SZÉCHENYI EGYETEM
UNIVERSITY OF GYŐR

2nd Conference on Sustainability – COS '24

DOI: 10.62897/COS2024.2-1.98

NEW WAYS IN RACE SPORTS – BE THE 21ST DRIVER

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Motorsport has long been a very popular and explorative environment within the automotive industry. Recently, simulated racing has gained significant popularity. The rapid evolution of artificial intelligence (AI) technology has led to the development of agents with superhuman capabilities, capturing attention across various domains. SimRacing provides an ideal platform for comparing these agents.

This paper presents a system capable of generating a digital twin of real-time racing events within a simulated virtual environment. By doing so, it enables simulator drivers and AI algorithms to compete against real racing professionals with minimal risk of crashes. We outline the essential system requirements and propose key specifications. Additionally, the paper details the primary sub-functions and system architecture for this purpose.

1. Introduction

Motorsport has always played a crucial role in automotive innovation and development. Car racing is not only a test of speed and technological performance but also serves as an experimental laboratory where new solutions can emerge. In recent years, simulated racing, or SimRacing, has garnered increasing attention from both racers and technology developers. This virtual platform offers racing enthusiasts the opportunity to test their skills in a realistic environment while eliminating the risks associated with real racing.

Furthermore, simulated racing represents not only a cost-effective alternative to real-world testing, but eliminates the need for physical resources such as fuel, tires, and vehicle parts, which are typically consumed in the real-world motorsports. By conducting races virtually, there is a significant reduction in carbon emissions, resource usage and waste generation. These factors directly contribute to the industry's sustainability efforts. Simulators, on the other hand, offer a controlled environment where drivers can practice, test new strategies, and refine their skills without incurring the high costs associated with physical testing. This financial efficiency makes SimRacing an attractive option for both amateur and professional racers seeking to optimize their preparation and performance.

The rapid development of artificial intelligence (AI) technologies has opened new horizons in simulated racing. AI-driven agents capable of superhuman performance are attracting growing interest from researchers and developers. These agents have demonstrated their effectiveness and innovative potential on the racetrack. SimRacing provides an ideal platform for testing and comparing the capabilities of these AI agents, enabling direct competition between real racers and AI with minimal risk.

This study presents a system capable of generating a digital twin of real-time racing events within a simulated virtual environment called the Driver 21 project, where you can be the 21st driver among 20 real-world racing drivers. The concept of a digital twin allows simulator drivers and AI algorithms to compete with real racing professionals without the risk of accidents. Furthermore, the system has been designed to accommodate multiple future use cases, ensuring that it not only meets current demands but also adapts flexibly to future developments and expansions. In the following sections, we detail the essential system requirements, propose key specifications, and describe the primary sub-functions and system architecture necessary for creating and operating the digital twin.

2. System descriptions

2.1. Digital twin of racing cars

A digital twin of a racing car is a highly detailed, virtual replica of the physical car, which includes its mechanical components, dynamics, and environmental interactions. This digital counterpart is created using a combination of data from the real car, advanced simulation technologies, and real-time data analytics. The digital twin is designed to mirror the behavior and performance of the actual car as closely as possible, providing a comprehensive representation of its characteristics and capabilities.

The utilization purpose of the digital twin will determine its level of detail and components. The digital twin continuously receives data from various sensors on the actual racing car, including telemetry data, engine parameters, tire pressure, suspension dynamics, and more. This data is used to update the virtual model in real-time, ensuring that it accurately reflects the current state of the physical car and providing a high-fidelity simulation environment.

Engineers and drivers can use the digital twin to run simulations of different racing scenarios, weather conditions, and track configurations, exploring a wide range of potential situations without the need for physical testing. The digital twin can predict how the car will perform under various conditions, helping teams to optimize setup and strategy for enhanced performance on the racetrack. By analyzing the digital twin, teams can identify potential issues or areas for improvement without risking damage to the actual car, facilitating iterative design and development processes.

Drivers can utilize the digital twin to practice and refine their driving techniques and strategies in a virtual environment that closely mimics real-world conditions. It allows for safe experimentation with different driving lines, braking points, and overtaking maneuvers, enabling drivers to hone their skills and improve their performance without the risks associated with on-track testing. Overall, the digital twin of a racing car serves as a valuable tool for engineers, drivers, and teams, offering insights, optimization opportunities, and performance enhancements in the highly competitive world of motorsport.

2.2. System analysis

The project requirements were influenced by several input factors. Before starting to create the requirements, a comprehensive analysis of the application areas was made. This analysis included the mapping of different functions and the assessment of their importance in different areas. This approach enabled us to make the parameters both comparable and scalable.

For a thorough evaluation, six different use cases were examined in detail. Each use case was analyzed based on seven different criteria. These criteria were then rated on a scale of 0 to 5, providing a clear and quantifiable measure of their importance in each context (see scoring system in ***Table 2***). This granular approach allowed us to get a nuanced view of how different features affect different aspects of the project.

The use cases besides Driver 21 included:

- TV broadcast, aimed at improving the viewing experience and engagement for audiences
- Race control support, which enhances the efficiency and accuracy of race management
- Track safety, dedicated to ensuring the safety of the racing environment for all participants
- A.I. self-driving development support, which aids in the advancement of autonomous driving technologies
- Race engineer support, which provides tools and insights to optimize race strategies and car performance.

Table 2: Scoring system description

	Real time / latency	Camera quantity	Camera resolution	Camera FPS	Position accuracy	System complexity	Bandwidth
0	Offline	N/A	N/A	N/A	N/A	N/A	N/A
1	>10s	1	<HD	30	<20m	1 data bus	<5Mbps
2	<10s	2	-	-	<5m	2 data buses	<30Mbps
3	<3s	4	HD	60	<2m	4 data buses	<50Mbps
4	<1s	6	-	-	<50cm	6 data buses	<100Mbps
5	<100ms	>6	4k	120	<10cm	10 data buses	>100Mbps

The results of the analysis are visually represented in the form of a radar diagram as shown in Figure 1. This diagram effectively illustrates the relative weight of each criterion among different functions. The radar diagram serves as a valuable tool for comparing the importance of individual criteria in different scenarios, highlighting which aspects are the most critical in each use case.

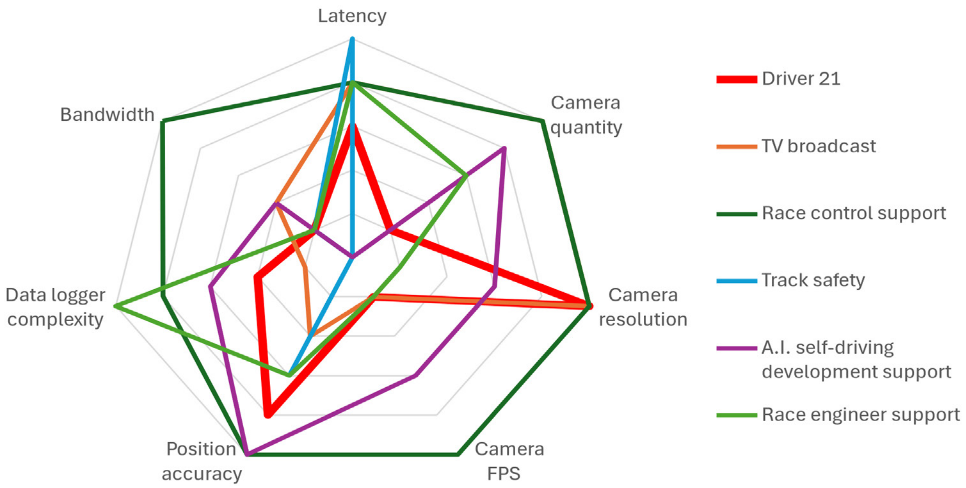

Figure 1: Radar diagram of the use case analysis

By displaying the data in this manner, the strengths and weaknesses of each feature relative to the seven criteria become evident. This not only facilitates the prioritization of requirements but also ensures that the most important aspects receive adequate attention. Consequently, this comprehensive analysis and its visual representation provided a solid foundation for project requirements, facilitating informed decision-making and strategic planning. From the radar chart, the necessary baseline requirements can be derived, ensuring that the Driver 21 use case is satisfied 100 %. By comparing these baseline requirements with our available resources, the requirements were assembled accordingly. To ensure that all necessary aspects are covered and to prioritize effectively, the radar chart was scrutinized to identify the core criteria that must be met for the Driver 21 use case. This detailed analysis provided a clear picture of the essential functionalities and their relative importance. By cross-referencing these fundamental requirements with our resource capabilities, strategic planning and resource allocation were conducted to meet the demands of the Driver 21 use case. This approach not only ensures that the key requirements are addressed but also allows for efficient utilization of resources. Thus, the radar chart has been instrumental in highlighting the critical requirements, enabling us to prioritize and structure the project requirements effectively. This structured approach ensures that project goals are met while optimizing resource utilization.

The primary goal of Driver 21 is accurate positioning, which has driven most of the requirements to ensure the highest precision in this area. To achieve this, several concepts were thoroughly examined and mapped out. Following this, comprehensive market research was conducted to determine available options and components that can be utilized off the shelf to achieve our objectives.

During this process, various scenarios were explored and evaluated for their potential. After excluding less viable options, detailed decision matrices were created to aid in selecting the most optimal solution.

These decision matrices enabled systematic comparison of alternatives based on key criteria such as accuracy, cost, and ease of integration. This ensured the selection of the optimal solution to achieve precise positioning in Driver 21.

3. System overview

The primary functions of the system are as follows:

- Measurement of the racing car's exact position, dynamics, and other technical parameters.
- Transmission of these data to the cloud.
- Storage, processing, and manipulation of the data in the cloud using algorithms tailored to specific use cases. This supports the creation of digital twins for the cars' positions and dynamics.
- Integration of the race simulator with the processed data to visualize the digital twins of the racing cars in the virtual space, enabling virtual races between simulator pilots, gamers, and the digital twins of real cars.

To achieve the above functionalities, four distinct functional units need to be developed:

- Onboard-System (OBS)
- Race track Infrastructure
- Cloud Infrastructure
- Simulator

3.1. Onboard-System (OBS)

The onboard-system is a critical component installed in every racing car participating in the virtual race. Its primary function is to transmit necessary data for creating digital twins of the racing cars, including precise position on the track, orientation, dynamic properties, and other technical parameters in real-time via a mobile network. This unit does not process data locally; it focuses on synchronized data transmission, allowing for a more compact and lighter system that integrates easily into racing cars.

The system collects data from various sensors on the car, such as GNSS for position tracking, accelerometers, and gyroscopes for measuring dynamics, and telemetry systems for monitoring engine performance and other technical parameters. Real-time data collection and transmission are crucial for maintaining the accuracy and reliability of the digital twin.

The onboard-system contains the following components: Dual GNSS receiver, IMU (Inertial Measurement Unit), Cameras, Main unit.

The main unit manages various peripherals, including cameras, GNSS receivers, and IMUs. It collects data from the racing car's CAN (Controller Area Network) system via CAN interfaces, ensuring comprehensive data acquisition. The main unit is responsible for time-synchronized data collection from all sensors and peripherals, transmitting the data in real-time to a remote cloud-based storage system via a built-in 5G module.

OBS partitioning

The main goal of the Driver 21 project is to ensure accurate and reliable positioning. During the project, several concepts and partitioning options were examined from a systems perspective. These options were analyzed in the context of comprehensive market research. Initially, various concepts were developed and then partitioned differently at the system level. Throughout the project, six different scenarios were developed where identical numbers corresponded to the same product. For example, in scenario C, as depicted in Table 1, the system comprises three distinct units: a camera unit, an inertial navigation system (INS) that integrates GNSS and an IMU with a compass, and a logger equipped with a 5G broadcast module. The purpose of this was to map which approach provides the best accuracy and reliability. Each option was analyzed in detail to understand its functionality and integration possibilities. The subsequent step involved market research to identify existing solutions corresponding to the developed options. Our objective was to select technologies that best aligned with the requirements of Driver 21 and required minimal development time and cost for integration. Throughout the evaluation process, options that were unavailable (B) in the specified partitioning or economically unfeasible (E and F) were excluded.

Table 2: System partitioning table

Functional elements	Scenarios					
	A	B	C	D	E	F
Camera	1	1	1	1	1	1
GNSS	2	2	2	2	2	2
IMU + compass	2	2	2	3	2	3
Logger + pipeline + sync	2	2	3	4	3	4
5G module	2	3	3	4	4	5

A decision matrix was developed from the remaining options to facilitate the selection of the optimal alternative. This matrix ranked the options based on objective criteria such as cost-effectiveness, integrability, development resources, competence, compatibility with existing technologies, and others, using a weighted scoring system. By aligning with the defined requirements of the Driver 21 project and leveraging data from market research, the most suitable solution was identified.

The evaluation led to the determination that the optimal solution for partitioning the positional sensor involves using separate GNSS and IMU units, as indicated in Table 1 under Option C. A comprehensive analysis of various concepts and market options ensured that the selected solution would be optimal both technically and economically, facilitating the successful implementation of the project.

By prioritizing positioning accuracy and leveraging market-available solutions, a robust set of requirements was developed to efficiently meet the objectives of Driver 21. This approach not only ensures adherence to the highest standards of precision but also optimizes resource utilization. The meticulous analysis and strategic planning inherent in this process have established a solid foundation for the project's successful implementation, addressing critical aspects and achieving primary goals effectively.

3.2. Race track infrastructure

The track infrastructure consists of two subunits:

RTK System: Supports precise positioning through Real-Time Kinematic setup, enhancing GNSS accuracy by providing real-time corrections. This ensures a much higher level of precision than a stand-alone GNSS receiver.

5G Network: Establishes a 5G mobile network along the track for full coverage, enabling real-time transmission of data from OBS to the cloud. High bandwidth and low latency are essential for handling large data volumes promptly and reliably.

Installation involves careful planning and calibration of hardware like RTK stations and optimization of the 5G network for consistent coverage.

3.3. Cloud Infrastructure

The cloud infrastructure is where data processing occurs. Key functions include:

- Time-synchronized storage of data recorded during the race for each racing car in a database. These data provide the basics for designing other use cases.
- Data convert process to ensure the predefined interface between database and simulator program
- Determining the localization and orientation of racing cars using sensor fusion algorithms and combining vehicle models. This functionality poses one of the greatest challenges in this project, as sensors like GNSS receivers, even with modern RTK systems, fall far short of the advertised centimeter-level accuracy in racing car speeds. High-precision GNSS receivers update positions at a frequency of 10-50 Hz, depending on the type. This implies that a racing car travelling at 300 km/h can cover a distance of approximately 1.5 to 8 meters between two position updates, introducing significant uncertainty into localization determination.

3.4. Simulator

Many high-quality racing simulators are available on the market, allowing virtual racing against virtual opponents or multiple live simulator drivers. These simulators are widely accessible and popular. The goal is to establish a cooperative relationship with an existing simulator company to integrate the digital twins of the racing cars into their platform.

The integration involves developing an interface that allows the simulator to access and use the real-time data from the digital twins. This interface must ensure that the virtual environment accurately reflects the conditions of the real-world race, providing a realistic and immersive experience for the virtual pilots. The integration process includes rigorous testing and validation to ensure that the performance and behavior of the digital twins in the simulator match those of the actual racing cars.

4. Racing car localization problem

As it has been mentioned earlier, the pose of the real car has to be estimated as accurately as possible to create its appropriate digital twin. The location estimation task can be performed with a wide range of sensors (Table 1), but everyone has some disadvantages: The GNSS measures the position directly, but significant noise and delay could occur (Falco et al., 2017), the IMU is biased, and the errors are double-integrated to calculate the position (Thrun et al., 2006), cameras can be utilized only in areas with full of well recognizable features, and often prior teaching is necessary (Bloesch et al., 2015), and the wheel encoder-based estimation (wheel odometry) that suffers from parameter uncertainty (Fazekas et al., 2021). Since the main focus is on the location of the vehicle, the core sensor is the GNSS, but it should be completed to reach the required estimation performance, i.e. 100 Hz frequency, delay-free timing, and centimeter-level accuracy.

A widely used method is the GNSS & IMU INS fusion. Due to the high-performance requirements, compensation for the biases of the IMU and the delay of the GNSS should be integrated into the fusion. In most of the algorithms, the mathematical method is the Kalman-filter, which assumes Gaussian noises. The nonlinearity can be handled with its two enhancements, the Extended and Unscented Kalman-filter (Gustafsson and G. Hendeby, 2012). Furthermore, suppose the accuracy is limited because of the unmodelled dynamic of the noises. In that case, the particle filter is the appropriate choice, with which the non-Gaussian errors, e.g. in the bias model of the IMU, can be captured.

When the focus is on the requirement to be as accurate as possible, the architecture of the state estimation filter has a high impact. In the loosely-coupled connection, the processed signals, e.g. GNSS position, orientation and velocities, are fused with the dynamic signals. However, in this way, there is no loopback to the raw signals process layer from the filtered ones that can limit the performance. Another way is the tightly-coupled architecture, where the raw pseudoranges and Doppler measurements are integrated into the estimation. It is clear that the lowest error of the final pose estimation can be reached in this formulation, but the algorithm will be more complex and difficult to manage in several contexts.

Furthermore, the accuracy can be increased by considering signals from the CAN network. However, these can not be accounted for directly, only as inputs of various vehicle models: wheel rotation and torque in the tire model for the longitudinal, steering encoder in the bicycle model for lateral, and suspension potentiometers in the roll/pitch model for vertical dynamics. Since the vehicle models are based on many parameters, a calibration algorithm is necessary also to properly include the information of these signals. This expansion of the filtering method generates more difficulty in the tightly coupled architecture, e.g. in the tuning process of the estimator. Nevertheless, in the era of machine learning when the computation effort and data demand are less matter, new AI-based ideas could be developed (Fazekas and Gáspár, 2024).

5. Conclusions

The development and implementation of a digital twin system within the Driver 21 project represents a significant advancement in the field of motorsport and simulated racing. This system offers a comprehensive and highly detailed virtual representation of real racing cars, providing valuable insights and optimization opportunities for engineers, drivers, and teams. By utilizing real-time data analytics, advanced simulation technologies, and AI-driven agents, the digital twin system bridges the gap between virtual and real-world racing environments. The primary goal of achieving precise positioning and reliable data transmission has driven the project's requirements and system architecture. Through careful market research, detailed analysis of different concepts, and strategic planning, the project has identified the most suitable technologies and components to meet these demands. The integration of a dual GNSS receiver, IMU, cameras, and a robust cloud infrastructure ensures accurate and real-time data synchronization, essential for creating high-fidelity digital twins. The Driver 21 project exemplifies the potential of digital twin technology in revolutionizing motorsport. It offers a versatile and scalable solution that not only meets current requirements but is also adaptable to future developments. The project's success underscores the importance of precision, innovation, and strategic planning in advancing the boundaries of simulated racing and automotive engineering. In addition to its technical achievements, the Driver 21 project also contributes to the sustainability goals of the automotive and motorsport industries. By shifting a significant portion of racing development and testing into the virtual realm, the system reduces the need for physical testing, lowering the consumption of resources such as fuel, tires, and vehicle parts. This virtual approach minimizes the environmental impact of traditional motorsport activities, promoting a more sustainable and eco-conscious future for the industry.

Nomenclature

- AI – Artificial intelligence
- CAN – Controller Area Network
- GNSS – Global Navigation Satellite System
- IMU – Inertial Measurement Unit
- INS – Inertial Navigation System
- OBS – Onboard-System
- RTK – Real-Time Kinematic

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