Intelligent Vehicle Maneuver Detection Based on Synthetic Gyroscope Data Calculated from GPS

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***Abstract*—Accurate detection and classification of driving maneuvers play a crucial role in understanding driver behavior, enhancing road safety, and preventing accidents. This study proposes an algorithm for maneuver detection based on GPS data. The method involves preprocessing raw GPS data, transforming coordinates into a local reference frame, and estimating gyroscope data using Krylov-Euler angles. Maneuvers are identified by detecting significant changes in angular velocity, and their boundaries are determined dynamically. A template-based approach is used to classify maneuvers into left turns, right turns, and U-turns, with templates constructed based on the total angle change during the maneuver. To evaluate the proposed method, we randomly selected 10 drivers who completed 54 trips, totaling 11 hours of driving, from the DriverSVT Dataset. The dataset includes trips recorded in different geographical settings. It has segments from urban areas, expressways, rural roads, and residential areas such as backyards. This diversity allows the algorithm to be tested in a variety of real-world driving conditions. The proposed method provides a robust way to analyze driving behavior. Experimental results demonstrate the effectiveness of the approach in accurately segmenting trips and classifying maneuvers.**

I. Introduction

With vehicle automation and intelligent transport systems evolving, the ability to recognize the driver's behavior is becoming increasingly important for providing real-time feedback and preventing accidents [1]. Understanding and predicting driver maneuvers is essential for improving road safety.

Many systems have been developed to predict and prevent potentially dangerous maneuvers of the drivers. Data from GPS, gyroscope, accelerometer and other sources are used as inputs to help identify maneuvers and assess their aggressiveness. Cameras inside the cabin capture the driver's face, analyzing their emotional state and concentration, while external cameras provide traffic information. There are studies that propose measuring the driver's blood pressure [2], fatigue level [3], and attention [4] to prevent dangerous maneuvers on the road using readings from sensors inside the cabin.

We propose an algorithm to match the trip readings with the type of maneuver. Using gyroscope data, we detect start and end of the maneuver. Maneuver boundaries are determined dynamically based on significant statistical changes in gyroscope readings, making this approach more adaptable and robust. Also we can track the angle of rotation and angular velocity at a given moment in time. This identifies left turns, right turns, U-Turns left and right. This algorithm can anticipate dangerous driving maneuvers by leveraging behavioral data, potentially warning the driver before a risky action occurs. Through this approach, the system could play a critical role in accident prevention by actively identifying and responding to hazardous driving tendencies.

The input data includes text files describing the trip. The type of maneuver is predicted from the readings from mobile phone sensors such as GPS and gyroscope. However, obtaining gyroscope data is not always feasible. To address this issue, our previous research [5] developed an algorithm that converts GPS data into gyroscope and accelerometer data. This transformed data can provide prediction of the type of road maneuver being performed. This will allow to apply the algorithm with only a GPS sensor in the car, eliminating the installation of additional sensors.

The proposed approach is applicable in real-time settings due to its low computational complexity. Calculations are based on lightweight statistical operations (mean, standard deviation, thresholds over sliding windows), which makes the method suitable for on-device implementation on smartphones or embedded vehicle systems. Limitations include sensitivity to GPS noise, particularly in urban environments with signal reflections, although smoothing techniques are employed to mitigate this. The system has been tested on real driving data, and practical examples are presented in the experimental section to demonstrate feasibility.

The rest of the paper is organized as follows. Section 2 provides an overview of existing approaches for detectinig maneuver boundaries and classifying maneuver type. Section 3 describes the proposed method for classifying maneuver types using GPS readings. In Section 4, the methodology from the previous section is applied to a real dataset. Section 5 summarizes the results, discusses future directions, and outlines limitations.

II. Related Works

This section describes approaches for driver profiling to detect maneuver's boundaries. It also reviews the existing approaches for determining the type of road maneuver.

A. Maneuver boundaries detection

Determining maneuver boundaries is a fundamental task for accurate analysis of driver behavior. The difficulty occurs due to the inconsistency in the duration of different maneuvers such as lane changes, turns, and braking. Traditional methods often use fixed-size sliding windows to segment maneuvers, but these can be inaccurate due to the dynamic nature of driving events. Such approach was implemented in [6], [7], [8].

Multiple window fusion methods have been investigated to improve the detection of maneuver boundaries. In [9] authors introduced multiple sliding windows of different sizes to create a more robust feature set that adapts to different durations of maneuvers. By combining short and long windows, the system can more accurately capture the boundaries of complex maneuvers.

Another approach used by researchers is to specify a set of rules, the execution of which indicates that a maneuver has been made. In [10] the authors developed a framework for unsupervised analysis of driver's style, where the first step is maneuver detection. Maneuvers are detected based on the turn radius R and longitudinal acceleration. If $R > 1000m$, the vehicle is considered to be moving straight, while $R < 1000m$ indicates a turn. Additionally, changes in longitudinal acceleration are analyzed to identify acceleration, braking, and constant-speed driving phases. This approach can detect both longitudinal and lateral maneuvers. However, its accuracy depends on predefined thresholds that may require calibration for different road types and driving conditions.

In addition, some researchers have integrated deep learning techniques such as convolutional neural networks (CNNs) to detect maneuver boundaries by analyzing smartphone sensor data (accelerometer and gyroscope). This approach [11] includes signal preprocessing, detecting significant changes in yaw rate and acceleration, and refining boundary detection with machine learning models like CNNs. This method enables real-time maneuver recognition without external sensors.

B. Maneuver type classification

Today, authors propose various approaches to solving the problem of maneuver type classification. For instance, researchers have utilized accelerometer data to identify patterns of parking, driving, and braking, implementing sliding windows to detect distinct events within specific timeframes [12]. Building on this, others have applied telemetry data to a more diverse array of driving conditions. One approach uses an energy-maximization algorithm (EMA) to extract and classify events from continuous driving signals, applying machine learning models such as CNNs, LSTMs, and random forests for high accuracy in maneuver classification across multiple datasets [13]. Another method uses multi-length sliding windows with a CNN model, producing a more robust feature set that improves classification accuracy. By fusing data from short and long windows, the model achieved a high F1 macro performance of 87.67% in predicting maneuvers such as lane keeping, braking, turning and lane changing [14].

Studies have integrated deep learning techniques, such as CNNs, RNNs, and FFNNs, to classify and cluster maneuvers based on sensor data, demonstrating reliable performance across 13 types of maneuvers [15]. This approach not only leverages different classifiers but also evaluates their combination to optimize detection accuracy, yielding a balanced accuracy of 0.90 and an F1 score of 0.71 on real driving data.

To improve maneuver detection in real world conditions, smartphone sensors, especially accelerometers and gyroscopes, are increasingly used.

Such input data allow not only the classification of maneuver types but also the characterization of how they are performed. For example, the authors of [8] use accelerometer, gyroscope, and speed data to determine one of four driving styles: normal, aggressive, distracted, drowsy, and drunk driving. The input signals from in-vehicle sensors are transformed into images, which are then classified by a CNN to assess the driving behavior.

Such systems make it possible to track and analyze driving patterns over time, enabling the creation of dynamic driver profiles. These profiles can be used to assess driving habits, detect risky behavior, and provide real-time feedback to improve road safety [1].

In this study, we propose our own method for detecting maneuvers during a trip. This algorithm uses readings from GPS sensor and focuses on identifying maneuver boundaries and distinguishing between different maneuver types.

III. Method

Figure 1 shows the general pipeline of the method. At the first stage, GPS coordinates are used as input data, which are pre-processed: interpolation, emission filtering and time scale transformation. Then, the coordinates are converted to a local system taking into account the orientation of the vehicle. Next, using Krylov-Euler angles, gyroscope data are calculated [5]. Based on manually marked maneuver templates, reference ranges are generated and used for maneuver detection. At the final stage, the algorithm determines the beginning and end of each maneuver and classifies its type.

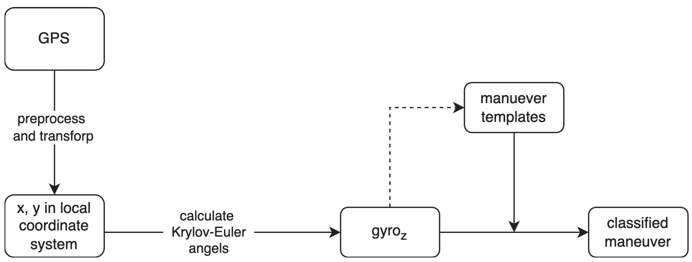

Fig. 1. Maneuver classification based on GPS data

A. Data Processing

The experiments involved the driversvt [16] dataset. It contains data from more than 50 drivers and more than 3000 minutes of video recordings synchronized with GPS trip data. As input data, we used data from GPS sensors.

The input data has a floating granularity ranging from 0.08 to 0.15 seconds. Values are not always available for every time interval, and identical nonzero GPS values may appear for different consecutive time intervals. These repeated values were merged (only the first occurrence was retained), and quadratic interpolation was applied. Additionally, zero-speed values at the beginning and end of the trip were removed. These preprocessing steps help reduce the impact of GPS noise and signal dropouts, especially in challenging environments such as urban canyons and tunnels.

As a result of interpolation, negative speed values could appear. These were replaced with zero speed, assuming that no movement occurred at that moment. Therefore, such cases were not considered in this study. Finally, outliers were removed by filtering out values that exceeded the 5% quantile threshold.

Next, to obtain gyroscope data from GPS readings the algorithm described in [5] was used. The input data consisted of GPS measurements. The first step was transforming the data into a local coordinate system. The described algorithm utilizes Krylov-Euler angles to compute the rotation of the displacement vector over a time interval along three axes.

After each rotation, the local coordinate system changes, so it must be reset to its initial state. To achieve this, a resulting quaternion is constructed, representing the total rotation at a given moment in time. These operations are applied sequentially to all pairs of vectors, forming an array of rotation angles along the three axes.

For zero or near-zero speed values, the gyroscope readings tend to be high in magnitude. Since the displacement is very small, any change in angle becomes highly sensitive. This situation typically occurs when the driver stops along the route, such as at a traffic light. To avoid noisy gyroscope data, computed values for speeds below 5 km/h were replaced with zeros.

Within a trip, a granularity of 0.1 seconds was excessive, as the duration of the analyzed trips was at least 5 minutes. Therefore, we aggregated the obtained values into 2-second intervals. A moving average was calculated, where the value at the end of each 2-second interval represents the average over that period.

B. Maneuver boundaries detection

In our previous study [7], we applied a fixed maneuver duration of 3 seconds. This approach eliminates the need to determine the exact boundaries of maneuver completion but is less sensitive to changes in driver behavior on the road. In this study, we detected both the start and end of each maneuver to improve the accuracy of the calculated metrics during maneuvers. The key assumption was that the gyroscope shows stable values during normal driving and changes during maneuvers.

In our study we applied the `Ruptures` library [17] to detect the start and the end of a maneuver in a time series of gyroscope data. The goal was to identify the points in time with a significant change in the motion dynamics marking the beginning and the end of a maneuver.

We used the `Pelt` algorithm implemented in the `Ruptures` [17]. This algorithm effectively identifies the points in the data where the statistical properties of the signal change (the mean or the variance) change significantly.

The problem of detecting the change point can be formalized as that of identifying the point where the statistical properties of the data change. Given a time series $\{y_1, y_2, ..., y_T\}$, the goal is to detect a set of such change points $\{\tau_1, \tau_2, ..., \tau_k\}$, that the data before and after each τ_i behaves differently. Mathematically, this can be defined as:

$$\mathcal{L}(y_1, ..., y_T, \{\tau_1, \tau_2, ..., \tau_k\}) = \sum_{i=1}^{k+1} \mathcal{L}_i(\{y_t : \tau_{i-1} < t \le \tau_i\}),$$

where: - $\mathcal{L}_i$ represents the loss function for the data in each segment.

- $\tau_0 = 0$ and $\tau_{k+1} = T$ represent the beginning and the end of the entire time series, respectively.

- The goal is to minimize the total loss $\mathcal{L}$, which estimates how well the segments fit the observed data.

Pelt's algorithm selects an optimal set of change points that minimizes the loss function - Radial Basis Function (RBF) cost function. The RBF cost function is designed to model nonlinear shifts in the data, which is often found in real signals such as gyroscope measurements. It performs a greedy search for each possible change point, balancing between matching the data and introducing too many change points (penalizing their number).

The RBF function between two segments:

$$\mathcal{R}(y_1, ..., y_T) = \sum_{i=1}^{T-1} \exp\left(-\frac{|y_t - y_{t+1}|^2}{\sigma^2}\right),$$

where σ is a parameter defining the width of the radial basis function. The function represents the smoothness or sharpness of the transition between segments, making it sensitive to sudden changes in signal dynamics. By minimizing the total RBF over the entire series, we can detect significant transitions in the data.

Thus, we obtained a set of points where changes in gyroscope readings occurred. The next step was to determine which of these intervals corresponded to actual driver maneuvers.

C. Maneuver type classification

In this study, we recognized five types of maneuvers: left turn, right turn, U-turn to the left, and U-turn to the right. These maneuvers are the most common and essential in everyday driving practice and, thus, represent a wide range of situations in which drivers must make decisions and take actions that directly impact road safety. The input data consisted of gyroscope measurements. The key idea was to detect a turn based on the total rotation angle during the maneuver.

To achieve this, it was necessary to compute reference angle ranges for each maneuver type. We analyzed 20 hours of trips and identified 200 maneuvers from GPS trajectories, with 50 examples for each maneuver type. Segments of trips containing maneuvers were selected, including ±5 seconds from the manually identified maneuver boundaries. Additionally, we identified 20 examples of lane changes to the left and right.

An algorithm for determining the maneuver boundaries was applied to the obtained data. We dropped the idea of calculating the turn angle from manually defined boundaries so that the method for determining the start and end of the maneuver was consistent with the approach used in the experiments. In other words, the same method was used to determine maneuver boundaries for both maneuver template generation and maneuver detection among all drivers.

Based on the detected maneuvers, the total turning angles for each maneuver type were calculated. The results are presented in Table I:

TABLE I
ANGLE RANGES FOR DIFFERENT MANEUVER TYPES

Maneuver Type	Minimum Angle	Maximum Angle
Left Turn	40	80
Right Turn	-80	-25
U-Turn Left	95	200
U-Turn Right	-180	-80

We also removed maneuvers with durations less than 2.5 seconds from consideration. Based on the template maneuvers found, there were no maneuvers with duration less than 2.5 seconds.

For lane change maneuvers to the left and right, the total rotation angles ranged from -5 to +5 degrees. This result is logical since during a lane change, the angle first shifts in one direction and then in the opposite direction to continue moving straight. Distinguishing lane changes from straight driving with such minimal angle variations is not feasible using this method. Therefore, these maneuver types were excluded from this study.

D. Vizualization

To compare the detected maneuvers with the driver's actual movement, the driving trajectory was reconstructed based on gyroscope data. The identified maneuvers were displayed in different colors to facilitate the evaluation of the algorithm's performance.

The detected change points were marked and visualized on the angular velocity graph over time. Points where the movement transitioned from a stable to a more dynamic state were plotted to visualize maneuver boundaries and were highlighted with a red dashed line.

Additionally, a linear velocity graph was used to assess how fast the driver was moving at the moment of the maneuver.

E. Validation

To evaluate the quality of the detected maneuvers, we conducted a selective manual review of driver trips. 10 drivers were randomly selected who made a total of 57 trips with a total duration of 11 hours. Among the selected drivers, there were trips that did not pass validation because there are trips in the dataset where the speed was zero or less then 5 km per hour. A sample of trips was visually analyzed to compare the identified maneuvers with actual driving behavior. This manual validation helped assess the accuracy of maneuver detection and ensured that the detected events corresponded to real driving actions.

IV. Results

The results obtained are shown in Fig. 2. The plot presents a left turn. The graph on the left displays the trajectory constructed using the original GPS data. The trajectory in the central graph was plotted in local coordinates after transforming the coordinate system. The trajectory on the right was reconstructed using the speed data and the computed gyroscope values.

In addition to the visual comparison, we validated the computed gyroscope values against real gyroscope readings recorded with a smartphone during personal test drives. The comparison is illustrated in Fig. 3 and demonstrates a close match between the synthetic gyroscope data derived from GPS and real gyroscope data, confirming the reliability of the reconstruction method.

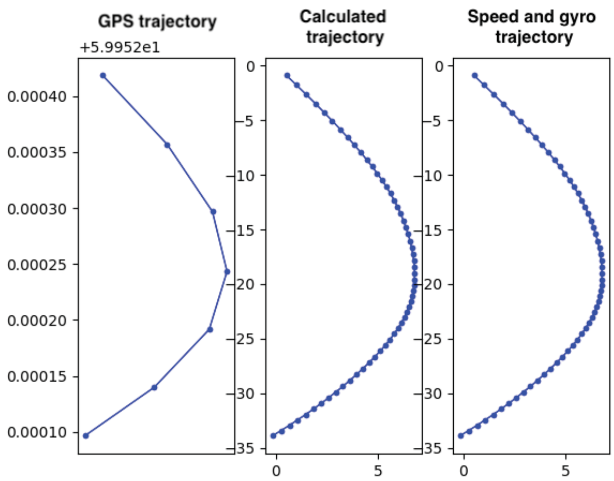

Fig. 2. Three driver trajectories calculated

A. Detection of Maneuver Boundaries

The ruptures library provided the boundaries. The sensitivity factor was found to be 4, which provides a balanced compromise between over-detection (breaking maneuvers into smaller segments) and under-detection (missing key some transitions between maneuvers). With these settings, the algorithm successfully identified most maneuver boundaries with high accuracy. The results highlight the robustness of the gap-based approach in detecting transitions in driver behavior, even when the input data contains noise or is variable due to external factors such as road conditions or specific driver styles.

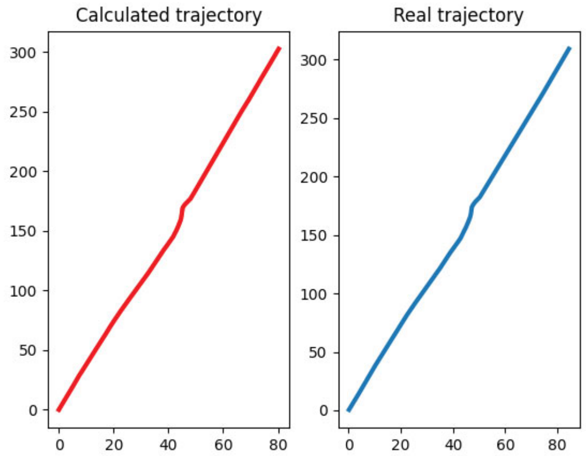

Fig. 3. Calculated and real trajectories

This sensitivity setting also ensured that the detected boundaries matched accurately the true, validated manual annotations, making the approach a reliable tool for further maneuver classification and analysis.

Figure 4 reveals the detected maneuver boundaries, with a sensitivity coefficient of 15, using the ruptures library.

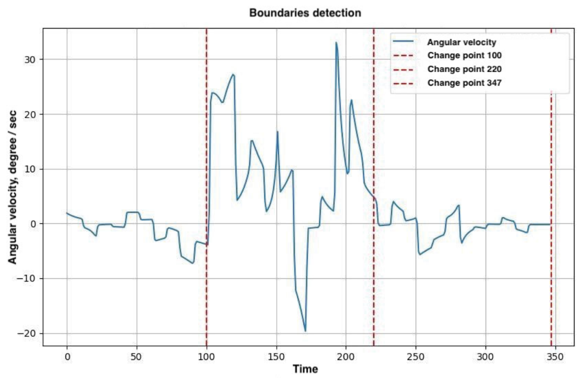

Fig. 4. Maneuver's boundaries

B. *Maneuver type classification*

Maneuvers were classified based on the obtained table of turn angle ranges for the maneuver given in Method. For maneuvers with found limits, the total angle for the maneuver was calculated and correlated with one of the maneuvers from the table, or marked as no maneuver.

Table II shows the frequency of each type of maneuver observed in the dataset. The right and the left turns were the most common maneuvers, with 135 and 120 occurrences, respectively. The right and the left lane changes were also frequent, with 110 and 90 detections. Aggressive braking and sudden acceleration were less common with 75 and 80 occurrences, respectively.

TABLE II
NUMBER OF DETECTED MANEUVERS CLASSIFIED BY TYPE

Maneuver Type	**Count**
Left Turn	30
Right Turn	61
U-Turn Left	21
U-Turn Right	20
No maneuver	497
Total	629

Figures Fig. 5, 6, and 7 illustrate an example of the algorithm's performance. The first graph represents the driver's trajectory, computed based on angular velocity data. Different colors indicate various maneuvers detected through the analysis of angular velocity changes. The second graph displays the angular velocity, where red lines mark transition points—locations where a change in driving behavior occurred. The bottom graph shows the linear velocity of the vehicle.

The duration of the trip shown in Fig. 5 was 10 minutes. This trip was divided into 16 segments, each corresponding to statistically significant changes in gyroscope readings. These segments are represented by different colors in the first plot. Within this trip, four right turns and one left turn were detected, while the remaining intervals were classified as straight driving without maneuvers. The points of change in gyroscope data are marked with red dashed lines. A visual analysis confirms that these changes correspond to actual variations in the driver's trajectory, accurately reflecting the real road situation. The average linear speed throughout the trip was 24 km/h.

The second and third trips, shown in Fig. 6 and Fig. 7, were significantly shorter, lasting approximately 2–3 minutes each. In the second trip, a single maneuver—a left U-turn—was detected. In the third trip, two maneuvers were identified: a left turn and a right turn, both of which align with the actual driving events. The green and red segments in Fig. 7 clearly indicate these maneuvers.

It is important to note that the analyzed trips were selected randomly. For all other manually validated results, the detected maneuvers matched the actual maneuvers performed by the driver, further confirming the accuracy of our approach.

As we can see, the proposed method successfully detects different types of maneuvers and effectively segments the trip into distinct phases. The transition points are well-aligned with changes in driving behavior, ensuring a logical division of the trip. Additionally, the maneuver labels are correctly classified, demonstrating the robustness of the approach in identifying and categorizing driving events.

The algorithm relies on quaternion-based estimation of Euler-Krylov angles using lightweight trigonometric operations. These computations are applied independently at each timestamp, resulting in linear complexity with respect to dataset size. Once the angles are estimated, maneuver boundaries are determined using statistical techniques such as thresholding and analysis of angular velocity changes. These steps

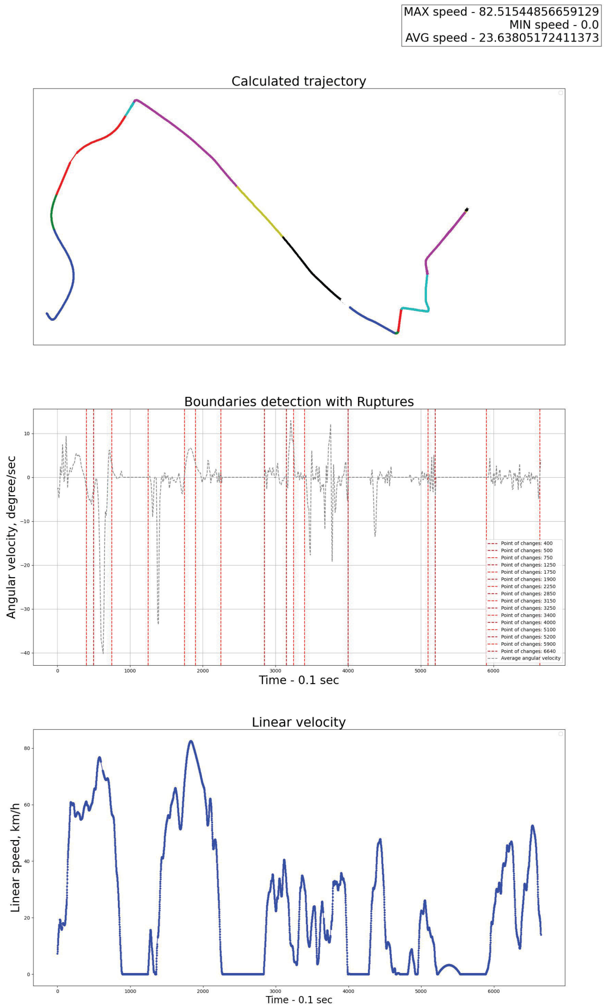

Fig. 5. Trip 1. Results

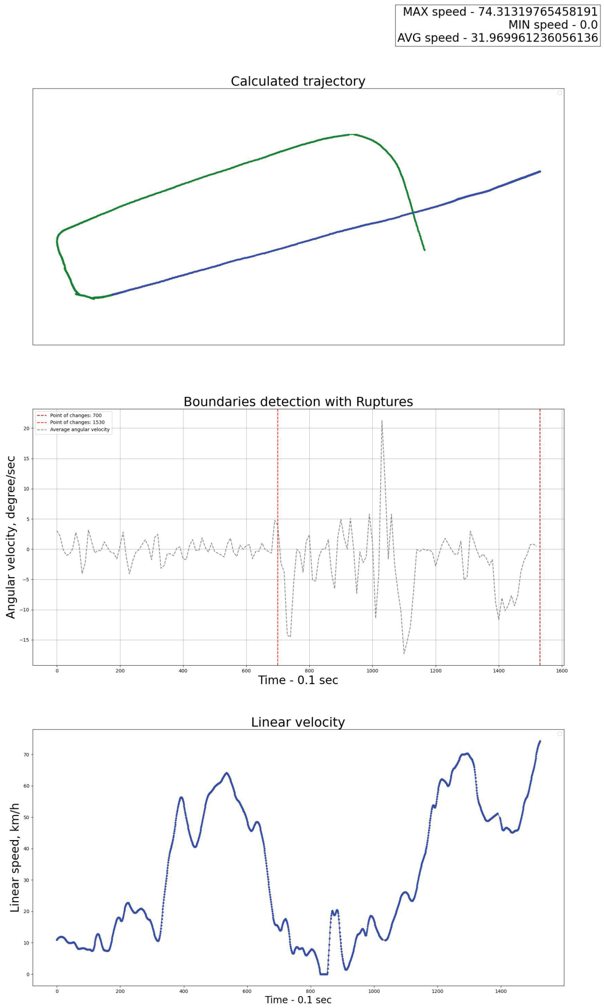

Fig. 6. Trip 2. Results

are computationally simple and scale well with larger datasets. Thanks to its low computational complexity, the method can be applied in real time, including on devices with limited processing power.

V. Conclusion

In this study, we proposed a method for maneuver detection based on GPS and gyroscope data that effectively identifies maneuver boundaries and classifies different maneuver types, allowing for a detailed analysis of driving behavior. By leveraging gyroscope-derived angular velocity and predefined maneuver templates, we successfully segments trips into distinct driving patterns. The results demonstrate that the method reliably detects left turns, right turns, and U-turns while filtering out minor lane changes that cannot be distinguished from straight driving using this method. The ability to accurately determine maneuver boundaries enables not only trip-level analysis but also the identification of driving style characteristics. In future research, we plan to synchronize our maneuver detection algorithm with in-cabin video recordings of drivers during trips. This will allow us to analyze how a driver's behavior changes depending on their emotional state and level of attention.

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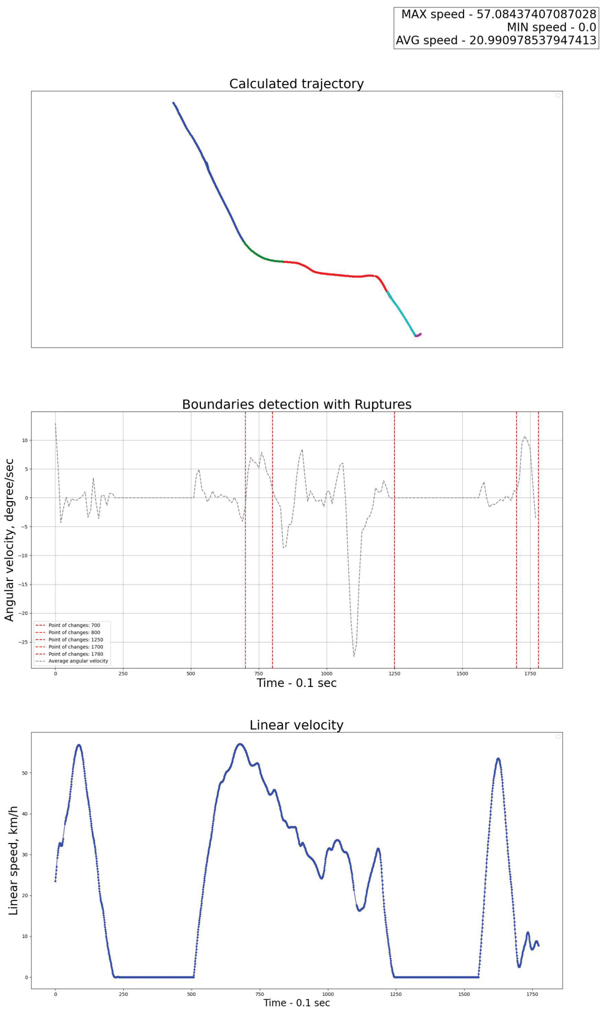

Fig. 7. Trip 3. Results

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