Advanced Sensor Configurations for High-Speed Autonomous Racing Vehicles

Manuel Mar, Vishnu Pandi Chellapandi, *Senior Member, IEEE*, Liangqi Yuan, *Graduate Student Member, IEEE*, Ziran Wang, *Senior Member, IEEE*, and Eric Dietz

***Abstract*—Autonomous racing is a dynamic and challenging domain that not only pushes the limits of technology but also plays a crucial role in the advancement and fostering of greater acceptance of autonomous systems. This article thoroughly analyzes challenges and advances in the design and performance of autonomous racing vehicles, focusing on Roborace and the Indy Autonomous Challenge (IAC). This review compares sensor configurations, artificial intelligence techniques, architectural nuances, and performance metrics on these cutting-edge platforms. In Roborace, the evolution from Devbot 1.0 to Robocar and Devbot 2.0 is detailed, revealing insights into sensor configurations and performance outcomes. The examination extends to the IAC, which is dedicated to high-speed self-driving vehicles and emphasizes development trajectories and sensor adaptations. By reviewing these platforms, the analysis provides a valuable comparison of autonomous driving racing systems and sensor suites, contributing to a broader understanding of sensor architectures and the challenges faced.**

***Index Terms*—Advanced sensor configurations, autonomous racing vehicles, dynamic path planning, high-performance autonomous systems, high-speed autonomous driving, real-time sensor fusion, sensor performance.**

I. Introduction

THE Society of Automotive Engineers has classified autonomous driving into six levels, ranging from basic driver assistance to full automation. At level 0, there is no automation, while level 5 represents complete autonomy, eliminating the need for human intervention [1]. These systems depend heavily on various sensors and software to accurately perceive their surroundings and achieve full automation without human intervention. As we move closer to this reality, the sensor industry is experiencing rapid growth and innovation to meet the challenges present by autonomous systems [2], [3]. In particular, autonomous ground systems, such as cars, trucks, and trains continue to grapple with specific unresolved challenges, fueling the motivation of researchers and engineers to dive into this area. Artificial intelligence (AI) plays a crucial role in addressing these challenges by enabling complex data processing, decision-making capabilities, and adaptive learning, which are essential for the efficient and safe operation of autonomous systems [4], [5], [6]. The world of motorsports, characterized by conditions, such as steep inclines, high-speed corners, and refined techniques, such as "lift and coast," presents its unique challenges. Racing circuits featuring vehicles, such as IndyCar, Formula E, and Formula 1 represent the pinnacle of high-performance design [7]. Technological innovations nurtured in these racing arenas often find their way into commercial vehicles [8]. With their deep understanding of vehicle dynamics and performance, racing drivers exhibit skills and techniques that are difficult to replicate through software or automated systems. Although sensors can process information faster than human senses, a racer's nuanced understanding often exceeds that of an average driver. Numerous autonomous racing competitions have recently emerged that challenge researchers [9], [10], [11], [12]. Fig. 1 illustrates the timeline of full-size autonomous racing races and significant milestones related to this field. These programs provide a platform for deeper insight, address existing problems, improve vehicle performance, and accelerate further development.

High-speed racing vehicles, as defined within the context of this research, encompass vehicles engineered to operate in stringent conditions, experience substantial lateral forces, and can achieve rapid acceleration [13], [14]. Technological sensor advances have led to various high-performance ground vehicle programs, each characterized by different metrics, propulsion systems, and performance results. The last decade has introduced multiple autonomous racing programs in which ground race vehicles were built specifically for racing purposes, where vehicles are handled at their limits [15]. Various competitions have been held, but this research will concentrate on two significant projects that involved developing full-sized autonomous racing vehicles for racing platforms: 1) Roborace and 2) the Indy Autonomous Challenge (IAC). Although sharing similar conceptual foundations, both programs diverge in aspects like race format, sensor suite, main propulsion source, and performance metrics.

Autonomous hardware for this research will be referred to as components in the vehicle that contribute to vehicle autonomy mobility, such as exteroceptive sensors (e.g., LiDAR,

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Manuel Mar and Eric Dietz are with the Polytechnic Institute, Purdue University, West Lafayette, IN 47907 USA (e-mail: mmar@purdue.edu; jedietz@purdue.edu).

Vishnu Pandi Chellapandi, Liangqi Yuan, and Ziran Wang are with the College of Engineering, Purdue University, West Lafayette, IN 47907 USA (e-mail: cvp@purdue.edu; liangqiy@purdue.edu; ziran@purdue.edu).

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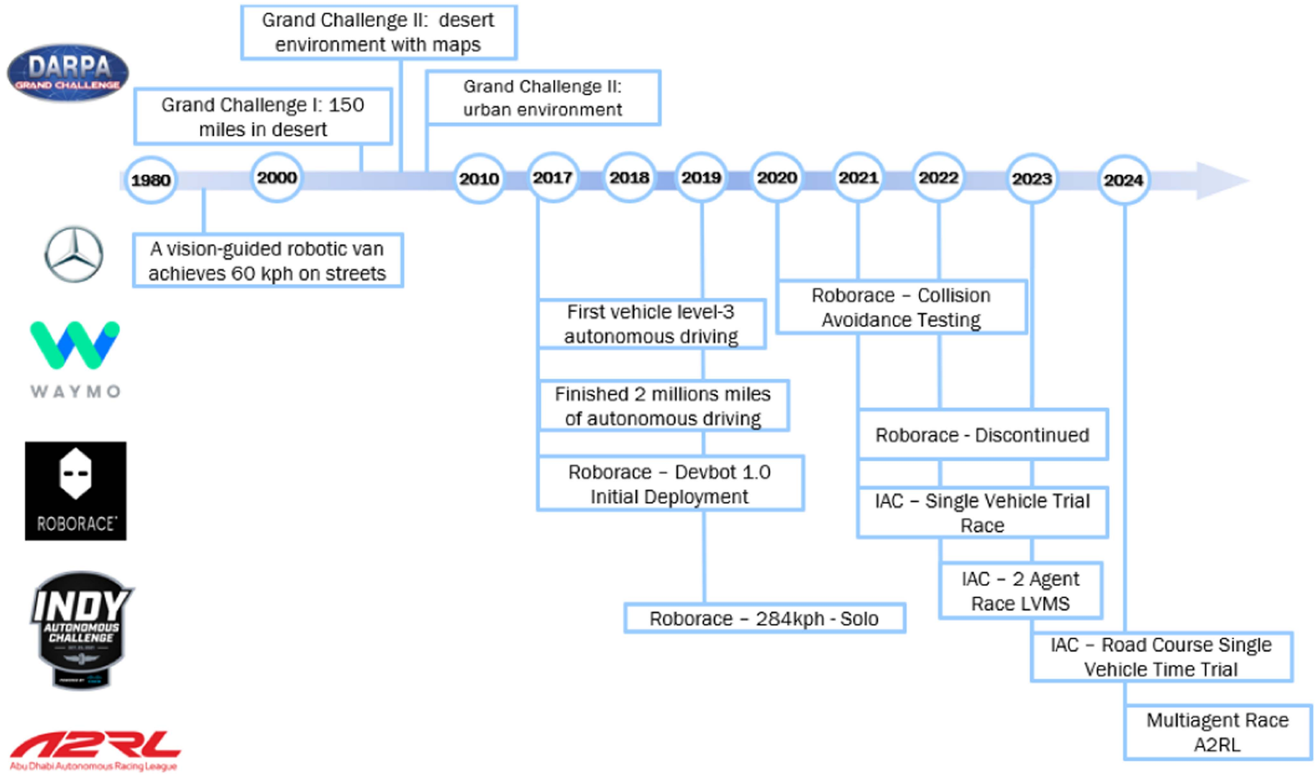

Fig. 1. Evolution of Autonomous Racing and Driving Challenges.

radars, cameras), localization (e.g., GNSS, GPS, IMU), central computer system onboard, and the network system (e.g., V2I, V2V, C-V2X) [16], [17]. Previous studies [18], [19], [20] have explored the autonomous racing domain, diving into aspects, such as vehicle dynamics, simulation, and lessons learned from operating racing vehicles. Building on this foundation, The general objective of this research is to provide a comprehensive review and analysis of the advancements, challenges, and performance metrics in the domain of autonomous racing vehicles, with a focus on the Roborace and IAC platforms. Our primary research question is to reveal robust directions for the research community and the automotive industry in developing these vehicles, specifically with respect to sensor integration, real-time processing capabilities, and system reliability under extreme racing conditions. It aims to explore the integration of sensor configurations, such as LiDAR, radar, and GPS, alongside AI-driven techniques for real-time decision-making and control. By examining the design, sensor architecture, and performance of these high-speed autonomous racing vehicles, the research seeks to identify critical limitations, propose improvements, and offer insights into future directions that can enhance the efficiency, safety, and reliability of full-scale autonomous racing technologies. This systematic investigation aims to bridge the gap between theoretical development of autonomous vehicles and the unique demands of high-speed racing environments, providing actionable insights for researchers and industry practitioners. The key contributions of this overview to the field of high-speed autonomous racing are as follows.

1) *Autonomous Racing Sensor and Integrated AI (Section II):* We provide a detailed display and overview of the current autonomous hardware stack in full-size autonomous vehicles, focusing on sensor integration and AI-driven capabilities within the context of autonomous racing.
2) *Sensor Characteristics and Architecture in Major Racing Competitions (Section III):* We analyze and describe the sensor characteristics and overall architecture used in major autonomous racing competitions, specifically Roborace and IAC, discussing the unique requirements and configurations of each race and car type.
3) *Performance Metrics and Evaluation in Autonomous Racing (Section IV):* We detail updates and breakthroughs in performance metrics and evaluation, particularly focusing on real-time responsiveness, speed, and positioning technologies as demonstrated in the Roborace series, Devbot 2.0, and IAC series.
4) *Analysis of Hardware Malfunctions and Future Directions (Section V):* We conduct a thorough review and analysis of hardware malfunctions documented during racing events, categorizing the specific challenges and problems encountered with each sensor type. In addition, we discuss future research directions, including real-time responsiveness, standardization, sensor fusion, and deep learning modeling, to enhance the performance and reliability of autonomous racing systems.

Table I emphasizes the research novelties and challenges addressed in this article, illustrating key differences between our work and similar surveys that address the same issues, clearly showcasing what other surveys do not cover.

TABLE I
COMPARISON OF RELATED SURVEYS OF SENSORS IN AUTONOMOUS RACING VEHICLES

Survey	Year	Focus	Vehicle Topology	Full size AV Overview	Future Directions	Performance Analysis Real-Time	Vehicle Sensor Error	Sensor Analysis
Betz *et al.*	2022	Software/Hardware	✗	✓	✓	✗	✗	✗
Rohan *et al.*	2022	Software	✗	✓	✓	✗	✗	✓
Paden *et al.*	2016	Software	✗	✗	✗	✗	✗	✗
Evans *et al.*	2024	Software	✗	✗	✓	✗	✗	✗
Betz *et al.*	2019	Software/Hardware	✓	✓	✓	✗	✗	✓
Ours	2024	Software/Hardware	✓	✓	✓	✓	✓	✓

II. SENSOR IN FULL SIZE AUTONOMOUS RACING PLATFORMS

This section provides an overview of the most relevant sensors used in AV applications, along with the AI-integrated algorithms employed on these platforms. Exteroceptive sensors, such as LiDAR, radar, cameras, and localization units, were selected for their critical role in environmental perception and object detection, which are essential abilities for high-speed vehicles that must track fast-moving objects, including vehicles overtaking from the sides, and resist strong lateral forces on corners due to quick braking or even crashes. In contrast to earlier programs, such as the DARPA Challenge, where AI algorithms were less developed, this section also emphasizes the application and evolution of AI techniques, highlighting their role in improving decision-making, control, and adaptability in full-size platforms.

There are similarities in key metrics for evaluating sensor robustness and performance in high-performance environments that include but are not limited to operational temperature range, IP rating, field of view (FOV), and scan rate. A detailed discussion of the specific characteristics and capabilities of each sensor type is discussed.

1) *Scan Rate:* The scan rate, or frame rate, is the frequency at which sensors update images or scans per second, varying based on sensor type. According to [15], the controller's reaction time at high speeds is significantly impacted by scan rates. The distance a vehicle travels between sensor updates can be estimated as

$$\Delta x = \frac{V}{f_{\text{scan}}} \tag{1}$$

where Δx is the distance traveled per scan, V is the vehicle speed, and f_{scan} is the scan rate. A large displacement can lead to missed detections of fast-moving objects. Increasing the scan rate to 100 Hz reduces the displacement to 0.45 m per scan, significantly improving perception accuracy.

2) *Field of View:* The FOV determines how much of the environment a sensor captures at any moment. While 360° coverage is ideal for complex environments, achieving this typically requires multiple sensors. The lateral coverage width (W) of a single sensor at a given range (R) can be estimated as

$$W = 2R\tan\left(\frac{\theta}{2}\right) \tag{2}$$

where θ is the sensor's FOV. For example, a LiDAR with an FOV of 120° and a range of 50 m provides a lateral coverage of

$$W = 2 \times 50 \times \tan(60^\circ) \approx 173.2 \text{ m}. \tag{3}$$

However, a single sensor may leave blind spots, needing multiple units for full coverage. Overlapping FOVs between LiDAR, cameras, and radar ensure continuous tracking fast-moving vehicles in racing scenarios

3) *Temperature Range:* As recommended by ISO 16750 [21], electronics for autonomous systems should operate within a temperature range of −40°C–85°C. However, sensors near high heat sources, such as gas engines, batteries, or exhaust systems, may require even greater temperature resistance.

4) *Ingress Protection Rating:* The IP rating measures the resistance of a sensor to shock and vibration. An IP rating of IP67 to IP69K [22] ensures robust sensors suitable for automotive applications, specially for high-performance vehicles.

5) *Electromagnetic Interference (EMI) Immunity:* Sensors must demonstrate resilience to EMI for reliable performance in electrically noisy environments, such as those generated by electric powertrains, wireless communication systems, or external sources. Compliance with standards like ISO 11452 [23] and CISPR 25 [24] provides a benchmark for immunity against radiated and conducted interference.

6) *Mean Time Between Failures (MTBF):* MTBF is a metric used to assess the reliability and safety of automotive systems. Higher MTBF values indicate more reliable systems, which are essential for critical applications in AVs. MTBF directly impacts vehicle maintenance costs, vehicle downtime, and overall safety, making it crucial in the selection of automotive sensors [25]. However, determining this value can be relative and depends on the conditions to which the device has been exposed. For perception sensors or other components, exposure to high-speed environments and vibrations can reduce the MTBF, leading to a shorter operational lifespan.

A. Radars

1) *Range:* For instance, at speeds of 100–320 km/h, vehicles cover approximately 28–89 m per second. This drastically

reduces the reaction time for overtaking maneuvers. Poor range resolution can lead to object merging or misidentification, resulting in unsafe decisions. In racing, where cars may be separated by only a few meters, a radar system with sub-10-cm range resolution is critical to distinguish between the leading car and background elements.

2) *Operating Frequency:* A 77-GHz radar with ultra-wideband (3–4 GHz bandwidth) is an optimal choice due to its range resolution (3–5 cm), allowing precise differentiation between closely spaced vehicles. Higher frequencies provide better speed measurement accuracy, as the Doppler shift resolution improves, making it easier to detect subtle velocity changes when passing. Also, 77-GHz radar offers a long detection range (250–300 m), enabling early identification of other agents and better trajectory planning [26].

3) *Noise Figure:* Radar noise from low signal-to-noise ratio (SNR), multipath interference, Doppler errors, and environmental clutter can degrade object detection and overtaking precision. False detections, ghost objects, and velocity miscalculations become critical risks. To mitigate this, high-SNR antennas, advanced filtering [Kalman, constant false alarm RateCNN - convolutional neural network (CFAR)], and optimized Doppler processing are essential for accurate tracking [27].

B. Lidar

1) *Range Resolution:* Accurate vehicle differentiation requires high range resolution. The resolution is given by

$$\Delta R = \frac{c}{2B} \tag{4}$$

where $c = 3 \times 10^8$ m/s is the speed of light and B is the LiDAR bandwidth. For a 1-GHz bandwidth, the resolution is 15 cm, sufficient to track vehicles during close overtakes at high speeds. [28]

2) *Point Density:* High point density, measured in points per second (pps), allows for detailed environmental mapping. The total point rate is given by

$$N = R_{\text{pps}} \times \theta_{\text{scan}} \times f_{\text{rot}} \tag{5}$$

where R_{pps} is the points per second, θ_{scan} is the vertical resolution and f_{rot} is the rotation frequency. In addition, a system achieving 2 M points/s ensures precise mapping [29].

3) *Motion Compensation and Doppler Effect:* Since LiDAR lacks inherent Doppler capabilities, velocity estimation relies on motion compensation. The displacement per frame is

$$\Delta d = \frac{V}{f_s} \tag{6}$$

where V is vehicle speed and f_s is LiDAR update rate. At $V = 80$ m/s and $f_s = 20$ Hz, a vehicle moves 4 m per frame. Predictive filtering and sensor fusion mitigate this issue [30].

4) *Latency and Decision Lag:* Processing delays impact reaction time. If the total system latency is t_d, the car moves

$$d_{\text{lag}} = V \times t_d. \tag{7}$$

For instance, $t_d = 50$ ms at $V = 80$ m/s, the car moves 4 m before updating its perception. Low-latency pipelines and real-time data fusion are critical for safety in high-speed racing. [31], [32]

C. Cameras

1) *Dynamic Range:* Cameras with high dynamic range (HDR) can simultaneously capture bright and dark areas, vital for scenarios, such as overtaking in direct sunlight, through tunnels or bridges. The HDR is quantified using the contrast ratio CR of the camera, which can be expressed as

$$\text{CR} = \frac{I_{\max}}{I_{\min}} \tag{8}$$

where $I_{\max}$ is the maximum intensity and $I_{\min}$ is the minimum intensity. A contrast ratio of 1000:1 or higher would be needed for effective maneuvers [33].

2) *Sensitivity:* The sensitivity of a camera indicates its ability to operate under low-light conditions. It is often quantified by the minimum light level required for proper image capture, measured in lux. A highly sensitive camera (e.g., 0.01 lx) ensures high image quality even in low-light environments. The relationship between sensitivity and image quality is expressed as

$$S = \frac{L}{\text{Lux}} \times \text{Frame Exposure Time} \tag{9}$$

where S is the sensor's ability to capture sufficient light at a given lux, and the exposure time is adjusted based on the available light. Testing for low-light scenarios ensures that the camera performs well in conditions such as driving at night, bridges, tunnels, etc. [34].

3) *Frame Rate:* The frame rate (fps) directly affects the camera's ability to capture fast-moving objects. The required frame rate for smooth object tracking can be estimated from the velocity and object displacement per frame

$$\Delta x = \frac{V}{\text{fps}} \tag{10}$$

where Δx is the object displacement per frame. At a speed of 150 mph (67.1 m/s) and a frame rate of 60 fps, the object displacement is

$$\Delta x = \frac{67.1}{60} = 1.12\ \text{m/frame}. \tag{11}$$

A higher frame rate (e.g., 120 fps) reduces displacement, making it easier to track objects at high speed. [35]

4) *Resolution:* Higher resolution provides more detailed images, critical for distinguishing small objects. The resolution is typically measured in megapixels (MP), and the effectiveness of the camera in harsh environments is

determined by the pixel density (P_{den}) over the FOV

$$P_{\text{den}} = \frac{P_{\text{total}}}{A} \tag{12}$$

where P_{total} is the total number of pixels, and A is the camera's effective area. For 2 MP cameras with a 120° FOV, the pixel density should be high enough to maintain detailed tracking of objects up to 100 m. Ensuring robust performance requires testing the camera's pixel integrity and clarity under motion and vibration [36].

D. Localization Sensors (GPS/IMU/GNSS)

1) *GPS Accuracy:* To ensure precise localization, GPS systems used in AVs should ideally provide submeter accuracy, with real-time kinematic (RTK) positioning offering centimeter-level accuracy. In addition, a high update rate of 10 Hz or higher is essential for rapid position updates. The positional uncertainty Δx at a given speed can be estimated as

$$\Delta x = \frac{V}{f_{\text{update}}} \tag{13}$$

where V is the vehicle's velocity, and f_{update} is the GPS update frequency. For example, at a speed of 160 mph (71.5 m/s) and an update rate of 100 Hz, the GPS positional uncertainty is

$$\Delta x = \frac{71.5}{100} = 0.71 \text{ m.} \tag{14}$$

This underscores the importance of high update rates in minimizing localization errors during high-speed maneuvers. RTK systems significantly mitigate this uncertainty by providing more accurate positioning data. [37]

2) *Gyroscope Bias Stability:* Accurate measurement of angular velocity is essential for vehicle heading control during high-speed turns. High-precision gyroscopes, with low bias, drift over time, ensure consistent orientation data. Gyroscopes used in AV racing should have a bias stability b_{gyro} of less than 0.1°/hr. The angular velocity error θ_{error} at a given time t can be expressed as

$$\theta_{\text{error}} = b_{\text{gyro}} \cdot t. \tag{15}$$

For bias stability of 0.1°/hr, after 1 h of driving, the accumulated heading error would be

$$\theta_{\text{error}} = 0.1^\circ/\text{hr} \times 1 \text{ hr} = 0.1^\circ. \tag{16}$$

This accuracy is crucial in ensuring stable orientation while the vehicle is traveling at high speeds during overtakes [38].

3) *Accelerometer Noise Density:* Accurate accelerometers are essential for detecting vehicle motion, acceleration, and changes in velocity. The noise density of accelerometers, which is measured in $\mu g/\sqrt{\text{Hz}}$, should be as low as possible for high-performance applications. Advanced systems should target noise densities of 50–100 $\mu g/\sqrt{\text{Hz}}$. The acceleration noise a_{noise} over a time period T can be estimated as

$$a_{\text{noise}} = \text{Noise Density} \cdot \sqrt{f_{\text{sampling}} \cdot T} \tag{17}$$

where f_{sampling} is the sampling frequency, and T is the time of measurement. For 100-Hz sampling and a noise density of 50 $\mu g/\sqrt{\text{Hz}}$ over 1 s

$$a_{\text{noise}} = 50 \cdot \sqrt{100 \cdot 1} = 500\,\mu g. \tag{18}$$

This level of precision helps maintain high-speed stability and ensures that accurate motion data are fed into the vehicle's control algorithms [39].

E. AI Integrated Autonomous Racing

1) *Kalman Filter:* Delay-aware robust control strategies enhance safety and reliability by compensating for sensors, actuators, and computation delays, incorporating adaptive filtering and predictive control. Multimodal sensor fusion and object tracking enhance perception systems, which are crucial for dynamic decision-making in high-velocity environments, by utilizing deep learning approaches, such as long short-term memory (LSTM) for object detection and trajectory prediction. Moreover, the integration of online learning of model predictive control (MPC) optimizes control actions in real-time, adapting to the highly dynamic racing conditions and improving AI-driven autonomous vehicle performance [40], [41], [42]

2) *Model Predictive Control:* Recent studies have focused on enhancing vehicle dynamics and trajectory optimization through innovative control strategies. One approach employs a robust Tube-MPC method for multivehicle racing on high-speed ovals, which integrates constraint-tightening techniques to manage uncertainties effectively [43]. Another research incorporates online learning in MPC to dynamically adjust control actions based on real-time data, optimizing performance under varying race conditions [44]. Furthermore, a combination of physics-constrained deep learning models has been developed to improve motion prediction accuracy, significantly enhancing vehicle autonomy and safety on race tracks [45].

3) *Recurrent Neural Network:* In autonomous racing, the "DeepRacing" framework leverages a realistic F1 game simulation to test and develop autonomous driving strategies using a combination of CNNs and LSTMs for dynamic decision-making in high-speed environments [46]. Complementing this, "MixNet" introduces a novel approach that combines deep neural networks with physics constraints to enhance motion prediction accuracy and trajectory feasibility in racing scenarios [47]. This model has been validated in the demanding conditions of IAC races showcasing its practical applicability and robustness in real-world applications. These innovations illustrate how advanced simulations and integrated learning approaches can significantly advance autonomous vehicle technologies in high-stakes environments.

III. Sensor Architecture in Full Size Autonomous Racing Platforms

This section presents the sensor architecture for full-size platforms along with some results that researchers encounter

TABLE II
SUMMARY OF SENSORS AND COMPONENTS

Sensor Type	Device	Made	Model	Series	Vehicle Model	Quant
Perception	LiDAR	Luminar	Hydra 3	IAC	AV-21	3
		Luminar	Iris		AV-24	3
		Ouster	Ibeo - OS1 -16/64	Roborace	D1/D2/Robocar	4
	Radar	Aptiv	ESR 2.5 - MRR	IAC	AV-21	2
		Continental	ARS548 RDI		AV-24	2
		N/A	N/A	Roborace	D1/D2/Robocar	4
	Camera	AlliedVision	Mako G319C	IAC	AV-21	6
		N/A	N/A	Roborace	D1/D2/Robocar	6
Localization	GNSS	Novatel	PwrPak 7	IAC	AV-21	2
		Vectornav	VN-310		AV-21/AV-24	1/4
		N/A	Electric -136kW	Roborace	D1/D2/Robocar	4
Powertrain	Engine	N/A	Electric -136kW	Roborace	D1/D2/Robocar	4
		Honda	Honda K20C	IAC	AV-21/AV-24	1
	ECU	Motec	M142	IAC	AV-21	1
		New Eagle	GCM 196 Raptor		AV-21	1
		Mclaren	N/A	Roborace	D1/D2/Robocar	1
Communications	Switch	Cisco	IE 3300	IAC	AV-24	1
		Cisco	IE 5000		AV-21	1
Computing	CPU	Dspace	Autera Autobox	IAC	AV-21/AV-24	1
		Adlink	AVA 3501		AV-21	1
		Speedgoat	MRT Targetmachine	Roborace	D1/D2/Robocar	1
	GPU	NVIDIA	NVIDIA Drive PX2	Roborace	D1/D2/Robocar	1
			Quadro RTX 8000	IAC	AV-21	1
			RTX A5000		AV-21/AV-24	1

when testing this software stack on these platforms. Table II provides a summary of the hardware employed, including sensor type, device, manufacturer, and model. This table summarizes the autonomy stack and hardware employed in these platforms, as well as the vehicle model for each competition. Descriptions and architectures of these sensors integrated into these platforms as given as follows. In addition Table III, summarizes the methodologies used for planning, controls, perception on these racing platforms along with the outcome and preliminary results.

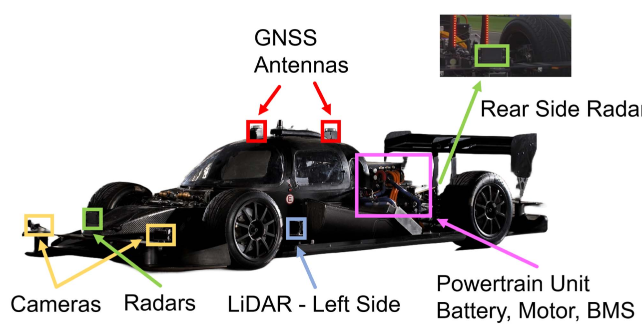

Fig. 2. Devbot 1.0 sensor architecture.

A. Roborace

Roborace was an autonomous vehicle racing series founded in 2016 to showcase the capabilities of autonomous systems technology and AI in an electric-powered vehicle [9]. There have been three different built versions for this race series: 1) Devbot (2016); 2) Robocar (2017); and 3) Devbot 2.0 (2018). In this section, we describe the vehicle architecture along with some of the testing metrics that were obtained from this project.

Roborace vehicles have more similarities than differences, the main difference between each version is the presence of a cockpit, aerodynamic design, and sensor placement.

1) Devbot 1.0: Roborace unveiled its inaugural autonomous vehicle, named Devbot. Constructed around a Le Mans Prototype (LMP) chassis, with four 135-kW electric power each wheel for a combining 500 HP, without an engine cover for better cooling and access [9]. The vehicle incorporated a cockpit seat in case human intervention tests were needed; this vehicle was intended to test all the hardware functionality before launching the latter vehicle racing series, such as Robocar and Devbot 2.0. The sensor suite incorporated into Devbot comprised computational power onboard among two primary electronic control units (ECUs). The NVIDIA Drive PX2 was responsible for high-level planning and decision-making, while the Speedgoat Mobile Target Machine catered to the real-time control tasks [48]. This vehicle also incorporated LiDARs, cameras, radars, and ultrasonic speed sensors that placement and make are shown in Fig. 2.

2) Robocar: The Robocar was built with a different concept design, it does not have a cockpit, therefore, there was no manual override for a racer or driver, the intention of this update was to run at even higher speeds compared to its predecessor by removing the weight of a driver. The competition format with this vehicle consisted of giving a university team a fully autonomous vehicle to run their software stack. This vehicle had an identical sensor suite as Devbot 1.0, two front and four surround cameras, five LiDARs, two radars in the front and back, and 17 ultrasonic sensors [48], the Robocar sensor architecture is presented in Fig. 3.

The control system's design is also bifurcated into two categories: 1) nonreal-time architectures featuring GPUs and 2)

TABLE III
MAJOR MILESTONES DURING RACES AND MALFUNCTIONS

Race	Reference	Year	Vehicle	Sensor	Technique	Task and Outcome
Roborace	Nobis *et al.* [56]	2019	Devbot 1.0	LiDAR	SLAM	**Localization and Mapping.** Accurately determining the positions and orientations of four LiDAR sensors, leading to small angular offsets in sensor readings during data fusion.
	Stahl *et al.* [57]	2019		LiDAR	Kalman Filter	**Localization.** Struggles with longitudinal estimation at high speeds due to the absence of unique features on straight race tracks and time delays in LiDAR data processing.
	Heilmeier *et al.* [58]	2019		LiDAR + IMU + GPS	Quadratic Optimization	**Trajectory Planning.** Robust implementation of planning and control at 150km/h and 80 % acceleration limits. Slow for online implementation.
	Wischnewski *et al.* [59]	2019		LiDAR + GPS	Kalman Filter	**Localization and State Estimation.** Estimation residuals are zero mean, giving a high-performance controller at top speeds of 150 km/h.
	Wischnewski *et al.* [60]	2019	Devbot 2.0	Vehicle Status	Gaussian Process	**Trajectory Planning.** Vehicle cannot adjust its acceleration limitation to different circumstances in different areas on the track.
	Betz *et al.* [61]	2019		Vehicle Status	Event Chain Analysis (ECA)	**Crash Explaination.** Velocity Planner Failures; Controller failed to switch to the emergency trajectory; Behavior planner communication 300 ms timeout; Maximum lateral error of 5 meters.
	Stahl *et al.* [52]	2019		Vehicle Status	Graph Learning	**Trajectory Planning.** Online planner tested in a physical vehicle with success at 212 km/h
	Hermansdorfer *et al.* [62]	2020		Vehicle Status	KPI Analysis	**Path Planning.** Software is more conservative for velocity, acceleration limits, and safety checks, while a driver reaches the handling limits by applying more limits on acceleration/deceleration rates.
	Renzler *et al.* [54]	2020		LiDAR	Distortion Correction	**Localization.** Successfully implemented in-vehicle platform, issue with LiDAR readings is solved.
	Massa *et al.* [63]	2020		LiDAR + IMU + GPS	Kalman Filter	**Localization and State Estimation.** Pointcloud noise, LiDAR calibration error, algorithm parameters tuning.
	Herrmann *et al.* [64]	2020		Vehicle Status	Sequential Quadratic Programming	**Vehicle Control.** Tested Velocity optimization algorithm up to 200 km/h in hardware-in-loop simulation.
	Hermansdorfer *et al.* [65]	2021		Vehicle Status	Gated Recurrent Unit Network	**Dynamics Modeling.** Model fails to extrapolate driving situations, more date required
	Schratter *et al.* [53]	2021		LiDAR + GPS	Normal Distributions Transform	**Localization and Mapping.** The used method for localization overloads the used CPU reaching 100%.
	Christ *et al.* [66]	2021		Vehicle Status	Vehicle Dynamic Model	**Trajectory Planning.** Tested on simulation and physical vehicle tests.
	Herrmann *et al.* [67]	2022		Vehicle Status	Sequential Quadratic Programming	**Vehicle Control.** Tested successfully in CPU (Simulation), solved the problem in less than 15 seconds with real-time data.
IAC	Lee *et al.* [68]	2022	AV-21	GPS + LiDAR	Kalmant Filter	**Path Planning.** Successfully implemented, nonetheless, GPS presented critical degradation during the test, which is warned safely, and the wall following navigation was activated.
	Wischnewski *et al.* [43]	2022		Vehicle Status	Model Predictive Control (MPC)	**Vehicle Control.** Top speed achieved 265 km/h and lateral accelerations up to 21m/s^2 on the Las Vegas Motor Speedway (LVMS).
	Meyer *et al.* [69]	2022		LiDAR	Clustering	**Wall Curvature Detection.** Wall detection worked even in the presence of occlusions, successfully deployed in an oval track.
	Schmid *et al.* [70]	2022		Vehicle Status	MPC	**Vehicle Control.** Description of vehicle architecture with some of the faced constraints.
	Karle *et al.* [46]	2022		Vehicle Status	LSTM-based Encoder-Decoder	**Trajectory Planning.** Tested in a Hardware-in-the-Loop (HIL) simulator and vehicle platform.
	Seong *et al.* [71]	2022		Vehicle Status	MI-HPO Model	**Vehicle Control.** Tested on track at Indianapolis Motor Speedway (IMS) and LVMS at speeds over 200 km/h. Model identification showed optimized dynamic parameters offline.
	Raji *et al.* [72]	2022		LiDAR+GPS	Nonlinear MPC	**Vehicle Control.** Tested on track at top speeds of 167 mph. The controller tried to reach a higher speed but could not due to a powertrain issue.
	Spisak *et al.* [73]	2022		GPS	Linear Quadratic Regulator (LQR)	**Vehicle Control.** Tested at top velocities of 65 m/s in an oval track with low error ($<$ 0.5 m), stability is guaranteed at 140 mph. Empirical tuning of the controller is not optimal.
	Betz *et al.* [74]	2023		Camera + LiDAR + Radar + GPS	Trace Point Measurement	**Full Self-Driving.** Critical variable end-to-end latency must be low and stable for developing robust autonomous driving software.
	Jung *et al.* [75]	2023		Camera + LiDAR + Radar + GPS	Full Vehicle System Overview	**Full Self-Driving.** Speeds up to 220 km/h were reached in a solo lap, and an acceleration pf 12.41 m/s2 was reached. Lack of generalization due to the closed environment and rules of the competition.
	Trauth *et al.* [76]	2023		Vehicle Status	End-to-End Optimization	**Full Self-Driving.** Deployed in the IAC race, a gradient-free algorithm based on testing optimization efficiently uses real testing time by ensuring desired software configuration.
	Raji *et al.* [77]	2023		Camera + LiDAR + Radar + GPS	Full Vehicle System Overview	**Full Self-Driving.** The head-to-head race crash resulted from a safety check setting the threshold for heading error too strictly at 6 degrees, not accounting for extreme real-world scenarios.
	Raji *et al.* [78]	2023	AV-21-Refresh	Vehicle Status	MPC	**Vehicle Control.** The proposed model presents less error than the classic single-track model within the scenario of a race course track, with limited testing time for tuning.
	Lee *et al.* [79]	2023		Camera + LiDAR + Radar + GPS	Kalman Filter	**Localization and State Estimation.** Tested in a vehicle. Even if there is degradation or loss of GPS/INS or an undesired given path, the proposed system reliably counteracts safely.

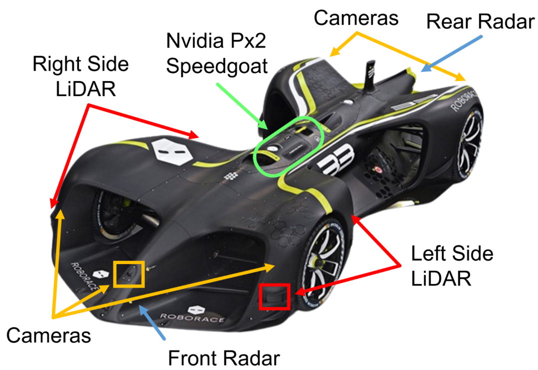

Fig. 3. Robocar sensor architecture.

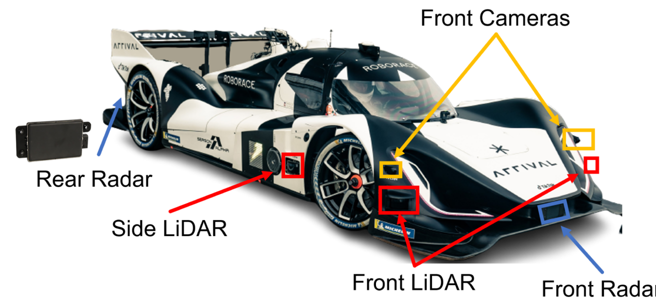

Fig. 4. Devbot 2.0 sensor architecture.

real-time architectures. The latter integrates the Speedgoat operating at 250 Hz, the IMU, and the differential GPS also at 250 Hz, while the LiDARs operated at 25 Hz [49], [50]; it also had a McLaren ECU on it [51]. Some results from one of the first tests done with this vehicle are listed as follows.

1) *Computing Issues:* The scan matching in PX2 overloads the ARM CPU, leading to occasional failures [49].
2) *Vehicle Alignment Concerns:* The single mass model used for trajectory planning does not account for the vehicle's alignment not always being tangent to the path, leading to lower acceleration in some turns [49].
3) *Localization Error:* Below 0.3 m, though improvements are possible with better algorithms or techniques [49].
4) *Safety Limitations:* A maximum speed limit of 50 km/h and maximum normalized longitudinal and lateral accelerations of 0.8 [49].

3) Devbot 2.0: Devbot 2.0, unveiled in late 2018, was not an improvement of Robocar but rather an enhancement of Devbot 1.0. Its sensor configuration mirrored its predecessors, using both Speedgoat and NVIDIA PX2 as core components. Higher speeds were reached with this vehicle, where the previous racing and crashing experience provides more insight for future software and firmware updates on this generation. The tests were held in different circuits: Zala-Zone, Hungary; Circuit de Croix-en-Ternois, France; Berlin Formula E racetrack, Germany and Monteblanco, Spain.

The OS1 LiDAR sensor suite, capable of 360-degree scans and 1024-point resolution for localization, is used. The mapping took advantage of 64-layer OS1-64, while 16-layer OS1-16 helped with localization. All sensors were positioned at a height of 1.1 m, including two GPS antennas. They also used the Oxford RT 4000 as a reference measurement system. The TUM team vehicle planner operated at an average rate of 16.8 Hz, and its capabilities were evaluated up to 212 km/h with a prediction of 200 ms to anticipate the movements of the leading vehicles [52].

During races, no GPS data under 20 cm was accessible, and the LiDAR-based localization's lateral error remained under 10 cm. The vehicle achieved speeds greater than 45 m/s and accelerations greater than 10 m/s^2. Time synchronization with the sensors was a challenge. For example, at 30 m/s, a 10-ms delay could lead to a 0.3-m error, which requires vehicle odometry [53]. In Zala, the Pisa Team made strides in the correction of the distortion of lithium and the compensation of the delay, attaining speeds of up to 90 km/h and lateral and longitudinal accelerations of 10 m/s^2 at a rate of 20 Hz [54]. Furthermore, the teams tested Kalman filters with LiDAR, IMU, and vehicle dynamic sensors. They reached a maximum speed of 90 km/h. However, they were not considered for estimation due to noise and delays in IMU acceleration measurements. During Roborace's Alpha Season, Graz University took the lead and clocked the fastest lap time of 1 min and 37.440 s at the Circuit de Croix-en-Ternois, averaging around 65 km/h [55].

A few of the performance and metrics parameters for this vehicle were as follows.

1) *State Estimation:* The enhanced H-infinity filter, which relied on-vehicle sensors, such as LiDAR, IMU, GPS, and Vehicle Odometry, maintained consistent estimation errors across laps, compared to extended Kalman filters (EKF) showed increased errors after each lap [55].
2) *Implications of High-Speed LiDAR Use:* The experiment showed that even at high speeds, with longitudinal and lateral accelerations of up to 10 m/s^2, accurate LiDAR measurement and correction can be achieved [54].
3) *Effect of Distortion on Dynamic Driving:* The distortion was less visible because the reflections were within the track's boundaries. The difference between distorted and corrected point clouds gradually decreased from the first to the fourth quadrant [54].
4) *Acceleration Discrepancies:* Differences observed in high acceleration values, possibly due to conservative estimations in the handling map or unaccounted for suspension dynamics.

B. Indy Autonomous Challenge

The IACs was founded to allow university teams to race high-speed self-driving vehicles against each other [75], [80]. This vehicle was initially developed and prototyped through the Deep Orange 12 project at Clemson University using the Dallara IL-15 chassis [81]. There have been two major versions of IAC, the first initial deployment which was released in 2021 (Dallara AV-21), and the second version which was released after the second semester of 2022. The general sensor architecture is shown in Fig. 4. Similar to Roborace, updates were required to adapt to the demands of high-speed racing and other complex scenarios. The primary modifications to the autonomous sensor stack improved the reliability of the localization system

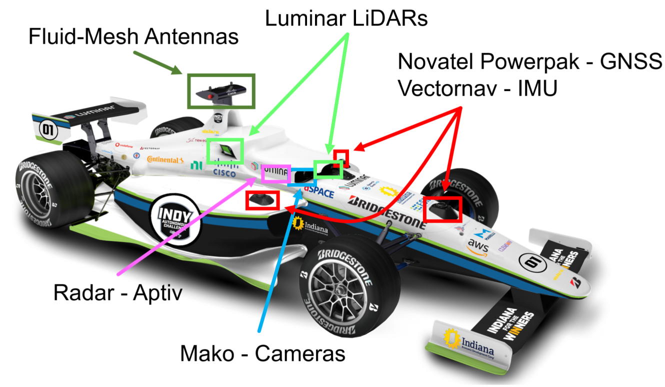

Fig. 5. AV-21 sensor architecture.

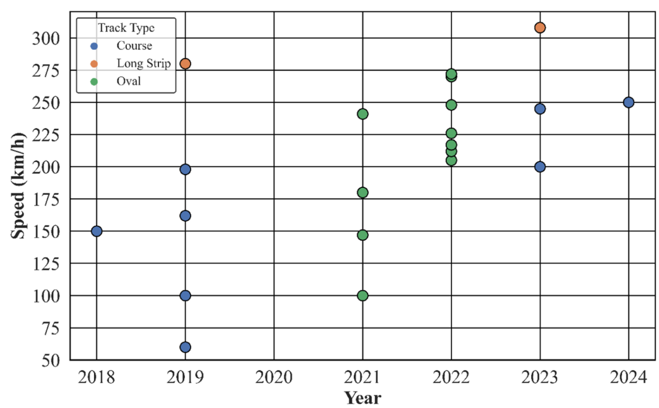

Fig. 6. Real-time performance speed metrics.

and the incorporation of an additional GNSS unit to improve system redundancy. In addition, considering the substantial data flow from various sensors, a revised network configuration was imperative to alleviate data congestion within the vehicle.

IV. Performance Metrics and Evaluation

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.

For example, Fig. 6 illustrates the relationship between the maximum speed (km/h) of various autonomous racing cars and the race series they participated in, classified by track type. It presents data points for three distinct race series: 1) Roborace; 2) IAC; and 3) A2RL. Each point is color-coded and shaped to denote the track type: Course (blue circles), Long Strip (orange crosses), and oval (green squares).

There is a significant variation in the speeds achieved according to the type of track and the series of races. For the Roborace series, the maximum speeds vary within 100 to 200 km/h range, and there is a notable point at 280 km/h on a Long Strip track. In contrast, the IAC series shows a more consistent speed range, predominantly between 100 and 250 km/h, mostly done on oval tracks. The A2RL series, at its first race, exhibits a speed of approximately 250 km/h on a course track. The long strip in Roborace and IAC suggests that such tracks allow for higher maximum speeds due to fewer turns and longer straight sections.

Table III presents a comprehensive overview of the significant achievements and technical challenges encountered in autonomous vehicle races. The table covers multiple years and features various autonomous vehicles, including Devbot 1.0 and Devbot 2.0 in Roborace, and AV-21 in IAC, illustrating the progression of technology and methodologies employed in these real-time platforms. This table delineates the sensors utilized, the approaches or methodologies implemented for specific tasks, and the resulting results upon deployment. It serves as a reference for examining the progress in the field, demonstrating how real-time autonomous vehicle racing cars can be used to explore increasingly complex approaches.

The Roborace series has notable developments from 2017 to 2021, such as the use of LiDAR for localization and mapping with Devbot 1.0 [56]; despite minor angular offsets, the precise determination of sensor positions marked a significant milestone. Subsequent entries, such as [52], reveal challenges with longitudinal estimation at high speeds due to featureless race tracks. Heilmeier et al. [58] introduced a robust trajectory planning method that, although effective at 150 km/h, faced limitations in real-time implementation. Another critical incident documented is the crash analysis for 2019 by [61], attributed to failure to velocity planner issues and delayed emergency response, highlighting the importance of reliable controller systems.

The transition to Devbot 2.0 saw advancements in trajectory planning and vehicle control. The authors in [48] and [60] demonstrated applying the Gaussian process and framework for improved planning and crash analysis. The focus on localization continued with Renzler et al. [54] successfully corrected LiDAR distortions, and Massa et al. [63], who tackled point cloud noise and calibration errors. The authors in [53], [62], and [64] contributed to path planning and localization, highlighting the need for efficient CPU usage and model extrapolation capabilities.

In the IAC series, the AV-21 vehicle was central in various studies from 2021 to 2024. Lee et al. [68] successfully implemented path planning despite GPS degradation, demonstrating resilience in navigation. The authors in [69] and [82] achieved high speeds and effective detection of wall curvature on oval tracks, respectively. The authors in [46] and [71] focused on trajectory planning and vehicle control using advanced models and hardware-in-the-loop simulators. In particular, the authors in [72] and [77] explored nonlinear MPC and addressed critical powertrain issues and crash scenarios, underlining the importance of robust safety checks.

V. Challenges and Future Research Direction

A. Hardware Limitations

1) LiDAR: LiDAR faces challenges, including its high cost, limitations in mechanical scanning, susceptibility to disturbances from external light sources, and safety restrictions for the human eye, which limit its detection distance to approximately 100 m [83]. The LiDAR used for this project was from

Luminar, the Hydra model [84]. Various challenges associated with LiDAR were identified as follows.

a) *Delay due to reflection:* A high number of reflections delayed the LiDAR perception process, leading to complications in object recognition, particularly at high speeds [85].

b) *Banking angle adaptation:* The hardware was modified to maintain a narrow opening angle on straight paths and to expand its FOV during turns. This adjustment was essential due to the constraints of its restricted vertical FOV, especially with fluctuating banking angles.

c) *Scan matching issue:* A LiDAR-based global position method cannot find a solution to match the scan while driving at high speed; therefore, two GPS measurements had to be integrated [86].

d) *Driver crash:* The LiDAR driver crashed during the start-up process, which caused the LiDAR to report the last before [87].

e) *Point-cloud density:* LiDAR provides a great tool with 3-D images; however, point clouds need to be processed and filtered to reduce the number of points; computation time for TUM was claimed to be 22 ms, and preprocessing achieved less than 20% of issues [85].

Some performances and results have shown promising results of the robustness of the sensors despite the high vibrations and the conditions of the scenario. For example, in [69], a high-precision wall detection with less than 0.11 m of error was presented, they could handle occlusions and provide consistent wall detection, even with interferences with a process time analysis of 15 Hz.

2) IMU and GPS: Localization has historically presented challenges, but various solutions have been developed and implemented [88]. In the context of highly dynamic scenarios involving ground vehicles, academic research has not addressed the resilience of these systems to substantial lateral forces. Specifically, within the domain of autonomous ground vehicle racing, numerous teams relied on conventional localization methods, including EKF and Sensor Fusion, as well as preexisting packages like Autoware's Robot Localization, which integrates wheel odometry and 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. The following sections detail the challenges encountered and successes on the racetrack.

1) *Data Filtering:* Different edges can cause inaccurate GPS data, which caused early crashes during testing, for example, a team crashed because of the GPS output data showing that the vehicle rotated 90 degrees between two data points [87].
2) *IMU-GPS Continuous Acceleration:* In the downward direction (z-axis), incorrect data led to a continuous increase in velocity estimation within the GPS. This eventually triggered export controls, stopping all GPS output [87].
3) *Update Failure:* A spin was caused because the GPS did not update the state estimator, causing a cumulative integration of errors [85].
4) *Severe Vibrations:* There was multiple positioning degradation of the two GNSS units of the first AV-21 version due to strong vibration [68].
5) *Need of Cellular or Internet Connectivity:* The lack of cellular connectivity introduced several issues, such as that the RTK would not receive the correction values in some areas [87], which is a problem in the remote testing track or specific areas of a large track.

3) Powertrain: Powertrain systems, which include all components responsible for generating and delivering power to the road surface, face primary challenges related to the reliability, durability, efficiency, and emissions of mechanical transmissions. Typically, these systems encounter suboptimal fuel efficiency, high levels of emission, and wear over time. Integrating complex electronic controls and hybrid technologies introduces system complexity and reliability issues.

1) *Mechanical Constraints:* During Indianapolis Motor Speedway (IMS) and Las Vegas Motor Speedway (LVMS) race events, vehicle speed was restricted due to hardware limitations and engine malfunctions, which prevented it from achieving the desired target speed even when the throttle was fully engaged [72].
2) *ECU Latency:* A wrong hard brake command was triggered by a hardware ECU module that is not related to the motion planner and controller [72].
3) *Tuning Issues:* Speed was limited due to a cable attached to the powertrain system being disconnected due to setting the limp mode of the engine. In addition, the controller requested full throttle during race time, and the throttle oscillated due to a nonideal tuning of the turbocharges and a malfunction of its mechanic [77].

4) Radar: Radar systems' limitations include lower resolution, multipath effects, sensitivity to environmental conditions (such as weather), and wavelength constraints, all of which can impact their performance in complex environments.

1) *Radar Noise:* The radar has more sensor noise than the LiDAR, where the radar sees higher deviations [40].
2) *Filter Adjustments:* Adjustment and fine-tuning of the radar for prone areas. Measurement of object velocity and its high sensor range was fundamental for overtaking scenarios [85].

B. Future Directions

1) Adaptive Algorithms for Real-Time Performance: Develop and implement adaptive learning algorithms that enable real-time adjustments to sensor configurations and the overall autonomy system [89], [90]. These algorithms could significantly improve performance and responsiveness by allowing vehicles to learn and adapt continuously to the intricacies of different racing scenarios. The focus should be on creating dynamic systems that use machine learning to optimize decision-making based on real-time data, ultimately improving racing efficiency and competitiveness [91], [92].

2) Standardization in Autonomous Racing Hardware: Future research could advocate standardizing sensor interfaces, communication protocols, and data formats on autonomous racing platforms. Establishing industry-wide standards would facilitate interoperability, encourage knowledge sharing, and accelerate the development of robust and versatile sensor architectures. This initiative could lead to a more collaborative ecosystem, where advancements in one platform can benefit the entire autonomous racing community, fostering innovation and accelerating progress in the field [93], [94].

3) Sensor Fusion Optimization: The integration of multimodal sensors, such as LiDAR, cameras, radar, GPS, and IMU, is being actively investigated to improve perception reliability, aiming for a comprehensive and precise representation of vehicle surroundings [95]. As the field evolves, future opportunities lie in developing dynamic sensor calibration methods to adapt to changing sensor positions, ongoing research in real-time processing techniques to achieve low-latency sensor fusion in dynamic environments, and the implementation of redundancy strategies to improve system robustness [96], [97], [99]. In addition, adaptive filtering approaches, such as Kalman and particle filters, offer opportunities to dynamically adjust parameters, ensuring optimal sensor fusion performance under various conditions.

4) Complex Dynamic Modeling Through Deep Learning and Federated Learning: Deep learning is widely used to model complex dynamics by processing sensor data sequences due to their ability to improve generalization in diverse driving scenarios (federated learning), ensuring adaptability and reliable performance [100], [101], [102], [103], [105]. Leveraging transfer learning, particularly in autonomous racing scenarios, presents an opportunity to extrapolate knowledge from pretrained models to specific conditions efficiently. The focus on data enhancement strategies is crucial to increase the diversity of training datasets, simulate environmental variations, and contribute to the development of more robust models. Furthermore, exploring uncertainty estimation techniques, such as Bayesian approaches or ensemble methods, holds promise to enhance the reliability of prediction modeling.

Looking ahead, future research will explore various sized autonomous race vehicles, provide benchmarks, and conduct deeper comparisons of hardware performance.

VI. Discussion

This section summarizes the key contributions and findings of this study, exploring how the techniques presented can benefit the research community and industry, and identifying future directions for the field of autonomous racing. Furthermore, it reflects on the interplay between racing and autonomous vehicles on the road, as well as the differences in the sensor technologies employed.

A. Key Contributions and Findings

1) Vehicle Topology and Sensor Configurations: We highlight the unique vehicle topology and sensor integration of full-size autonomous racing platforms, Roborace, and the IAC. A comparative analysis reveals differences in sensor suite configurations across various platforms and iterations of vehicles.

2) Performance Metrics and Challenges: Performance metrics, such as sensor accuracy, latency, and robustness under racing conditions were evaluated, highlighting advances and existing limitations. Insights into vehicle sensor errors and results from experimental runs provide valuable data for future optimization and considerations when integrating sensors.

3) Future Directions for Sensor Integration: Emerging trends in sensor handling and integration indicate opportunities to adopt new platforms and configurations. These trends emphasize modularity and rapid adaptability for racing environments.

B. Contributions to Real-World Applications

1) Bridging Research Into Practice: Autonomous racing serves as a controlled “moving lab” where experimental sensors, AI models, and algorithms are tested under extreme conditions, pushing the limits of current technology. The findings of racing platforms can inform the development of safer and more robust road-going autonomous vehicles by leveraging insights into sensor fusion, localization, and high-speed navigation.

2) Unique Aspects of Racing Platforms: Racing vehicles differ significantly from commercial autonomous systems due to their modularity, focus on performance, and reduced emphasis on occupant safety. These distinctions allow the field to pioneer advanced technologies. However, many findings from autonomous racing may not directly translate to commercial vehicles in the same way. Autonomous racing is evolving into its own distinct industry, with no inherent need or plan to adapt its technologies for commercial use. Instead, much of the work will remain uniquely tailored to the specific demands of racing platforms.

C. Interplay Between Racing and Commercial Autonomous Vehicles

1) Mutual Benefits: Robustness and performance testing in racing vehicles contribute to improving sensor configurations and AI models for road vehicles. Conversely, developments in commercial systems, such as safety protocols and sensor miniaturization, can benefit autonomous racing platforms.

2) Differences in Sensor Configurations: The sensor technologies in full-size autonomous racing platforms have similarities to those in commercial vehicles, but their configuration and usage differ greatly to meet the demands of high-speed racing without a driver. Safety measures are specifically designed for racing environments, prioritizing precision and rapid decision-making rather than driver safety.

In racing, sensors operate at much higher frequencies to track rapid changes in speed and position, but their performance can degrade significantly at speeds over 150 mph. This requires a deep understanding of their limitations and strategies to compensate. In addition, the processing demands are far greater, as real-time decisions at high speeds require low-latency systems and advanced computing power.

Another key difference is how sensor data are used. Racing platforms rely on advanced sensor fusion techniques, combining inputs from LiDAR, cameras, and radar to create accurate models of the environment. This ensures reliable localization and obstacle detection, even under the challenging and dynamic conditions of a race.

3) Potential for Industry Expansion: Should the field of autonomous racing continue to expand, it may catalyze the commercialization of specialized hardware, including sensors and computing units, tailored to the unique demands of high-speed autonomous platforms.

VII. Conclusion

Through a comprehensive analysis of the Roborace and IAC platforms, this study has highlighted the critical role of sensor integration, real-time data processing, and robust decision-making algorithms in achieving competitive autonomy. The findings underscore the importance of LiDAR, radar, and camera fusion for precise environmental perception, as well as the need of high-frequency localization systems to maintain stability at extreme speeds. Despite improvements in sensor technology and AI-driven autonomy, challenges, such as sensor latency, environmental adaptability, and system robustness remain key areas for further research and development.

Key lessons from both racing platforms reveal that while autonomous systems can process data faster than human drivers, achieving real-time responsiveness and predictive control remains an ongoing challenge. The implementation of Kalman filters, MPC, and deep learning models has significantly improved trajectory planning and vehicle stability. However, performance limitations due to computational overhead, sensor noise, and unexpected environmental variations highlight the need for continued refinement in both hardware and software architectures. In addition, hardware malfunctions and localization errors in high-speed racing conditions emphasize the need for greater system reliability and redundancy.

The competitive nature of autonomous racing fosters rapid innovation, potentially leading to the emergence of specialized manufacturers and startups dedicated to high-performance hardware and software for racing applications. As the demand for advanced sensors, AI models, and testing environments grows, these developments will continue to benefit both motorsports and commercial autonomous systems. Managing multiagent scenarios, particularly with more than two vehicles at high speeds, remains an unresolved challenge in this domain. This study categorizes these challenges, objectives, and notable outcomes, analyzing the implementation of distinct software stacks in real-time industrial autonomous vehicles. As outlined in Table III, each year sees an increasing reliance on data-driven, AI-based, and innovative solutions to address high-speed scenarios, overtaking maneuvers, and multicar situations on oval and road course tracks. This research provides a broad overview of progress in the field since the inception of these platforms while also identifying future challenges that remain unaddressed. In addition, the discussion section explores the interplay between racing and commercial autonomous vehicles, contributions to real-world applications, and why certain racing-specific challenges may not necessarily translate directly to production vehicles.

In the future, the integration of high-resolution sensors, the improvement of AI-driven decision-making, and the improvement of communication networks will be essential to push the boundaries of autonomous vehicle performance. Future research should focus on developing more efficient sensor fusion techniques, reducing latency in decision-making processes, and improving the adaptability of autonomous systems to dynamic racing environments. In addition, as insights from high-speed autonomous racing continue to influence the development of commercial autonomous vehicles, the technologies and methodologies explored in this study will play a pivotal role in shaping the future of intelligent transportation systems.

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