variety of situations as cars grow more automated. In line with worldwide developments in transportation technology, the report provided insightful information about how suspension control facilitates next-generation smart mobility [6].

Kimball et al. (2024) presented a comprehensive survey of adaptive control and reinforcement learning techniques applied to active and semi-active vehicle suspension systems. The reviewed literature was categorized based on control objectives, modeling complexity, and learning methodologies. The synthesis identified cases where reinforcement learning outperforms classical controllers while also addressing ongoing challenges such as safety assurance, learning efficiency, and physical consistency of learned control policies [7].

A case study was conducted to enhance ride comfort and stability using an advanced reinforcement learning controller applied to a full-vehicle active suspension system. The proposed method integrated a deep reinforcement learning framework that continuously interacts with the system environment without explicit system modeling. A multi-degree-of-freedom vehicle model captured vertical, pitch, and roll dynamics with higher accuracy. The controller simultaneously minimized suspension deflection, tire load variation, and body acceleration, demonstrating reinforcement learning as a robust and self-optimizing approach for complex vehicle dynamics [8].

The study combined the design and simulation of PID and LQR controllers for an active suspension system with the objective of improving ride comfort and handling stability. A quarter-car model was developed, and system responses were analyzed under multiple road excitation inputs. Simulation results revealed that the LQR controller exhibited faster dynamic response and lower energy consumption than the PID controller. Sensitivity analysis further demonstrated that the LQR approach achieved an effective balance between control performance and effort while maintaining system stability [9].

A fuzzy logic control strategy was proposed for vehicle active suspension systems to enhance ride comfort and road handling across varying road surfaces. The authors developed a rule-based fuzzy controller capable of dynamically adjusting suspension forces without requiring an exact mathematical model. Simulation results showed significant reductions in body acceleration and suspension deflection compared to passive suspension systems. The study highlighted fuzzy control as an effective solution for handling nonlinearities and uncertainties present in real driving environment. The proposed approach dynamically regulates suspension forces without relying on an exact mathematical representation of the system. Simulation outcomes indicated that the fuzzy logic–based controller significantly reduced body acceleration and suspension displacement when compared with conventional passive suspension

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configurations. The authors emphasized the capability of fuzzy control techniques to effectively handle nonlinear behavior and uncertainties present in real-world driving environments. This work establishes a strong basis for integrating fuzzy logic with other intelligent control strategies to further enhance active suspension system performance [10].

The study introduced an online reinforcement learning based control strategy for active suspension systems. The controller learns optimal control actions by interacting with the AQM in real time, without requiring prior knowledge of the system dynamics. The learning agent is trained using quarter-car model dynamics to minimize suspension travel and body acceleration through a Q-function–based approach. Simulation results demonstrated the controller's ability to adapt to different road profiles across a range of driving conditions. Compared to traditional control methods, the reinforcement learning approach showed improved ride comfort and road-holding performance. Additionally, the algorithm exhibited strong real-time adaptability and robustness against model uncertainties, highlighting the potential of reinforcement learning for future self-adaptive suspension control systems [11].

The work presented a physics-guided deep reinforcement learning framework for controlling a quarter-car active suspension system. The learning process incorporated physically realistic actuator limits and kinematic constraints to ensure compliance with fundamental physical principles. Stiffness and damping outputs were bounded according to established literature while optimizing ride comfort under ISO-standard road excitations. The results demonstrated significant reductions in body motion metrics, confirming that embedding physical constraints during training improves system stability and enhances generalization to previously unseen disturbances [12].

The authors demonstrated that online learning techniques can effectively manage variations in road profiles and system parameters while optimizing ride comfort and handling constraints for a quarter-car suspension model. The study addressed practical deployment aspects such as computational complexity, convergence characteristics under nonstationary operating conditions, and the trade-off between adaptation speed and system stability. These findings are particularly valuable for real-time implementation in vehicle hardware and hardware-in-the-loop (HIL) testing environments [13].

A full-vehicle active suspension system was developed using a fuzzy logic controller to enhance ride comfort and vehicle stability. The multi-degree-of-freedom model represented vertical, pitch, and roll dynamics at all four wheels. Active control forces were applied using wheel acceleration and velocity feedback to reduce body vibration, suspension movement, and tire force fluctuations. Simulation analysis under different road conditions showed better comfort and improved road handling compared to conventional passive suspension systems [14].

The presented a Physics-Guided Reinforcement Learning framework that integrates data-driven learning with physical modeling for automotive active suspension control. By embedding physical constraints into the reinforcement learning process, the proposed approach ensured stable and physically consistent control actions aligned with vehicle dynamics. Physics-based priors guided the learning agent to achieve an effective balance between ride comfort and road handling while reducing training complexity and improving convergence speed. Simulation results showed that the PGRL framework outperformed conventional reinforcement learning and model-based controllers, particularly under nonlinear and unpredictable driving conditions, demonstrating the promise of hybrid control approaches for advanced suspension applications [15].

III. METHODOLOGY

A. *Simulation Setup:*

The CARLA simulator is used as a virtual driving environment to test and evaluate autonomous vehicle performance under different driving conditions in a safe and controlled manner. It allows experiments to be conducted without real-world risks. During simulation, virtual sensors such as LiDAR, GPS, and vehicle motion sensors are used to collect environmental and vehicle data. LiDAR helps in creating a three-dimensional view of the surroundings by sending laser beams and measuring their reflections, which assists in detecting roads, lane markings, and obstacles.

B. *Controlling Steering (Lateral Control):*

To interpret the environment, intelligent processing algorithms analyze LiDAR data to identify lanes, road features, and nearby objects. Vehicle speed regulation is handled through longitudinal control, where a PID controller governs acceleration and braking to achieve smooth and stable motion. Steering control is managed through lateral control methods such as Pure Pursuit or the Stanley controller, which assist the vehicle in maintaining lane alignment and negotiating turns.

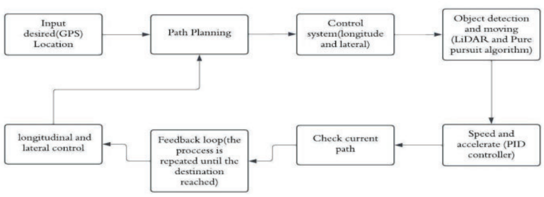

Fig. 1 General block diagram of vehicle control

Fig. 1 is the general block diagram of vehicle control and Fig. 2 PID graph for throttle, steering and Break: The figure illustrates the variation of vehicle velocity (v) with respect to time (s), along with the PID controller responses for throttle, steering, and braking.

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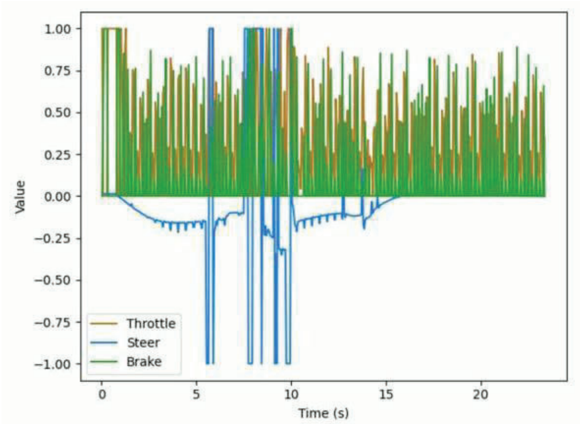

Fig. 2 PID Graph

For lateral control, LiDAR data is utilized to perceive surrounding vehicles and environmental features. The top and side view visualizations generated using MeshLab provide spatial awareness of obstacles and road layout.

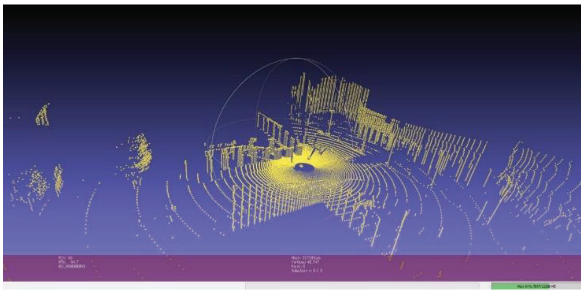

Fig. 3 Side view of LIDAR

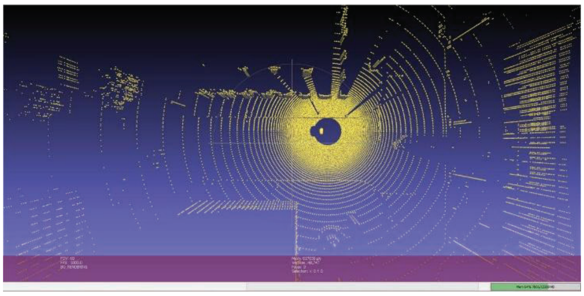

Fig. 4 Top view of the LIDAR

Configurable Parameters:
start_gps = {"x": 109.93, "y": -9.334, "z": 0.0, "yaw": -89.609}
goal_gps = {"x": -41.66, "y": 52.194, "z": 0.0, "yaw": -90.161}
* TARGET_SPEED_KMH = 10.0 → Car tries to maintain ~10 km/h.
* ARRIVAL_DISTANCE = 5.0 → Considered “arrived” if within 5m of the goal.
* LOOKAHEAD_BASE = 6.0 → Pure pursuit look ahead base distance.
* REPLAN_TIMEOUT = 6.0 → If no progress for 6 seconds, replan route.

The PID control algorithm is implemented in this work to regulate the vehicle’s speed in a smooth and stable manner. It operates by continuously monitoring the error between the target speed and the measured vehicle speed. Using this error information, the controller adjusts throttle and braking commands to maintain stability. This approach allows the vehicle to travel at a consistent and safe speed without abrupt changes in motion. The controller enhances overall driving performance by ensuring smooth speed control across varying road conditions.

$$U(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \quad (1)$$

Where: $e(t)$= error between desired and actual value, Kp, Ki, Kd= proportional, integral, and derivative constants.

C. *Pure Pursuit Algorithm:*

The Pure Pursuit algorithm is applied in this article to manage the steering control of the autonomous vehicle. It enables the vehicle to track a predefined path by continuously directing the steering toward a forward reference point known as the look-ahead point. As the vehicle progresses, this reference point updates dynamically, allowing smooth and precise turning behavior. The algorithm determines the appropriate steering angle required to maintain proper lane alignment. This approach ensures stable, safe, and natural vehicle motion during autonomous driving. Pure Pursuit Steering Angle Equation:

$$\delta = tan^{-1}\left(\frac{2L\sin(\alpha)}{L_d}\right) \quad (2)$$

Where: L= wheelbase of the car, α= angle between the vehicle’s heading and look-ahead point, L_d= look-ahead distance.

D. *Traffic Signal Detection Script:*

The traffic signal detection script is implemented in this work to enable the autonomous vehicle to identify and respond appropriately to traffic lights. The script allows the vehicle to detect red, yellow, and green signals within the CARLA simulation environment. When a red signal is detected, the vehicle automatically comes to a halt, and once the signal changes to green, the vehicle resumes motion in a safe manner.

```
# Traffic light cycle timings
RED_TIME = 10.0
YELLOW_TIME = 10.0
GREEN_TIME = 10.0
cycle_time = RED_TIME + YELLOW_TIME + GREEN_TIME
sim_time = 0.0

# Spawn traffic and walkers with 10 km/h speed
print("Spawning traffic and pedestrians...")
actor_ids = spawn_traffic_and_walkers(world, client, traffic_manager, num_vehicles=20, num_walkers=30, vehicle_speed=10.0)
```

Fig. 5 Traffic signal direction script

The script is developed in Python and applies logical conditions to control the vehicle’s actions based on the detected traffic signal state. This functionality enables the autonomous vehicle to comply with real-world traffic regulations, promoting safe and orderly driving behavior. Fig. 5 illustrates the operation of the traffic signal detection script within the simulation, where the vehicle stops when a red signal is observed, remains stationary.

IV. RESULT

Fig. 6 presents the CARLA simulator generating a realistic urban environment with multiple vehicles moving along the roadway. The vehicles navigate smoothly through the streets, closely resembling real-world driving behavior. The presence of buildings, trees, and street lighting

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contributes to detailed and natural-looking surroundings. This simulated scene provides an effective platform for analyzing vehicle motion and traffic behavior under realistic conditions.

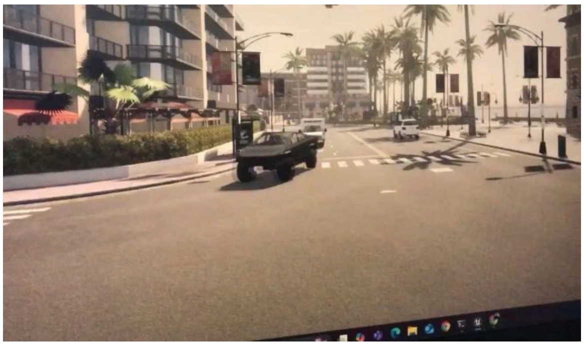

Fig. 6 Random vehicles are moving

Fig. 6 to ensure effective lane maintenance, the PID controller parameters were evaluated using MATLAB. The simulation environment was employed to analyze vehicle motion along the roadway. Graphical representations were used to observe the vehicle's actual trajectory and assess its lane-following accuracy. This visual analysis supported fine-tuning of the PID controller gains.

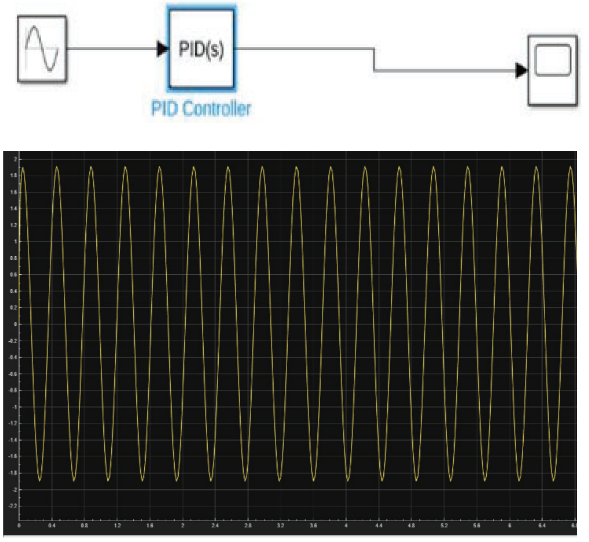

Fig. 7 Graphical representation of the car follows traffic signals and prevents collision

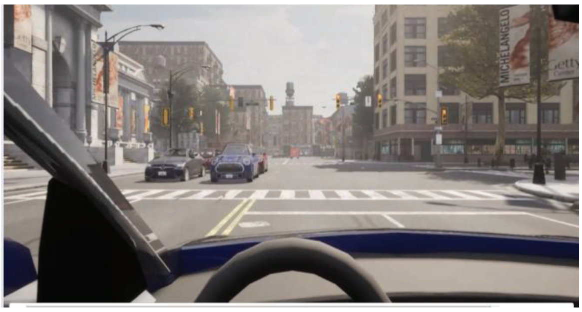

Fig. 8 The car follows traffic signals and prevents collision

The automobiles in Fig. 8 are depicted in their designated lanes as moving properly. Each automobile obeys the traffic light rules perfectly during its trip. The motors are waiting when the signal is red and are in motion when it is green. They also reduce speed or even stop completely to let people pass the street without any danger. The car drivers are set to make it impossible for the cars to collide or for the pedestrians to get injured. This contributes to demonstrating the city traffic regulations enforced in reality. The area is very lifelike, showcasing the buildings, the palm trees, and the unobstructed road. It indicates that the cars could proceed safely if they only obeyed signals and rules. The vehicles shown in Fig. 9 are observed traveling correctly within their assigned lanes. Each vehicle strictly follows traffic signal regulations throughout its route, remaining stationary during red signals and proceeding only when the signal turns green.

Fig. 9 Vehicle detecting traffic signals and displaying speed information

The vehicles also slow down or stop when necessary to allow pedestrians to cross the road safely. The driving logic is configured to prevent collisions between vehicles and ensure pedestrian safety. This scenario effectively demonstrates the enforcement of real-world urban traffic regulations. The environment appears highly realistic, featuring detailed buildings, palm trees, and clear roadways. The results indicate that safe vehicle movement can be achieved through proper compliance with traffic signals and driving rules.

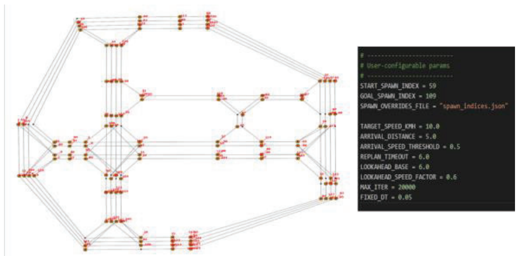

Fig. 10 CARLA road graph and simulation parameters for vehicle navigation

Fig. 10 illustrates the CARLA road network graph along with the associated spawn point indices. Each orange marker represents a location on the map where a vehicle can either begin or conclude its journey, while the red numbers indicate the unique identifiers assigned to these spawn points. The connecting lines between nodes represent the road network and highlight the possible driving routes between locations. This visualization is useful for selecting appropriate start and destination points for autonomous navigation tasks.

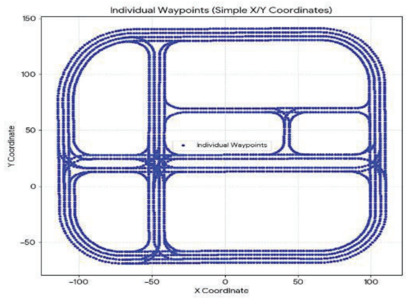

Fig. 11 Plot of Individual Waypoints

Fig. 11 displays the individual waypoints generated within the CARLA simulation environment. Each light blue marker represents a reachable location on the roadway where the vehicle is allowed to travel. The X and Y coordinates indicate the precise positions of these waypoints on the map. The simulator generates a route map in which the starting location is defined as the origin and the destination is identified as the target point.

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