A Qualitative Review of Full Sized Autonomous Racing Vehicle Sensors: A Case Study

Manuel Mar[a] and Eric Dietz

Department of Computer Information Technology, Purdue University,401 Gran St, West Lafayette, U.S.A.

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.

2008 – DARPA Challenge
2016 – Roborace - Devbot 1.0 – Initial Deployment
2017 – Roborace - Robocar Testing
2019 – Roborace - Robocar - Speed Record - 284 kph
2019 – Roborace - Devbot 2.0 – Multi-vehicle Competittion
2020 – Roborace - Devbot 2.0 – Collision Avoidance Test
2021 – IAC - Single Vehicle Trials Race
2022 – IAC - Multiagent Race at LVMS
2023 – IAC - Road Course Single Vehicle Time Trial
2024 – A2RL - Multiagent Abu Dhabi YAS Marina Circuit

Figure 1: Autonomous Racing Milestone.

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

[a] https://orcid.org/0000-0003-3245-7964

Mar, M. and Dietz, E.
A Qualitative Review of Full Sized Autonomous Racing Vehicle Sensors: A Case Study.
DOI: 10.5220/0012634800003702

In *Proceedings of the 10th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2024)*, pages 311-318
ISBN: 978-989-758-703-0; ISSN: 2184-495X

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 extereoceptive 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

Table 1: Sensor Summary Roborace and IAC Vehicle Model.

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	N/A	Roborace	D1/D2/Robocar	1
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
		NVIDIA	Quadro RTX 8000	IAC	AV-21	1
		NVIDIA	RTX A5000		AV-21/AV-24	1

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 AVA-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 $10m/s^2$. 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).

- **Vehicle Alignment.** The trajectory planning relies on a single mass model, which fails to consider the vehicle alignment that may not always be tangent to the path. This oversight results in reduced acceleration during certain turns (Caporale et al., 2019).

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 exteroceptive 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 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 crashed 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.

Group	Type	Track	Speed (kmh)	Multiagent	Series	Car Type	Source
TUM	Course	Formula E	150	No	Roborace	Devbot 1.0	(Stahl et al., 2019b)
Graz	Mix	Zala Zone	100	No	Roborace	Devbot 2.0	(Zubaca et al., 2020)
Graz	Road Course	Circuit de Croix	162	No	Roborace	Devbot 2.0	(Schratter et al., 2021)
Pisa	Mix	Zala Zone	60	No	Roborace	Devbot 2.0	(Massa et al., 2020)
TUM	Road Course	Modena	198	No	Roborace	Devbot 2.0	(Stahl and Diermeyer, 2021)
Roborace	Long Strip	Elvington Airfield	280	No	Roborace	Robocar	(Roborace, 2019)
TUM	Oval	IMS	241	No	IAC	AV-21	(Betz et al., 2023)
Euroracing	Oval	IMS	180	No	IAC	AV-21	(Raji et al., 2023a)
KAIST	Oval	IMS	147	No	IAC	AV-21	(Lee et al., 2023a)
KAIST	Oval	LOR	100	No	IAC	AV-21	(Lee et al., 2023a)
TUM	Oval	LVMS	270	Yes	IAC	AV-21	(Betz et al., 2023)
Euroracing	Oval	LVMS	272	No	IAC	AV-21	(Raji et al., 2023a)
Euroracing	Oval	LVMS	226	Yes	IAC	AV-21	(Raji et al., 2023a)
KAIST	Oval	TMS	205	Yes	IAC	AV-21	(Lee et al., 2023a)
KAIST	Oval	LVMS	248	No	IAC	AV-21	(Lee et al., 2023a)
KAIST	Oval	LVMS	212	Yes	IAC	AV-21	(Lee et al., 2023a)
MIT-PITT	Oval	IMS	217	No	IAC	AV-21	(Spisak et al., 2022)
Polimove	Long Strip	SSC	308	No	IAC	AV-21	(IAC, 2022)
KAIST	Course	Monza	200	No	IAC	AV-21	(Lee et al., 2023a)
Euroracing	Course	Monza	245	No	IAC	AV-21	(Raji et al., 2023b)

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

A2RL (2023). Abu dhabi autonomous racing league. Accessed: Jan. 16, 2024.

Ahangar, M. N., Ahmed, Q. Z., Khan, F. A., and Hafeez, M. (2021). A survey of autonomous vehicles: Enabling communication technologies and challenges. *Sensors*, 21(3):706.

Ayala, R. and Mohd, T. K. (2021). Sensors in autonomous vehicles: A survey. *Journal of Autonomous Vehicles and Systems*, 1(3).

BBC (2016). Driverless roborace car speeds around donington. https://www.bbc.com/news/av/37214619. Accessed: Oct. 08, 2023.

Betz, J. et al. (2022). Autonomous vehicles on the edge: A survey on autonomous vehicle racing. *IEEE Open Journal of Intelligent Transportation Systems*, 3:458–488.

Betz, J. et al. (2023). Tum autonomous motorsport: An autonomous racing software for the indy autonomous challenge. *J Field Robot*, 40(4):783–809.

Betz, J., Wischnewski, A., Heilmeier, A., Nobis, F., Stahl, T., Hermansdorfer, L., Lohmann, B., and Lienkamp, M. (2019). What can we learn from autonomous level-5 motorsport? In *9th International Munich Chassis Symposium 2018: chassis. tech plus*, pages 123–146. Springer.

Buehler, M., Iagnemma, K., and Singh, S. (2009). *The DARPA urban challenge: autonomous vehicles in city traffic*, volume 56. springer.

Caporale, D., Fagiolini, A., Pallottino, L., Settimi, A., Biondo, A., Amerotti, F., Massa, F., De Caro, S., Corti, A., and Venturini, L. (2018). A planning and control system for self-driving racing vehicles. In *2018 IEEE 4th international forum on research and technology for society and industry (RTSI)*, pages 1–6. IEEE.

Caporale, D., Settimi, A., Massa, F., Amerotti, F., Corti, A., Fagiolini, A., Guiggiani, M., Bicchi, A., and Pallottino, L. (2019). Towards the design of robotic drivers for full-scale self-driving racing cars. In *2019 International Conference on Robotics and Automation (ICRA)*, pages 5643–5649. IEEE.

Dow, J. (2017). Roborace pits (wo)man versus autonomous racing machine around hong kong track. https://electrek.co/2017/12/13/roborace-woman-vs-autonomous-racing-machine/. Accessed: Oct. 05, 2023.

Fingas, J. (2018). Roborace's self-driving car isn't faster than a human (yet). https://web.archive.org/web/20180621015907/https://www.engadget.com/2018/05/14/roborace-self-driving-car-versus-human/. Accessed: Oct. 05, 2023.

Frederick, R. (2023). *Autonomous Vehicles Handling Analysis for an Indy Autonomous Challenge Car*. PhD thesis, The University of Alabama, Tuscaloosa.

IAC (2020). Indy autonomous challenge. https://www.indyautonomouschallenge.com/.

IAC (2022). Indy autonomous challenge racecar and ream polimove set new land speed record for autonomous racecar. [Accessed 22-02-2024].

Kelion, L. (2017). Driverless roborace car crashes at speed in buenos aires. https://www.bbc.com/news/technology-39027477. Accessed: Oct. 08, 2023.

Knight, M. and Blendis, S. (2016). Driverless "roborace" car makes street track debut in marrakech.

Lee, D., Jung, C., Finazzi, A., Seong, H., and Shim, D. H. (2022). Resilient navigation and path planning system for high-speed autonomous race car. *arXiv preprint arXiv:2207.12232*.

Lee, D., Nam, H., Ryu, C., Nah, S., Moon, S., and Shim, D. H. (2023a). Enhancing state estimator for autonomous race car: Leveraging multi-modal system and managing computing resources. *arXiv preprint arXiv:2308.07173*.

Lee, D., Nam, H., Ryu, C., Nah, S., and Shim, D. H. (2023b). Resilient navigation based on multimodal measurements and degradation identification for high-speed autonomous race cars. In *2023 IEEE Intelligent Vehicles Symposium (IV)*, page 1–8.

Luminar (2021). Hydra. https://levelfivesupplies.com/wp-content/uploads/2020/08/Luminar-Hydra-Datasheet.pdf. Accessed: Jan. 02, 2024.

Mar, M., Chellapandi, V., Yuan, L., Wang, Z., and Dietz, E. (2024). A review of full-sized autonomous racing vehicle sensor architecture.

Massa, F., Bonamini, L., Settimi, A., Pallottino, L., and Caporale, D. (2020). Lidar-based gnss denied localization for autonomous racing cars. *Sensors*, 20(14):3992.

Moore, T. and Stouch, D. (2014). A generalized extended kalman filter implementation for the robot operating system. In *Proceedings of the 13th International Conference on Intelligent Autonomous Systems (IAS-13)*. Springer.

NVIDIA (2016). Nvidia px2. https://developer.nvidia.com/drive/px2.

On-Road Automated Driving (ORAD) Committee (2021). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. SAE International.

Raji, A., Caporale, D., Gatti, F., Giove, A., Verucchi, M., Malatesta, D., Musiu, N., Toschi, A., Popitanu, S. R., Bagni, F., et al. (2023a). er. autopilot 1.0: The full autonomous stack for oval racing at high speeds. *arXiv preprint arXiv:2310.18112*.

Raji, A., Liniger, A., Giove, A., Toschi, A., Musiu, N., Morra, D., Verucchi, M., Caporale, D., and Bertogna, M. (2022). Motion planning and control for multi vehicle autonomous racing at high speeds. In *2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)*, pages 2775–2782. IEEE.

Raji, A., Musiu, N., Toschi, A., Prignoli, F., Mascaro, E., Musso, P., Amerotti, F., Liniger, A., Sorrentino, S., and Bertogna, M. (2023b). A tricycle model to accurately control an autonomous racecar with locked differential. *arXiv preprint arXiv:2312.14808*.

Renzler, T., Stolz, M., Schratter, M., and Watzenig, D. (2020). Increased accuracy for fast moving lidars: Correction of distorted point clouds. In *2020 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, page 1–6.

Roborace (2016). Roborace. Accessed: Oct. 01, 2023.

Roborace (2019). The world's fastest autonomous car robocar guinness world record. [Accessed 22-02-2024].

Sarkar, S. and Mohan, B. (2019). *Review on Autonomous Vehicle Challenges: AICC 2018*, pages 593–603.

Schratter, M. et al. (2021). Lidar-based mapping and localization for autonomous racing. In *Proc. Int. Conf. Robot. Autom.(ICRA) Workshop Opportunities Challenges Auton. Racing*, page 1–6.

Speedgoat (2016). Mobile real-time target machine. https://www.speedgoat.com/products-services/real-time-target-machines/mobile-real-time-target-machine.

Spisak, J., Saba, A., Suvarna, N., Mao, B., Zhang, C. T., Chang, C., Scherer, S., and Ramanan, D. (2022). Robust modeling and controls for racing on the edge. *arXiv preprint arXiv:2205.10841*.

Stahl, T. and Diermeyer, F. (2021). Online verification enabling approval of driving functions—implementation for a planner of an autonomous race vehicle. *IEEE Open Journal of Intelligent Transportation Systems*, 2:97–110.

Stahl, T., Wischnewski, A., Betz, J., and Lienkamp, M. (2019a). Multilayer graph-based trajectory planning for race vehicles in dynamic scenarios. In *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, page 3149–3154.

Stahl, T., Wischnewski, A., Betz, J., and Lienkamp, M. (2019b). ROS-based localization of a race vehicle at high-speed using lidar. In *E3S Web of Conferences*, volume 95, page 04002. EDP Sciences.

Tumeo, A., Ceriani, M., Palermo, G., Minutoli, M., Castellana, V., and Ferrandi, F. (2017). Chapter 3 - real-time considerations for rugged embedded systems. In Vega, A., Bose, P., and Buyuktosunoglu, A., editors, *Rugged*

Embedded Systems, pages 39–56. Morgan Kaufmann, Boston.

Wojtanowski, J. et al. (2014). Comparison of 905 nm and 1550 nm semiconductor laser rangefinders' performance deterioration due to adverse environmental conditions. *Opto-Electronics Review*, 22(3).

Yeong, D. J., Velasco-Hernandez, G., Barry, J., and Walsh, J. (2021). Sensor and sensor fusion technology in autonomous vehicles: A review. *Sensors*, 21(6):2140.

Zhu, Q. et al. (2021). Control informed design of the IAC autonomous racecar for operation at the dynamic envelope. In *Proc. Int. Conf. Robot. Autom.(ICRA) Workshop Opportunities Challenges Auton. Racing*, page 1–7.

Zubaca, J., Stolz, M., and Watzenig, D. (2020). Extended h filter adaptation based on innovation sequence for advanced ego-vehicle motion estimation. In *2020 IEEE 3rd Connected and Automated Vehicles Symposium (CAVS)*, pages 1–5. IEEE.