Enhanced Lateral Control for Masterful Defensive Driving

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***Abstract*—In this project, we propose an advanced autonomous racing system for the F1tenth platform, integrating a robust Lateral control for defensive racing using April Tag opponent detection and sophisticated defensive racing strategies. The primary focus is to enhance the vehicle's race performance, robustness, and real-time capabilities while maintaining stability and functionality in high-speed, head-to-head racing scenarios. Defensive racing plays a crucial role in ensuring safe and effective navigation, enabling vehicles to react to other racers' movements, anticipate potential risks, and adapt their trajectories accordingly, thus reducing the chances of collisions and accidents. The success of the project will be evaluated based on improvements in detection metrics, racing performance, real-time operation, robustness, and adaptability to future enhancements. Our proposed solution has the potential to revolutionize autonomous racing on the F1tenth platform, providing a safer, more intelligent, and competitive racing experience with a more stable control.**

***Index Terms*—Autonomous racing, F1tenth platform, YOLOv5,Apriltag, defensive racing strategies, real-time capabilities, object detection, path planning, vehicle control, collision avoidance, robustness, adaptability, performance evaluation.**

1. Importance

The incorporation of defensive racing strategies in autonomous vehicles plays a pivotal role in ensuring their safe navigation through complex and dynamic racing environments. With the increasing number of autonomous vehicles on the track, the likelihood of collisions and race incidents rises significantly, underscoring the crucial importance of defensive racing techniques in maintaining a secure and efficient race atmosphere.

A robust defensive strategy empowers autonomous vehicles to adapt swiftly to various racing situations that may arise during a race. These situations can range from changes in track conditions, variations in vehicle performance, to the unpredictability of competitors' behavior. The ability to adapt to such dynamic circumstances is paramount for ensuring the longevity and competitiveness of autonomous racing vehicles throughout the entirety of a race event.

By implementing and continuously refining defensive racing techniques, autonomous vehicles can attain better overall performance, heightened safety standards, and enhanced reliability. Defensive strategies enable vehicles to anticipate and respond effectively to potential risks, proactively mitigating the chances of accidents and improving the overall race experience for both the participants and spectators.

The successful integration of defensive racing approaches in autonomous vehicles contributes to the wider acceptance and integration of autonomous technologies in various transportation and mobility scenarios. By demonstrating their capability to navigate complex racing environments while prioritizing safety, autonomous vehicles can foster trust among users and stakeholders, thereby accelerating the adoption of autonomous technologies beyond racing applications.

Ultimately, the adoption and advancement of defensive racing strategies in autonomous vehicles hold the potential to revolutionize not only the racing industry but also the broader transportation landscape. By combining cutting-edge technology with meticulous safety measures, autonomous vehicles can redefine the standards of performance, efficiency, and reliability, paving the way for a future where autonomous transportation systems become an integral part of our everyday lives.

2. Problem Formulation

In this project, our primary objective is to design and develop an autonomous racing vehicle that goes beyond mere speed and agility by incorporating robust defensive racing strategies. By utilizing an advanced lateral controller, we seek to create a vehicle that can not only excel in high-speed racing scenarios but also navigate with utmost precision and safety in a dynamic and unpredictable racing environment.

To achieve this, our project encompasses several key aspects that require careful consideration and innovative solutions: (1) Real-time detection and tracking of the position, speed, and trajectory of surrounding vehicles using advanced sensors and computer vision techniques, such as April tag detection; (2) Anticipation and reaction to the actions of other vehicles, including overtaking, blocking, or maintaining position, while minimizing the risk of collisions and other race incidents; (3) Adaptation to changing racing conditions, such as variations in track layout, surface conditions, or vehicle performance, to maintain a competitive edge while preserving safety; (4) Efficient management of vehicle resources, including energy consumption and tire wear, to ensure optimal performance and reliability throughout the race event; (5) Continuous learning and updating of the vehicle's defensive racing strategy based on real-world racing experiences, to improve its performance and adaptability over time. Addressing these challenges involves tackling various subproblems, such as real-time decision-making, path planning and control, multi-agent interactions, and dynamic environment adaptation, to enable the autonomous racing vehicle to safely and effectively navigate complex racing scenarios while employing defensive racing strategies.

3. Challenges

The development of an autonomous racing vehicle that employs robust defensive racing strategies presents several significant challenges, which must be addressed to ensure its safe and effective performance in dynamic and uncertain racing environments. These challenges include:

1) **Real-time detection and tracking:** The vehicle must be able to quickly and accurately detect and track the position, speed, and trajectory of surrounding vehicles using advanced sensors and computer vision techniques, such as April tag detection. This requires overcoming challenges related to sensor noise, occlusions, and limited field-of-view, while also ensuring low-latency and high-frequency updates to facilitate timely decision-making and control.
2) **Dynamic decision-making:** The autonomous racing vehicle must be capable of making real-time decisions that enable it to anticipate and react to the actions of other vehicles, including overtaking, blocking, or maintaining position. This requires the development of decision-making algorithms that can handle uncertainty, a robust controller, consider multiple objectives, and balance aggressive and defensive strategies to minimize the risk of collisions and other race incidents.
3) **Path planning and control:** To navigate complex racing scenarios effectively, the autonomous racing vehicle must be able to generate and follow optimal racing lines that account for the dynamic nature of the racing environment, such as variations in track layout, surface conditions, or vehicle performance. This involves the development of efficient and robust path planning and control algorithms that can adapt to changing conditions and provide smooth and stable vehicle trajectories. Establishing diverse pure pursuit lines is crucial for maintaining control and ensuring the vehicle's lap time remains competitive.
4) **Multi-agent interactions:** The vehicle must be capable of understanding and predicting the actions of other vehicles in the race, to enable it to make informed decisions and execute defensive strategies effectively. This requires the development of models and algorithms for multi-agent interactions, considering factors such as the heterogeneity of vehicle capabilities, varying driver behaviors, and the complex interplay between cooperative and competitive elements in racing.
5) **Resource management:** In real world racing, the autonomous racing vehicle must efficiently manage its resources, such as energy consumption and tire wear, to ensure optimal performance and reliability throughout the race event. This requires the development of advanced control and optimization techniques that can balance the trade-offs between performance, safety, and resource utilization.
6) **Continuous learning and adaptation:** To improve its performance and adaptability over time, the autonomous racing vehicle must be capable of continuously learning and updating its defensive racing strategy based on real-world racing experiences. This involves the development of machine learning and data-driven methods that can extract valuable insights from racing data and adapt the vehicle's decision-making, control, and resource management strategies accordingly.

4. Related Works

In recent years, there has been a growing interest in developing autonomous racing vehicles capable of safely and effectively competing in dynamic and uncertain racing environments. Several approaches have been proposed and implemented to address the various aspects of autonomous racing, such as detection, tracking, decision-making, path planning, control, and multi-agent interactions.

One notable work in the field of autonomous racing is the use of Mixed-Integer Quadratic Programming (MIQP) for racecar control in head-to-head competitions [1]. This method enabled the vehicle to optimize its trajectory by considering both its own and opponents' motion constraints. Another study investigated autonomous head-to-head racing in the Indy Autonomous Challenge simulation race, which focused on applying reinforcement learning and game-theoretic techniques to improve racing performance [2]. A different approach proposed a game-theoretic model predictive control with data-driven identification of vehicle models for head-to-head autonomous racing [3]. This method aimed to improve the vehicle's performance by anticipating and reacting to other vehicles' actions and adapting its racing strategy accordingly.

Other researchers have focused on the development of hierarchical control architectures for multi-agent autonomous racing [4]. This approach divided the racing problem into multiple levels, with each level addressing specific aspects such as trajectory generation, control, and decision-making. The integration of game-theoretic planning and control barrier functions has also been explored to enhance the performance of autonomous racing vehicles in multi-vehicle competitive scenarios [6]. In addition, a study on game-theoretic planning for self-driving cars in multi-vehicle competitive scenarios demonstrated the potential of utilizing game theory to generate optimal trajectories and strategies for autonomous vehicles in complex racing environments [5].

In the realm of computer vision and object detection, researchers have applied deep learning techniques, such as YOLOv3 [7], YOLOv4 [8], and YOLOv5, to achieve real-time detection and tracking of surrounding vehicles. These methods have been shown to provide accurate and low-latency updates on the position, speed, and trajectory of other vehicles, which are crucial for effective decision-making and control in autonomous racing.

Fig. 1: Car setup

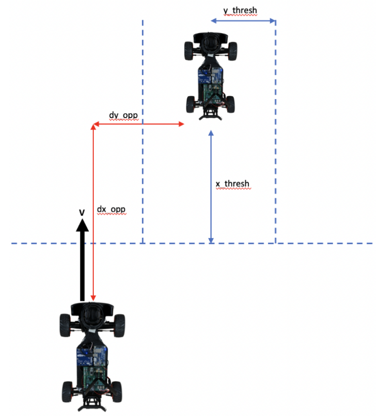

Fig. 3: Diagram showing tunable thresholds for deciding when to switch race lines.

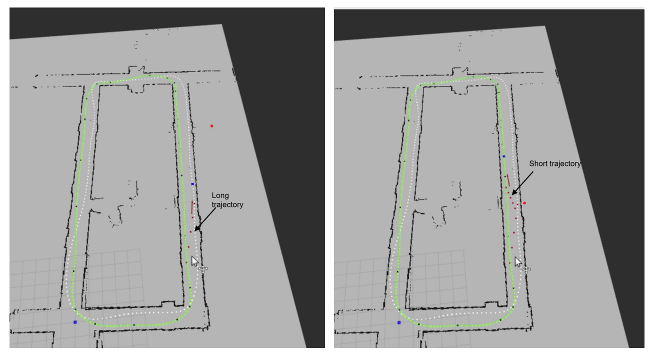

Fig. 4: Screenshot of Rviz while the F1Tenth car is running. The car first performs a merge with a long trajectory, since the April Tag was approaching slowly. It then performs a merge with a short trajectory, since the April Tag was approaching quickly.

In summary, various methods and techniques have been proposed and implemented to tackle the challenges of autonomous racing. However, there remains room for improvement, particularly in the development of robust defensive racing strategies that can ensure safe and effective performance in dynamic and uncertain racing environments.

5. Methodology

In this section, we delve into the methodological framework that facilitates the proficient transition of autonomous racing vehicles between distinct racing lines, taking into account a host of parameters and constraints. To ascertain the pose of the competing vehicle, we strategically augmented our setup with an Intel RealSense depth camera, positioned at the rear of our vehicle, as depicted in Figure 1. This arrangement empowers the car with an enriched perception of its surroundings, thereby enhancing its autonomous decision-making capabilities in real-time racing scenarios.

A. Lateral Control

The controller strategy comprises three main components: decision to switch, calculating merging path, and steering angle considerations. The vision node is responsible for tracking the opponent's lateral offset, distance behind, and calculating the opponent's velocity at each timestep. The optimal merging trajectory of the defending car designed to obstruct an overtaking car is depicted in Figure 2.

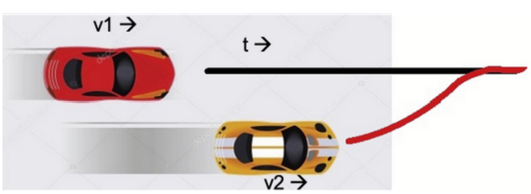

Fig. 2: Overtaking manuever

To facilitate the decision-making process, tunable parameters of x_{thresh} and y_{thresh} are introduced as shown in Figure 3. These thresholds determine when the vehicle should switch racing lines based on the opponent's position and velocity. If the opponent is projected to cross x_{thresh} in the next timestep and is laterally outside y_{thresh}, the vehicle switches racing lines.

In dynamic racing scenarios, the vehicle must react quickly to the opponent's movement. When the opponent approaches at a high velocity, the car needs to switch lines faster to block it. If the opponent approaches at a slow velocity, the car has more time to switch lanes and can gradually merge. The merge distance becomes a linear function of the opponent's velocity, allowing the vehicle to respond more promptly. A cubic spline is interpolated between the current position and merge distance along the next racing line, ensuring a smooth transition. The difference between slow and fast approach is depicted in Figure 4.

The steering angle is critical for maintaining vehicle stability during the merging process. A PD (Proportional-Derivative) controller is added to smooth out changes in steering angle when merging, while the maximum steering angle when merging is clamped according to the car's current velocity to reduce tire slip and ensure safe cornering.

Moreover, it is essential to calculate the maximum allowable steering angle while considering the lateral acceleration limits. To accurately determine the lateral acceleration of the autonomous race car, we meticulously designed and executed a constant radius test. This involved facilitating the car to maintain a steady acceleration while traversing a tightly constrained circle with a radius of 0.866 meters. To automate this process, we leveraged Python programming language to script an algorithm that incrementally ramped up the car's speed at specific time intervals.

The pivotal point of this test was to identify the precise velocity at which the car began to slip off its predefined circular path. Such an event denotes the limit of the car's grip or traction, which is a crucial data point for understanding the vehicle's lateral dynamic capabilities. The testing of the lateral acceleration of our car in Levine hall can be found in this video. This location was specifically selected due to its surface properties, which closely approximate the frictional conditions of the terrain on which we intended to deploy the vehicle for its ultimate performance testing.

Upon obtaining the data from these tests, we proceeded to compute the lateral acceleration. The calculation utilized the velocity at the onset of slip, thereby providing us with a quantifiable measure of our vehicle's lateral acceleration capability under extreme conditions. This data is invaluable in fine-tuning our car's control algorithms and ensuring optimal performance in high-speed, high-lateral load scenarios commonly encountered in autonomous racing.

$$\text{Lateral } g = ay = \frac{v^2}{r} \tag{1}$$

$$\frac{(2.4\,\text{m/s})^2}{0.866} = 6.65 = 0.68\,g \tag{2}$$

Then we proceed to the calculation of the maximum allowable steering angle while considering the lateral acceleration limits which involves the following steps:

1) Define the parameters:
   - $a_{\text{y\_max}}$: Maximum allowable lateral acceleration (tested using constant radius test)
   - V: Vehicle's longitudinal speed (straight-line speed)
   - L: Wheelbase of the vehicle (distance between front and rear axles)
   - δ: Steering angle
2) Establish a relationship between lateral acceleration (a_{y}), vehicle speed (V), and turning radius (R):
$$a_{\text{y}} = \frac{V^2}{R} \tag{3}$$
3) Calculate the maximum turning radius (R_{max}) allowed based on the maximum allowable lateral acceleration ($a_{\text{y\_max}}$) and vehicle speed (V):
$$R_{\text{max}} = \frac{V^2}{a_{\text{y\_max}}} \tag{4}$$
4) Determine the relationship between steering angle (δ) and turning radius (R) using the small angle approximation, which assumes small steering angles and low-speed scenarios:
$$R \approx \frac{L}{\tan(\delta)} \tag{5}$$
5) Compute the maximum allowable steering angle (δ_{max}) using the maximum turning radius (R_{max}) and the wheelbase (L):
$$\delta_{\text{max}} \approx \arctan\left(\frac{L}{R_{\text{max}}}\right) \tag{6}$$
6) Calculate
$$\theta_{PID} = \theta * K_p + \frac{(\theta - \theta_{previous})}{\Delta t} * K_d \tag{7}$$

To maintain vehicle stability and control while merging, it is necessary to limit the rate of change in the steering angle using a PID controller:

1) Calculate the desired steering angle change rate ($\Delta\theta_{\text{desired\_rate}}$) using the PID controller output:
$$\Delta\theta_{\text{desired\_rate}} = \frac{(\theta_{\text{PID}} - \theta_{\text{previous}})}{\Delta t} \tag{8}$$
2) Limit the steering angle change rate ($\Delta\theta_{\text{limited\_rate}}$) by introducing a maximum allowed rate of change (max_rate):
$$\Delta\theta_{\text{limited\_rate}} = \min\Big(\max\left(\Delta\theta_{\text{desired\_rate}}, -\text{max\_rate}\right), \text{max\_rate}\Big) \tag{9}$$
3) Compute the new limited steering angle change ($\Delta\theta_{\text{limited}}$):
$$\Delta\theta_{\text{limited}} = \Delta\theta_{\text{limited\_rate}} \times \Delta t \tag{10}$$
4) Calculate the new limited steering angle (θ_{limited}) by adding the limited steering angle change ($\Delta\theta_{\text{limited}}$) to the previous steering angle (θ_{previous}):
$$\theta_{\text{limited}} = \theta_{\text{previous}} + \Delta\theta_{\text{limited}} \tag{11}$$
5) Update the previous steering angle (θ_{previous}) with the new limited steering angle (θ_{limited}):
$$\theta_{\text{previous}} = \theta_{\text{limited}} \tag{12}$$

B. Opponent Detection

For opponent detection it is neccesary to have a view at the rear to make sure we see the opponent. So, we installed an Intel RealSense camera on the rear of our vehicle, as depicted in Figure 1. This helps us detect the car behind using computer vision techniques. With the camera mounted behind, we considered various approaches for opponent detection starting from simple to complex approaches and we chose april tag due to its robustness. The different approaches we chose are explained below.

1) YOLO: YOLO, short for "You Only Look Once," is a groundbreaking real-time object detection algorithm that has gained widespread popularity for its exceptional speed and accuracy. This deep learning-based approach uniquely combines the tasks of object localization and classification into a single neural network architecture. Instead of scanning an image multiple times with different scales and aspect ratios, as is common in traditional object detection methods, YOLO examines the entire image only once. This efficient process significantly reduces computational requirements while maintaining high accuracy rates. The algorithm divides the input image into a grid, and each grid cell predicts bounding boxes and class probabilities for the objects within it. The predictions are then combined to generate the final object detection output. YOLO has undergone several improvements and iterations since its initial release, resulting in even faster and more accurate models that continue to be widely used in various computer vision applications. However, we encountered challenges when trying to integrate PyTorch, ONNX, and CUDA on Nvidia Jetson Xavier hardware. The device's limited computational power posed difficulties, resulting in a low frame rate (15 FPS) for object detection at high speeds.

2) Color based approach: Color-based detection is a computer vision technique that identifies and segments objects within images or videos based on their color properties. This approach is effective when objects exhibit distinct colors that are easily distinguishable from the background or other objects in the scene. The process typically involves converting the input image from the default RGB (Red, Green, Blue) color space to an alternative color space, such as HSV (Hue, Saturation, Value) or Lab, which better represents color information. Then, a color threshold or range is defined to isolate the desired objects based on their unique color characteristics. Morphological operations, such as erosion and dilation, may be applied to reduce noise and improve segmentation results. Finally, contours or bounding boxes are extracted to represent the detected objects, which can then be used for further analysis or processing in various applications.

Initially, we employed an approach that relied on detecting the orange color, as it was a prevalent color in the lidar data for all the cars. However, we found that this method lacked robustness and failed to perform consistently under varying lighting conditions. As a result, we decided against using it in our final solution.

3) Apriltag: Our methodology incorporates AprilTag detection to enhance the accuracy and robustness of estimating the pose and distance of the target object from the camera. AprilTag is a visual fiducial system that utilizes easily detectable and decodable markers. To leverage this system, we attach an AprilTag to the target object and capture images or video frames with the camera.

After capturing the frames, we preprocess the images and utilize the AprilTag detection library to identify and decode the tag. The library provides us with the unique identifier of the tag as well as the corner coordinates within the image frame. Additionally, we calibrate the camera to determine its intrinsic parameters, which include the focal length, optical center, and distortion coefficients.

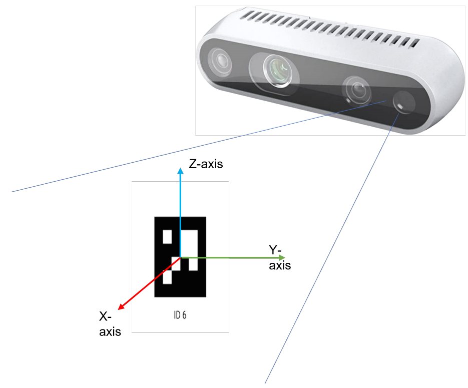

Fig. 5: April Tag detection from the Realsense camera.

With the known dimensions of the AprilTag and the camera's intrinsic parameters, we can compute the extrinsic parameters. These parameters offer crucial information about the position and orientation of the tag in the camera's coordinate system. By extracting the translation vector, we can obtain the x and y pose of the tag. Furthermore, using the focal length, Field of View (FoV), width of the image captured and Euclidean distance, we calculate the precise distance between the tag and the camera.

This approach not only enables accurate estimation of the object's pose and distance but also holds immense value for various applications such as robotics and navigation. By leveraging these coordinates, we can also track the opponent's velocity by calculating the change in x coordinates between each camera frame.

By integrating AprilTag detection into our methodology, we enhance our ability to estimate the target's pose and distance, facilitating precise measurements and enabling advanced applications in fields such as robotics and navigation.

6. Results

Our project successfully addressed and overcame four key challenges which was mentioned earlier in the Challenges Section in developing a robust autonomous racing system. We achieved real-time detection and tracking of surrounding vehicles, which forms the backbone of our dynamic decision-making ability. Our work on path planning and control allowed for effective navigation in diverse racing scenarios, and our efforts in managing multi-agent interactions ensured that the vehicle can respond accurately to the actions of other participants in the race. While we have made strides in addressing these significant challenges, the aspects of resource management and continuous learning and adaptation present avenues for further research and development.

The evaluation of our concept proved successful across both simulation and hardware testing. We have documented this process in an engaging video presentation, offering a direct visualization of our system in operation within both the simulated environment and the physical F1TENTH vehicle.

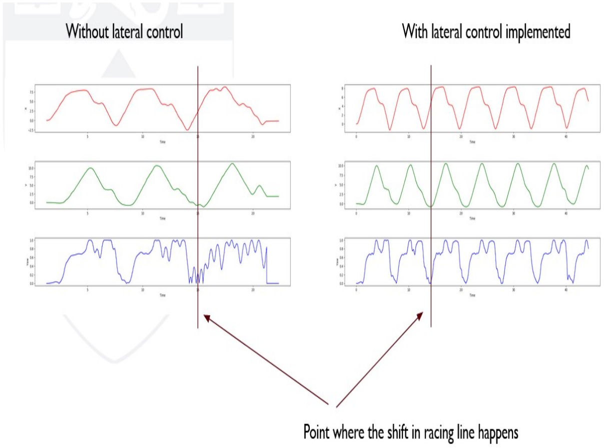

Fig. 6: X Y and yaw position of the car

We also prepared a comprehensive presentation that provides an in-depth overview of our control mechanism. You can also find the source code of the algorithm in our Github repository.

We initiated our testing phase with a simulation of the vehicle's racing line shift, without implementing the lateral control. This initial run served to establish the vehicle's baseline characteristics. We observed a marked increase in the car's yaw rate during high-speed shifts, a result of not accounting for lateral acceleration and the absence of control implementation.

Upon introducing our lateral control algorithm into the simulation, the effect was both instant and profound. The vehicle, previously unsteady during line shifts, began to exhibit a smooth transition between racing lines. We have documented this transformation in a video, which provides a side-by-side comparison of the car's performance with and without the implementation of our lateral control algorithm.

To further illustrate this improvement, we logged the X and Y coordinates as well as the yaw position of the car during its run. These logs clearly demonstrated that without our control algorithm in place, the vehicle's yaw becomes unstable following line shifts, leading to eventual crashes. In stark contrast, when operating under the guidance of our lateral control, the car was capable of completing multiple laps without a single incident but with a slight disturbance in yaw angle. This data, depicted in Figure 6, highlights the transformative impact of our lateral control algorithm on the stability and performance of the vehicle during high-speed maneuvers

Having verified the effectiveness of our control algorithm in simulation, we proceeded to implement it on the physical F1TENTH car. Initial testing at low speeds, using an April tag as a simulated opponent, yielded a noticeably unstable performance when the vehicle shifted racing lines without the aid of our lateral control. However, the implementation of our lateral control algorithm transformed this performance, enabling smooth and controlled line shifts. To optimize this performance, we fine-tuned our control gains. A comparison of the vehicle's performance, with and without our lateral control, can be seen here.

We then escalated the testing to higher speeds and initiated the lateral control to simulate racing line shifts mimicking defensive maneuvers when an opponent was detected by the onboard camera. Notably, our algorithm also calculates the velocity of the opposing vehicle and adjusts the shifting trajectory accordingly. The car demonstrated short, swift line shifts for opponents approaching at higher speeds and longer, calculated shifts for slower opponents. The real-world demonstration of these varying scenarios can be viewed here. These transitions were smooth and stable, with the vehicle maintaining its momentum without unnecessary time loss for self-adjustment.

Finally, we assessed the effectiveness of our algorithm in a racing environment by simulating a race in RViz. We compared the time lost by the overtaking car and the defending car during various maneuvers. A video of the Rviz simulation can be found here. The results, presented in Table 1, revealed our defending car to be highly efficient, able to slow down the overtaking car while incurring minimal time loss. This reinforces the effectiveness of our algorithm in real-world racing scenarios, blending control, vision, and strategy for an advanced autonomous racing experience.

Ego car lap time (original)	6.308 s
Ego car lap time (lateral controller)	6.338 s
Speed difference to opponent	-1 m/s
Opponent lap time (with increased speed)	6.1 s
Opponent lap time (against ego car defending)	6.5 s

TABLE I: Results from running lateral controller car defending against opponent in Rviz. The opponent's lap time increases by 0.4s while the defending car maintains only with a minor increase in laptime.

7. Conclusion and Future work

In conclusion, our project has achieved remarkable success in the integration of a lateral controller aimed at defensive driving within the framework of an autonomous race car's operation. By utilizing a forward-facing LiDAR system and supplementing this with a rear-facing camera, we were able to equip the vehicle with a close to 360-degree awareness of its environment. This comprehensive situational awareness forms the cornerstone of our high-speed defensive driving system.

The ability to calculate the car's lateral acceleration through a constant radius test was instrumental in determining the optimal steering rate. This rate ensures the maintenance of tire grip during high-speed lane changes, thereby enhancing the vehicle's stability and control. The simplicity of our control algorithm belies its effectiveness. The blend of a PD control system with a custom high-level planner allowed the vehicle to execute high-speed maneuvers with a level of smoothness that prevented any loss of control.

The role of the Intel RealSense depth camera was pivotal in our system's operational success. It was adept at detecting opponents and accurately assessing the relative distance and velocity. This information was then used to initiate defensive maneuvers, with the controller adjusting trajectories based on the opponent's speed. The successful combination of these control and vision components constituted a significant milestone in our project.

Looking ahead, the potential for further improvements is vast. The implementation of YOLO models for efficient car detection and the compatibility with high-powered Nvidia GPUs promise an enhanced level of refinement and efficiency in the autonomous racing experience.

As we push the boundaries of autonomous racing vehicle performance, we are excited about the prospect of testing the lateral controller at higher velocities. This would allow us to better understand the limitations of lateral acceleration and develop strategies to optimize performance within these constraints. We also anticipate refining our opponent detection capabilities to increase accuracy, particularly in velocity estimation.

In the real-world racing scenario, managing resources such as energy consumption and tire wear becomes crucial, especially when the car is engaged in defensive maneuvers. To ensure optimal performance and reliability throughout a race event, it is essential to develop advanced control and optimization techniques. These techniques need to balance performance, safety, and resource utilization in an ever-changing race environment. Our work is a significant stride toward this new era of competitive autonomous racing, and we look forward to the exciting challenges and opportunities it presents.

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