Motorcycle Riding Safety Through Smartphone-Based Driving Recommendation Systems

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Abstract: Efficient vehicle dynamics management is critical for high-performance driving and intelligent transportation systems. This paper focuses specifically on an informatics-driven, smartphone-based recommendation system that leverages sensor data and predictive modeling techniques to inform rider decisions without implementing explicit closed-loop control mechanisms. Using a discrete waypoint representation, the model derives road curvature and friction-limited corner speeds while considering acceleration and braking constraints. A forward-backward algorithm computes a feasible speed profile, ensuring adherence to physical and regulatory limits. Furthermore, we extend the model to multi-vehicle coordination, demonstrating its applicability to platooning scenarios. By synchronizing vehicle speeds and braking points, we can optimize traffic throughput in road bottlenecks, mitigating shockwaves and improving flow efficiency. This approach bridges the gap between performance driving techniques and intelligent transportation systems, providing a foundation for real-time speed advisory and autonomous driving applications.

Keywords: advance system for drivers, smartphone, mobile application, motorcycle safety, road safety

1. INTRODUCTION

The Autonomous Vehicle (AV) sector currently stands as one of the most actively researched domains, with a recent study forecasting a substantial increase in the AV market within the Asia-Pacific region, from 1.63 billion USD in 2022 to 20 billion USD in 2029 (Forecasts, 2023). Nevertheless, the high cost of sensors and devices used in AVs serves as a barrier, hindering their widespread adoption (Litman, 2023). While production-level vehicle autonomy has reached level 4, research such as (Litman, 2023) suggests that level 5 autonomy will not be embraced before 2040. Another hurdle in the AV field is the limited access to pertinent research (Hawkins, 2022), often deemed proprietary and thus not readily available within the academic domain.

Precise knowledge regarding the curvature trajectory at a specific location represents a crucial determinant for control systems and vehicle dynamics. Presently, nearly all newly manufactured automobiles incorporate a suite of safety features, including cruise control, adaptive lighting, automatic parking, lane departure warnings, and collision avoidance systems, among others. Regrettably, these safety systems are largely absent from motorcycles. Numerous research studies as showed in (Cosmino 2022; Damon 2023; Decae, 2023) have demonstrated that a significant proportion of motorcyclists fail to reduce speed prior to entering a turn and engage the brakes when the risk of losing control is notably elevated. Furthermore, there exist roadways where the legal speed limit exceeds the recommended velocity for a given road segment. Consequently, during a sharp turn, riders tend to abruptly decelerate, resulting in front wheel lock-up and potential motorcycle instability. Compliant with recent European Union legislation, the installation of an anti-lock braking system is obligatory for all motorcycles produced since 2016 with an engine displacement exceeding 125cc. Nonetheless, the majority of motorcycles on the road remain devoid of these critical safety systems, moreover, applications and systems capable of providing real-time riding recommendations will constitute a broad area of interest for future research.

Building on the rapid evolution of smartphone platforms such as Android Auto and Apple CarPlay, our initial goal was to explore how a mobile device could be synchronized in real time with a motorcycle's dynamics—particularly to assist novice riders in enhancing their riding techniques. Over the course of our work, we also identified that this approach could extend to automotive platooning scenarios, such as a convoy navigating curved roads led by an inexperienced driver, which can create a bottleneck. To support both contexts, we aim to develop a prediction and recommendation application that interfaces seamlessly with users, investigating response times, maximum allowable GPS position requests, data transmission and processing speeds, and the integration of online mapping tools.

2. RELATED WORK

The concept of utilizing sensors and mobile phones within the realm of autonomous vehicles has gained significant traction in recent years. This trend aligns with the ever-expanding capabilities of smartphones, coupled with advancements in sensor technology, to provide crucial data for navigation and safety systems.

In this domain, Calimoto and Detecht exemplify specialized motorcycle navigation applications that leverage smartphone technology and GPS to enhance rider safety and experience. Calimoto provides optimized routing, real-time traffic updates, and personalized recommendations, improving both convenience and security. Detecht similarly integrates route planning, hazard alerts, and a crash detection system that notifies emergency contacts in the event of an accident, thereby underscoring the potential for smartphone-based solutions to foster safer and more community-oriented motorcycling practices.

Presently, the predominant approaches have shifted towards more accessible alternatives, employing only two fundamental sensors—a monocular camera and an inertial measurement unit (Shabestari, 2023). Another crucial factor in advancing recommendation systems to enhance riding safety, as highlighted by various researchers, is the comprehensive examination of the rider's posture to gain a holistic understanding of the human-machine interface. Riders commonly adjust their body position during riding for diverse reasons. The authors in (Stolle, 2022) have devised and assessed an on-road capable measurement system characterized by high accuracy and robustness, designed for detecting the upper body posture of riders in riding experiments. The conclusion drawn is that both the rider's posture and motorcycle inclination are essential factors in the development of out-of-the-box recommendation solutions.

Furthermore, in pursuit of advancements in the field, researchers (Zong, 2022; Shabestari, 2023) are currently exploring an interesting concept involving the integration of innovative methodologies in remote sensing and artificial intelligence (AI). This approach aims to facilitate motorcycle detection and distance estimation through the utilization of video camera systems. In contrast to these camera-centric methods, our proposal primarily leverages onboard smartphone-based sensing, placing emphasis on the rider's perspective through direct measurements of position, motion, and environmental context. While different in focus, this approach is inherently complementary and can be fused with camera-based detection systems to enhance overall accuracy and coverage. By integrating real-time data from smartphones with external video monitoring, a more robust, multimodal framework emerges, offering improved distance estimation, hazard detection, and a more holistic view of traffic conditions.

3. METHODOLOGY AND IMPLEMENTATION

The underlying concept of our proposed methodology entails the development of a simulated model akin to a digital twin of the motorcycle. Notably, this model incorporates inherent errors affecting the observable state variables of the actual motorcycle, namely speed and position. To achieve this, we formulated a simplistic kinematic model for the motorcycle, characterized by theoretically infinite resolution (in terms of sampling time and quantization resolution). Subsequently, we subjected the state variables to perturbation and decimation transformations to closely replicate real-world conditions. After these transformations, the emulated outputs were inputted into the predictive algorithm to estimate the initial generated variables. It is noteworthy that the primary advantage of this approach lies not merely in its capacity to minimize instantaneous approximation errors, but rather in its capability to simulate the model in advance, thereby facilitating predictive analysis.

To evaluate the predictive algorithm's effectiveness in providing real-time recommendations to motorcycle riders, we developed an automated evaluation system comprised of several interconnected components, as depicted in Figure 1.

This system serves as the foundation of our methodology, allowing us to simulate and analyze rider behavior in various road conditions. The following subsections detail each component's role in the evaluation process, clarify their functionalities and interactions within the broader framework.

- **Movement Model (Model)**: This component is designed to produce a trajectory represented as GPS positions over time, complete with fine-grained speed data. This is an analytical model, considered to be the "truth".
- **GPS Position Emulation Block (Perturbation)**: This block emulates GPS positions resembling those acquired from a mobile phone (a discreate system that introduces errors due to sampling period, quantization noise and position approximation by the GPS system). Essentially, it simulates positional adjustments based on the output of the Movement Model.
- **Motion Speed Emulation Block**: This block is responsible for emulating the motion speed as reported by the motorcycle. Basically, it samples (decimate) the motion model output and adds some quantization and measurement error.
- **Predictive Algorithm**: The predictive algorithm utilizes the outputs from the emulation blocks to make estimations regarding the real-time position and traveling speed.

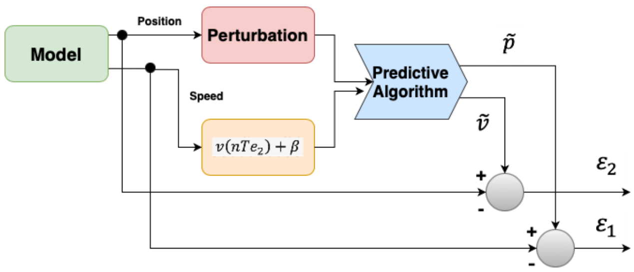

Fig. 1. Automated evaluation system.

In this specific case, a Linear Regression Predictive Algorithm was implemented.

Input Data:

- Movement Model: Trajectory data with GPS positions and associated speeds (sampling period 1ms).
- GPS Position Emulation Block: Simulated GPS positions (sampling period - 100ms – given by the smart phone limitation).
- Motion Speed Emulation Block: Simulated motion speed (sampling period 20ms, resembling real-time driver reaction).

Algorithm Structure:

- Linear regression is applied to predict the actual position and travel speed based on the input data.
- The model considers the relationship between the movement model's trajectory, GPS position emulation, and motion speed emulation to make predictions.

The primary objective of these estimations, in conjunction with the inclination and cartographic road data obtained from the map, is to generate practical driving recommendations for motorcycle riders. These recommendations can include advice on speed adjustments, route changes, or safety precautions.

Given the context of our study, the choice of a Linear Regression Predictive Algorithm is justified by several factors. Firstly, linear regression is a widely used and well-understood technique in predictive modeling, particularly in scenarios where there exists a linear relationship between the independent and dependent variables. In our case, the predictive variables derived from the emulated motorcycle model, such as speed and position, can often exhibit linear relationships with the road conditions and rider behavior.

Additionally, linear regression provides transparency in model interpretation, allowing us to understand the relative importance of different input features in predicting the output variable. This transparency can be invaluable in gaining insights into how road conditions and rider actions influence the motorcycle's behavior.

Furthermore, linear regression is computationally efficient and relatively simple to implement, making it well-suited for real-time applications such as ours. Its simplicity allows for quick model training and prediction, which is essential for providing timely recommendations to motorcycle riders.

Lastly, by utilizing linear regression, we can establish a baseline predictive model against which more complex algorithms can be compared. This serves as a pragmatic approach to assessing the effectiveness of our predictive algorithm and potentially exploring avenues for improvement in future iterations of our research.

While the Linear Regression Predictive Algorithm serves as a solid foundation for our study, there are several areas where improvements can be made to enhance its effectiveness and robustness.

One area for improvement lies in the refinement of feature selection and engineering. Although linear regression is relatively straightforward, the predictive power of the model heavily depends on the quality and relevance of the input features. Exploring additional features derived from the motorcycle's dynamics, road conditions, and rider behavior could potentially improve the model's predictive accuracy.

Furthermore, the linear nature of the regression model may limit its ability to capture complex nonlinear relationships present in the data. Considering more sophisticated modeling techniques, such as polynomial regression or machine learning algorithms like decision trees or neural networks, could offer better performance in capturing nonlinearities and interactions among variables.

Additionally, incorporating more comprehensive data preprocessing techniques to handle outliers, missing values, and noise could further enhance the model's robustness and generalization ability.

3.1 Hardware

For the purposes of experimentation, the Samsung Galaxy A54 was selected as the test device due to its economical nature and inclusion of the sensors commonly accessible in the consumer market. The device operates on the Android 13 operating system. Comprehensive technical specifications are provided in Table 1, which is presented subsequently.

The used smartphone is compatible with the majority of prevalent satellite systems, although primarily functioning on a single band.

In the realm of Android sensor calibration, a conventional 3-axis coordinate system is employed to represent data from a multitude of integral sensors, which encompass the accelerometer and gyroscope. When the mobile device assumes an upright orientation with its display oriented towards the user, the X-axis extends horizontally and orients to the right, the Y-axis is vertically aligned and extends upwards, and the Z-axis characterizes the direction away from the front surface of the screen.

Table 1. Phone specifications.

Model	Samsung Galaxy A54
Processor	Samsung Exynos 1380 2.4 GHz
Operating system	Android 13
Memory	256 GB, 6 GB RAM
Display	5.3 inch, 1080X2340 pixels
Sensors	A-GPS, GLONASS Geomagnetic Sensor, Accelerometer & Gyroscope – Invensense MP 65M – 6 axis Magnetometer Proximity Barometer
Battery	Li-Ion 5000 mAh

3.2 Software

The primary software application was developed using the Java programming language within the Android Studio Electric Eel | 2022.1.1 development environment. Its primary function is to facilitate the creation of mobile applications and establish a connection between the end user and the motion sensors associated with the mobile device.

For navigation and guidance purposes, an online mapping tool known as Here Maps (Hodgson, 2022) was employed, necessitating an initial configuration to enable integration with the mobile device. This integration process involved the utilization of data and specialized files sourced from the official HERE Premium SDK 4.x. A premium licensing model was selected, offering access to offline capabilities and other location features such as navigation for cars, trucks and pedestrians, electronic horizon, toll cost calculation, advanced data sets like speed limits, inclines, curvature, and more.

In the context of the Here Software Development Kit (SDK) Application Programming Interface (API), the *CoreRouter Class* assumes the responsibility of route calculation for various transportation modes, including automobiles, motorcycles, trucks, and pedestrians. Within an Android application, the initiation of route calculation is accomplished by invoking the method *CoreRouter.calculateRoute (RoutePlan, CoreRouter.Listener)*.

This method affords the capability to specify routing preferences and waypoints according to specific user requirements.

Based on generating a comprehensive GPS positioning dataset, we conducted an Android-based data collection process in collaboration with Here Maps. Specifically, we selected the route from Brasov to Poiana Brasov, Romania, which yielded a dataset comprising 846 GPS coordinates. This dataset corresponded to a travel distance of 11.81 kilometers (as illustrated in Figure 2). Notably, the route computation was conducted asynchronously, specifically tailored for the vehicle travel mode. In this mode, a minimum of two coordinates, one for the starting point and one for the destination, were provided. Additionally, various routing options, such as the preference for the fastest or shortest route, ferry crossings, etc., were considered within a geographical radius of 5,000 kilometers.

The methodology offers two distinct modalities for result delivery:

- Geospatial Representation: The outcome is conveyed through a graphical representation on a map, delineating potential connections between the two reference points, inclusive of any intermediary points, if present.
- Sequential Navigational Guidance: The result is presented in a textual format, furnishing detailed step-by-step riding instructions.

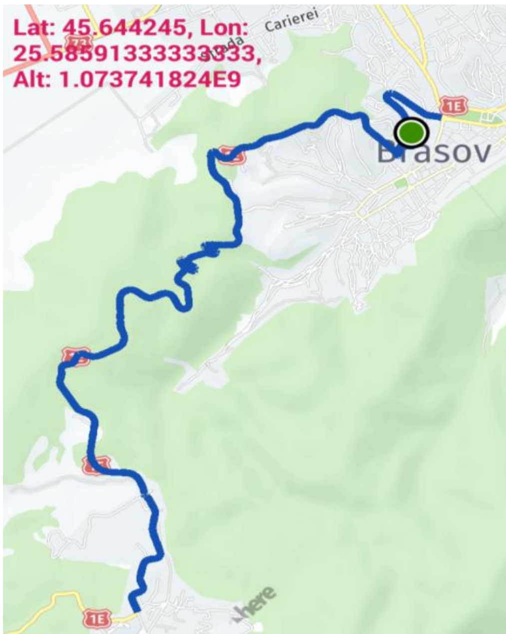

Fig. 2. Route generation by HereMaps.

4. THE MATHEMATICAL FORMALISM

Let a route (road centerline) be parameterized by its arc length $s \in [0, S]$, where S is the total length of the route. In 2D, we represent the route as:

$$r(s) = \begin{bmatrix} x(s) \\ y(s) \end{bmatrix} \tag{1}$$

The heading $\theta(s)$ of the road at arc length s is given by:

$$\theta(s) = arctan\left(\frac{y'(s)}{x'(s)}\right) \tag{2}$$

mining $x'(s) \neq 0$. (If the route is given in latitude/longitude, a coordinate transformation project it to (x, y) in a local plane.)

The first step in the model involves extracting and preprocessing waypoints from the road geometry. To make this data suitable for further calculations, it needs to be transformed into a local cartesian coordinate system (x, y) and parametrized using the arc length, s.

To elucidate the process by which route coordinates are derived, a specific route segment, comprising a sequence of curves, initially oriented to the right, was selected for analysis, and the intermediate points within this segment were depicted as shown in Figure 3.

A fundamental property we need to compute is curvature, which describes how sharply the road bends.

Curvature k at a point on a (2D) curve can be computed by:

$$k = \left|\frac{d\theta}{ds}\right| \tag{3}$$

where θ is the heading (direction) of the path, and s is the distance along the path.

Fig. 3. Markers in the curve sequence - detailed in the right.

The radius of curvature R is:

$$R = \frac{1}{k} \tag{4}$$

For the study route segment, a dataset comprising 54 GPS coordinates was automatically generated, exhibiting an average inter-coordinate spacing of 10,477 meters. The generation of GPS coordinates by HereMaps is contingent upon the characteristics of road segments, with the length of these segments being influenced by the underlying road geometry.

Specifically, when the road is linear, longer distances separate the generated segments, while in areas with pronounced curvature, segments are shorter, resulting in denser placement of points to maintain fidelity to the road's geometric attributes.

If map waypoints are sparse or have small jumps, and the data is too coarse for accurate curvature calculation, additional points can be interpolated, or spline fitting can be applied to obtain a smooth, continuous parametric curve or a well-sampled piecewise linear path.

In practice, for a set of discrete waypoints (x_i, y_i), we use a finite difference to approximate $\frac{d\theta}{ds}$. For each triplet of consecutive points $(A,\ C, B)$, (see Figure 4) we can compute curvature as:

$$k_i \approx \frac{2 \cdot \mathcal{A}_{ABC}}{\|A-C\| \cdot \|B-C\| \cdot \|B-A\|} \tag{5}$$

The area of the triangle ($\mathcal{A}_{ABC}$) is determined using the cross product, which represents a classic discrete curvature formula.

Given three consecutive waypoints $A = (x_1, y_1), C = (x_2, y_2)$ and $B = (x_3, y_3)$ as shown in Figure 4, we can approximate curvature k as follows:

1. Compute the area of the triangle formed by the three points using the determinant formula:

$$\mathcal{A} = \frac{1}{2}|x_1(y_2 - y_3) + x_2(y_3 - y_1) + x_3(y_1 - y_3)| \tag{6}$$

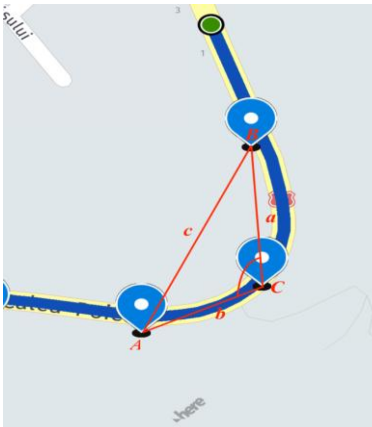

Fig. 4. Triangle consisting of three successive coordinates.

Alternatively, using the cross-product representation:

$$\mathcal{A} = \frac{1}{2}|v_1 \times v_2| \tag{7}$$

Where,

$$v_1 = (x_2 - x_1, y_2 - y_1),\ \ v_2 = (x_3 - x_2, y_3 - y_2) \tag{8}$$

and the cross product in 2D is computed as:

$$v_1 \times v_2 = (x_2 - x_1)(y_3 - y_2) - (y_2 - y_1)(x_3 - x_2) \tag{9}$$

2. Compute the edge lengths:

$$a = \sqrt{(x_3 - x_2)^2 + (y_3 - y_2)^2}$$
$$b = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{10}$$
$$c = \sqrt{(x_3 - x_1)^2 + (y_3 - y_1)^2}$$

3. Estimate the curvature using the circumradius R The circumradius R of the triangle is given by:

$$R = \frac{abc}{4\mathcal{A}} \tag{11}$$

The curvature is then:

$$k = \frac{1}{R} = \frac{abc}{4\mathcal{A}} \tag{12}$$

Once we have the curvature $k(s)$ at multiple waypoints, we integrate it to recover trajectory as follow:

1. Compute the Tangent Angle $\theta(s)$ - at a waypoint can be obtained by integrating the curvature:

$$\theta(s) = \theta_0 + \int_0^s k(\sigma) d\sigma \tag{13}$$

Where θ_0 is the initial direction of the road.

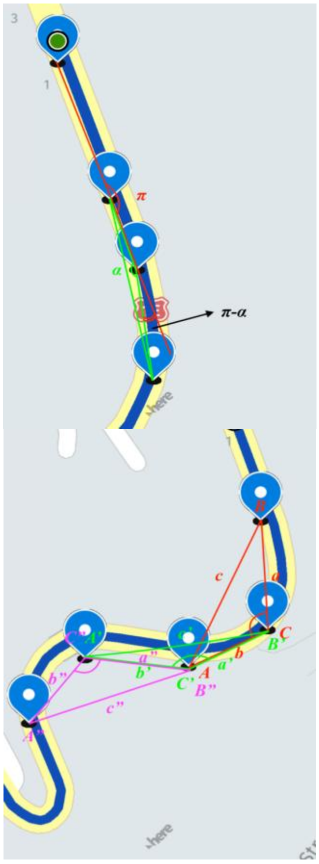

Fig. 5. Progressive curve calculation.

2. Compute the new Position (Trajectory) – using the integrated tangent angle. We can update the position along the trajectory:

$$x(s) = x_0 + \int_0^s \cos(\theta(\sigma)d\sigma) \tag{14}$$

$$y(s) = y_0 + \int_0^s \sin(\theta(\sigma)d\sigma) \tag{15}$$

In discrete form, for small steps sizes Δs:

$$\theta_{i+i} = \theta_i + k_i\Delta s$$
$$x_{i+i} = x_i + \cos(\theta_i)\,\Delta s \tag{16}$$
$$y_{i+i} = y_i + \sin(\theta_i)\,\Delta s$$

Where (x_i, y_i) are the current waypoint coordinates.

Within the domain of rally racing, a pivotal preparatory stage preceding the commencement of the race involves traversing the racecourse and recording pertinent information. The course particulars are typically communicated to race participants through the utilization of numerical designations ranging from 1 to 6, which serve to indicate the level of difficulty associated with the bends in the route. Therefore:

- 1 - 180^O turn (or the famous “hairpin turn”)
- 2 - 90^O turn
- 3 - turn between $70^O - 90^O$
- 4 - turn between $50^O - 70^O$
- 5 - turn between $30^O - 50^O$
- 6 - turn between $10^O - 30^O$ (almost straight road)

Together with the angular orientation of the curve, the notations must encompass an extensive array of supplementary data pertinent to the driver. For instance, it is imperative to recognize that not all curves categorized as grade 3 exhibit uniform characteristics; some may extend over greater distances, while others may be comparatively shorter. These variations exert a discernible influence on the driver's acceleration capabilities and optimal braking thresholds.

Beside how closed the turn is, certain details can be added, such as:

- L or R –Left or Right turn
- < (open) - the exit from the curve is gradual
- > (close) – turn that closes as you advance
- (depending on the curvature length):
    - short - „short”
    - lg - „semi-long”
    - vlg - „long”
    - xlg - „very-long”
- ! (Attention) – characteristic of the road that requires a high degree of attention
- Br (Break) - warning of caution when after a straight stretch of road follows a tight curve

The distances between successive turns are defined at intervals of 10, 20, 30, 50, 70, 100, 150, 200, and 500 meters. The significance of these distances is pronounced when the visibility of the turn is obscured.

For each determined curve angle, a numerical assignment ranging from 1 to 6 is made in accordance with the associated level of difficulty. Employing the parameters of point-to-point distance, the specific angular orientation of the curve corresponding to the established difficulty levels (ranging from 1 to 6), the direction of the curve, and the inter-point distance, a comprehensive road analysis can be conducted. Subsequent to this analytical phase, a motorcycle's movement was simulated along a road segment, where we annotated the entry points of the curve, along with their type and associated difficulty levels, positioned in the upper left corner of the display (see Figure 6).

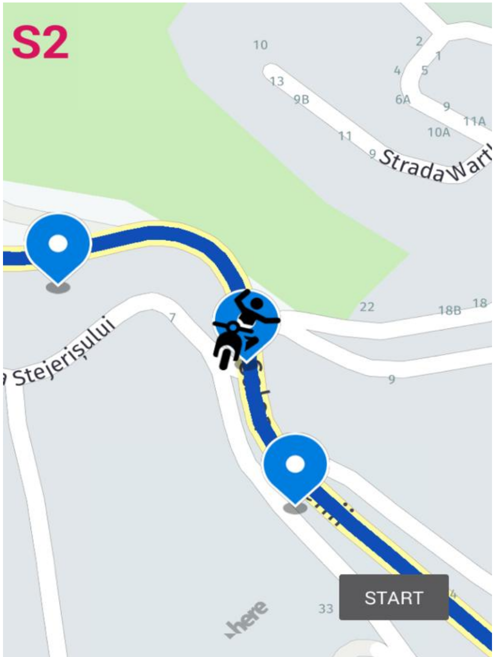

Fig. 6. Android app simulation.

This information is graphically presented at the base of the display, taking the form of a circular representation featuring various hues, as illustrated in Figure 7. The color schema employed in this visualization corresponds to distinct states of the motorcycle's orientation relative to the earth's surface. Specifically, a green hue signifies that the motorcycle maintains an upright alignment. As the degree of tilt surpasses a predefined threshold, the color transitions from green to orange, and subsequently to red, mirroring the increasing magnitude of inclination.

When the operator possesses a higher level of experience, they tend to negotiate curves with a significant degree of motorcycle tilt, denoted by the red indicator. It is worth noting that traveling within the orange and red regions of this display is indicative of the likelihood of an elevated average speed. Consequently, the rate at which information is relayed through the display is heightened by default, ensuring that the motorcyclist receives pertinent data in a timely manner.

Furthermore, the presence of the red color serves as an alert that certain components of the motorcycle may come into contact with the road surface, necessitating a heightened sense of vigilance on the part of the driver.

One of the paramount considerations in motorcycle riding pertains to prevailing meteorological conditions. The maneuvering approach to negotiating a curve on a motorcycle varies significantly when confronted with diverse road surface conditions, such as dry, wet, or ice-covered surfaces.

Under discussion for commencing the journey, it is advisable to consult a pre-ride itinerary detailing the route, including the current-day weather forecast, in conjunction with a specified set of minimum specifications, as illustrated in Figure 8.

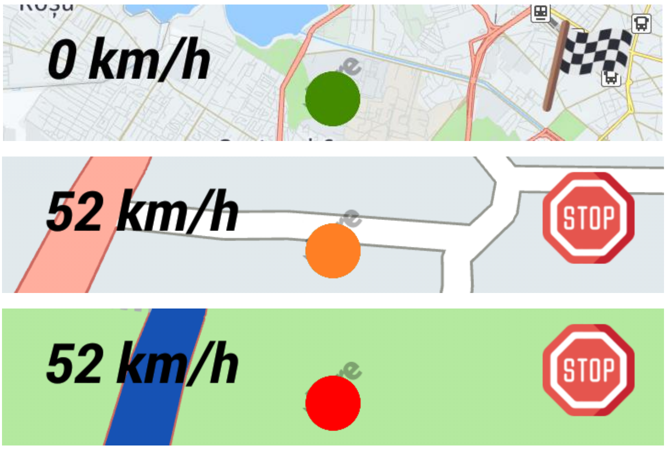

Fig. 7. Leaning indicator.

Fig. 8. Road itinerary.

Upon activation of the Racing flag button, the application transitions into navigation mode. Concomitantly, while the vehicle is in motion along the roadway, driver instructions are rendered on the left side of the screen in red, and these instructions are concurrently conveyed via a voice assistant to ensure the driver's attention remains unswayed from their mobile device. The application leverages the GPS to ascertain the vehicle's present location and subsequently assesses its proximity to any nearby curves. Should such proximity be detected, a series of instructions pertaining to each specific curve are algorithmically generated and prominently displayed on the screen, as depicted in Figure 9.

Fig. 9. Navigation mode.

5. EXPERIMENTAL TEST AND DISCUSSION OF RESULTS

At this stage of the research, our primary focus was to evaluate the synchronization between the position of the motorcycle and the offline simulation computing the leaning angle. Given the absence of access to motorcycle parameters and the reliance on GPS-based positioning, our hypothesis was that the synchronization would be influenced by the accuracy and responsiveness of the GPS data and inertial sensors integrated into the mobile phone.

Anticipated outcomes included assessing the promptness, synchronization, and accuracy of recommendations provided by the system in conjunction with GPS and inertial sensors data. We anticipated that riders' qualitative feedback would shed light on the effectiveness of the system in delivering timely and accurate recommendations, with potential variations based on riders' levels of previous experience.

To investigate the synchronization between the position of the motorcycle and the offline simulation of leaning angles, we conducted motorcycle tests using a Honda CRF series motorcycle (2010 model) on a simulated route from Brașov to Poiana Brașov. A mobile phone, securely mounted on the motorcycle using a Quad-lock handlebar mount, utilized GPS and inertial sensors data to determine the position and provide real-time recommendations to riders. Riding instructions were delivered to riders via an intercom system integrated into their helmets. Due to the absence of a standardized OBD2 connector in most motorcycles, we relied on the internal sensors of the mobile phone to collect data on speed, acceleration, tilt, and GPS.

The motorcycle tests involved six riders from two distinct categories: novice and experienced, each having traveled the route several times. Our aim was to evaluate how riders' behavior varied when provided with information about the upcoming curve's difficulty level.

Our findings revealed that novice riders exhibited a tendency to ride at higher speeds and initiate braking earlier when equipped with knowledge of the forthcoming curve's difficulty level. This behavior was particularly pronounced in areas characterized by limited visibility and optimal navigational conditions, such as smooth roads free from irregularities, potholes, or slippery substances, and without significant weather fluctuations.

During the tests, we collected qualitative feedback from riders regarding the promptness, synchronization, and accuracy of the recommendations provided by the system. Additionally, GPS and inertial sensors data were analyzed to correlate system performance with riders' levels of previous experience.

These observations underscore the importance of further refining the synchronization between motorcycle position and offline simulation, as well as optimizing the integration of GPS and inertial sensors data to enhance the effectiveness of the system. Future research will focus on addressing these challenges to improve system performance and ultimately enhance rider safety and adaptability on the road.

The integration of GPS and inertial sensor data offers significant benefits in platooning applications by enhancing coordination and traffic flow. Leveraging real-time vehicle-to-vehicle (V2V) communication reduces reaction delays, allowing vehicles to anticipate deceleration without relying on visual cues like brake lights. A curvature-based approach further optimizes efficiency by providing lead time for smooth acceleration and braking sequences. By computing an ideal corner speed and braking point, all vehicles navigate turns uniformly, eliminating inefficiencies from individual speed adjustments. Smoother, predictable maneuvers enable closer yet safe spacing, increasing throughput in high-traffic areas. Additionally, the platoon can dynamically adjust its shared speed profile based on real-time conditions, such as friction changes from the lead vehicle, ensuring instantaneous and uniform updates. This adaptability enhances overall platoon efficiency, safety, and responsiveness to dynamic road conditions.

Although the present study focuses on refining motorcycle riding support through GPS-driven synchronization and leaning-angle simulation, these findings naturally extend to multi-vehicle platooning scenarios. In particular, providing uniform and timely curve-related guidance to all vehicles within a convoy could mitigate sudden speed variations—commonly known as shock waves—thereby improving overall traffic flow. Integrating the same predictive engine with interconnected vehicles would facilitate synchronized braking and acceleration maneuvers, minimizing disturbances in curved road segments or other bottleneck areas. This broader applicability underscores the potential for our approach to enhance not only individual rider safety but also collective efficiency in heterogeneous traffic environments.

6. CURRENT LIMITATIONS OF THE SOLUTIONS

In the domain of navigation systems, a prevalent challenge pertains to road sections featuring tunnels, with added complexity arising when said tunnels encompass variations in elevation. The envisaged application has been specifically engineered to undertake automatic alignment of the mobile device's position within the road network and its corresponding map, even when GPS data proves to be less than precise. Furthermore, the system accommodates scenarios where both GPS and GSM signals are lost, employing extrapolation techniques to update the device's position based on the driver's velocity and various tunnel-specific parameters.

This extrapolation methodology leverages the *LocationDataSourceAutomotive* class, which harnesses positioning data derived from a GNSS module that can compute an estimated path. A supplementary challenge involves route calculation, entailing the placement of markers known as waypoints onto the map. Despite the road's ostensibly linear character, marker positioning does not invariably coincide with the road's central axis or the intended travel direction. Given that the curve calculation algorithm hinges on angle deviations from the initial marker position, erroneous marker placements introduce systemic inaccuracies. Neglecting these API constraints often results in the algorithm erroneously identifying a curve with a minuscule angle, even when the path remains straight. Additionally, the route calculation process may generate successive waypoints at the same geographical location.

Subsequently, two limitations pertain to hardware aspects. While in transit, the mobile device is typically mounted on a motorcycle's handlebars via a specialized bracket or placed within a transparent-surfaced bag on the fuel tank to facilitate rider interaction. Extended exposure to direct sunlight and protracted usage, spanning 4 to 5 hours, may induce overheating of the mobile device. Moreover, the device's accelerometer readings can be influenced directly by the motorcycle's vibrations during motion, potentially yielding inaccuracies.

As a countermeasure, data collection from the device's internal accelerometer has been constrained to the OX axis orientation. OY axis values are adjusted in accordance with the support structure on the handlebars, while OZ axis readings are disregarded under the assumption of device non-rotation. Periodic calibration of the device's internal sensors is also recommended, as they may experience drift and recalibration over time.

Improvements can also be made at the hardware level by employing a more efficient smartphone mount equipped with a vibration damper (e.g., Quadlock) and a UV-protective film capable of reducing the overheating of the phone.

7. CONCLUSIONS

This research emerged from practical observations of inadequate driver adaptation to diverse road conditions, prompting the development of a mobile motorcycle recommendation application aimed at enhancing the riding experience. The project focused on integrating data from an online mapping service, calibrating internal smartphone sensors, and creating an interface that delivers intuitive, secure, and efficient guidance to riders. While still at the proof-of-concept stage, the application demonstrates the feasibility of leveraging smartphones for real-time motorcycle advice.

Preliminary findings indicate that the application's impact on different rider profiles varies: whereas more aggressive riders may require meticulous and highly personalized recommendations, average riders can benefit sufficiently from more generalized feedback. The system's flexibility thus accommodates varying degrees of complexity in both rider behavior and environmental conditions.

Limitations identified during testing have inspired avenues for future work. Enhancements under consideration include the incorporation of real-time motorcycle data from additional sensors, expanded utilization of online mapping resources, graphical interface refinements, and extended testing in complex scenarios such as intersections with intermittent traffic signals. Furthermore, machine learning and artificial intelligence present significant opportunities to personalize guidance based on each rider's habits and to refine motorcycle parameters dynamically, fostering a more adaptive and user-oriented system.

Beyond motorcycle applications, the foundational principles of this approach can also be applied to vehicle platooning on curved road segments, where synchronized maneuvering helps minimize sudden speed fluctuations—often referred to as "shock waves." By providing uniform predictive guidance to each vehicle in a convoy, the solution holds promise for improving overall traffic flow and safety, illustrating a broader potential impact that extends well beyond its original design scope.

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