Keywords: Autonomous Vehicles, Racing, Motorsports, High-Speed, Sensors, Autonomy Hardware, Vehicle Architecture, High-Performance, ADAS, Electric Vehicles.

Abstract: This paper explores into the challenges and advancements encountered in the development and operation of full-sized autonomous cars built for motorsports competitions. Concentrating on a qualitative examination of the sensor configuration, structure, and real-time assessment of vehicle platforms in the Indy Autonomous Challenge and Roborace. The scrutiny is centered on recent years’ research and the vehicles’ performance in demanding conditions, systematically highlighted and summarized in this paper. The analysis furnishes a more concise and condensed comprehension of the prevailing trends in such competitions, offering insights into the future of autonomy in the coming years.

1 INTRODUCTION

Advanced Driver Assistance Systems (ADAS), as defined by the SAE, encompass six levels of automation (On-Road Automated Driving (ORAD) Committee, 2021). These systems heavily depend on an array of sensors and software to accurately perceive their surroundings, to achieve full automation without human intervention. As we move closer to this reality, the sensor industry is witnessing rapid growth, innovating to meet the challenges that autonomous systems present (Ahangar et al., 2021). Notably, autonomous ground systems such as cars, trucks, and trains continue to grapple with specific, unresolved challenges, motivating researchers and engineers to dive into this area (Yeong et al., 2021).

The world of motorsport, characterized by conditions like steep inclines, high-speed cornering, and the nuanced techniques such as “lift and coast”, presents its unique set of challenges. Racing circuits featuring vehicles like IndyCar, Formula E, and Formula 1 represent the pinnacle of high-performance design. The technological innovations nurtured in these racing arenas often find their way into commercial vehicles (Sarkar and Mohan, 2019). Racing drivers, with their deep understanding of vehicle dynamics and performance, exhibit skills and techniques that are difficult to replicate via software or automated systems. While sensors can process information faster than human senses, the nuanced comprehension a racer possesses often surpasses that of an average driver. In recent times, numerous autonomous racing competitions have emerged that challenge engineers and researchers (Buehler et al., 2009), (Roborace, 2016), (A2RL, 2023), (IAC, 2020). These programs provide a platform to gain deeper insights, address existing issues, and elevate vehicle performance and development. Some of these competition milestones are shown in Figure 1.

![Figure 1: Autonomous Racing Milestone.](image-url)

High-speed racing vehicles, as defined within the context of this research, encompass vehicles engineered to operate under stringent conditions, experiencing substantial lateral forces, and capable of achieving swift acceleration. Over the past decade, technological advancements in sensors have spawned...
an array of high-performance ground vehicle programs, each characterized by distinct metrics, propulsion systems, and performance outcomes. The last decade has introduced multiple autonomous racing programs where ground race vehicles were built specifically for racing purposes, vehicles are handled at their limits (Betz et al., 2022). This research will concentrate on two significant projects that involved the development of full-sized autonomous racing vehicles for racing platforms: Roborace and the Indy Autonomous Challenge. These programs show distinctions in their racing architecture, conceptual frameworks, and performance metrics. Nonetheless, they also share commonalities, particularly concerning sensor and software performance in real-time scenarios. Building upon the foundation laid by (Mar et al., 2024), this study will predominantly delve into the sensor setup of each vehicle model, describing specific challenges these sensors may encounter during testing. Subsequently, we will offer a comprehensive overview of their real-time performance based on previous tests.

2 SENSOR SETUP

When considering the vehicle hardware configuration, the selection of specific devices involves several possible combinations influenced by both technical and non-technical factors. Similar to traditional motorsports competitions; these selections are not only dictated by technical considerations but also by non-technical factors, notably the availability of sponsors. It’s noteworthy that, unlike conventional racing, sponsors in autonomous racing have a direct impact on the final vehicle design and the choice of hardware components.

In this section, we present a comprehensive table summarizing the sensors used in the vehicles from the studied competitions, namely Roborace and the Indy Autonomous Challenge (IAC).

2.1 Roborace

Roborace, inaugurated in 2016, introduced three distinct vehicle models: Devbot (2016), Robocar (2017), and Devbot 2.0 (2018). While there are notable differences in design across these models, the sensor architecture remained consistent for the three different versions of this series. The sensor suite included LiDARs, cameras, radars, and ultrasonic speed sensors as the exteroceptive sensors, which are shown in Table 1. The computational backbone consisted of the NVIDIA Drive PX2 (NVIDIA, 2016) for high-level planning and perception processing while the Speedgoat Mobile Target Machine (Speedgoat, 2016) was used for real-time control tasks (Betz et al., 2019) and ensuring low-latency communication with the vehicle’s actuators, it facilitated rapid adjustments based on the decisions made by the high-level planning system.

The integration of LiDARs, cameras, and radars systems provided a 360-degree environmental perception. Four LiDARs working in tandem with six cameras contributed visual input for object recognition and enhanced understanding of the race environment. Additionally, four radars added layers of sensing, reinforcing the vehicles’ ability to detect and respond to surrounding objects. This sensor fusion strategy created a sophisticated perception framework, boosting the vehicles’ overall awareness on the race track.

The transition from Devbot 1.0 to Robocar and Devbot 2.0 exemplified a systematic approach to sensor placement and testing objectives. The initial design of Devbot 1.0/2.0, featuring a Le Mans Prototype (LMP) chassis, carefully considered scenarios involving potential human intervention. In contrast, the cockpitless design of the Robocar gave a distinct futuristic design, stressing the intent to test the vehicle at elevated speeds without direct human intervention. This design choice reflected a forward-looking vision, emphasizing a commitment to pushing the boundaries of performance. Furthermore, the powertrain design displayed a deliberate effort to replicate the advancements achieved in the electric Formula E, leveraging its widespread popularity. This emphasis is notably reflected in the choice of electric motors as the primary propulsion source for these vehicles, with detailed power specifications provided in Table 1.

2.2 Indy Autonomous Challenge

Introduced in 2020 and hosting its inaugural race in 2021, this series debuted with the AV-21 model, initially engineered by Clemson University’s Deep Orange project (Zhu et al., 2021). Mimicking the physical appearance of the Indy Car series and adopting a cockpitless design, which emphasizes the avoidance of direct human intervention during testing.

The selection of sensors, detailed in 1, aimed at redundancy for decision-making and perception. LiDAR, Radar, and Cameras were chosen, offering flexibility for usage individually or in fusion. This selection is intended to equip the vehicle with a comprehensive understanding of its dynamic environment, crucial for navigating at high speeds. LiDAR technology, with three units, played an important role in addressing challenges such as reflection delays and
adapting to banking angles. The Radar introduced an additional layer of redundancy, enhancing the vehicle’s capacity to detect and respond to dynamic changes in the racing environment for medium and large-range detection. The multi-camera setup facilitated comprehensive visual coverage, contributing to object recognition, lane tracking, and an overall understanding of the racing environment (Ayala and Mohd, 2021). While originally designed for industrial applications such as surveillance, machine vision or robotics, the cameras were repurposed for autonomous racing. Which were not intended for exposure to high lateral forces and vibrations. For localization, two GNSS units were used initially; however, due to some challenges during initial tests an additional unit was inserted later which was intended to address signal loss or inaccuracies at higher speeds. All sensors had the highest refresh rates in the market, a crucial feature for a racing context, where split-second decisions are imperative. IAC AV-21 incorporated two robust embedded computers equipped with the NVIDIA Quadro RTX 8000 GPU and the RTX A5000. Additionally, the selection included the ADLink AWA-3501 and Autera Autobox. These devices were selected mainly because of the harsh conditions this car experimented with, embedded systems by definition are designed to perform specific tasks (Tumeo et al., 2017). The powertrain configuration remained consistent with that of an Indy Car, which was not altered. Additionally, the choice of data transfer mechanisms and electronic control units (ECU) was provided by combining industry and commercial devices, resulting in data acquisition rates that exceeded standard levels.

## 3 REAL TIME PERFORMANCE

The real-time performance evaluation of autonomous racing vehicles is crucial to assess their capabilities and address challenges encountered during high-speed racing scenarios. This section delves into the dynamic aspects of the Roborace and IAC vehicles, emphasizing real-time challenges and outcomes.

### 3.1 Roborace

As this remains a motorsports competition, the speeds achieved during each event or race are of significant importance. The summarized speeds, as shown in Table 2 exhibit a gradual acceleration in both Roborace and the IAC. At the same time, competitors require extensive software development and validation, a substantial portion of which occurs off-the-track.
3.1.1 Devbot 1.0

The preliminary rollout of the vehicle underwent testing at UK Donington Park (BBC, 2016) and the Marrakech Formula E Street Track. During the latter session, the vehicle completed 12 laps in a time frame of 30 minutes (Knight and Blendis, 2016). These tests were conducted to assess and evaluate the initial deployment of sensors and the overall real-time performance on the track. After that, the deployment of Devbot 1.0 at the Buenos Aires EV Grand Prix in 2017 witnessed two significant events. In the first event, the vehicle completed the course track, reaching a maximum speed of 186 km/h. In the second event, a collision occurred when one of the vehicles miscalculated a corner while traveling at high speed, resulting in a crash (Kelion, 2017). ‘Devbot’ raced against humans in two different experiments. The first one on the Hong Kong Central ePrix track, in which a non-professional driver got 86 seconds compared to Devbot’s time of 94 seconds, surpassing Devbot by 8 seconds, where both reached top speeds of 150-160 km/h (Dow, 2017). In 2018, a professional driver repeated the experiment and raced against Devbot 1.0 in Rome for the opening of the Formula E event. In this case, the pro-driver outperformed the Devbot by 26 seconds (Fingas, 2018).

University teams initiated the testing of their software platforms by executing three autonomous laps on the Berlin Racetrack, achieving top speeds of up to 150 km/h. The use of a global optimal planner for path generation ensured smooth on-track performance with no notable hardware issues or delays. The lateral error was minimal, reaching a maximum of 0.8 meters (Stahl et al., 2019b). Another study conducted by (Caporale et al., 2018) demonstrated a low lateral error of 0.3 meters. This study employed sensor fusion state estimation and a non-linear MPC controller in the initial version of Devbot on a road course track for two laps. In both instances, the computing and sensor architecture exhibited robust performance without significant issues, allowing the vehicles to achieve high speeds of up to 150 km/h.

In (Caporale et al., 2019), various challenges were identified in the autonomous vehicle system. One notable issue pertained to computing, specifically the overload of the ARM CPU during scan matching on the PX2, resulting in occasional failures. Additionally, concerns were raised about vehicle alignment during trajectory planning. The use of a single mass model failed to account for instances where the vehicle’s alignment did not align perfectly with the path tangent, consequently leading to reduced acceleration, particularly in certain turns.

A final test was performed with the Robocar where the vehicle was pushed to the limit and reached 280 km/h to set a new record (Roborace, 2019), there has not been any disclosure of data or study that was done during this test.

3.1.2 Devbot 2.0

Devbot 2.0 experienced extensive testing across various race events, including the Zala Zone, Circuit de Croix, Montebanco Spain, Modena, and others. In a study conducted by (Stahl et al., 2019a), the vehicle planner achieved an average rate of 16.8 Hz, demonstrating capabilities up to 212 km/h with a 200ms prediction to anticipate the movements of the leading vehicle. Tests carried out at the Zala Zone Hungary and the Circuit de Croix-en-Ternois in France showcased lidar-based localization with a lateral error consistently below 10 cm. The vehicle achieved speeds exceeding 45 m/s and accelerations greater than 10m/s². Challenges arose in time synchronization with sensors, as a 10ms delay at 30m/s could result in a 0.3m error, necessitating vehicle odometry (Schratter et al., 2021). (Renzler et al., 2020) addressed lidar distortion correction and delay compensation at Zala, reaching speeds up to 90 km/h with accelerations of 10ms at a 20Hz rate. Teams also experimented with Kalman filters in conjunction with LiDAR, IMU, and vehicle dynamic sensors, achieving a peak speed of 90 km/h. (Zubaca et al., 2020) set a lap record of 1 minute and 37.440 seconds at Circuit de Croix-en-Ternois, averaging approximately 65 km/h.

Some of the performance and metrics parameters are:

- **State Estimation.** The Improved H-infinity Filter, utilizing vehicle sensors like LiDAR, IMU, GPS, and Vehicle Odometry, consistently maintained estimation errors across laps. In contrast, the Extended Kalman Filter (EKF) exhibited growing errors after each lap (Zubaca et al., 2020).

- **High-Speed LiDAR Use.** The study demonstrated that even when subjected to high speeds and accelerations reaching up to 10 m/s² in both longitudinal and lateral directions, precise LiDAR measurements and corrections can be achieved (Renzler et al., 2020).

- **Effect of Distortion on Dynamic Driving.** Distortion was less visible when objects were present due to reflections being within the boundaries of the track. The difference between distorted and corrected point clouds decreased progressively from the first to the fourth quadrant (Renzler et al., 2020).
3.2 Indy Autonomous Challenge

The IAC conducted tests and races on various tracks, including Indianapolis Motor Speedway, Las Vegas Motor Speedway, Texas Motor Speedway, Lucas Oil Raceway (Oval) and Monza Circuit. Initially, university teams led the deployment of the AV-21, with the first shakedown occurring at Lucas Oil Raceway at lower speeds, not reaching the vehicle’s dynamics’ peak performance because of the physical limitations of the track itself.

Table 2 provides insight into vehicle speed performance and race formats. Similar to Roborace, achieving higher speeds correlates directly with the availability of track time and space, allowing researchers and engineers to simulate and enhance the software stack’s robustness and validity. Numerous publications and issues have surfaced in connection with this race series (Betz et al., 2022), highlighting challenges in integrating the hardware stack, including perceptive failures and occasional powertrain issues. Anticipating such problems is crucial, as the technology may encounter errors even under normal conditions, and exposure to vibrations and lateral forces can further accentuate sensor limitations.

Lidar faces challenges, including its high cost, limitations in mechanical scanning, susceptibility to disturbances from external light sources, and safety constraints for the human eye, which curtail its detection distance to approximately 100 meters (Wojtanowski et al., 2014). The LiDAR used for this project was from Luminar, the Hydra model (Luminar, 2021). Various challenges and solutions associated with LiDAR functioning were identified:

- **Delay due to Reflection.** A high count of reflections induced a lag in the LiDAR perception process, leading to complications in object recognition, particularly at high speeds (Betz et al., 2023)
- **Banking Angle.** The hardware underwent alterations to narrow its opening angle on straight paths and broaden its field of view (FOV) when negotiating turns. This modification was necessary to address limitations in its vertical FOV, particularly in response to changing banking angles.
- **Scanning Issue.** A global positioning method relying on LiDAR encounters difficulties in finding a scan matching solution at high speeds. Therefore, integration of two GPS measurements became necessary. (Lee et al., 2023b)
- **Driver Crash.** The Lidar driver crashed during the start-up process which caused the lidar to report the last before (Frederick, 2023).

In the context of highly dynamic scenarios involving ground vehicles, there has been a paucity of academic research addressing the resilience of localization systems under substantial lateral forces. Specifically, within the domain of autonomous ground vehicle racing, numerous teams relied on conventional localization methods, including Extended Kalman Filters (EKF) and Sensor Fusion, as well as pre-existing packages like Autoware’s Robot Localization (Moore and Stouch, 2014), which integrates wheel odometry and Inertial Measurement Unit (IMU) data. Some attempts have also been made to incorporate LiDAR as a backup localization source. However, due to computational demands, the reliability of LiDAR at speeds exceeding 100 mph remains a concern. To succinctly summarize, the following sections detail the challenges encountered and the successes achieved on the racetrack:

- **Data Filtering.** Different edge cases can cause inaccurate GPS data which caused early crashes while testing, for instance one team crashed due to when the GPS output data showed that the car rotated 90 degrees between two data points (Frederick, 2023).
- **Vibrations.** Multiple positioning degradation of GNSS units due to strong vibration (Lee et al., 2022).
- **Need of Cellular or Internet Connectivity.** Lack of cellular connectivity introduced several issues such as the RTK would not receive the correction values in some areas (Frederick, 2023), this indeed is a problem in remote testing track or specific areas of a large track
- **ECU Latency.** Erroneous hard brake command was initiated by a hardware Electronic Control Unit (ECU) module, unrelated to the motion planner and controller (Raji et al., 2022).
- **Tuning Issues.** Speed was limited due to a cable that was attached to the powertrain the system was not connected, limiting the speed. Additionally, the controller requested full throttle during race time, and there was oscillation of throttle due to a non-ideal tuning of the turbocharges and malfunction of its mechanic (Raji et al., 2023a)
Table 2: Real Time Speed Performance Benchmark.

<table>
<thead>
<tr>
<th>Group</th>
<th>Type</th>
<th>Track</th>
<th>Speed (km/h)</th>
<th>Multiagent</th>
<th>Series</th>
<th>Car Type</th>
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<td>Devbot 1.0</td>
<td>(Stahl et al., 2019b)</td>
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<td>(Zubaca et al., 2020)</td>
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<td>(Lee et al., 2023a)</td>
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<td>No</td>
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<td>(Raji et al., 2023b)</td>
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4 CONCLUSIONS

Both Roborace and IAC faced common challenges in real-time performance, such as the need for precise sensor fusion, adaptation to high-speed dynamics, and constant adjustments to hardware limitations. The robustness of LiDAR and GNSS systems in extreme conditions became a recurring theme. As the autonomous racing landscape evolves, ongoing real-time evaluation of these vehicles remains at the forefront, posing open questions for the assessment of real-time frameworks.

This research highlights and identifies recurring patterns and challenges in past autonomous vehicle racing platforms, and it is an extension of (Mar et al., 2024). Specifically, it accentuates controllability in two competitions involving full-sized racing vehicles that achieved speeds surpassing 300 km/h. The analysis uncovers a trend suggesting an upward trajectory in speed; however, there is no distinct surge in the number of vehicles participating in multiagent racing scenarios. Across these studies, it is noteworthy that no more than two vehicles have been subjected to real high-speed racing competition. The qualitative assessment of sensors is based on participant publications and publicly accessible data. A subsequent study will explore diverse vehicle sizes, providing a more quantitative analysis of sensor capabilities in high-stress and off-road scenarios.

REFERENCES


