A data acquisition system to capture extreme human driving behaviour

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***Abstract*—Assessing and encoding human driving expertise while handling challenging events, primarily during drifts, can unveil new insights regarding the professional response to extreme driving which can be integrated into Autonomous Vehicles (AVs) safety procedures. Considering the complex and dynamic data related to both human behaviour and car devices, this research area urges the inclusion of Artificial Intelligence (AI) strategies for the extraction of interdependencies and patterns that encode human driving expertise. To do so, acquiring data that comprises the pilot and vehicle performances is of utmost importance. The present work proposes a specially designed data acquisition system to collect data regarding the vehicle dynamic movement and the associated human behaviour while driving in challenging environments. Distinct sensing devices are placed across the vehicle to retrieve the vehicle position, acceleration, angular rotation, steering orientation, among others. Data was collected from professional drivers during official racing events, and initial processing results show spatial and temporal coherence with the racing performances. The preliminary analysis of the data also reveals potentially extreme events during the race.**

***Index Terms*—Autonomous Vehicles, Driving Safety, Expert Driving, Behavioural Engineering, Sensing System**

I. Introduction

Devising Autonomous Vehicles (AVs) has attracted enormous attention and investment of major academic and industry players worldwide. Nevertheless, the public opinion regarding AVs is still controversial, and the feeling of distrust regarding safety and reliability prevents acceptance and holds back AV deployment.

For a regular driver, an unexpected event associated with loss of car control will likely result in a road accident. Thus, providing AV with expert human behaviour during these extreme situations would result in optimised performance and increased safety. A multidisciplinary and integrated view of the problem, exploring how car technologies, behavioural engineering and Artificial Intelligence (AI) may be articulated to improve performance, will represent a step forward towards the deployment of safer AV.

Drifting is one of the most challenging driving scenarios, at which professional drivers aim to excel. Also known as aggressive driving [1] or high sideslip cornering [2], [3], drifting is a non-linear car driving dynamics, highly complex to model due to the large uncertainty in quantifying the associated variables, such as tire behaviour [4]. Figure 1 illustrates a drifting manoeuvre, characterised by a high sideslip angle (β), i.e. the angle formed between the velocity vector and the longitudinal axis of the vehicle. Despite existing studies focusing on capturing the vehicle dynamics under such conditions, the motivation relied on the ability to trigger or maintain drifting instead of preventing or compensating it [2], [5]–[8].

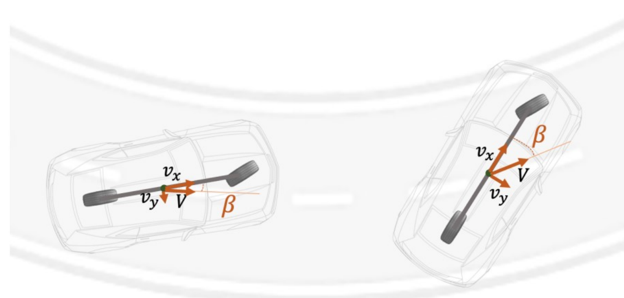

Fig. 1. Drift event with high sideslip angle.

The main goal of the research is to identify key patterns and map expert handing of drifting driving events. To do so, collecting data in real life environments, from expert driving, can provide new insights into the identification of loss of control, the circumstances that lead to such events and how to best respond to overcome them. This work proposes the data acquisition system to achieve these objectives. The sensing devices, selected to jointly measure car and pilot, are thoroughly described regarding their configuration, compatibility, communication and operation. The prototype was tested in official racing events, exploiting the real-world environment and criticality of the driving experiment. The spatial and temporal coherence with the driver's performance demonstrates the system suitability to capture both driver and vehicle behaviour.

Section II discusses studies on related areas of driving and vehicle dynamics. Section III describes the methodology for the definition of the data acquisition protocol, and Section IV delves into the specification of the prototype proposed, including its key components and configuration. Analysis conducted

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on data acquired in real-world-experiments is presented in Section V. Finally, in Section VI are discussed the conclusion and envisioned future work.

II. Related Work

Vehicle dynamics allows modelling the dynamics of a vehicle in motion, based on laws of physics and algebraic analysis that, according to given input parameters, determine the resulting motion. The dynamic behaviour of a car is the result of the combination of the moving forces associated with the vehicle tyres, gravity and aerodynamics during driving [7], [9], [10].

Regarding human performance, most studies on driving focus on human's fatigue and drowsiness [11]–[14]. However, the study of the human response under extreme driving conditions in real environments is a more challenging and less covered topic. Prior work carried out has identified patterns of brain-body behaviour in a professional race driver [15]. It was found that upon unexpected events such as loss of control (while drifting and managing tight curves) the brain signals of the professional driver displayed patterns associated with expertise, which underlines an expert handling of those events. Other studies such as [16]–[18] and [19] focused on the expert driver behaviour, which can be segmented into different styles and levels according to [20]. In [21], [22] are discussed strategies to imitate the human driving skill for an AV. Nevertheless, many open issues of human driving behaviour remain unexplored, and many factors influence and determine this behaviour [23], being personal traits, experience, and skill at the core of the driving strategy [24], [25]. Therefore, innovative approaches to deploying findings in in-body and in-vehicle technologies for safe driving are required.

Regarding the literature review addressing driving challenges, most studies focus on intersections [16]–[18] or blind corners [19]. Despite demanding, these are common tasks while driving, distinct from the drifting critical event, where the driver loses control of the car. Capturing drifting events and the expert human response to them are the main targets of this work.

III. Methodology

The present section discusses the measurement variables to consider and the environment for data acquisition[1].

Figure 2 illustrates the architecture of the proposed experimental setup, highlighting the environment where data will be collected, the expected variables to retrieve and how these will be handled.

[1]Data collection both in Portuguese and European Championships were enabled through partnerships with the Portuguese Minho Car Club (CAM - https://camminho.com/), the Portuguese Automobile and Karting Federation (FPAK https://www.fpak.pt/) and internatinal Fédération Internationale de l'Automobile (FIA https://www.fia.com/), as well as specific racing teams.

A. Dataset Design

The envisioned dataset to detect extreme driving events and extract the associated expert human response comprises two main sets of variables: static variables, and active variables. These variables relate to each data acquisition experiment, as shown in Figure 2. The former are associated with all relevant variables that interfere with the driving scenario, but that do not change during the experiment, such as the type of vehicle, its horsepower, its weight (in the front and rear axis), the weather, the track conditions and map, the driver skill, among others. These will act as weighing parameters in the final model.

As for the active variables, these are the time series associated with the acquisition of the vehicle dynamics and the human response, during a driving experiment. More precisely, these variables are associated with the motion of the car (direction, speed, and general driving behaviour) and the simultaneous human response (steering response, acceleration/braking response) to the car's motion.

The active variable collection resorts to the prototype further discussed in Section IV. The definition of which variable to collect was also based on drifting control studies. Whereas [2], [8] resort to built setups, [5]–[7] resort to similar sensing devices as the ones selected to retrieve the driving dynamics parameters.

The sensing devices capture the active variables in relation to a set of axis and rotations, which are illustrated in Figure 3.

B. Requirements

A set of key requirements for the data acquisition prototype have been defined in order to retrieve data capable of fulfilling the technological challenges and goals previously mentioned. These have also been discussed with the racing teams for their approval.

The key requirements for the prototype are as follows:

- not to interfere with the drivers' performance;
- agnostic from the vehicle specifications, being transferable between vehicles;
- fast and easy assemble and dissemble in the vehicle;
- low cost and low power consumption system;
- acquire data at a sampling rate adequate for capturing extreme events;
- capture the vehicle position and movement, including acceleration and rotation;
- capture the human steering, throttle and braking inputs;
- guarantee data synchronisation amongst all variables collected;
- collect and store experimental data for an uninterrupted period of 1h;
- store data collected for offline data analysis.

Information regarding the pilot, vehicle and driving experiment setup (static variables) need to be retrieved to associate with the active variables.

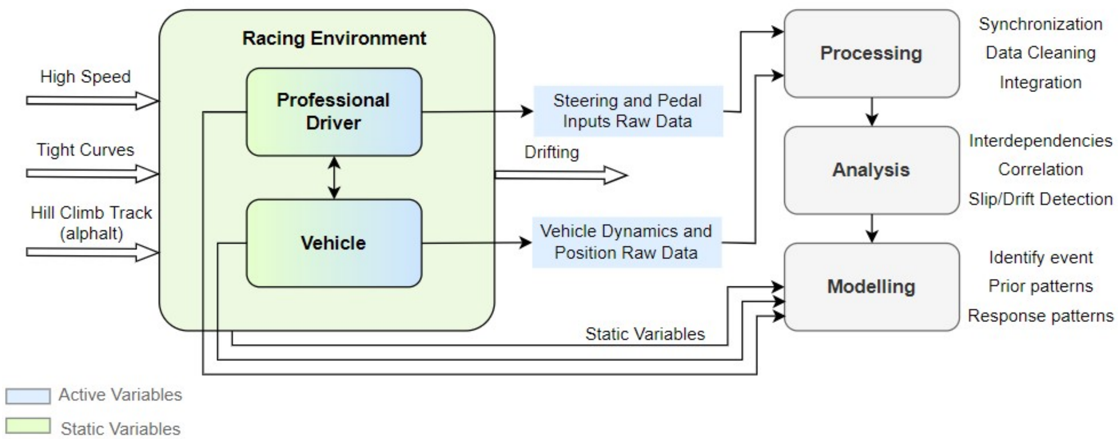

Fig. 2. Architecture of the experimental setup and parameters involved.

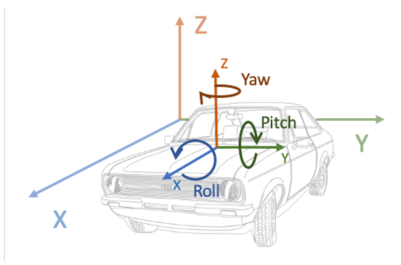

Fig. 3. Vehicle and its rotation axis.

IV. Data Acquisition Prototype

Considering the active variables to retrieve, regarding the vehicle movement and the human input actions, and taking into account the elicited requirements, the proposed prototype comprises a single controller that guarantees synchronous data collection from eight sensors, and storage in an SD card. Figure 4 illustrate the active variables to capture, the sensing equipment used and the information that can be retrieved from its analysis.

A. Equipment

The prototype includes several sensing devices, which purpose, selected component and configurations are detailed in the present section.

1) Controller: The controller contains the developed software for the synchronous activation and data collection from all sensors, and respective storage in the SD card. The controller manages three Inertial Measurement Units (IMUs), two magnetometers, two accelerometers, one Global Positioning System (GPS), one clock and one SD card shield, guaranteeing a synchronous data collection at 150 Hz.

The prototype controller is an ESP32 DEVKIT-V1[2]. The ESP32 is a powerful low power consumption controller, that contains a Xtensa Dual-Core 32-bit processor, Flash (4MB), ROM (448 KB) and RAM (520 KB) memory surpassing other controllers such as Arduino. The selected controller comprises 36 General-purpose input/output (GPIO) pins. ESP32 can communicate with its peripherals using Inter Integrated Circuit (I2C) and Serial Peripheral Interface (SPI) communication protocols. The controller contains two I2C bus interfaces, being capable of managing through those up to 128 slaves. In each I2C bus all sensors must have a different I2C address.

2) IMU: The IMUs are responsible for capturing the motion of a given object, therefore being one core piece in the proposed system. The prototype includes three IMUs, placed at the front and rear of the vehicle, and at the steering wheel. These sensors will enable the extraction of the acceleration and rotation of the vehicle (and the comparison between the front and the rear) during challenging events, as well as extract the behaviour of the steering input actions triggered by the driver (the angular rotation of the steering wheel and how fast the change was induced).

The selected IMUs are the MPU6050[3]. These have 6 Degrees-of-Freedom (DoF), associated with a 3 axis accelerometer and 3 axes gyroscope. The acceleremoter capture the acceleration perceived by the sensor in the X, Y and Z axis, whereas the gyroscope retrieves the angular velocity in the same 3 axis. Each has different ranges available, which define their sensitivity. The accelerometer can be set to measure ± 2, 4, 8, 16 g, whereas the gyroscope can measure ± 250, 500, 1000, 2000 °/s. These are configurable through the allocated registers (see datasheet). A smaller range is associated with more sensitive measurements. The range set is associated with the higher values the system can retrieve, for which adequately selecting the range to the problem is paramount for meaningful detailed data. Respecting the project needs, the acceleration and angular rotation experienced can be captured within a 2g acceleration and 250 °/s configuration.

The offset values are retrieved in the beginning of the data

[2]https://www.adrobotica.com/wp-content/uploads/2019/07/Datasheet_ESP8266_esp32_en.pdf

[3]https://invensense.tdk.com/wp-content/uploads/2015/02/MPU-6000-Register-Map1.pdf

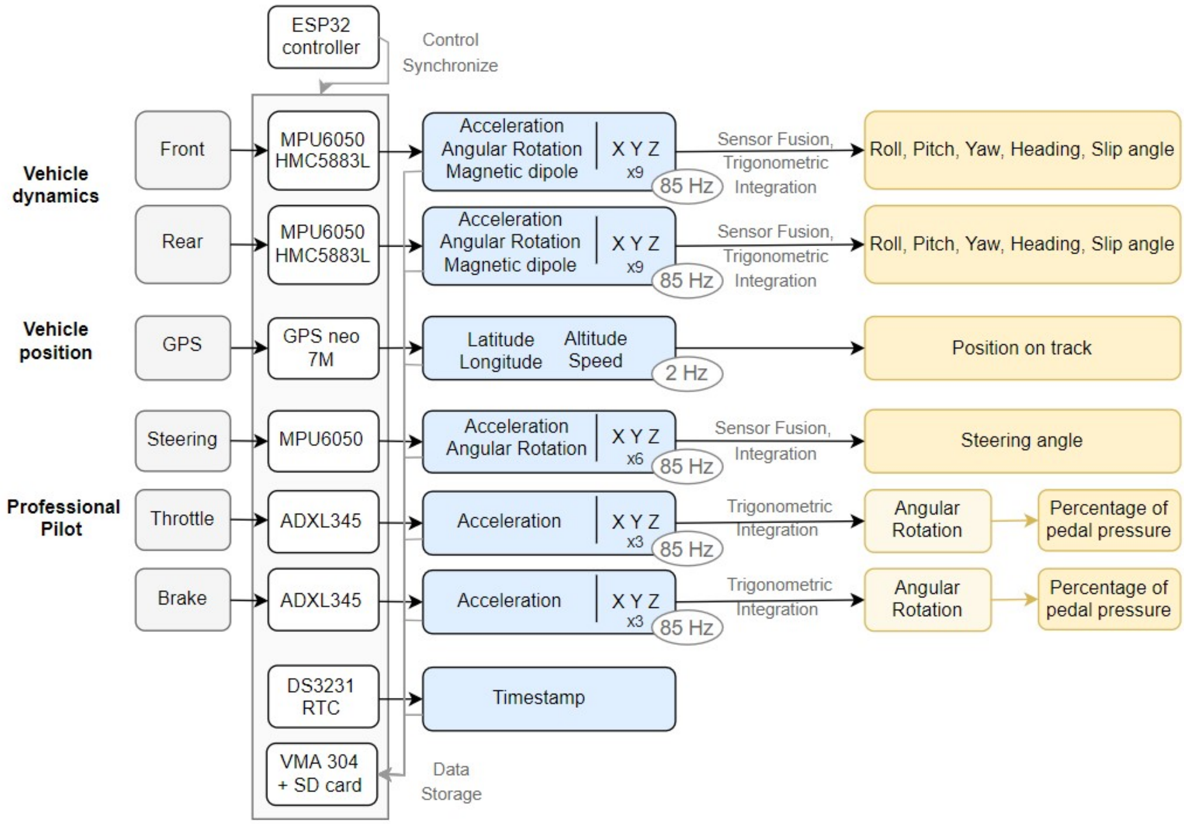

Fig. 4. Data acquisition systematisation, with active variables measured, equipment to collect them, and retrieved information.

collection for posterior calibration. The vertical acceleration captures the gravity acceleration value of 1g.

Since gyroscope tend to accumulate drift error over time, and accelerometer data is affected by external forces, two 3 axis HMC5883L magnetometers[4] are coupled with the MPU6050 placed in the front and rear of the vehicle, creating a 9 DoF IMU. The inclusion of the magnetometers extends the possibility for sensor fusion (either resorting to a complimentary filter [26] or Kalman filter [27], [28]) and therefore more accurately study the vehicle movement. Furthermore, magnetometer data can be used to extract the heading (yaw) of the vehicle, which is pivotal when studying drifting.

Both the MPU6050 and HMC5883L communicate via I2C protocol. The MPU6050 I2C address is 0x68, but it can be set to 0x69 by activating one pin of the sensor. Since, as discussed, the controller can only have up to two sensors with the same I2C address (one per I2C bus), the possibility to shift the MPU6050 address has enable the usage of three of these sensors (the one in the front and rear are set to 0x69 and the one in the steering wheel to 0x68). The HMC5883L I2C address is 0x1E, being each associated to one of the controllers' I2C bus along with the coupled MPU6050.

3) Throttle Accelerometers: Similarly to the built-in accelerometers of the MPU6050, two individual 3axis accelerometers are used to capture the driver actions in the gas and brake pedals. The target measurement is the percentage of input in each of these pedals. Without suffering error drift over time, the accelerometers not only provide the readiness with which the driver triggers an action, but, the retrieved acceleration measurements can be converted into angular position of the pedal. The accelerometers can be placed behind the pedals, considering that these never reach vertical inclination and therefore no Gimbal Lock [27] effect will arise. In this sense, the accelerometers represent a great solution to measure the expert pilot input in terms of percentage of throttle and brake of the car.

The selected accelerometers are the ADXL345[5]. These can also be configured to a ± 2, 4, 8, 16 g, but in the scope of their usage, a ± 2g provides accurate measurements. The selection of acceleremoters to capture pedal input was also based on the need to include sensing devices with alternative I2C address. The ADXL345 also communicate with the controller via I2C protocol, with the address 0x53 (each accelerometer in a separate ESP32 I2C bus interface).

4) GPS: The GPS provides information of the vehicle's positioning during the experiment. As data will be collected during official racing events, the information of the vehicle position on the track not only can be matched against the

[4]https://cdn-shop.adafruit.com/datasheets/HMC5883L_3-Axis_Digital_Compass_IC.pdf

[5]https://www.analog.com/media/en/technical-documentation/data-sheets/ADXL345.pdf

official race track, as it will help identify if scenarios prone to challenging events during the race and evaluate their impact in the remaining variables collected.

The GPS neo-7M[6] enables data collection of the latitude, longitude, altitude and speed, to a frequency up to 10Hz. Since the collection of this data is associated with receiving satellite signal rather than a specific ESP32 command, and due to the high volume on continuous data collected, the GPS measurements are currently taken at a 2Hz. This sampling frequency surpasses usual GPS data collection of 1Hz.

5) Clock: The prototype includes a clock responsible for each measurement timestamp. For efficiency purposes, the timestamp is stored once per second, along with the measurements taken within this time span (150 samples). The clock's timestamp when the prototype is activated is used to name the file in the SD card, enabling the collection of consecutive experiments without overwriting information.

A DS3231[7] Real-Time Clock (RTC) was selected based on its accuracy and long lasting inner battery that does not accumulate error over time. This sensor also communicates with the ESP32 via I2C, with the address of 0x68. Therefore, two MPU6050 are set to 0x69 and only one is in the address 0x68.

6) Data Storage: The data collected requires offline processing and analysis. In this sense, data storage of all experiments is paramount. Storing information into a device as a laptop or tablet is unsuitable in the experimental environment. Therefore, the data measurements retrieved from the three MPU6050, two HMC5883, two ADXL345, GPS neo7M and DS3231 during a given experiment are stored in a single text file in a SD card.

The VMA304 SD Card Logging Shield[8] enables the storage of the data related to all sensing devices in a SD card of variable memory size. Currently, a 32GB SD card is being used. The SD card shield communicates with the ESP controller via SPI protocol. The software within ESP32 includes an initial function that provides visual feedback that the writing operation of the data in the card is properly functioning.

7) Power Supply: Complying with the need of a self-sufficient prototype, the power supply is a fundamental piece of the puzzle. The power supply must, in one hand, comply with the power limitations of the ESP32 controller (receive maximum of 5V as steady as possible) and, in the other hand with the power requirements of each sensing device included (minimum of 2.5V for operation). A common 10000mAh powerbank can comply with these limitations and guarantee power stability for more than 1 hour.

To conduct the energy to each sensor of the proposed prototype, six four meter long F/UTP cables enable the placement of the sensors in the desired positions in the vehicle. Connectors with breaking mechanism enable the secure attachment and detachment of the cables from the controller board.

[6]https://content.u-blox.com/sites/default/files/products/documents/NEO-7_DataSheet_%28UBX-13003830%29.pdf

[7]https://datasheets.maximintegrated.com/en/ds/DS3231.pdf

[8]https://www.velleman.eu/downloads/29/vma304_a4v01.pdf

B. Software

The ESP32 contains the software to control all sensing devices in the prototype, activated when the power supply is on. The software was developed resorting to ARDUINO IDE. The software enables data collection in a synchronised manner at a 150 HZ sampling frequency (the GPS data is collected when signal is available at maximum 2Hz).

The 150Hz sampling frequency enables meaningful collection of a drifting scenario, since it corresponds to a sample every 6.67 milliseconds. A speed of 120 Km/h (maximum street limit) implies that a sample is taken at every 22.2 centimetres, and at 200Km/h (typical maximum velocity reached in hill climb races) a sample is collected every 37 cm, which enables the full capture of a drifting motion.

Figure 5 represents the flowchart for data acquisition. The *Setup* corresponds to the activation of each sensor within the prototype. The MPU6050 and ADXL345 accelerometers are configured to 2g and the gyroscopes to 250º/s during *Configure Range* stage. Then, the file where data will be stored is created. For optimisation purposes, during the *LOOP* stage content is appended in the file every 1 second. This stage runs until the prototype is turned off.

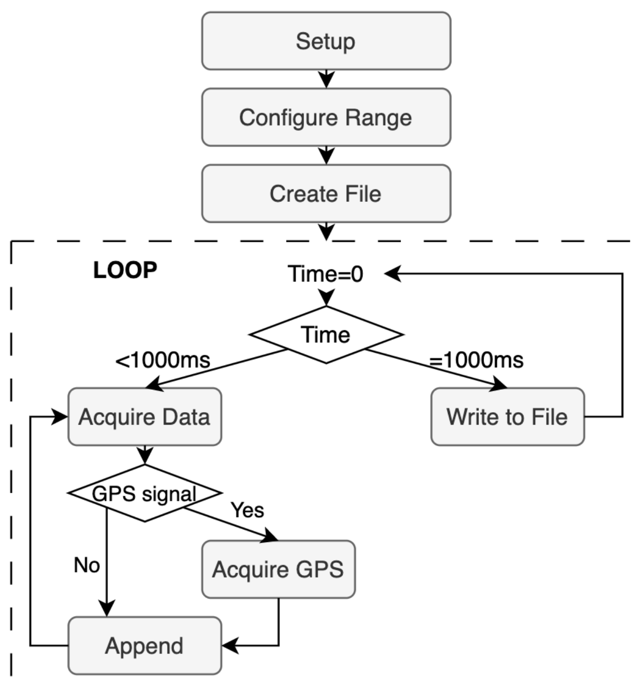

Fig. 5. Flowchart of the prototype controlling software.

V. Data Retrieval and Analysis

Following the established partnerships with racing organisations and racing teams, the prototype has already been tested during the race *Rampa da Penha* of the Portugal JC Group Hill Climb 22 Championship (organised by FPAK), and on the *Rampa da Falperra* of the European Hill Climb Championship organised by FIA.

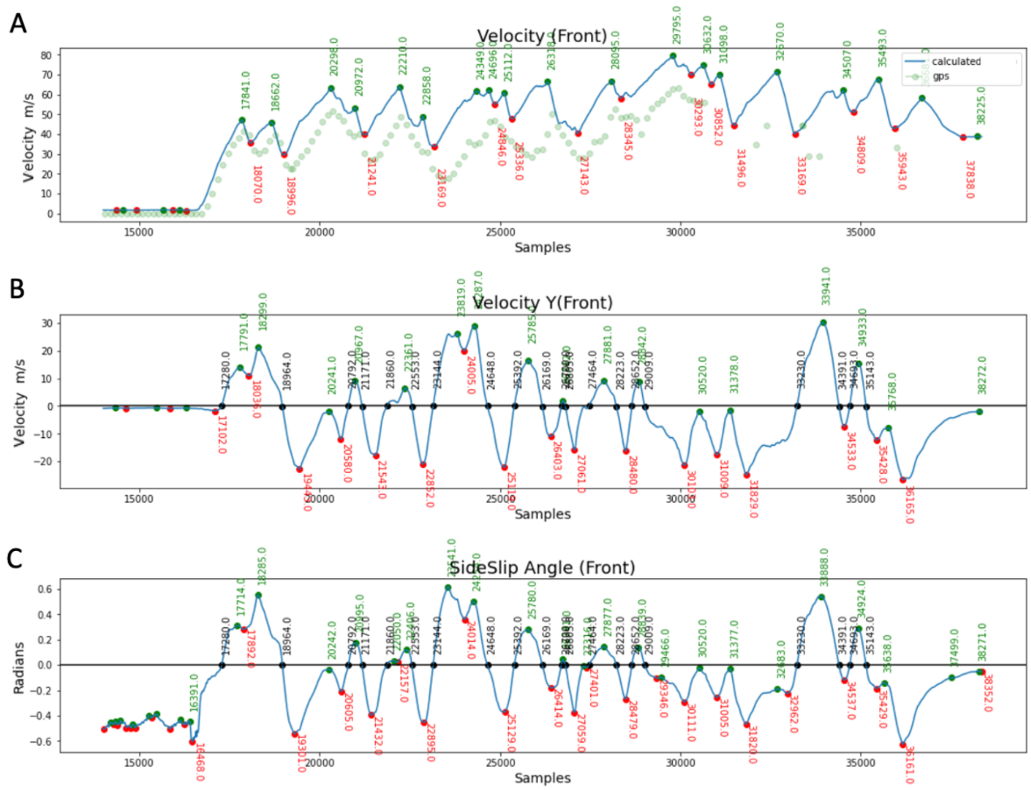

Fig. 6. Data analysis: (A) velocity; (B) lateral velocity; (C) sideslip angle.

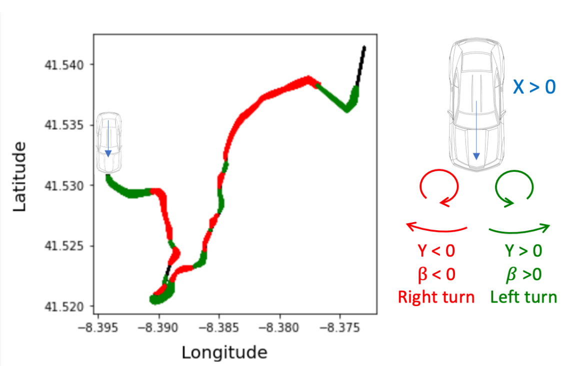

Fig. 7. Spatial display of sideslip angle, highlighting its intensity and turning direction.

The prototype collected and stored data from all sensors, which then underwent the sensitivity, calibration, filtering, and processing techniques associated with the type of measurements taken. To assess the robustness of the proposed system, initial results focus on the spatial and temporal consistency with the racing performance.

Considering that drifting is characterised by a high sideslip angle, which relates longitudinal and lateral velocity, computed by $\beta = \arctan(v_y v_x)$, accelerometers data from the front and rear of the vehicle was integrated to velocity. GPS data, which retrieves latitude, longitude and speed, is used for race track matching and comparison purposes. Figure 6 (A) illustrates the velocity measured in the front of the vehicle (magnitude using longitudinal and lateral components), as well as the velocity retrieved from the GPS, which presents a 93% correlation. Figure 6 (B) focuses on the lateral velocity, which strongly affects the likelihood of a drifting event. As the vehicle is always moving forward, longitudinal velocity remains positive, and lateral velocity determines the signal of the sideslip angle, which is presented in Figure 6 (C). The local maximum and minimum of the data are annotated in green and red dots, respectively. The black dots represent the zeros of data, which are the same for the lateral velocity and sideslip angle. When lateral velocity is positive, so it is the sideslip angle. Considering the axis notation presented in Figure 3 (which is aligned with the axis at the front of the car), a positive lateral velocity indicates turning to the left (in relation to the starting point), and a negative lateral velocity a turn to the right.

Figure 7 illustrates this relation in the spatial coordinates of the track. The spatial positioning was retrieved from the GPS's latitude and longitude data, which was interpolated to 150 Hz. In green are represented positive sideslip angles and in red negative sideslip angles. As visible, these match left and right turns, respectively, of the track itself. Furthermore, the intensity of the β is illustrated by the size of the plot for each timestamp. It is visible that not only does the calculated turning side match the track turns, but that the tightest part of each turn is associated with higher sideslip angles, and that the tighter the curve, the highest values of β are reached.

The spatio-temporal coherence and consistency of the results obtained, in relation to the driving experiments conducted, strongly supports the ability of the proposed system to retrieve meaningful data from driving scenarios, which can then be used to identify drifting events and map the associated professional driving response.

VI. Conclusions and Future Work

Identifying critical driving scenarios, extracting the patterns prior to these events and the expert strategies to regain control of the vehicle can unlock novel driving assistance systems with increased safety. To this end, the proposed data acquisition system aims to be a step forward in the deployment of such systems.

The sensing system acquires data from both vehicle dynamics and expert human driving performance, which will be used to determine the patterns prior and posterior to drifting events. Key sensors, activated and synchronised by a single controller, focus on the extraction of these data, stored for posterior analysis.

The prototype has been tested in real-world-environment racing events and the results associated with the analysis of the spatial temporal coherence with the racing experiments support the ability to use the proposed system to infer critical events while driving.

The preliminary data analysis has unveiled the presence of extreme driving events, and future work will focus on the application of machine learning algorithms to extract the desired interdependencies and patterns between drifting events and the corresponding expert handling.

Acknowledgment

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