Development of a Methodology for Monitoring and Prediction of Road Surface Conditions in Highly Automated Driving

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***Abstract*—This paper addresses vertical dynamics comfort in Highly Automated Driving (HAD). Based on the assumption that a reduction of vertical acceleration inputs will result in increased passenger comfort, we develop an approach to minimize the effect of road surface anomalies on HAD users. We propose a participative method to identify, process and distribute road quality data using a plurality of vehicles exchanging information with a central server. By activating automated responses to warn about, avoid or counteract the appearance of any type of discomfort prompted by vertical vibrations, we strive to increase the maturity of HAD technology.**

I. Introduction

The accelerating development of self-driving vehicles has triggered the progressive transition from active, full-time performance by a driver towards completely automated systems in charge of the entire driving task, with no human action needed. Market players have set milestones to achieve higher degrees of vehicle automation that will gradually delegate responsibilities from the driver to the vehicle [1]. Higher automation levels will lead to safety, environmental and economic benefits, such as a drop in accident rates, lower emissions, and less traffic congestion. It will also result in greater quality of life by shortening traveling time and allowing passengers to carry out other activities, such as working, relaxing or accessing entertainment [2].

The present study will develop within a context of Highly Automated Driving (HAD). Although its technology is not implementation-ready as of today, HAD is planned to be the first degree of automation where the driver delegates responsibility for motion control and environment supervision to the vehicle. Although drivers must be ready to actively intervene in the event of a conflictive situation, HAD will allow drivers to deviate from attentive roadway and traffic monitoring and enable them to engage in parallel activities that are not related to the driving task itself [1].

Given that the driver is no longer in charge of driving and may visually fixate still objects within the vehicle, his propensity to motion sickness and other negative symptoms will increase. This occurrence may be accentuated by vertical accelerations resulting from bad road surface quality (e.g. bumpy roads, and singularities like potholes or speed bumps), generating dissatisfaction with HAD. The existing solutions, such as different driving modes, will not meet the new comfort requirements imposed by HAD. Based on the assumption that a reduction of vertical vibration inputs will enhance passenger comfort, we predict that processing road surface quality to improve vertical comfort will help to increase maturity of HAD technology.

In this paper, we present a participative methodology that maximizes vertical dynamics comfort by monitoring vertical accelerations, using a plurality of vehicles exchanging information with a central server. The recorded data, followed by the aggregated, off-board analysis of the information gathered by different vehicles, provides comfort-relevant and periodically updated information on road surface quality. Hence, when a vehicle covers a HAD route that has been monitored before, the system will use the available data to activate automated responses to warn about, avoid or counteract the appearance of any type of discomfort prompted by vertical vibrations. Possible responses could include alternative routes with better surface conditions, automatic speed and drivetrain adaptions or driver notifications. Although the methodology developed increases the technology maturity of HAD, it is not a necessary feature for successful HAD completion. Comfort-maximizing vehicle responses will only take place as long as they are compatible with passenger and third-party safety.

The contributions of this paper are:

- The design of an end-to-end approach to process road surface quality data for comfort maximization in HAD
- The development of adequate and automatic vehicle responses to minimize the effect of vertical accelerations
- The theoretic evaluation of the method to assess the robustness of the system

Related work is reviewed in Section II. Section III presents the designed method to identify and minimize the effect of road anomalies on passenger comfort. Section IV assesses the weaknesses of the system, and proposes solutions increase its performance. The paper is concluded in Section V.

II. Related Work

There are multiple methods that record and interpret the vehicle environment, most of which focus on passenger safety or road maintenance and employ on-board monitoring devices.

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[2] BMW Group, Process Driving Dynamics
The results of this work have been submitted for patent application at the European Patent Office with the reference Nr. 17163475.1

Based on the time point of detection, monitoring can be divided into *ex-ante* and *ex-post* methods. *Ex-ante* methods detect events in their environment before reaching them (e.g. camera-based and laser methods). *Ex-post* refers to empirically measuring information by physically tackling an event. Although the first recording vehicle does not benefit from the collected information, other vehicles may anticipate said events if warned (e.g. monitoring a slippery curve). Although *ex-ante* technology is indispensable for environment recognition in HAD, its reliability is still insufficient for road surface anomaly detection, leading to its disposal for our approach.

The pothole patrol [3] is an *ex-post* method that strictly monitors potholes using an external accelerometer. It pairs measured acceleration values with their corresponding location to identify potholes geographically. Related events such as speed bumps are discarded using machine learning algorithms.

Similar *ex-post* systems use smartphone accelerometers to monitor events encountered. Mednis et al. [4] developed a smartphone-based pothole detection system that associates acceleration measures with the GPS position. After statistical analysis, it classifies potholes into different types and bundles. Astarita et al. [5] also used smartphones to monitor and locate any type of road anomaly. Statistical off-board analysis categorizes detected events by means of severity based on their impulse, obtained from raw acceleration data.
SmartRoadSense [6] introduced an informative crowdsourcing approach to monitor road quality using a mobile app. After measuring accelerations and processing the aggregated data, average road quality clusters are plotted on a map interface.

However, and despite the demonstrated efficiency of smartphones, built-in accelerometers have been chosen as monitoring hardware for the method on the following grounds:

- Smartphones may require reorientation algorithms given their random orientation in vehicles
- False accelerations will be measured if users operate a monitoring smartphone
- Measuring with smartphones requires the active engagement of users (e.g. run the necessary applications)
- Not all drivers own a smartphone

In HAD, the vehicle is responsible for motion control. Thus, its head unit (HU) should at some point receive information to activate an automated reponse. The following works, although not devised for HAD, includes the HU as a processing unit:

Google [7] designed a crowdsourcing approach to monitor road quality from multiple vehicles. The HU correlates the geographic position with the road quality indicators (RQIs) resulting from on-board vertical vibration recordings. The location-based information from all vehicles is then forwarded to a central server, where it is contrasted with stored historic data. Average values for RQIs in every location are continuously updated upon reception of new data.

Chen et al. [8] developed a road condition real-time warning device to notify the driver ahead of exceptional road conditions of any kind. Participating vehicles detect critical values surpassing predefined thresholds and send them to a back end for central analysis. The back end aggregates and contrasts the information from all vehicles, and organizes the data in a downloadable location database that notifies drivers about known critical events ahead.

General Motors [9] also studied participative sensing of events and conditions with a plurality of vehicles acting as data collection as well as advisory-receiving units. If a monitored magnitude surpasses a predefined threshold, the corresponding safety metrics are calculated and sent to a central server along with the event location. When a vehicle approaches a safety-relevant event stored in the server, it issues a driver notification to warn about the upcoming event. Events may include accidents, traffic congestion, potholes or icy patches.

Several authors study the crowdsourcing of road quality data followed by central processing for posterior decentralized distribution. The application fields are passenger safety, road maintenance, and informative notifications. No related work evaluates the effect of road surface on vertical comfort, and no studies consider high automation contexts, thus preventing the development of automated responses to minimize the effect of vertical motion.

This leads to the refinement of the contributions of the approach proposed in this paper:

- The application of road quality monitoring to a HAD environment, including:
  - Motion control authorization, i.e. automated dynamic responses without the intervention of a human driver
  - The hierarchical integration and compatibility with other systems and algorithms required for HAD
  - The compliance with new standards imposed by HAD
- The focus on vertical comfort as the key customer feature, i.e. the minimization of events prompting undesired vertical accelerations affecting the passengers
- A description of all subsystems and algorithms required
- The consideration of any type of road surface anomaly, including benevolent events such as rail crossings or speed bumps
- Adequate task allocation between the involved entities
- The minimization of hardware and software resources
- The use of the aggregated and organized information to activate an appropriate automatic response for the specific event confronted

III. Approach

The designed ex-post system is composed of two entities:

- A plurality of participating vehicles
- One central server or back end

Both entities communicate bidirectionally, i.e. every vehicle receives and sends data from/to the central server, but vehicles do not communicate with each other. The method developed includes on-board (vehicle) and off-board (back end) processing steps. It can be divided into four parts (see Fig. 1):

A) Continuous Measuring
B) RQI Calculation, Interpolation and Coding
C) Data Analysis

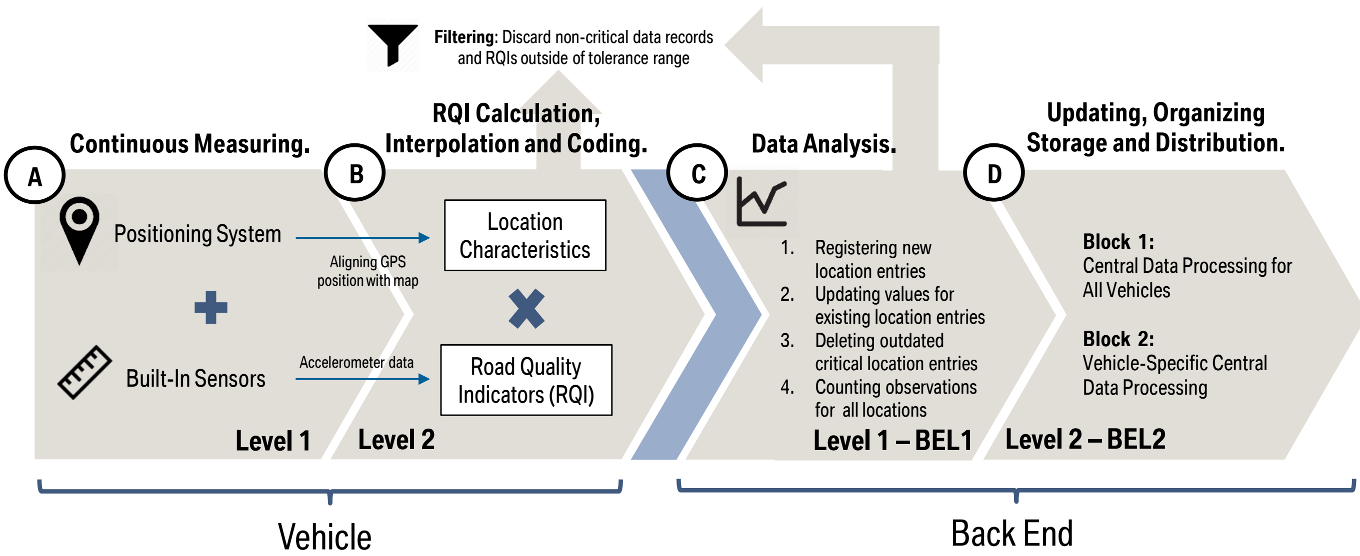

Fig. 1. Process flow of the methodology. Steps A and B are also named Vehicle Levels 1 and 2. Steps C and D correspond to Back End Levels 1 and 2.

D) Updating, Organizing, Storage and Distribution

A. Continuous Measuring

As seen in Section II, vertical accelerations are an indicator of road surface quality, and built-in accelerometers constitute the best solution as monitoring devices. Since the aim is to increase passenger comfort, it is important to measure accelerations as close to the passengers as possible. Thus, the optimal positioning accelerometers would be underneath or within vehicle seats, which have the least relative motion with respect to passengers. Accelerometers have a measurement frequency of 100-400Hz. Considering that the maximum speed planned for HAD is 130km/h [10], the monitoring accuracy can be determined with the following calculation:

$$\Delta x = \frac{130km}{h} \cdot \frac{1h}{3600s} \cdot \frac{1000m}{1km} \cdot \frac{1s}{400} \simeq 0,09m = 9cm \quad (1)$$

Given that anomalies are usually greater than 9cm, and that they are perceived twice (front and rear axes) by multiple vehicles, the probability of false negatives can be neglected.

As mentioned in Section II, a positioning system is necessary to geographically locate monitored events. GPS receivers have an update frequency of 1-5Hz and provide additional information such as time of recording (t), vehicle velocity (v) and heading (h) aside from delivering vehicle position. Given the tolerances of the GPS system, the measured position may not match a position on the vehicle cartography software and locate the vehicle outside of its actual track. It is therefore necessary to align GPS and map coordinates (see Fig. 1).

Pinpointing the exact position of an anomaly within a road, including affected lane(s) or position within lane, can be determined by high-precision maps. In this case, the GPS is complemented by camera-based measurements of the distances from the vehicle to the outer edges of the road.

B. RQI Calculation, Interpolation and Coding

Vertical accelerations are not sufficient to recognize a comfort-critical location, but they provide raw data for the calculation of comfort-relevant parameters, also known as Road Quality Indicators (RQIs). RQIs are quantitative acceleration-based parameters that determine whether a location is critical (comfort-compromising) or not by comparing it to threshold values obtained from empirical comfort studies. A location will be considered critical as soon as one RQI surpasses its associated threshold. Despite the lack of studies to determine RQIs and thresholds for vertical comfort, the present method will rely on longitudinal and lateral comfort RQIs.

Given a series of raw vertical acceleration measurements throughout time, we consider the following RQIs:

- $\overline{x}$, the average acceleration value
- $A = a_{max} - a_{min}$, the amplitude of the function
- T, the period of the function

The measurement frequency of GPS receivers is lower than the acceleration measurements (1-5Hz vs. 100-400Hz). This leads to the generation of location windows with multiple acceleration measurements when pairing (interpolating) location characteristics and RQIs (see B in Fig. 1). In order to code the pairing, a data record f with the following format is generated:

$$f = (j, \overline{x}, A_{max}, T, T_{max}, T_{min}, t, v, h, k, s) \quad (2)$$

with

- j being the location in (latitude; longitude) coordinates
- $\overline{x}$, A_{max}, T, T_{max}, T_{min} being RQIs for location j
- t being the recording time, considering that RQIs are a dynamic variable over time
- v being the vehicle speed, considering that RQIs vary depending on the instantaneous speed of the vehicle
- h being the heading of the vehicle in bidirectional roads
- k, s being vehicle (k) and sensor (s) identification codes

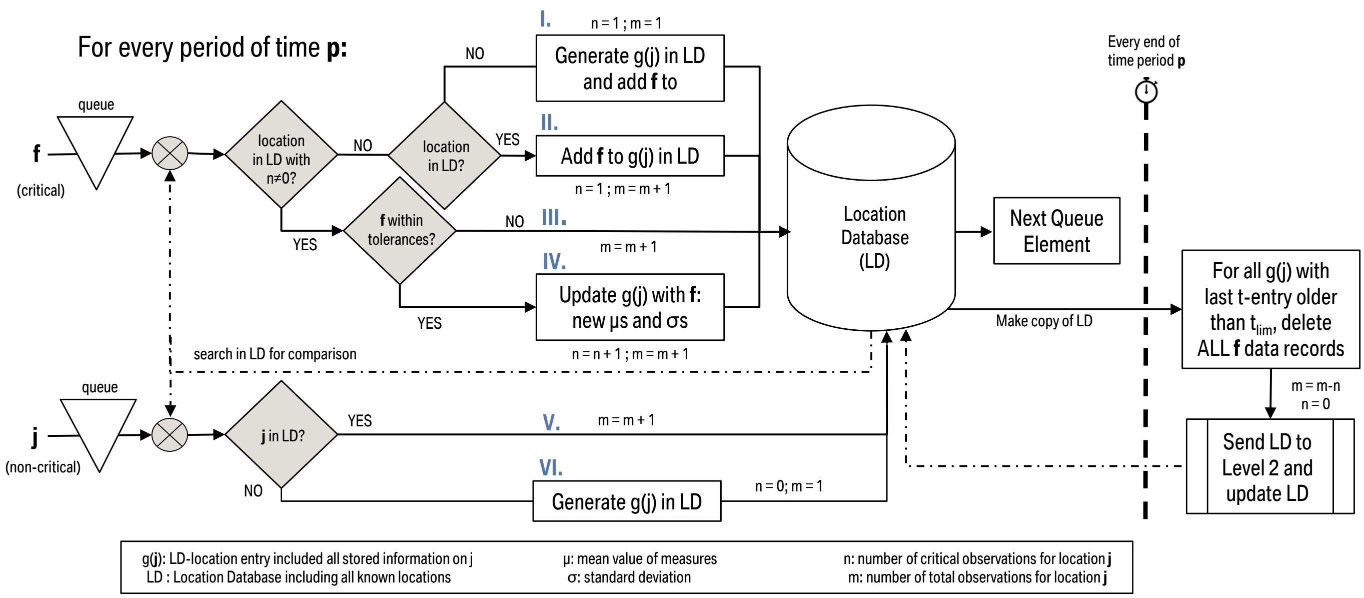

Fig. 2. Structure of Back End Level 1 (BEL1)

Data records resulting from data interpolation enter a filtering algorithm: if any of the RQIs in a data record f surpasses its associated threshold value, the corresponding location is labeled as critical and the data record f is sent to the back end via mobile network. Otherwise, if all RQIs are within their thresholds (non-critical location), the only value delivered to the back end are the location coordinates j.

C. Data Analysis (BEL1)

As depicted in Fig. 1, the back end is divided into two parts: Back End Level 1 (BEL1) and Back End Level 2 (BEL2).

Fig. 2 shows that the inputs for BEL 1 correspond to the outputs of the filtering algorithm in B: data records (f) for critical locations, and location coordinates (j) for non-critical locations. With them, BEL1 carries out four main operations:

- Registering new location entries
- Updating values for existing location entries
- Deleting outdated critical location entries
- Counting how often a location is monitored

The product of BEL1 is the Location Database (LD). The LD stores all information on all known locations in individual, location-specific entries: $g(j)$. A location is known when it has been monitored by a vehicle, and may or may not be critical. In order to distinguish between critical and non-critical, all known locations have two counters:

- The number of critical observations (n)
- The total number of observations (m)

Unknown locations are not included in the LD.

For every known non-critical location ($n = 0$, $m > 0$), the LD contains a counter with the number of critical observations equal to zero as well as the total number of observations.

For every known location labeled as critical ($n > 0, m \geq n$), the LD contains the n and m counters, and a normal distribution for every RQI, with their mean values (μ) and standard deviations (σ). It also gathers all individual RQI measurements of critical locations, and their associated v, t, k and s.

There are six possible processing paths (cases I to VI, written in blue in Fig. 2) in BEL 1. Cases I to IV correspond to the data analysis of critical locations, whereas Cases V and VI process locations where no anomalies have been monitored. The inputs are processed in a first-in-first-out queue, i.e. chronologically upon reception. The inputs are compared to the available LD information in order to direct them to the appropriate case.

Case I corresponds to a scenario where an anomaly is detected in a location j that has never been monitored before. In other words, the first time a monitoring vehicle records information on a location, it obtains critical data for that location. In this case, the algorithm generates a new LD entry, $g(j)$, where it adds the information contained in the vector f received. It initializes the counters $n = 1$ and $m = 1$.

In Case II, a known location that is stored as non-critical is labeled as critical for the first time. The algorithm is in charge of adding f to the existing LD entry $g(j)$, labeling the location as critical with $n = 1$ and increasing the m counter by 1.

Case III discards all incoming f that deliver inconsistent data with the stored RQI distributions, i.e. outside a confidence interval of $\mu \pm \alpha\sigma$. Inconsistent values may be delivered by defective sensors or may be the result exceptional circumstances (e.g. temporary obstacles). It increases the m-counter by 1.

Case IV processes cases within the confidence interval described above. It updates existing critical $g(j)$ with the new f. It adds all information in the data record to the lists in $g(j)$ and recalculates its statistical parameters. According to the counter logic, it increases both counters by 1.

Cases V and VI correspond to locations classified as non-critical when monitored. If a location is already in the LD, it updates the amount of total observations (Case V). If the location is not in the LD (Case VI), it generates a $g(j)$ entry for j and initializes both counters.

Every end of a time period p, a copy of LD is made. In the LD copy, all critical $g(j)$ whose last t-element is older than t_{lim} are reset. This is done in order to delete outdated information in the LD. The cause of outdated information may be road works or the removal of temporary obstacles leading to the disappearance of anomalies.

After deleting outdated locations, the copy of LD is sent to BEL2, and the LD copy replaces the previous LD in BEL1.

D. Updating, Organizing, Storage and Distribution

The structure of BEL2 is divided into two main blocks:

- Block 1, central data processing for all vehicles, taking place once for every time period p
- Block 2, the on-demand, vehicle-specific data processing, taking place once for every vehicle request (see Fig. 3)

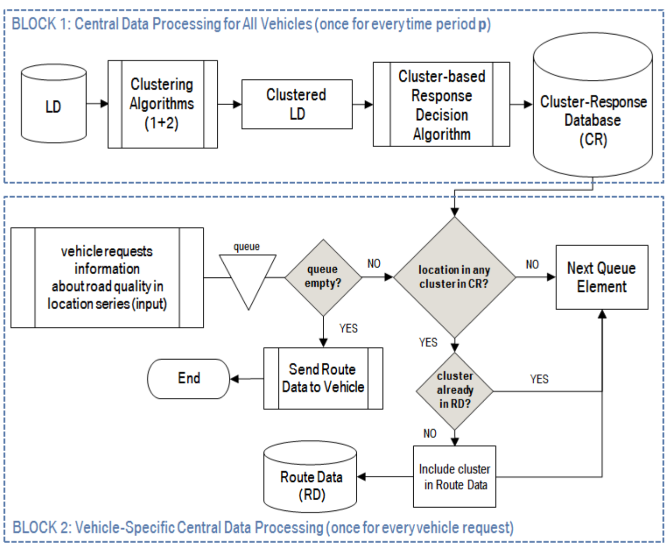

Fig. 3. Structure of BEL2

The LD copy received form BEL1 is subjected to a two-step clustering algorithm that bundles locations based on their position and their criticality. In the first step, adjacent critical locations are grouped to form clusters, and so are adjacent non-critical locations. Regarding critical clusters, longer road sections with bad surface conditions form bigger clusters with more locations than small road singularities, whose clusters may count with as little as one location. The second clustering step simplifies the clusters by omitting small, non-critical clusters surrounded by larger critical segments. It also adds accuracy by adding critical clusters within other critical clusters, for exceptionally severe singularities.

The output of the clustering algorithms is called Clustered LD. It includes a list of clusters that contain their corresponding locations with the same $g(j)$ format as in the LD.

The Clustered LD then enters the Cluster-based Response Decision Algorithm. This algorithm is in charge of associating an appropriate automatic response to every cluster, starting from the standard driving configuration. The standard driving configuration of a given road segment is the setting that the car will adopt in non-critical situations. This configuration is based on the speed limits and recommendations for the road segment in question, as well as on the dynamic constraints from other systems with higher priority rank (see Fig. 4).

The standard driving configuration will also be the setting for unknown locations and for locations that have been labeled as critical a negligible amount of times in comparison to its total amount of observations (leading to the conclusion that the critical observations are not representative of the actual state of the road), i.e. locations with a low n/m ratio.

The suitable response for a critical cluster is a series of modifications with respect to the standard driving configuration, selected from a predefined array of responses that includes:

- Speed adaptions of a certain percentage
- Driving mode changes and drivetrain adaptions
- Offering the most comfortable route: the one with the smallest amount, size and intensity of critical clusters
- Any combination of two or more responses listed above
- Maintaining the standard driving configuration

The association of a cluster to an adequate response is based on three criteria (see Fig. 4): the standard driving configuration for the analyzed road segment, the RQI magnitudes of the locations in the cluster, and the n/m ratio. A successful pairing will be made possible by machine learning, using comfort-oriented training sets of participants rating their comfort perception in a plurality of driving scenarios. Algorithms are then trained by comparing user feedback to the acceleration patterns recorded, enabling the system to predict the optimal response to a road anomaly given an acceleration pattern.

The clusters and their assigned responses are stored in the Cluster-Response Database (CR).

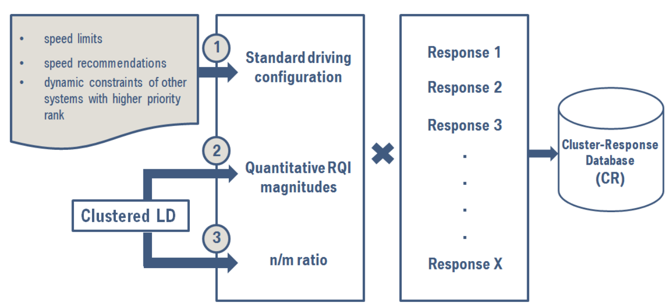

Fig. 4. Structure of the Cluster-based Response Decision Algorithm

When willing to cover a route with HAD, the driver enters the desired route in the HU. The vehicle then requests information on the concerned locations to the CR, and, whenever available, downloads the cluster containing the location and its associated response via mobile network1 (see Fig. 3).

The pairing cluster-response for all requested locations is stored in a downloadable package called Route Data (RD).

The RD is specific for every vehicle request and can only be downloaded after scanning all requested locations in the CR. As soon as the RD has been downloaded and all other systems required for HAD completion are ready, the vehicle will be allowed to start the drive. The vehicle will be able to activate all comfort-maximizing responses without needing further connectivity to the back end.

When a drive is finished or aborted, the RD is deleted in order to avoid on-board data accumulation. A new, updated version of the route will need to be downloaded again if the driver wishes to resume it or cover it one more time.

IV. Evaluation

The purpose of this section is to assess the robustness of the system by identifying its weaknesses and proposing solutions to overcome them. Robustness will lead to increased accuracy and reliability, resulting in higher overall performance.

A. Comfort Studies

Section III highlights the necessity to carry out empirical studies to provide scientific evidence on how vertical dynamics affect comfort in HAD. They should include:

- The determination of acceleration-based parameters that are indicators of vertical comfort: RQIs.
- The quantification of thresholds for every RQI to distinguish comfortable from uncomfortable phenomena. Given the subjective nature of comfort, they should represent as many users as possible.
- The design of experiments and machine-learning training sets to determine RQIs and thresholds. In order to consider the entire susceptibility spectrum and assess a wide range of driving situations, said studies should include:
  - The comfort ratings of a large number of participants
  - As much situational data as possible: Different events at different speeds, with different vehicles, etc.

B. Machine Learning

At higher speeds, road surface events trigger higher acceleration measurements [11]. Thus, vehicles monitoring at different speeds can lead to inaccurate or incorrect location labeling. As studied by Eriksson et al. [3] the use of machine learning can help assess the criticality of a road anomaly regardless of the speed. Appropriately trained machine learning algorithms should recognize acceleration patterns for a variety of driving situations involving different singularities, different speeds and different vehicles, and be able to evaluate location characteristics regardless of the circumstances. Machine learning algorithms will interpret the acceleration patterns and changes resulting from a road anomaly, and should ideally be based on the training sets developed in the comfort studies.

Given the variations in their construction, two different monitoring vehicles will measure different accelerations when driving over the same event at the same speed, leading again to wrong location labeling. By using training data from different source vehicles, machine algorithms should establish correction factors to properly interpret the incoming data delivered by different vehicles.

C. Definition of a Standard Architecture

Depending on their architecture, any given vehicle may include different monitoring hardware placed in different positions of the vehicle, again leading to measurement discrepancies. To avoid data loss when connectivity is interrupted, vehicles should also include a buffer to store information temporally, until connectivity is re-established.

The definition of a standard architecture where all participating vehicles comply with multiple hardware (geometric) and software (electronic) requirements will neutralize the variations due to sensor type and placement, and provide a common framework for all on-board processing steps. It will also increase the scalability of the approach because no hardware and software modifications will be required depending on the specific constraints of different models.

D. Adequacy of Vehicle Responses to the Events Tackled

Vehicles may react to critical clusters in a way that does not improve comfort. If the system does not associate the correct response to a critical cluster and all prior steps of the methodology are operating correctly, the problem may reside in the Cluster-based Response Decision Algorithm not interpreting the trained patterns properly. If this were the case, all machine learning algorithms should undergo supervision, including the training sets to identify RQIs and their thresholds.

Using the standard driving configuration may also be hazardous when tackling severe anomalies in unknown locations. The shock provided by unexpected singularities at higher speeds may not only constitute an uncomfortable event, but also compromise passenger safety.

This type of situations will require the presence of safety algorithms outranking the system presented in this work and imposing a safety response over that of the system. If any system in charge of guaranteeing safety requests an action that contradicts a planned response of the methodology at any moment, the response of the methodology will be canceled in the interest of passenger or third party safety.

The parallel systems and algorithms operating for optimal completion of HAD will require a hierarchy in case two or more algorithms request contradictory action.

E. Algorithm Hierarchy for HAD

HAD will operate numerous systems simultaneously. Said systems may be in charge of passenger safety, passenger comfort, providing informative digital services, etc. Vehicles will combine their own detection sensors with back end information (including maps and digital services) to identify their surroundings and extract information of relevance from them [12]. Some examples of HAD systems include:

- Safety systems in charge of real-time environment sensing and interpretation.
- Safety systems in charge of real-time driver sensing
- Informative systems (back-end-based) to alert the driver about temporary events of importance
- Comfort-maximizing systems, such as the methodology developed in this study

- Systems in charge of environmental and economic efficiency

Motion control may be influenced indirectly by several systems simultaneously, and in given scenarios some systems may request contradictory or incompatible action. In this case, the HAD driving function will need to process all the commands received from systems and prioritize some based on the environment of the vehicle

Although the methodology developed increases vertical comfort for HAD, and consequently increments the maturity of HAD technology, it is not a necessary feature for the successful HAD completion. HAD will be completed successfully when the safe transportation of passengers from a starting point to a desired destination is achieved. Hence, HAD will always prioritize passenger and third-party safety as well as conflictive or uncertain scenarios that could potentially result in safety-compromising situations over comfort. Comfort-maximizing vehicle responses will only take place as long as they are compatible with safety-related motion control and do not interfere with any potentially hazardous situations.

V. Conclusion

This paper studied vertical dynamics comfort in Highly Automated Driving (HAD). Based on the assumption that a reduction of vertical vibration inputs result in increased passenger comfort, we designed a participative approach to identify and minimize the effect of road anomalies on passengers by activating automated vehicle responses. The study was complemented by a robustness evaluation to assess method weaknesses and increase system performance.

To the best of our knowledge, the proposed method is the first to address vertical comfort in HAD. This leads to unprecedented considerations with respect to existing work, such as motion control permission, the neutralization of road anomalies by means of automated vehicle responses, or new comfort standards.

The achievement of HAD will not guarantee the adoption of the technology as long as the driver cannot pleasantly benefit from the free time during traveling. We believe that the operation of a method of such characteristics will constitute a fundamental factor for market acceptance of HAD. We also think that the modular structure of methodology developed allows adjustments without any significant repercussion on prior or posterior steps. Changing monitoring sensors, RQIs and thresholds, algorithm structures or vehicle responses will not demand modifications at other stages.

The system designed offers good scalability opportunities. It can grow along with the gradual adoption of HAD, starting monitoring in highways regionally, and progressively expanding to other types of roads and geographic areas. The complexity of acceleration-based RQIs may also increase along with the geographic growth based on the lessons learned and the situational data accumulation in earlier implementation stages.

The machine learning algorithms incorporated also constitute scalable subsystems: higher participation rates will refine event pattern recognition, threshold quantification and response associations, improving system performance.

Regarding future work, and based on the findings of Section IV, three aspects remain open for further development:

1) The conduction of comfort studies to determine RQIs and their thresholds, and the recording of as many driving situations as possible.
2) The development of machine learning algorithms to correctly interpret different situations. Supervised learning using a large amount of known road events as training examples should enable algorithms to successfully classify all types of events.
3) Method extensions to longitudinal and lateral comfort, since automated trajectory planning may lead to disruptive longitudinal and lateral motion.

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