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On the human-machine gap in car racing: A comparative analysis of machine performance against human drivers

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ABSTRACT Automobile racing presents a formidable challenge, demanding drivers to operate their vehicles at the limits of friction while maintaining control. Achieving optimal performance requires extensive coaching for car owners and demonstrative methodologies in race-driving coaching exhibit considerable potential to enhance the learning process. However, since the learner should be in the driver's seat, this methodologies can greatly benefit from autonomous and consistent vehicle operation capabilities at performance levels comparable to or exceeding those achieved by professional human drivers. This study presents a real-world comparison of an in-house developed autonomous racing system against five highly skilled race-car drivers in a five-lap time trial race under identical conditions. Temporal, trajectory and dynamic performance metrics describing the driving performance of each participant were obtained and discussed to gain insights into the human-machine performance gap. Our findings demonstrate that the autonomous driving system can perform at a very high level, outperforming highly skilled racing drivers. Notably, the autonomous system excelled in areas such as consistency and smoothness, dynamically generating precise trajectories with lower dispersion than the human participants. The system also maintained optimal slip angles and required fewer significant steering corrections, indicating smother driving. Our analysis showcases where the autonomous system falls short of the best human drivers, providing clear directions for further development to close the performance gap on the racetrack. These results underscore the potential of autonomous racing systems as real-life racing demonstrators and therefore their utility for enhancing race-driving coaching.

INDEX TERMS Autonomous Racing, Human-Machine Performance Gap, Racing performance metrics, Race driving coaching, Model Predictive Control.

I. INTRODUCTION

THE motorsport industry has changed significantly in recent years to the point where the driver now faces extremely high demands. Racing drivers have to handle a variety of motor and cognitive activities at once. They constantly listen to their teams, make adjustments to their strategy, and, probably more crucially, maintain an eye on the opponents while quickly and precisely controlling the car. However, the most challenging part of racing a car is pushing it to its physical limits to maximise the lap performance.

There is a wealth of literature on how to achieve high driving performance on a racetrack [1], however, endowing drivers with this capability, if even possible, requires extensive coaching. The question at this point is: can we improve human driving performance?. Latest advances in Artificial Intelligence (AI) have shown that human capabilities can be equalled and even improved [2], [3], however, we have not yet witnessed such a milestone in the world of motorsport.

One of the most recent contributions of AI developments to the world of motorsport is the development of autonomous racing. The goal of autonomous racing is to complete a race in the shortest amount of time, whether or not there are other competitors. To do this, full and advanced control of the vehicle's dynamics that enable the car to reach its handling limit is necessary. How to properly control the car's motion during really extreme manoeuvres is the key challenge and one of the most important tasks in autonomous racing.

Interest in autonomous racing has grown significantly and

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FIGURE 1. RIMAC autonomous vehicle designed to race at the limits of handling.

for several reasons. First, autonomous racing technology would allow racing teams to test different car configurations reliably and identify problems without the need for expert racing drivers, minimising costs accordingly. Second, human drivers could benefit from a practice-based learning method where the car serves as their coach, shows them the perfect trajectory, and teaches them how to handle the car at high-performance driving. It is well known that experiential and demonstrative learning methodologies improve teaching. This active engagement allows individuals to not only grasp theoretical concepts but also refine their motor skills and coordination through repeated practice [14]. By immersing themselves in practical experiences, students, and in our case racing drivers, can gain valuable insights into the intricacies of body movement, spatial awareness, and muscle memory, and take ownership of their learning journey. However, a fundamental cornerstone for developing highly effective autonomous test platforms or experiential learning systems for racing is making sure that the autonomous racing systems performs at the level of experts.

Similar to the work in [13], we benchmark autonomous and human racing. However, our work considers multiple human drivers in the comparison, and reports multiple instances where the Autonomous Racing System (ARS) outperforms human drivers. In our study, we demonstrate how our ARS is capable of competing against and defeating experienced racecar drivers in a five-lap race on a technically demanding racetrack. We benchmarked our racing system against five racing drivers and compared lap times and dynamic behaviours over segments on the track. In this groundbreaking comparison, it is shown how the proposed ARS can utilise the force budget on the tires to the same extent as skilled racecar drivers can in the real world. Our autonomous racing approach maximises vehicle performance while minimising lap time through the optimisation of numerous vehicle variables, leveraging an accurate hybrid model of the vehicle based on both data and physical knowledge. Being our focus the human-machine gap in car racing, we highlight here that our autonomous racing system is only compared against human professional drivers, therefore no comparisons against other autonomous racing systems is provided.

The main contributions of this paper can be summarised as follows.

- **Outperforming Human Drivers:** Our ARS surpasses the performance of human drivers in 3 out of 5 instances, during time trial races. This illustrates the remarkable competency and competitiveness of current autonomous driving systems.
- **Precise Lap-by-Lap Performance as compared to human drivers:** Our results showcase a new standard in accuracy and precision, offering a detailed analysis of performance lap by lap comparing autonomous and human race driving.
- **Smoother Driving Experience as compared to human drivers:** Beyond mere speed, our ARS achieves a smoother driving experience. This not only enhances the overall ride quality but also can contribute to increased safety and efficiency on the racetrack.
- **Enhanced Tire Management as compared to human drivers:** Our study reveals a strategic advantage in tire management for longer performances. The ARS, with its lower slip angle generation, demonstrates a superior ability to conserve tire integrity over extended duration, promising enhanced endurance and stability.

In essence, our research not only demonstrates the capabilities of our Autonomous Racing System (ARS) in achieving very high speeds but also highlights its contributions in surpassing human performance, ensuring precision, promoting smooth driving, and revolutionising tire management strategies for prolonged races. Our work showcases and discusses autonomous racing capabilities at performance levels comparable to or exceeding those achieved by professional human drivers, which constitutes an essential feature of modern racing test platforms and coaching systems. In fact, teaching how to race by demonstration requires the learner to be in the driver's seat, making it imperative to use an autonomous driving system that can effectively demonstrate driving techniques. Our paper presents such a system and we hope this work serves as a foundational reference for using autonomous driving in the context machine-aided race or even urban driving coaching.

II. RELATED WORK

The idea of utilising computers for teaching humans dates from the early 1970s and was introduced under the umbrella concept of Intelligent Tutoring Systems (ITS) [4]. Computers have been extensively used to teach humans through a combination of visual and hearing cues. The use of simulators opens the door to teaching approaches that also include touch. The work in [5] developed a system for training a computer agent to operate a crane. The agent then teaches a human how to use the crane utilising haptic feedback. This kind of system is of paramount importance in motorsport Coaching, where the objective is to teach a particular set of physical skills.

Specially in the world of motosports, the emergence of autonomous racing technology raises as an opportunity to teach

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driving skills using the best possible intelligent instructor: the vehicle itself. Numerous studies have examined the development and performance of autonomous racing systems and their components [16]. However, a comprehensive comparison between human drivers and autonomous vehicles in the context of racing over a designated number of laps remains uncharted territory, except for the work in [13], where an autonomous racing system is compared against a professional human race driver.

Given the diverse scope of our study, we categorise the relevant literature into two distinct groups: one is focused on autonomous driving within racetrack environments, and the other is centered on comparing human drivers with machine-driven systems in motorsports. Regarding autonomous racing, diverse motion control, and planning algorithms have been employed to achieve faster lap times, either by determining and utilising the best racing line [17] or by directly optimising a driver model [15]. Within this context, in [7], the authors use a state-of-the-art RL algorithm to control a simulated racing car. Trained on data gathered from human drivers or other RL agents, the system required three continuous days to reach peak performance. They conclude that driving the optimal lap in a professional simulator requires more than end-to-end RL and a better representation of the current and future states seems to be necessary. Also in the Machine Learning (ML) arena, [8] propose a control scheme consisting of a feed-forward-feedback structure incorporating a Neural Network (NN) based model. This achieves considerably low tracking errors while eventually reaching 0.95g accelerations. They suggest a further investigation of NN structures for modelling vehicle dynamics on its full operating range.

Autonomous racing competitions like the Indy Autonomous Challenge (IAC) and Formula student have contributed significantly to the development of autonomous driving technology that works at the handling limits [22]. The works in [9]–[11], [18], [23] showcase different perception, planning, control and general software aspects of their contributions, notably highlighting the robustness, flexibility and improved safety provided by Model Predictive Control (MPC) approaches. Our autonomous racing system builds on this research trend by leveraging the real-time optimisation, constraint handling, and adaptability provided by MPC. For a comprehensive survey of the state-of-the-art in autonomous racing, including the perception, planning and control tasks, refer to [16].

Concerning the disparity between human and autonomous driving in motorsport, there is a limited number of studies that directly compare human and autonomous driving systems in this field. This gap poses a challenge for integrating autonomous racing technology into race coaching, as validating its performance against professional drivers is a prerequisite for its utilisation in race driving coaching. Starting with simulation-based works, in [7] the authors conduct a study comparing thirteen participants to their autonomous driving system in a professional racing simulator. Two of the thirteen drivers were professionals, and the other eleven were drivers with lower degrees of experience. They emphasised that the brake had the greatest influence on lap quality, demonstrating that the AI takes much longer to learn how to brake than how to steer and accelerate. In addition, they assert that this method can be utilised to develop manoeuvres for more effective training of humans. Last but not least, their racing system outperformed the best human in simulation. In [12], the authors present a simulated comparison of their autonomous racing software in Gran Turismo Sport simulator. Their approach exceeds the fastest driver in a dataset of more than 50,000 human gamers while also achieving autonomous racing performance that surpasses what the built-in AI had so far been able to accomplish in simulation. In contrast, our work presents a real-life comparison with both human and our autonomous racing system driving at the limits of handling.

The work in [8] compares its proposed autonomous system with an experienced driver with amateur racing experience in a real-life scenario. The authors demonstrate that their system matches the performance of an amateur racecar driver but does not surpass the highest levels of human performance. Both participants completed 10 trials on a 1 km track with a maximum cornering speed of 41 kph. The autonomous system exhibited greater consistency in its trajectories and lap times compared to the human driver. Similarly, [13] compares the fastest laps of human and autonomous drivers around a racetrack, though including a professional driving in the comparison. Key performance indicators reveal that while the human driver outperforms the autonomous system in most areas, the autonomous system follows smoother trajectories. In comparison to [8], [13], our work includes comparisons against a larger group of drivers with varying levels of racing experience, including professionals. Our work is similar in spirit to the real-life comparison between autonomous and human drivers, both amateur and professional, presented in [19]. However, our autonomous racing system outperforms human drivers in several key areas including lap time, consistency, and smoothness. Additionally, our study offers a more comprehensive analysis by focusing on full laps rather than open track sections.

III. AUTONOMOUS RACING SYSTEM

A standard Autonomous Racing System (ARS) architecture is composed of hardware and software layers designed to optimise vehicle performance on a racetrack. The hardware handles sensing and actuation, while the software layer processes sensor information and makes decisions, serving as the autonomous racing "brain."

A. SYSTEM ARCHITECTURE

Our ARS architecture comprises two hardware layers for sensing and actuation, and a software layer where the autonomous racing brain operates, as shown in Fig. 2. The ARS software is structured into three primary layers: Perception, Path Planning, and Motion Planning and Control.

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a: Perception

The Perception layer enables the car to understand its environment, determine its location within it, and communicate its current dynamic state to the next layer. Specifically in this work, it estimates the vehicle's pose on the racetrack using a digital representation of the environment, which can be created either offline or online. In our case, the racetrack borders are mapped offline a fed to the ARS system for localisation purposes.

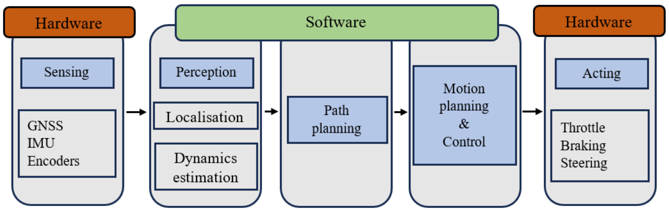

FIGURE 2. Autonomous racing system architecture. Similarly to many robotic systems, it comprises sensing devices that collect data, which is then analysed by perception, planning, and control modules. These modules work together to generate control commands, directing the actuators.

b: Path Planning

The Path Planning layer is responsible for computing the set of waypoints the car must follow. In our study, this layer uses information from a precomputed optimal trajectory. This optimal line is calculated by solving a non-linear optimisation problem with the Interior Point OPTimiser (IPOPT) solver [20]. This process involves a non-linear version of the vehicle model and a prediction horizon slightly longer than one full lap of the racetrack, ensuring a global optimum.

c: Motion Planning and Control

The Motion Planning & Control module predicts the optimal motion along the path and computes the best actions to control the car. In this section, we focus on this module, highlighting how it enables our framework to achieve high-performance autonomous laps.

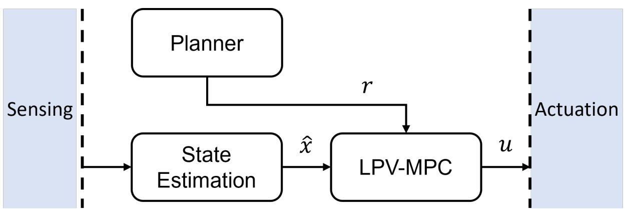

FIGURE 3. Motion planning and control architecture. Using the vehicle's estimated state and a reference optimal path, our LPV-MPC produces actuation commands that optimise lap time.

B. MOTION PLANNING & CONTROL

Due to the high level of dynamic interdependence between planning and control tasks, we have chosen a combined approach to handle both responsibilities simultaneously. We leverage the widely recognised concept of Model Predictive Control (MPC), employing a particular formulation known as Linear Parameter Varying (LPV) as presented in [6].

LPV-MPC involves a quadratic optimisation process with key equations aiming to minimise the time it takes to drive a certain distance and adhere to the waypoints from the preceding layer. The main objectives include the reduction of understeer and oversteering actions, as well as penalties for rapid changes in throttle, braking, and steering.

The following optimisation problem is solved at each time k to determine the control actions (u_k) considering that the values of x_k and u_{k-1} are known:

$$
\begin{aligned}
\min_{\Delta U_k} \quad \mathrm{J_k} = & \sum_{i=0}^{H_p-1} \Big((r_{k+i} - x_{k+i})^T Q (r_{k+i} - x_{k+i}) \\
& + \Delta u_{k+i} R \Delta u_{k+i} \Big) + x_{k+H_p}^T Q x_{k+H_p} \\
\text{s.t.} \quad & \\
& x_{k+i+1} = x_{k+i} + \big(A(x_{k+i}, u_{k+i}) x_{k+i} \\
& \qquad + B(x_{k+i}, u_{k+i}) u_{k+i} \big) dt \\
& u_{k+i} = u_{k+i-1} + \Delta u_{k+i} \\
& (F_{yF}^2)_k + a (F_{xF}^2)_k \leq b^2 \\
& (F_{yR}^2)_k + a (F_{xR}^2)_k \leq b^2 \\
& X_k \in X_c \\
& U_k \in \Pi \\
& \Delta U_k \in \Delta \Pi \\
& x_{k+0} = \hat{x}_k \ ,
\end{aligned}
\tag{1}
$$

where $x = \begin{bmatrix} X & Y & \theta & v_x & v_y & \omega \end{bmatrix}^T$ is the vehicle state vector, being X and Y the coordinates in the ground plane, θ is the heading of the vehicle, v_x and v_y are the longitudinal and lateral linear velocities, respectively, and ω is the angular speed over the orthogonal axis to the ground, also referred as the yaw rate. $\hat{x}$ represents the estimated state vector, $r = \begin{bmatrix} X_r & Y_r & 0 & 0 & 0 & 0 \end{bmatrix}^T$ is the reference vector provided by the path planner, $u = \begin{bmatrix} \delta & TB \end{bmatrix}^T$ is the control input vector representing the steering angle and the combined throttle and braking variables, respectively. F_{xF}, F_{yF}, F_{xR}, F_{yR} represent the lateral (y) and longitudinal (x) forces in both front (F) and rear (R) tires. Factors a and b are used to give shape to the tire force constraints and limit therefore the overall force produced. H_p is the control prediction horizon used equally for both the state and control input prediction. The tuning matrices $Q \in \mathbb{R}^{6x6}$ and $R \in \mathbb{R}^{2x2}$, are semi-positive definite to obtain a convex cost function. The time discretisation is carried out using the Runge-Kutta method with a constant sampling time dt. Constant sets X_c, Π and $\Delta\Pi$ constrain the model states, inputs, and their variations, respectively.

These equations encapsulate the foundation of our autonomous racing system, providing the framework for optimal motion planning and control. The particular parameter values are car-dependant and confidential in our case.

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C. IMPLEMENTATION AND OPTIMISATION

A significant element of our technique lies in implementing the dynamic model and constraints within the optimisation problem. Achieving peak performance requires a deep understanding of the vehicle's physical limits and operating within them. Developing a highly representative dynamic model was a meticulous process, involving extensive identification work, particularly concerning tires and brake degradation. To obtain the necessary data, we performed manoeuvres on the track, pushing the system, especially the tires, to their dynamic limits. We utilised an Unscented Kalman Filter (UKF) based method to fit individual modules of our vehicle model, including the tire model, powertrain model, steering model, and brakes model.

For the tires, we employed the Pacejka tire model representation to capture their behaviour under different conditions [24]. This involved determining the available force budget for the tires in various dynamic situations, ensuring the model could adapt and perform optimally under different conditions. One of the most challenging tasks was accurately modelling the tires' response, as it required an in-depth understanding of the complex interactions between the tire forces and the vehicle dynamics. Additionally, we developed a powertrain model that relates the throttle input to the generated acceleration at the wheels. Given the high weight of the car, the brakes experienced significant stress during racing, leading to considerable degradation. To address this, we collected extensive data to study the brakes' behaviour and developed a degradation model within the brakes model to account for this wear and tear over time.

Once the prediction model and constraints are properly set, our strategy optimises control actions (throttle, brake, and steering angle) over a seven-second prediction horizon. The control action for the current moment is then sent to the actuation layer. We formulated the optimisation problem as a quadratic problem and solve it using a High-Performance Interior-Point Method (HPIPM) solver [21]. By employing an LPV formulation of the vehicle model, we encapsulate all non-linearities within the model itself, allowing us to use a linear formulation for the otherwise non-linear problem. This approach provided a versatile solution, offering significant advantages over a completely linear model while managing the complexities of non-linear dynamics.

The subsequent sections will focus on our experimental methodology, detailing how our racing system performs as compared to multiple human racers. Following this, we will present the results obtained from these experiments.

IV. EXPERIMENTAL SETUP

To assess the performance of our ARS and validate that it can be used for human driver coaching, we adopt the most effective method: a real-world race against five experienced racing drivers. Each participant competes individually for five consecutive laps pushing the car to its handling limits and controlling the upcoming heat-related tire and brake degradation.

The test car, shown in Fig. 1, is a 385 horsepower, 1978 kg automatic KIA Stinger GT 3.3 that has been modified to conduct research on autonomous driving. It allows, on one side, the same actuation as any human, i.e., controlling throttle, braking, and steering. On the other side, it has been equipped with a sensing net composed of a set of thirteen cameras, a LiDAR, four-wheel encoders, an inertial measurement unit (IMU), and a Global navigation satellite system (GNSS) which is enhanced by using Real-time kinematic positioning (RTK). In the sensing layer, encoders, IMU, and GNSS run at 10, 5, and 200 ms, respectively. The complete software stack operates at 50 ms, and the actuation layer sends commands every 10 ms. It was implemented in C++ and runs on a Nvidia Jetson Xavier module.

Race setup. Due to its complex nature, featuring a mix of fast and slow corners, each unique, and a braking zone that requires deceleration from over 200 kph to 50 kph, we selected the Navak centre, shown in Fig. 4, as our testing environment. Our race format is a time trial, where only one car competes on the track at a time. In a time trial, each car runs individually against the clock to set the fastest time, rather than competing directly against other cars simultaneously. Each driver starts the experiment from the same starting line, beginning from a halted position.

Equal climatic conditions—dry tarmac, sunshine, and temperatures between 28 and 30 degrees Celsius—were available for every participant. The car is equipped with new brake pads and tires before each race, and the tire pressure is checked before each race to make sure it is optimal and equal for each competitor. Finally, to ensure fairness and compensate for the ARS's greater circuit layout knowledge, the drivers are permitted to practice on the racetrack for an hour right before the race. Note that all of them were already familiar with this racetrack.

FIGURE 4. Top view of Navak racetrack used in the experiment.

Human drivers. We involved five racing drivers with skills ranging from experienced to expert in different categories. D1 is a professional driver with several years of driving experience on racetracks. Driver D2 competed for fourteen years in karting and six years in national car racing. He won two national car racing championships and he is officially racing nowadays. D3 has ten years of karting experience, seven years in hill climb, and one year in Formula Renault

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2.0. He won nine national championships and one Central European championship. He is still racing nowadays. Driver D4 has twenty-seven years of nonstop karting, rallying, and hill-climb competition experience. He won fourteen national championships and is still racing today. Driver D5 has fifteen years of experience in circuit and hill-climb racing. He won three national car racing championships.

V. AUTONOMOUS VERSUS HUMAN DRIVER COMPARISON

In this section, we evaluate our ARS using the scenario introduced in Section IV. We compare the lap times obtained by our approach with the those achieved by the five human drivers. Additionally, we have analysed and compared their resulting performances in terms of trajectory and dynamic performance. It is important to highlight that during the initial stages of a coaching process, simultaneous multi-vehicle racing is discouraged. Therefore, we have decided to focus on time trial races for this study.

To achieve a more detailed and fine-grained analysis, we have defined six sections along the racetrack, as illustrated in Fig. 5, and analysed the results accordingly. Additionally, several Key Performance Indicators (KPIs) are presented to compare all the participants, including our ARS.

A. LAP TIME COMPARISON

In the five-lap time trial race, the ARS outperforms three of the five candidates' lap times finishing in 3rd position. The

TABLE 1. Lap times per participant in seconds.

Laps	ARS	D1	D2	D3	D4	D5
1	100.82	100.40	99.59	97.93	100.75	101.61
2	95.50	95.41	94.05	92.79	95.61	95.66
3	94.99	95.46	93.85	92.63	95.64	95.00
4	94.14	95.41	93.44	93.14	95.56	94.50
5	94.95	95.66	95.00	92.48	95.86	94.75

lap times for each driver are shown in Table 1, and a few statistics are shown in Fig. 6. From the latter, we can observe that the variability in lap times is somewhat similar across all drivers. On one hand, D1 and D4 exhibit the lowest time variability, despite being the slowest. On the other hand, D3 is the fastest participant and also has relatively low lap time variability compared to the rest. To further investigate how the ARS (Automated Racing System) differs from the other participants in terms of lap times, we examine the section times shown in Fig. 7. This allows us to analyse the overall performance of each participant in more detail. In comparison to the others, S1, S3, and S6 display some of the strongest performances for the ARS, while S5 and S6 exhibit the most intriguing behaviour. In this two last sections, the ARS adopts a radically different racing approach. It significantly reduces its speed in the middle of S5 to accelerate faster out of the corner, allowing it to get back on the throttle earlier. This allows our ARS to enter S6 at a much faster velocity, preserving a faster speed profile than the other participants during the long straight section, and therefore cutting S6 time in certain cases by more than one second, although losing time in S5. Finally, when we examine S5 and S6 together, we see that the ARS loses an average time of 0.73 seconds in S5 but gains an average time of 0.91 seconds in S6 when compared to the mean time of the rest of the participants. This suggests that ARS's strategy in these two sections is better than the rest of the competitors. By sacrificing time in one section to gain significant advantage in the next, the ARS showcases strategic decision-making aimed at maximising overall lap time performance. This analysis underscores the potential of ARS systems for strategic planning and execution, suggesting avenues for demonstrative coaching methodologies that emphasise adaptability, risk assessment, and optimisation of key race segments to enhance driver performance on the track.

B. TRAJECTORY COMPARISON

For this comparison, we focus on a smaller region of the racetrack. In particular, we use sections 2 and 3, shown in Fig. 5, due to its high dynamic requirement (Fig. 8A). Furthermore, to make the presentation of the result more understandable, we compare only ARS against participants D3 and D5 which were the fastest in these two sections (see Fig. 7). In Fig. 8C, each lap for each of the three participants considered is represented as a projection onto the track centerline. We can observe a slightly different racing line in the case of ARS compared to the participant one, especially around middle S3 where the late apex approach allows the vehicle to meet the inner side to reach more speed in the last part of the section. We also looked at the mean absolute deviation (MAD) of the trajectory in Fig. 8D, a reliable indicator of each driven trajectory's dispersion for their respective line, to analyse the consistency of the trajectory. In general, the consistency of path deviation by the ARS demonstrates that the planning and control approach was not only accurate but also precise. Despite driving at the limit, the ARS's low path dispersion can also be explained by the use of a highly accurate localisation system and a higher-frequency computing system. As a result, the ARS achieves a higher level of consistency by minimising trajectory deviation over laps.

C. DYNAMIC PERFORMANCE COMPARISON

This analysis provides the most information about the car's dynamic behaviour. Despite the interesting information coming from the throttle, braking, and other vehicle variables, in this performance analysis, we focus on accelerations at the center of gravity, slip angles at the front and rear axles, and steering wheel reactions which all together reveal more accurately the driving style and the differences in how forces are transferred to the tires.

In this section, the same three participants are compared using information from sections S2 and S3 as well as some KPIs that were obtained throughout the entire race. In Fig.

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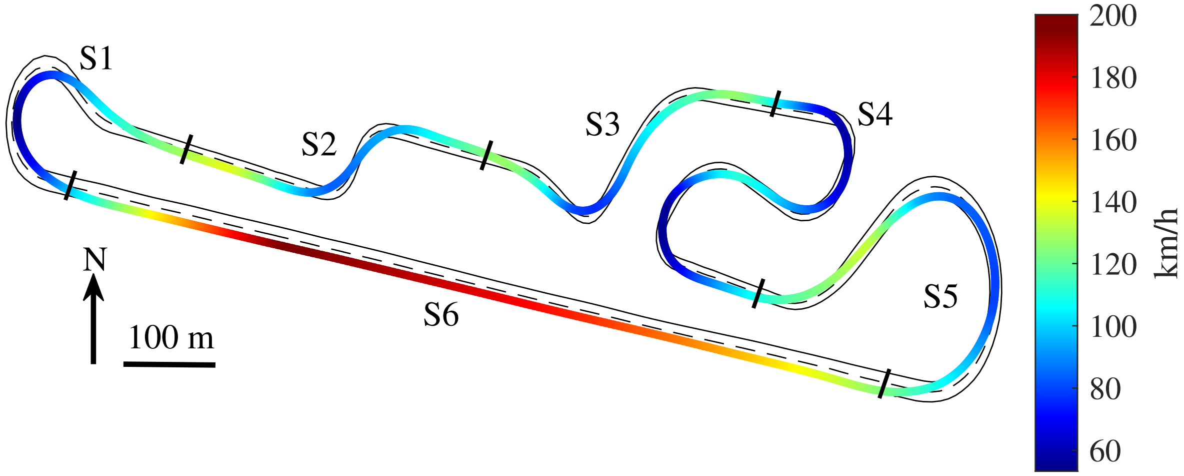

FIGURE 5. Navak racetrack divided by sections. The ARS trajectory is represented as a function of the speed.

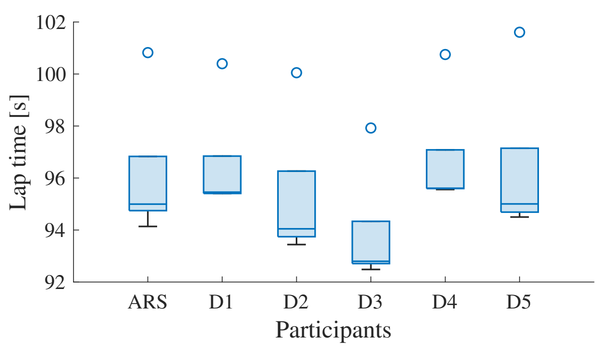

FIGURE 6. Lap time comparison. Center lines show the medians; box limits indicate the 25th and 75th percentiles; whiskers extend to minimum and maximum values; circles are considered outliers relative to the first lap.

TABLE 2. Average values (5 laps) for selected KPIs.

KPIs	ARS	D1	D2	D3	D4	D5
lap time (s)	96.08	96.45	95.19	93.83	96.68	96.3
max. speed	197.0	195.1	194.3	194.9	187.9	192.5
speed (kph)	105.1	103.6	105.9	106.4	104.1	104.9
MOA (m/s^2)	5.19	5.31	5.54	5.65	5.48	5.51
times steering > 15deg/50ms	26	40	56	66	59	56
|front slip angle|	3.723	4.634	4.848	4.736	5.086	4.845
|rear slip angle| (deg)	1.328	1.753	1.995	2.447	2.106	2.024

8.B, we show the overlay of G-G diagrams for one of the laps, and Fig. 8.F shows the five lap's Mean Overall Acceleration (MOA). The five laps' average velocities for these sections are shown in Fig. 8.E. Finally, to help the discussion, we introduce some useful performance indicators in Table 2. Note that in the following we refer to the distance along the centerline as S_c for simplicity.

Acceleration analysis. The fact these three participants are taking different lines makes the overall acceleration profile look a bit different between them. According to that, ARS has a later peak in MOA which relates to a stronger corner exit due to the late apex line strategy (see Fig. 8.F at around $S_c = 770$ and $S_c = 1100$). This behaviour can be seen in Fig. 8.B as well where, while generating $\pm$ 1G of lateral acceleration, the ARS also maximises the longitudinal one. However, when driving at the limit of handling, going significantly quicker in some places automatically means going slower in others. This is what we observe in Fig. 8.E at around $S_c = 700$ and $S_c = 1000$ when ARS is compared to D3 and D5. We detect that the average MOA can be a reliable indicator of driving performance. D3 and D5 generate a higher average MOA, which explains the faster velocity profile and reveals superior performance in these two sections. In particular, both racing drivers go on average 0.16 and 0.12 seconds faster than ARS in S2 and S3, respectively. Nevertheless, by observing the whole race average MOA in Table 2 we see that ARS generates less amount of overall acceleration than D5 while being faster, which already indicates that the D5 driving style is producing some not useful acceleration, although we cannot conclude that from D3. Different driving styles may generate behaviours like oversteering and understeering obtaining then high non-useful accelerations. When it comes to driving styles, smoothness and aggressiveness might have an impact on the outcome. An aggressive driver explores the limits of grip and traction more frequently, though not necessarily with greater resolution than a driver who is more cautious and approaches the limit more gradually. Avoiding weight transfer pikes at all costs will result in the best

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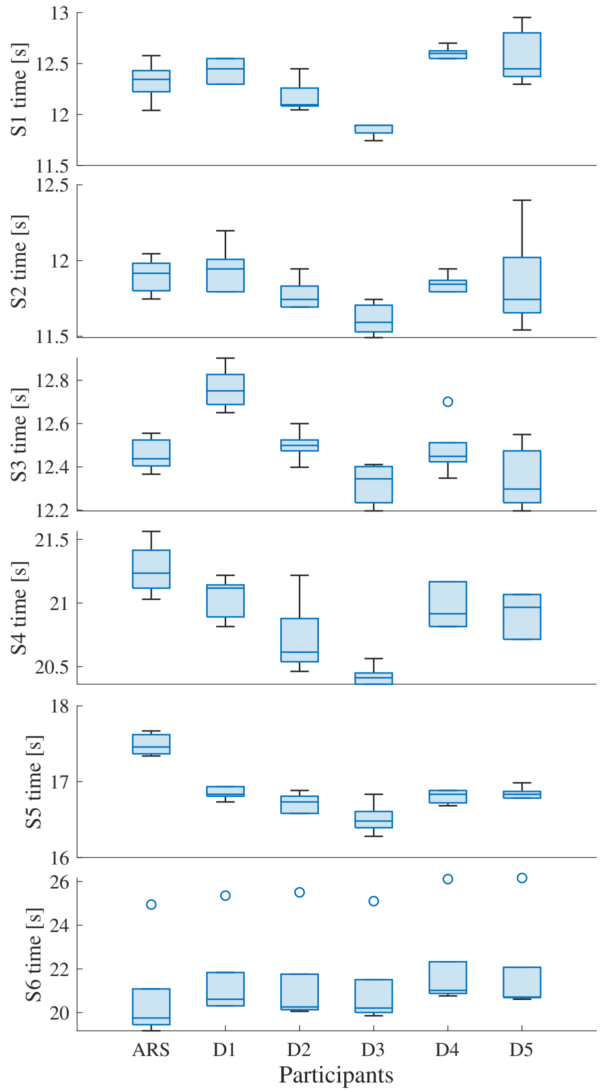

FIGURE 7. Sections time comparison. Centre lines show the medians; box limits indicate the 25th and 75th percentiles; whiskers extend to minimum and maximum values; circles are considered outliers relative to the first lap.

outcomes, but we should also try to cut down on the amount of time we spend not making the most of our available grip, as is happening to D5. ARS is more conservative and approaches the limit more cautiously and gradually than human racing drivers. On the other hand, we observe that there is room for improvement in the overall acceleration at the entrance of the corners.

Steering analysis. The number of steering corrections per interval of time is also a good performance indicator. They can tell us about smoothness and aggressive behaviours. We report the average number of times per lap that each participant makes a steering wheel correction greater than 15 degrees in 50 milliseconds in Table 2. Both human drivers, D3 and D5, have a very high number of steering wheel corrections compared to ARS. This demonstrates an advantage in softness while racing, which will result in a more stable driving style and better tire maintenance, notably in longer races. Additionally, after conducting a correlation study on the entire experiment data, we discover a statistically significant and high positive correlation with the MOA variable and both slip angles, but especially the rear one.

Slip angle analysis. Slip angle is a key concept when it comes to generating cornering force in a race car. Since the analysis of these variables is so intriguing, the data from Table 2 have been visualised in Fig. 9. As it can be seen, the ARS operates with far lower slip angles, front and rear, than the other participants. A lower generation of slip angles is equivalent to a lower generation of lateral tire forces and is typically associated with worse cornering performance. However, as previously mentioned in the acceleration analysis, an aggressive style might lead to oversteering and understeering behaviours that do highly increase the slip angles but do not make the car faster. As a consequence, we can see that D3 has an aggressive style but makes better use of the grip provided by the tires than D5, which is aggressive but frequently oversteers and understeers, making ARS faster overall in the race with much less slip angle. Aside from the high correlation found in the steering analysis, we can also see a statistically significant and very high correlation between the amount of rear slip angle produced and the variable MOA. This suggests trying to find a higher rear slip angle to enhance the overall acceleration. As a result, while a race is decided by the amount of time each participant takes to finish, we have chosen to examine other aspects of the outcome in better detail in this section. We may conclude that ARS has a more precise, smooth, and stable driving style than the other participants.

VI. CONCLUSION

In this paper, we have presented the first real-world autonomous racing comparison against five skilled and highly skilled racing drivers in a five consecutive laps race, where the proposed autonomous system was able to outperform three of the racing participants. The proposed autonomous system focuses on planning and control tasks and benefits from exhaustive vehicle dynamics and tire limit identification to achieve the highest racing performance on the racetrack. The comparison highlights areas where our software can outperform experienced racing drivers, like consistency and smoothness. It was able to dynamically generate an accurate and precise set of trajectories leading to lower path dispersion than humans. The levels of slip angles and the small number of significant steering corrections point to considerably smoother driving and suggest better maintenance of the tires during longer races than human racecar drivers. Additionally, the analysis reveals where the autonomous racing system is not able to reach the "best" racing drivers' level of performance and provides clear indications of which aspects we have to focus on to close the human-machine gap in the racetrack.

The insights gained from this work are crucial for developing demonstrative approaches to race-driving coaching. By

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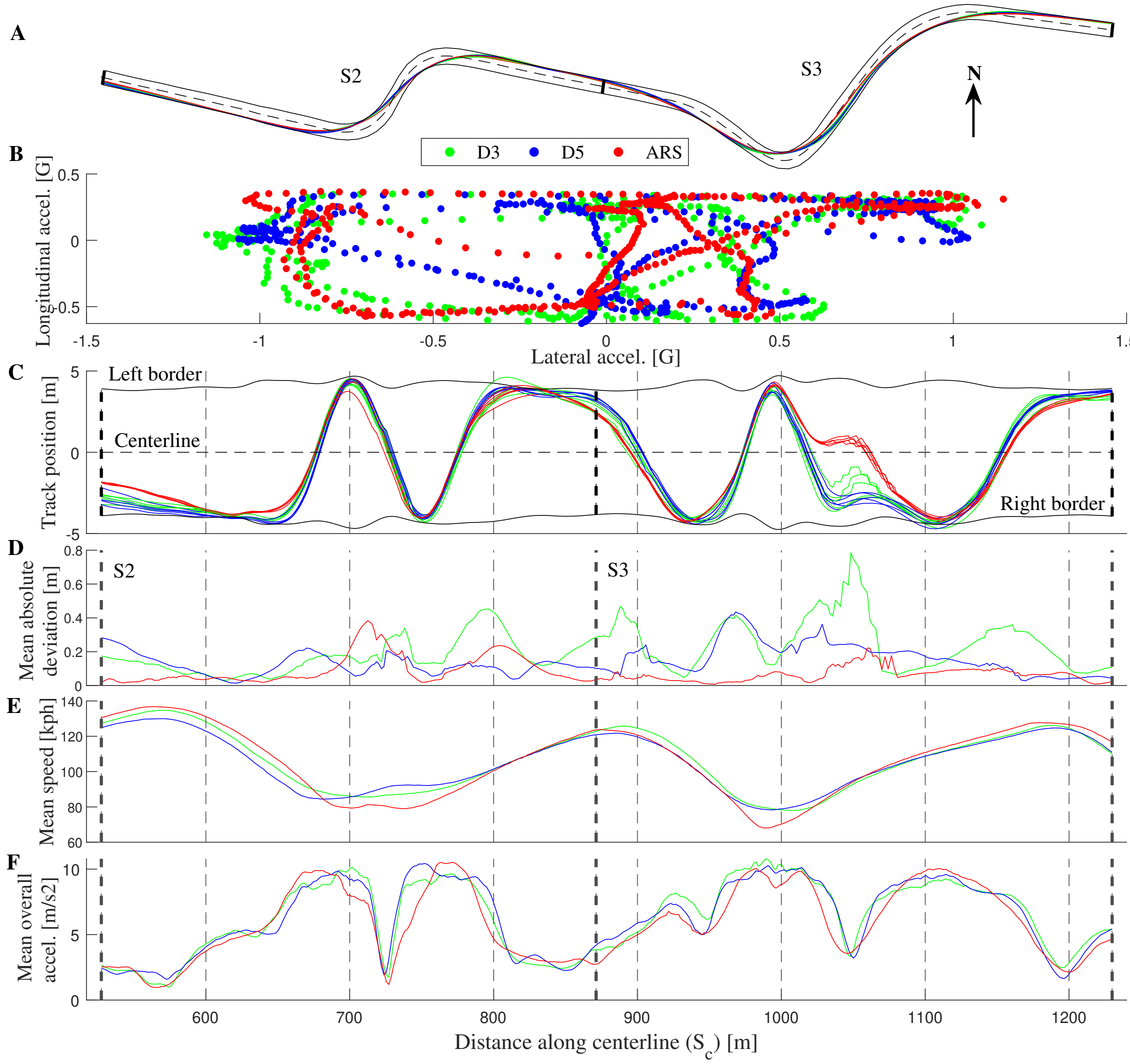

FIGURE 8. Autonomous system and two human racing drivers. (A) Two track sections (S2 and S3) were chosen for analysis. (B) G-G diagram of a single lap. (C) Track and trajectory projection onto the centerline. (D) MAD path for two human drivers and the autonomous system. (E) Average speed on S2-S3 for the five laps. (F) MOA computed as $\sqrt{a_x^2 + a_y^2}$. Note that accel. stands for acceleration.

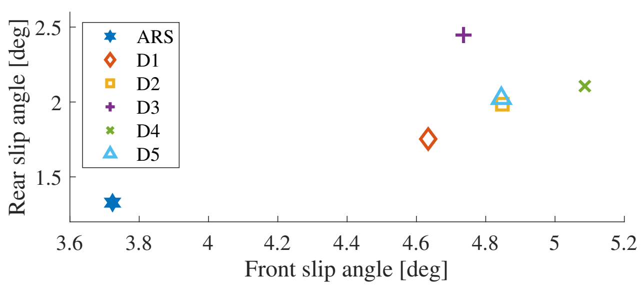

FIGURE 9. Mean absolute slip angles from the entire race.

understanding the specific areas where the ARS excels, such as maintaining consistent slip angles and minimising steering corrections, race-driving coaches and students can adopt similar principles and strategies to improve their teaching techniques and performance.

Future work will focus on multi-agent racing scenarios and extending ARS perception capabilities, exploring the potential of different environment representations. Additionally, world models can be used to enhance predictive accuracy, adaptation, and risk mitigation capabilities of both ARS and ARS-based race coaching methodologies.

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