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RESEARCH ARTICLE

A Motion for No Motion: The Redundancy of Motion Feedback in Low-Velocity Remote Driving of a Real Vehicle

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ABSTRACT Ensuring safety remains one of the biggest challenges for the widespread adoption of automated vehicles (AVs). Remote operation of AVs is a promising approach to address this, allowing remote operators to intervene when AVs encounter edge cases. However, remote operators are out-of-the-loop from the conventional driver in vehicle environment interaction, impacting their situation awareness and ability to safely control or assist the vehicle. In the scenario of remote driving, this is more evident since multimodal feedback is required to replicate the conventional driver-vehicle environment-interaction. In addition to visual and auditory modalities, motion feedback has been proposed as a way to bridge the gap between remote driving and in-vehicle driving. However, since motion feedback is cost-intensive, it might hinder rapid upscaling of remote driving systems. Thus, this study evaluated whether motion feedback adds value to driving performance and experience of the remote operator in low-velocity scenarios. Driving performance and experience were assessed and compared using objective and subjective metrics in three conditions (in-vehicle driving, and remote driving with and without motion feedback). The findings show that in remote driving, motion feedback fails to provide significant improvements. When compared to in-vehicle driving, remote driving performance and experience remain significantly worse. This suggests that motion feedback, in its current form, is redundant in low-velocity scenarios and that a simplified Remote Driving Station (RDS) may be sufficient in these scenarios. Future work should optimize simplified RDS designs, enhance feedback and human-machine interfaces and explore different driving scenarios for safe and efficient remote driving.

INDEX TERMS Teleoperation, remote driving, automated vehicles, motion feedback, driving performance, driving experience.

I. INTRODUCTION

Higher levels of AVs will not be able to resolve all challenging traffic situations on their own [1]. In particular, edge cases (e.g., construction sites, malfunctioning traffic lights or bad visibility conditions [2]) which are difficult for AVs to be trained may persist, making it even more challenging for AVs to cope with. Hence, human fall back solutions are also required to secure the smooth introduction of AVs, avoiding issues during such edge cases. Remote operation of AVs, where this paper focuses, is considered as a bridge from Society of Automotive Engineers (SAE) level 4 to 5, which could lead to faster and safer implementation [3]. However, AV remote operation comes with a plethora of challenges, not only from a technical but also from a Human Factors perspective (for a comprehensive discussion see [4]).

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Remote operation of AVs consists of three parts: remote monitoring, remote assistance and remote driving [3], [5], [6], [7]. Remote monitoring refers to the observation of the vehicle without directly controlling it. This means that the remote operator cannot modify the motion or the decision of the vehicle, only observe its status. Remote assistance entails providing guidance or instructions to assist the vehicle without executing the dynamic driving task. Remote driving is the direct remote control, i.e., executing the dynamic driving task in both lateral and longitudinal direction using steering wheel and pedals. Similarities can be found between remote driving and simulator driving, as both involve operating a vehicle (real or simulated) without physically being inside. Therefore, the drivers have to rely on the limited or artificial feedback they are provided. In both scenarios, drivers have to adapt to reduced sensory input and depend on feedback cues to maintain control, situation awareness and performance. This paper will explore the redundancy of advanced RDS and their impact on remote operators' driving experience and performance.

Remote driving, however, presents its own challenges. The two most significant challenges are latency for signal transmission and the lack of situation awareness [1], [8], [9], [10]. One of the primary sources of latency is the network connection that is used for communication between the vehicle and the RDS. Several studies were conducted to decrease latency, for example by switching from 4G to 5G mobile networks [11], [12], while different design alternatives for the RDS have been also explored depending on their purpose [13]. Missing information about the environment and the absence of feedback from the vehicle in the RDS could further hamper also situation awareness. Remote operators are out-of-the-loop from the conventional driver-vehicle-environment interaction, since they are placed in RDS outside of the vehicle impacting their situation awareness and ability to safely and effectively control the vehicle. Meanwhile, remote driving has proven to increase occupants' motion sickness [14]. During remote control, visual, auditory and motion feedback might be limited or do not exist, but could be required to replicate the conventional driver-vehicle-environment-interaction. However, it is unclear with current research to what extent all the feedback is required, and in which scenarios.

Five main challenges have been identified by using real-life experiment data and interviewing experts [2]: human cognition and perception (workload and presence), lack of physical sensing (motion and steering feedback), video and communication quality, impaired visibility, remote interaction with humans, and lastly lack of sound (auditory feedback). Most of these challenges are related to a source of information that needs to be provided to the remote operator who is out of the loop with the remotely operated AV and the traffic environment surrounding it. This paper will explore the importance of providing the remote operator more feedback from the vehicle and the environment to bring them more in the loop and decrease the gap from the conventional driver-vehicle-environment-interaction. There is the expectation that this will increase the remote operators' driving performance and experience, contributing to the safe and effective remote control of the vehicle.

This paper will focus on evaluating whether motion feedback, while potentially beneficial based on existing simulator studies, is necessary in low-velocity scenarios during real remote driving. The low-velocity scenarios are explored since remote driving is slowly adopted for parking lots, logistic hubs and areas with restricted access including industrial zones. However, if motion feedback is critical this will significantly rise the costs for the remote driving station, hampering the wide and fast adoption of this technology even in such simple use cases. Hence, this paper will prove if motion feedback is redundant through one of the first, to the authors' knowledge, real remote driving human factors experiment about motion feedback.

II. RELATED LITERATURE

A. DRIVING PERFORMANCE AND EXPERIENCE

Remote operators' driving performance and experience optimally should be similar with the one of drivers' during in-vehicle driving. However, it might be significantly different but still safe and effective to help the vehicle overcome the edge cases. Hence, fully capturing driving performance and experience is essential to understand the effectiveness of remote driving and its performance compared to in-vehicle driving. This section explores metrics and evaluations methods needed for the assessment of driving performance and experience. Driving performance metrics are essential for comparing driving conditions and assessing performance of the remote operator. Various metrics have been used in literature to assess driving performance and experience. Combining both types of metrics is essential to advance remote driving technologies, ensuring safe, comfortable, and effective control by remote operators.

As far as driving performance is concerned, mean velocity, maximum velocity and velocity deviation are important metrics that capture the stable vehicle behavior and can be used to investigate the trade off between speed and accuracy during task performance [8], [15], [16]. Smooth longitudinal acceleration and deceleration (i.e., changes in the velocity over time) ensure occupants' comfort [17] and vehicle stability. This is mostly captured by using metrics such as root mean square (RMS) and maximum acceleration and deceleration [8], [15]. For the longitudinal dynamics, the throttle reverse rate (TRR) is also used capturing the frequency of throttle pedal adjustments and indicating velocity modulation [18]. The throttle position is mostly used, but the longitudinal acceleration can replace it since it also illustrates the velocity changes over time. Lateral Control is usually quantified by metrics such as lateral acceleration, lateral deviation, mean lane center position difference (LCPD), and standard deviation LCPD [8], [19]. These are mostly focused on the position of the vehicle.

Meanwhile, steering wheel metrics could also be employed, such as steering wheel reversal rate (SRR, i.e., the frequency of steering wheel adjustments), maximum steering angle, mean steering wheel angle, and RMS of steering wheel position. Steering wheel velocity indicates reaction speed to hazards [8], [19], [20].

While driving performance focuses on objective metrics, driving experience captures driver's subjective perception. The overall driving experience combines immersion and presence, confidence and control, situational awareness and workload. Immersion and telepresence capture the driver's subjective sense of being "in" the driving environment, which is essential to create a realistic driving experience. Immersion and telepresence can be assessed through a questionnaire dedicated for remote driving by Georg et al. [21]. Another important aspect for driving experience is the feeling of confidence and control over the vehicle. Confidence and control refer to the driver's ability to trust their skill and the vehicles responsiveness and its ease of use [22]. Situation Awareness is a person's understanding of what is currently happening [23]. Translated to remote driving, this means that the remote driver fully understands the driving environment of the vehicle. Common methods to measure situation awareness are Situation Awareness Global Assessment Technique (SAGAT) [24] and Situation Awareness Rating Technique (SART) [25]. The advantage of the SART is that it can be conducted after a scenario is completed, in contradiction with the SAGAT, where the scenario is interrupted, thus potentially distorting the measurement. Another crucial metric for driving experience is workload. Workload of remote drivers reflects the mental and physical effort that is required during remote driving. A common method to measure workload is the NASA Task Load Index (NASA-TLX) [26]. The NASA-TLX measures perceived workload across six dimensions: mental demand, physical demand, temporal demand, performance, effort and frustration. This provides an overall assessment of the task difficulty. Furthermore, there are questionnaires designed to capture the overall driving performance with general questions about elements mentioned above [27]. Finally, a comprehensive questionnaire dedicated to remote driving assesses aspects like presence, emotion, and motion sickness, providing a broad view of the driver's experience [28].

B. FEEDBACK

Feedback is a critical element influencing remote operators' driving performance by maintaining their situation awareness and bringing them more in the loop. The types of feedback that are contributing to in-vehicle or simulator driving performance and experience are the visual [12], [29], [30], auditory [31], [32], [33], motion and steering [34], [35] feedback. Inadequate feedback can lead to performance issues [36]. In this work, we will focus on the motion and vibrational feedback.

Based on existing driving simulator studies, motion and vibrational feedback could enhance remote driver's performance [28]. Motion feedback indicates the full transmission of the vehicle motion to the remote operator, while vibrational feedback provides targeted motion cues. Research shows that dynamic seat adjustments, such as tilting based on object proximity, improve control and awareness [37]. Motion feedback can also be optimized using motion-cueing strategies, which are used in simulators to more accurately recreate real-world sensory experiences [38]. Filter-based approaches like the classical, adaptive, optimal filters, and model predictive control (MPC) are commonly used in motion cueing [39]. These methods provide more realistic motion replication within the simulator's mechanical constraints [40]. Meanwhile, they can also mitigate simulator sickness, making the virtual driving experience more comfortable [41]. Casqueiro et al. [42] demonstrated that increasing motion intensity as objects get closer enhances situation awareness. Siegler et al. [43] found that motion cues prevent unrealistic deceleration rates, while Feenstra et al. [44] showed that motion feedback improves vehicle control by reducing the steering wheel reversal rate. These are representative examples that illustrate the impact of motion feedback to driving experience and performance in driving simulators.

Despite the promising results of motion feedback in driving simulator studies, its impact on remote driving performance and experience has not been widely tested in remote driving scenarios with real-life driving [3]. Meanwhile, for the motion feedback to be utilized, a moving base simulator is required increasing the RDS costs significantly. Therefore, it is imperative to examine if motion feedback is redundant for remote operators' driving performance and experience in different scenarios, before concluding and setting the requirements for remote drivers required feedback. This paper will explore this in low speed scenarios.

III. RESEARCH OBJECTIVES AND HYPOTHESES

The primary aim of this research is to investigate the difference in driving performance and experience between in-vehicle driving, remote driving with motion feedback and remote driving without motion feedback during low-velocity tasks, with the objective to assess whether motion feedback is redundant in these scenarios. To achieve this, two main research hypotheses are stated. The first hypothesis corresponds to an analysis from a high-level perspective, covering a complete planned route (H1). While the second hypothesis corresponds to a more detailed analysis, examining the outcomes for specific driving tasks (lane following, obstacle avoidance and braking) (H2).

- **H1 (Effect of motion feedback):** When motion feedback is provided to the remote driving station (RDS), remote operators demonstrate driving performance and experience closer to in-vehicle driving during low-velocity driving scenarios compared to when there is no motion feedback.

It separates into two sub-hypotheses:

- **H1.1 (Driving performance):** Participants show driving performance closer to in-vehicle driving during low-velocity driving scenarios when motion feedback is provided compared to no motion feedback. This is indicated by more stable velocity, smoother accelerations and more controlled steering,
- **H1.2 (Driving experience):** Participants report driving experience closer to in-vehicle driving during low-velocity driving scenarios when motion feedback is provided compared to when there is no motion feedback. This is indicated by the overall driving experience, immersion and telepresence, confidence and control, situation awareness and workload.

The second research objective focuses on determining whether motion feedback influences driving performance in remote driving during specific driving tasks. The following hypothesis is proposed:

- **H2 (Task-specific performance):** When motion feedback is provided, remote operators demonstrate driving performance and experience during specific driving tasks at low-velocity driving scenarios closer to in-vehicle driving compared to when there is no motion feedback. This is indicated by reduced deviation from task-specific reference points and closer to in-vehicle driving performance. The specific driving tasks are lane following, obstacle avoidance, braking and bumps.

IV. METHODS AND MATERIALS

This experimental study investigates the driving performance and experience during a series of driving sessions conducted under three primary conditions: **(a) In-vehicle driving:** Participants control the vehicle directly from inside the vehicle as they would in any other vehicle. **(b) Remote driving condition with motion feedback:** Participants control the vehicle from a Remote Driving Station (RDS), receiving motion feedback through a dynamic platform in addition to the visual and auditory feedback. **(c) Remote driving condition without motion feedback:** Participants operate the vehicle from the RDS without any motion feedback, relying solely on visual and auditory feedback. To mitigate bias resulting from learning effects, the order of conditions is counterbalanced across participants. All possible six sequences of conditions were performed almost equally. The within-subjects design allows for a direct comparison of each participant's performance and experience across different driving conditions. Ethical approval was granted in the Ethics Application with number 4560 by the Human Research Ethics Committee of Delft University of Technology.

A. OVERVIEW EXPERIMENT

The experiment was conducted on a closed test track area. The area is approximately 50m x 20m and is located behind the TU Delft Faculty of Mechanical Engineering at Delft, The Netherlands. The RDS is located inside the Department of Cognitive Robotics B34. Due to the size of the test track, the maximum velocity it limited to 11 km/h during remote driving. To make the conditions comparable, the participants were instructed to adhere to this limitation also during in-vehicle driving. The safety driver was monitoring their velocity and suggested correction if they exceeded the limit. However, during in-vehicle driving it was physically possible to drive faster. A sketched top view of the track is illustrated in Figure 1, as designed to accommodate different tasks.

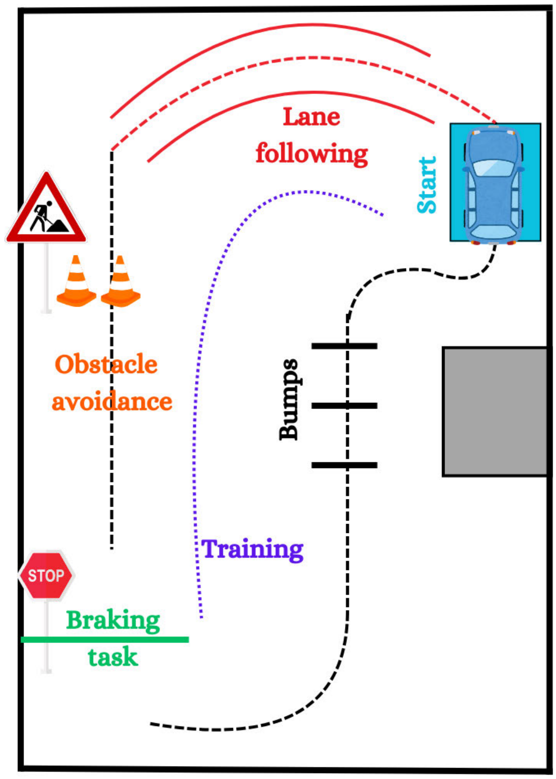


FIGURE 1. Sketch top view of track, with all tasks designed.

B. TASKS

The test track has been modified to accommodate different tasks that the participants have to perform while driving (Figure1). These include lane following, obstacle avoidance, braking and driving over bumps. More specifically, before the start of every condition, the participants were asked to perform a training task. The training path started from braking position and ended at the start, as illustrated with the blue line in Figure 1. Afterwards, the safety driver took over and placed the vehicle on the starting position. This was repeated for each condition for them to get accommodated with the vehicle and the RDS. Then, the participants drove five laps in the test track. However, due to data loss of the fifth lap for some participants, the fourth lap is analyzed for all participants to ensure consistency. Every lap ends with a parking task at the "Start" point (Fig. 1), to ensure that each lap started from the same position. The performance of the training is not recorded. Furthermore, the parking task was affected by the need to reposition the vehicle by the safety driver due to difficulties from the participants to align it properly. Hence, these data were not explored.

The participants were instructed in the beginning to balance velocity and precision with the following statement during the briefing: "Your objective is to complete each task as accurately and as quickly as possible. Please focus on balancing velocity with precision, as your overall performance will be evaluated based on both." Additionally, for each task, the participant was given a definition of successful completion in the briefing prior to the experiment. These are presented below together with the description of each task. **Lane following**: From the starting position, at the parking spot, the first task is lane-following. The lane is marked with continuous red tape on the outer lanes and a dashed line of red tape in the middle. The performance is measured by analyzing the GNSS data, and calculating the distance of the center of the vehicle with respect to the center of the lane. Successful completion: "The center of the vehicle is aligned with the center of the lane as much as possible during the lane-following task". **Obstacle avoidance**: The second task is avoiding an obstacle, which consisted of fences. The performance is measured by analyzing the GNSS data. For the driven path within a specific range of GNSS coordinates, the minimum distances of the vehicle center from the fences are calculated. From these, the maximum value is identified to determine the distance at which the obstacle was passed. Successful completion: "The distance between the side of the vehicle and the obstacle is more than 1.5m". **Braking**: After the obstacle avoidance task, there is a braking task before a stop sign, which was aligned also with a green line. The performance is measured by calculating the vehicle distance from the green line at the moment that the velocity is zero within a specific range of GNSS coordinates. Successful completion: "Stopping at the exact point before the stopping sign and the green line". **Bumps:** The next task is driving over the bumps while keeping the center of the vehicle aligned on the red tapes which are located at the middle of the bumps. The performance of the task is measured by analyzing the IMU data. More specifically, the vertical acceleration is used. Perfect alignment with the red tape would mean that the vehicle passes over the bumps there is no rotational motion in the vehicle. Successful completion: "The center of the vehicle is aligned with the center of the lane as much possible".

C. APPARATUS

The Remote Driving Station (RDS) used for remotely driving is illustrated in Figure 2, together with all the required hardware setup. The left side of the figure depicts the vehicle, which includes all components necessary for remote driving (e.g., cameras, router, microphone and control system). The right side of the figure shows the RDS, consisting of a motion platform, steering wheel, pedals, monitors and a router. In the center of the figure, the signals are exchanged via dedicated software, which will be later described.

The experimental vehicle employed in this study is a 2009 Toyota Prius. This vehicle is equipped with multiple sensors. Eight cameras are mounted onto the roof of the vehicle, providing a 360-degree view of the surroundings. In addition to the cameras, the vehicle is equipped with multiple LiDAR and RADAR sensors and a Global Navigation Satellite System (GNSS). The latter is used for the localization of the vehicle. It also functions as an Inertial Measurement Unit (IMU) that capture translational accelerations and angular velocities. The data from the IMU is sent to the motion platform to provide motion feedback. Vehicle control is facilitated by through the Controller Area Network (CAN) bus.

The RDS is comprised of several components: a motion platform, three high-resolution monitors (curved 32 inch, 60Hz), a steering wheel, pedals, and a racing seat. Each of these elements contributes to creating an immersive and realistic driving experience.

At the heart of the RDS is a 6-degrees-of-freedom (DoF) motion platform manufactured by Gforcefactory.[1] This advanced motion platform allows for dynamic movements that simulate real driving conditions. To facilitate direct control of the vehicle, a Logitech G920 steering wheel and pedals are implemented.[2] For a more realistic steering feel, force feedback is implemented in the form of a spring and auto centering. The steering wheel has a small motor which can generate different types of feedback. This motor can be activated using *ff_effect* from the force feedback framework for Linux.[3] There are six types of options possible, one of them being spring. The center position of the spring is set manually as well as the maximum force to left and right and the spring stiffness in both directions. Within the RDS, auditory feedback is provided to the operator via noise-canceling headphones. The headphones receive the sound from the car captured by a RODE NT-USB Mini microphone[4] which is located directly next to the driver.

A crucial software component is Autoware,[5] an open-source software stack on the Robot Operating System 2 (ROS2). Autoware provides a framework for automated driving applications. The software stack includes all functions that are necessary to drive a vehicle autonomously from localization and object detection to route planning and control. At the same time, it enables a quick switch between automated driving and remote driving. The RDS and the vehicle maintain connectivity through a 5G network, using Hyperpath for low-latency communication. Hyperpath creates a multi-connectivity peer-to-peer mesh VPN (Virtual

[1] Gforcefactory motion simulators | Edge 6D 6DoF Motion Simulation — https://www.gforcefactory.com/edge-6d

[2] Logitech G920 Driving Force — https://www.logitechg.com/de-de/products/driving/driving-force-racing-wheel.html

[3] https://www.kernel.org/doc/Documentation/input/ff.txt

[4] RODE Microphone–https://rode.com/de/microphones/usb/nt-usb-mini

[5] Autoware —https://autoware.org/

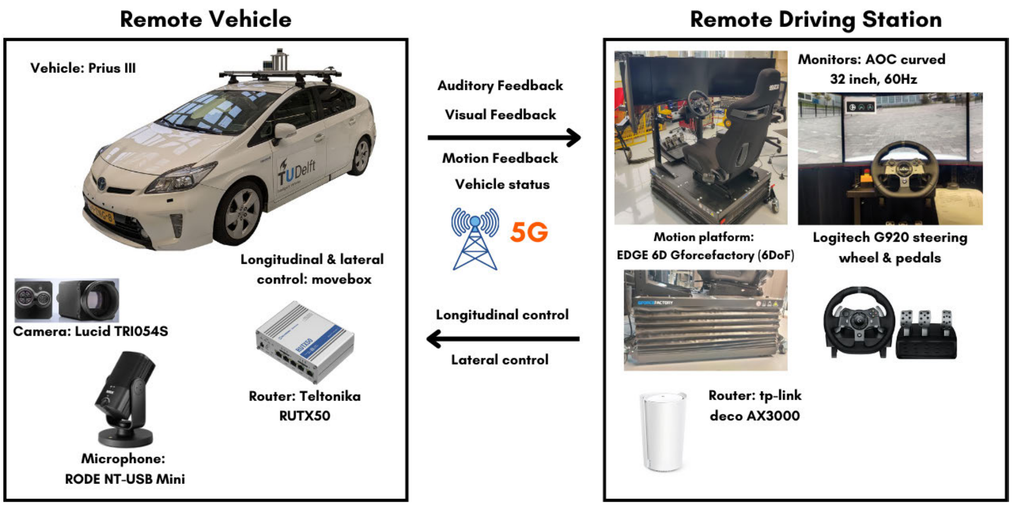


FIGURE 2. Overview hardware setup.

Private Network) between the vehicle and the RDS.[6] The protocol used is the User Datagram Protocol (UDP). For the real-time streaming of the camera footage, WebRTC is used [45]. The round-to-round latency was estimated around 100 - 400 *ms*. A video of the setup is available online.[7]

D. PARTICIPANTS

A total of 20 participants (6 female) was recruited for this experiment (Age: $M = 25.4$, $SD = 2.6$). Participants were recruited from university channels leading to a low standard deviation (i.e., there was less age difference between youngest and oldest). Also, participants were screened based on Motion Sickness Susceptibility Questionnaire (MSSQ) [46], and questions about their driving experience prior to invitation. To avoid confounding effects of MS to driving experience and performance, we excluded those very susceptible (Category E) to motion sickness to secure reliable data collections. This approach also aligns with assumption that future remote drivers will be screened for motion sickness susceptibility before hired. Participants were also asked for their driving experience in years and the kilometers they had driven in the last 12 months. The distribution of driving kilometers is presented in Table 1. Most participants have driven between 2000 and 5000 km within the last 12 months. The initial threshold to exclude people was less than 2000 km. However, for recruitment reasons and to create a more gendered-balanced distribution, some participants with less than 2000 km in the last 12 months were also invited.

E. PROCEDURE

All participants were given a detailed description of the experiment and a written version of the explanation. They were asked to provide written informed consent before participation. Prior to the trials, participants were briefed only on the tasks they had to perform but not what the aim of the study and the motivation was. This was explained in the debriefing after the experiment. Participants received a 10-euro voucher for compensation at the end of the experiment. The total duration of the experiment was approximately 90 minutes.

Every time participants reached the ''Start'' point or the braking task, they were asked about their level of MISC (MIsery SCore). If a participant reached a MISC of six or higher, the experiment would be immediately stopped. No participant reached this limit. At the ''Start'' point, the safety driver repositioned the vehicle, if needed, to be properly aligned and provided again control to the participants. After the completion of a condition, participants filled in several questionnaires using a laptop outside of the RDS. The set included an overall driving experience, a confidence and control, an immersion and telepresence, the Situation Awareness Rating Technique (SART) and the NASA task load index (NASA-TLX) questionnaire. In the condition where motion feedback was provided, a short questionnaire about the motion feedback was also completed. The modified questionnaires can be found in the A.

[6]HyperPath — https://www.hyperpath.ie/
[7]https://www.youtube.com/watch?v=L-vyPfsthSw

TABLE 1. Driving distance last 12 months, distribution by gender.

Distance (km)	0–2000	2000–5000	5000–10000	10000–15000	15000+	Total
Female	2	2	1	0	1	6
Male	1	9	2	1	1	14
Total	3	11	3	1	2	20

F. DEPENDENT VARIABLES

During the experiment, various metrics were recorded to assess both the participants' driving performance and experience under the different conditions. These measures provide insights about the differences of in-vehicle and remote driving under different configurations. For the analysis of the objective data, the data from the fourth lap is used. According to literature, there is a significant deviation in the driving performance and experience after a few laps, where the participants adapt to the driving scenario and remote setup/vehicle [18].

1) DRIVING PERFORMANCE

Objective performance data were continuously collected from the vehicle to evaluate the driving performance. The following performance metrics were recorded: **Velocity:** The velocity of the vehicle was recorded through the embedded sensors in the steer-by-wire control system, providing insights into participants' velocity behavior during different tasks. The mean of the velocity is used as a metric to represent the "stable velocity" of H1.1. **Longitudinal and Lateral acceleration:** The acceleration data were captured using the Inertial Measurement Unit (IMU) from the GNSS. The root mean square (RMS) of the accelerations is used to assess the smoothness of driving maneuvers. Before analysis, a Butterworth filter (cutoff = 2 Hz) and a moving average (window = 20) are applied on the data to filter out the noise from the IMU. This metric aligns with H1.1, reflecting smoother accelerations as an indicator of more controlled driving performance. **Steering wheel position:** The steering input was measured in a range from -1 to 1, representing the extreme steering positions. The RMS of the steering position is used as a metric for assessing steering behavior. This metric relates to H1.1, where more stable and controlled steering behavior indicates improved driving performance.

Additional GNSS data was recorded to calculate metrics that will assess the driving performance for each task: More specifically, the GNSS data is used to calculate the distance between the vehicle's path and the closest reference points. Depending on the task, either the mean, maximum or minimum distance is used as a metric. This metric relates to H2, showing whether motion feedback impacts performance in task-specific performance by affecting deviations from task-specific reference points. For the obstacle avoidance task, the results should be interpreted as followed: ideal passing distance is $2m$ (distance from fence to obstacle) + approximately 1 m (GNSS is located in the center of the vehicle, so half of vehicle width) + 1.5 m required passing distance. This makes the optimal distance in the data set approximately $4.5m$, resulting in a distance of 1.5 m between the obstacle and the vehicle. To assess the performance of the "Bumps" task, the vertical acceleration is measured. Where driving aligned with the middle of the bumps, higher vertical accelerations results will appear. Otherwise, rotational accelerations will appear as well, decreasing the vertical accelerations. Before analysis, a Butterworth filter is applied to filter out the noise from the IMU (cutoff = 5 Hz).

2) DRIVING EXPERIENCE

Subjective measurements were collected to evaluate the participants' overall driving experience, their feeling of immersion and telepresence, confidence and control, workload and situation awareness. These metrics relate to H1.2, assessing whether participants report a driving experience closer to in-vehicle driving with motion feedback. All modified questionnaires can be found in A.

Overall driving experience was measured using a questionnaire based on a questionnaire by Zhao et al. [28]. This metric connects to H1.2, where higher scores indicate that participants perceive a better overall driving experience. The items were answered on a 5-point Likert scale, with poles dependent on the item. **Immersion** was assessed using a questionnaire on immersion and telepresence by Georg et al. [21] This metric supports H1.2, where higher score represent a higher feeling of immersion and telepresence. The items were answered on a 7-point Likert scale (from 1 = "strongly disagree" to 7 = "strongly agree"). **Confidence and control** was measured through a modified version of questionnaire evaluating participants' confidence while driving, vehicle control, and ease of use [22]. This metric relates to H1.2, indicating whether motion feedback increases participants' confidence and control. The items were answered on a 7-point Likert scale (from 1 = "strongly disagree" to 7 = "strongly agree"). **Workload** was evaluated using the NASA Task Load Index (NASA-TLX) [26]. The NASA-TLX consists of different items assessing mental, physical and temporal demand, performance, effort and frustration. The workload is determined as an overall score over all the items. This metric aligns with H1.2, where lower scores indicate a lower workload, which reduces cognitive and physical demands. **Situation Awareness** was measured by the Situation Awareness Rating Technique (SART) [47], with higher scores indicating better situation awareness. The SART questionnaire consists of different items assessing the variability and complexity of the scenario, the alertness, familiarity and focus of the driver, and other. The overall situation awareness is determined as an overall score over all the items. The situation awareness is relevant to H1.2, showing if different remote driving configurations enhances remote drivers' driving experience. An additional questionnaire about the motion feedback was conducted after each condition with motion feedback. All these questions are answered on a 7-point Likert scale (from 1 = "strongly disagree" to 7 = "strongly agree"). This questionnaire contained the following three questions:

- *The motion feedback helps to judge the state of the vehicle.*
- *The driving experience is more realistic when there is motion feedback.*
- *The motion feedback helps in perceiving the road surface.*

G. STATISTICAL ANALYSIS

The primary aim of this study was to investigate whether motion feedback influences driving performance and the remote operator's experience, particularly in low-velocity scenarios, to determine if simplified Remote Driving Systems

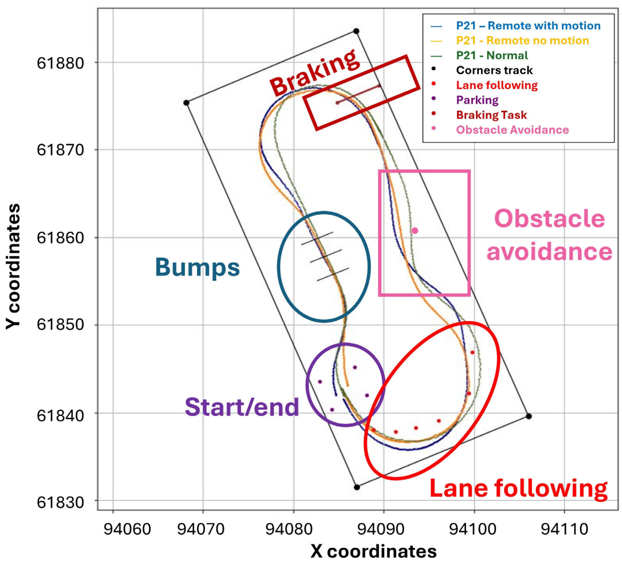


FIGURE 3. GNSS data of one participant, lap 4 of all conditions, including locations of tasks.

(RDS) are sufficient for such scenarios. To evaluate this, the condition where motion feedback is provided is compared with the conditions of in-vehicle driving and remote driving without motion feedback. Because of the non-normal distributed nature of the data, for both the objective and subjective data, a Wilcoxon signed rank test is performed to quantify the significant differences. A Wilcoxon test is a non-parametric pair-wise test that can be used to compare two related groups. As the experiment is a with-in subject study, the groups are related. All the analyses are conducted between two conditions. Therefore, there are three types of analysis: In-vehicle driving vs. remote driving with motion feedback (In-vehicle vs. Motion), In-vehicle driving vs. remote driving without motion feedback (In-vehicle vs. No motion) and remote driving with motion feedback vs. remote driving without motion feedback (Motion vs. No motion).

V. RESULTS

This section presents the findings of the statistical analysis. The results are initially discussed from a high-level perspective, covering the completed planned route, i.e., the full lap (H1). The focus then shifts to a more detailed analysis, examining the outcomes for each driving task (H2). The driven path, by only one participant for clarity in the figure, together with the tasks designed as points, is illustrated in Figure 3.

A. DRIVING PERFORMANCE (H1.1)

For the analysis of hypothesis H1.1, the objective data from the fourth lap is used. As described in Section IV-G, a Wilcoxon signed rank test is performed. The analysis has been conducted between the experimental conditions. The results of the Wilcoxon tests for the significant findings are illustrated in Table 2.

TABLE 2. Comparison of conditions per metric.

Comparison	Velocity	Steering pos.	Long. acc.	Lat. acc.
In-vehicle vs. Motion	$W = 0.0$ $p < 0.001$	$W = 31.0$ $p = 0.004$	$W = 0.0$ $p < 0.001$	$W = 0.0$ $p < 0.001$
In-vehicle vs. No Motion	$W = 0.0$ $p < 0.001$	$W = 28.0$ $p = 0.003$	$W = 1.0$ $p < 0.001$	$W = 0.0$ $p < 0.001$
Motion vs. No Motion	$W = 100.0$ $p = 0.869$	$W = 101.0$ $p = 0.898$	$W = 77.0$ $p = 0.312$	$W = 62.0$ $p = 0.114$

TABLE 3. Mean and standard deviation of metrics measured for H1.1.

Condition	Velocity		Steering pos.		Long. acc.		Lat. acc.	
	M	SD	M	SD	M	SD	M	SD
Motion	3.858	0.756	0.302	0.028	0.201	0.043	0.296	0.063
No motion	3.884	0.678	0.303	0.018	0.207	0.044	0.312	0.060
In-vehicle	6.297	0.559	0.286	0.009	0.274	0.046	0.529	0.078

Note. Velocity = mean velocity (km/h), Steering pos. = RMS steering position ($-$), Long. acc. = RMS longitudinal acceleration (m/s^2), Lat. acc. = RMS lateral acceleration (m/s^2).

The values measured for the dependent variables velocity, steering position, longitudinal and lateral acceleration were significantly higher ($p < 0.004$) in both conditions of remote driving (motion/no motion feedback) compared with in-vehicle driving. No significant difference was identified between the remote driving conditions (motion/no motion feedback) for any of the metrics stated above. The mean values and standard deviation of the metrics are presented in Table 3. Mean values in all the metrics are similar across conditions with less than 4% differences between conditions. At the same time, despite the lack of significant differences, the standard deviations between no motion and motion illustrate differences ranging from 10-35%. This is higher in the steering position, which is four times more than the one of the in-vehicle condition. To investigate the learning effect over the conditions, an additional analysis is performed. The effect of the order, in which the conditions were performed, illustrates no significant difference between the orders.

B. DRIVING EXPERIENCE (H1.2)

To assess the driving experience, participants responded to multiple questionnaires after every condition. All items can be found in A.

1) OVERALL DRIVING EXPERIENCE

The questionnaire about overall driving experience contains seven items. In the remote driving condition with motion feedback, participants scored their ability to sense the road surface significantly higher ($W = 66$, $p = 0.034$) compared to remote driving without motion feedback. For the comparison between in-vehicle driving and both remote driving conditions, all items were significantly higher for in-vehicle driving (for all items: $p < 0.03$). The analysis per item can be found in E. The results of these questionnaire are shown per item in Figure 4. Figure 4 presents the overall driving experience questionnaire per item in the form of boxplots. Item 4a (Overall assessment) reveals a significantly higher median for in-vehicle driving compared to the remote driving conditions. While the medians for both remote conditions are comparable, the standard deviation for the no-motion condition is notably larger, reflecting greater variability among participants. Items 4b, 4d, and 4e exhibit significantly higher medians for in-vehicle driving as well. Although the medians for the two remote driving conditions are similar, the motion condition shows a larger standard deviation, suggesting larger variability. A similar trend in the median is observed for Item 4f (Predictability of velocity). For Item 4c (Attention), the median remains consistent across all conditions. However, the standard deviation in the motion condition exceeds the mean, while it remains below the mean for in-vehicle driving. Lastly, Item 4g (Road surface perception) highlights a significant increase in the median for the motion condition compared to the no-motion condition. The standard deviation, however, is larger in the no-motion condition, indicating higher variability in participant responses.

2) IMMERSION AND TELEPRESENCE

Participants reported significantly higher on all items in in-vehicle driving compared to both remote driving scenarios (for all items: $p < 0.001$). The analysis per item can be found in E. Between the two remote driving conditions, no significant differences have been found. **Confidence and control:** The questionnaire on confidence and control revealed significantly higher ratings for in-vehicle driving compared to both remote driving conditions (for all items: $p < 0.001$, E for individual analysis). **NASA-TLX:** For the NASA-TLX, a final workload score was calculated for each conditions (Table 4). Participants reported significantly lower workload for in-vehicle driving compared to both remote driving conditions $W_{motion} = 0.0$, $W_{nomotion} = 3.5$, $p_{both} < 0.001$). No significant differences were found between remote driving with and without motion feedback. **SART:** The SART questionnaire provided a final situation awareness score for each condition (Table 4). Participants rated their situation awareness significantly higher in the in-vehicle driving condition compared to both remote driving conditions ($W_{motion} = 192$, $W_{nomotion} = 196$, $p_{both} < 0.001$). Between both remote driving conditions, no significant differences were found.

For the motion-feedback questionnaire, participants scored the items on a 7-point Likert scale (minimum value: 1, maximum value: 7). The mean and standard deviation of the results are shown in Table 4 per item, together with the mean and standard deviation for the NASA-TLX and the SART. The SART scores reveal a notable difference between the in-vehicle driving condition and the remote driving conditions, with mean scores more than 30% higher for in-vehicle driving. Standard deviations remain consistent across conditions. For the NASA-TLX, the means of both remote driving conditions (motion/no motion) are approximately 70% (more than 80% for motion) higher compared to in-vehicle driving. The standard deviations for the NASA-TLX are the largest in the remote driving with motion feedback, reflecting a greater variability in task load.

TABLE 4. Scores from Questionnaires per Condition (SART, NASA-TLX, and Motion Feedback Questionnaire).

Condition	SART		NASA-TLX		MF_1		MF_2		MF_3	
	M	SD	M	SD	M	SD	M	SD	M	SD
Motion	16.59	6.19	60.8	18.11	4.9	1.56	5.6	1.07	5.55	1.56
No motion	16.30	6.11	55.15	13.42	-	-	-	-	-	-
In-vehicle	24.23	6.42	32.55	12.46	-	-	-	-	-	-

Note. SART = Situation Awareness Rating Technique; NASA-TLX = NASA Task Load Index; MF_1,2,3 = Motion Feedback Item 1,2, and 3; M = mean; SD = standard deviation. All items can be found in .

TABLE 5. Mean and standard deviation of metrics measured for H2.

Condition	Lane follow		Obstacle		Braking		Bumps	
	M	SD	M	SD	M	SD	M	SD
Motion	1.674	0.612	4.843	0.510	5.143	0.692	0.426	0.076
No motion	1.706	0.537	5.043	0.737	5.231	0.706	0.445	0.074
In-vehicle	1.538	0.502	4.561	0.470	4.624	0.461	0.567	0.074

Note. Lane follow: distance (m), Obstacle avoidance: distance (m), Braking: distance (m), Bumps: vertical acceleration (m/s^2).

C. TASK-ORIENTATED PERFORMANCE (H2)

As described earlier in this paper, every task has been assigned a definition of successful completion. To measure the performance, the GNSS data is used to calculate the distance. The raw GNSS data from one participant is illustrated in Figure 3, as well as the locations of the tasks. The shadowed area, is the area used to calculate the obstacle avoidance as explained to Section IV-F. The evaluation of the performance is done per task. The mean and standard deviation of all tasks are shown in Table 5, while they are also illustrated in Figure 5 as boxplots.

The mean values for the lane following, obstacle avoidance and braking tasks show small differences across the conditions, with less than a 10% variation in most metrics. The vertical acceleration during the bumps shows a larger difference (>20%), with the in-vehicle driving condition showing a higher mean value compared to the motion and no motion conditions.

The results of the statistical analysis are presented in Table 6. The analysis of the lane-following task revealed no significant difference in the average distance from the center line between in-vehicle driving and both of the remote driving conditions. In contrast, the obstacle avoidance task, which was evaluated using the maximum distance that the car deviated from the reference line, showed a significantly smaller distance to the obstacle in in-vehicle driving compared to both remote driving conditions. For the braking task, significant differences in performance were observed, with participants stopping at a greater distance from the stopping line during both remote driving conditions compared to in-vehicle driving. Finally, in the bumps task, the vertical accelerations were significantly higher during the in-vehicle driving condition. No statistically significant

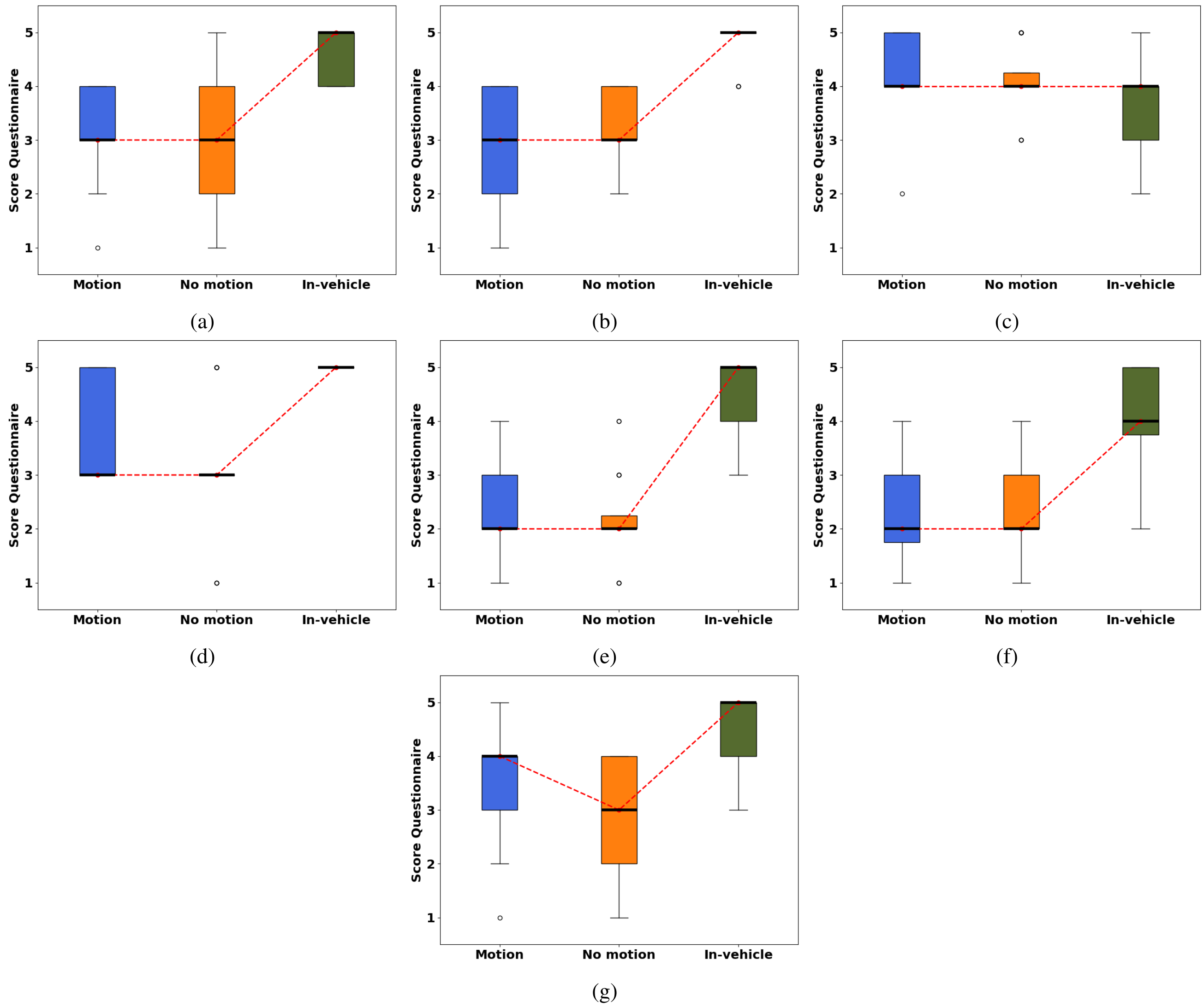


FIGURE 4. Distribution of overall driving experience questionnaire (a) Overall assessment, (b) Realistic, (c) Attention, (d) Presence, (e) Sense of Velocity, (f) Predict Velocity, (g) Road Surface, for three conditions: Motion (blue), No Motion (orange), and In-vehicle (green). Each box represents the inter-quartile range (IQR), with the thicker horizontal line indicating the median. Whiskers extend to the data points within 1.5 times the IQR, data points beyond this represent outliers. Likert scale ranges from 1–5.All items in A.

TABLE 6. Statistical analysis for task-orientated performance across conditions.

Comparison	Lane follow	Obstacle	Braking	Bumps
In-vehicle vs. Motion	$W = 74.0$ $p = 0.261$	$W = 49.0$ $p = 0.036$	$W = 37.0$ $p = 0.009$	$W = 9.0$ $p < 0.001$
In-vehicle vs. No Motion	$W = 64.0$ $p = 0.132$	$W = 32.0$ $p = 0.005$	$W = 25.0$ $p = 0.002$	$W = 4.0$ $p < 0.001$
Motion vs. No Motion	$W = 97.0$ $p = 0.784$	$W = 79.0$ $p = 0.349$	$W = 97.0$ $p = 0.784$	$W = 70.0$ $p = 0.202$

Note. Tasks: lane follow, obstacle avoidance, braking and bumps.

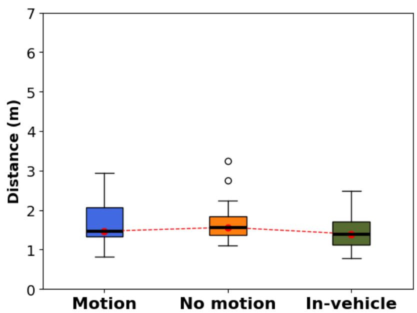
differences were observed between the two remote driving conditions in any of the tasks.

VI. DISCUSSION

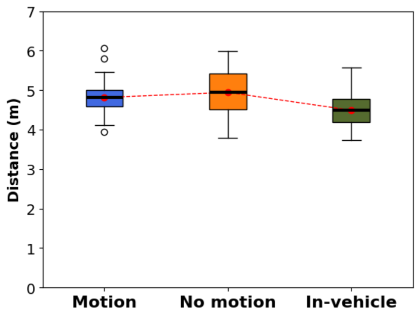
This study aimed to assess how much motion feedback affects remote driving performance and experience, and whether it is redundant information during low-velocity tasks. The results are initially discussed from a high-level perspective, covering the full lap (H1). The focus then shifts to a more detailed analysis, examining the outcomes for each specific task (H2).

A. RESULTS ON H1.1 (DRIVING PERFORMANCE)

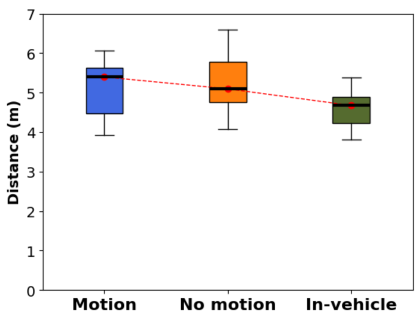
The results show that motion feedback had no significant effect on performance metrics like mean velocity, RMS of the steering position, and RMS of the longitudinal and lateral accelerations, between the two remote driving conditions. This indicates the redundancy of the motion feedback in low speed scenarios. However, significant differences were observed between in-vehicle and remote driving conditions for all these metrics, indicating that remote driving performance lags behind in-vehicle performance, regardless of additional feedback or not. However, this did not cause any safety concerns during the experiment. In remote driving, the velocity was significantly lower compared to in-vehicle



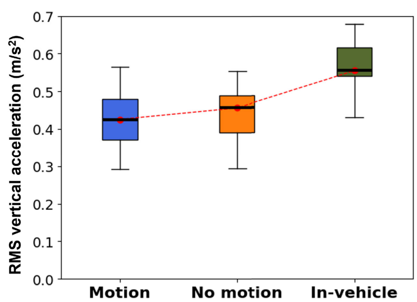
(a) Distance (m) to center of lane in lane following task.



(b) Distance (m) in the obstacle avoidance task.



(c) Distance (m) to stopping line in braking task.



(d) RMS vertical acceleration (m/s^2) during bumps.

FIGURE 5. Distribution of performance per task for three conditions: Motion: blue, No Motion: orange, In-vehicle: green. Each box represents the inter-quartile range (IQR), with the thicker horizontal line indicating the median. Whiskers extend to the data points within 1.5 times the IQR, data points beyond this represent outliers. Likert scale ranges from 1–7.

driving. This is consistent with findings in prior studies like Zhao et al. [18] who observed similar behavior among remote drivers. The study also showed a higher steering reversal rate in remote driving, which is also in line the with higher RMS of the steering position found in our study. There is a two-stage mechanism in adapting to a driving simulator, where participants first made a mental effort to better control their steering actions, before seeking to be more precise and stable. This is aligned with research on adaptation of perceptual-motor tasks [48], [49], [50].

For RMS of both the longitudinal and lateral accelerations there is no significant difference between the two remote driving conditions. However, the longitudinal and lateral accelerations are significantly higher during in-vehicle driving compared to remote driving. While lower RMS longitudinal acceleration values may indicate a smoother and more comfortable driving style, this difference is likely due to the large difference in mean velocity. The limited space and the requirement to brake at specific points could have led to higher accelerations in the higher velocities during in-vehicle condition. Higher velocities produce greater changes in accelerations over time, resulting in higher RMS values even if the underlying acceleration patterns are similar. Thus, the increased accelerations observed in in-vehicle driving can be explained by the higher mean velocity, rather than reflecting any difference in driving performance.

These findings do not support the hypothesis (H1.1) that motion feedback brings remote operator more in the loop increasing their driving performance closer to in-vehicle driving, as no significant findings were observed between the two remote conditions. This suggests that motion feedback is redundant information in low speed scenarios, meanwhile this needs to be tested further for higher speed scenarios. It could be possible that motion feedback is not enough to bridge the gap in-vehicle and remote driving in other scenarios. However, this has not been tested in real-life driving, rather than some simulator studies indicated that the combination of auditory and motion feedback improved driving performance in simulator [28].

B. RESULTS ON H1.2 (DRIVING EXPERIENCE)

The analysis of subjective data contributes to our understanding of how driving experience is affected in different remote driving conditions. Regarding the overall driving performance, the results clearly indicate significant difference in all items when comparing in-vehicle driving to both remote driving conditions. This highlights a critical finding: the driving experience in remote driving is not on par with that of in-vehicle driving, while the lack of motion feedback in remote driving is not associated with worse driving experience.

Regarding the immersion and telepresence, despite the importance of vibrations on the feeling of presence [51], [52], this was not captured between the motion and no motion condition. Furthermore, all items were significantly lower in both remote driving conditions compared to in-vehicle driving. The longitudinal perception was rated significantly higher than the lateral perception in both remote driving conditions, while no such difference was observed in in-vehicle driving. This could be related probably with the visual feedback and its transmission to the RDS during sustained cornering. Hence, the focused improvement of the lateral perception could play a crucial role in decreasing the gap between remote and in-vehicle driving. Potential measures to enhance lateral perception include improved motion cueing for sustained lateral accelerations during cornering or advanced visual feedback systems which can provide smooth visual transmission during cornering. Regarding confidence and control of the vehicle, the participants reported higher confidence and control in in-vehicle driving than in both remote driving conditions. Included items in this questionnaire are: " I had good control over the vehicle" and " I felt confident in my ability to drive the vehicle". The results of these items reported better control over the vehicle and more confidence to drive it in in-vehicle driving. Realistic feedback in the pedals and steering wheel could improve the feeling of confidence and control and reduce the gap to in-vehicle driving. However, Papaioannou et al. [14] illustrated that confidence and control in remote driving was related with perceived safety aspects, rather than steering wheel characteristics (feedback support, communication, the level of feedback forces, and returnability). Therefore, training of the remote operators and their adaptation [53] to the system interaction could increase their confidence and control.

Regarding workload, the results indicate an increase in workload during both remote driving conditions compared to in-vehicle driving. This could be related to multiple explanations. One of these could be that there was a lack of synchronization between different modalities. Some participants also reported this during the experiment. Additionally, the detachment from the environment in remote driving conditions can play a role. This detachment leads to a decoupling of the perception from the actual environment, resulting in a limited representation of the vehicles surroundings [54]. Meanwhile, significant cognitive resources are allocated to transferring the previously acquired driving skills to a driving simulator [55], such as the RDS, or mentally fill the gaps due to delays. This increases the workload even further. Between the two remote driving conditions, there is no significant difference, which implies that the motion feedback did not alter the workload, and the challenges are similar in both cases. Regarding situation awareness, the results indicate significant difference between in-vehicle driving and both remote driving conditions. Higher situation awareness in in-vehicle driving can be explained on the different levels of situation awareness by Endsley (perception of the elements in the environment, comprehension of the current situation and projection of the future status) [56]. Firstly, at level of perception of elements in the environment, during in-vehicle driving, drivers have direct access to all the sensory information of the environment. This is in contrast with remote driving where the perception is limited by the representation of the environment. Secondly, at the level of comprehension or understanding of the situation, in in-vehicle driving it is easier and more intuitive to understand relationships between elements in the environment. The adaptation to driving simulators requires time and individuals differ widely in the time they need to adapt [53]. In remote driving, a delay or misaligned in information can make this more difficult. Lastly, the deficits on the other two levels also cause a reduction at the level of projection of future status, making it more difficult for remote driver to predict the evolvement of situations. Regarding the motion feedback, the positive perception of it, indicates that drivers recognize its potential benefits, even if these do not directly translate into measurable performance improvements in the context of this study. This confirms the findings from Li et al. [57], who investigated the remote drivers' perception, needs and requirements when remotely operating a level 4 AV using a teleoperation system in the real world. Findings of the study show that remote drivers would like to have enhanced physical feedback to overcome one of the biggest difficulties while driving remotely.

In summary, while participants reported a positive attitude towards driving experience with motion feedback, the overall results do not support the hypothesis (H1.2). The findings indicate that motion feedback might be redundant and does not bring the remote driving experience closer to in-vehicle driving, as significant gaps remain in driving performance, overall driving experience, immersion, confidence, workload and situation awareness between the two conditions.

C. RESULTS ON H2 (TASK-ORIENTATED PERFORMANCE)

The results show no significant differences between any of the conditions for the lane-following task. Similar performance compared to in-vehicle driving during lane-following could suggest that the overall perception of the remote operator is good with the guidance of the outer lanes. However, this might also be due to the much lower velocities at which the task is completed during remote driving.

An in-depth analysis of the raw GNSS data revealed a pattern where most participants tended to position themselves more to the right rather than staying in the center of the lane, as requested during the task description. This behavior may be explained by a tendency for drivers to control the vehicle position based on the outer lanes. The presence of road markings effects the lateral lane position, since drivers tend to focus on the Tangent Point (TP), i.e., a point on the inner side of the lane, where the driver's gaze direction becomes tangential with the lane edge [58], [59]. In their effort to remain within their designated lane (on the driver's side, left), they often overcompensated, resulting in a shift towards the right instead of keeping the vehicle in the center of the lane.

Regarding the obstacle avoidance task, there is a significant difference in performance between in-vehicle driving and both remote driving conditions. As explained in the methods, the optimal total passing distance would be approximately 4.5 m. The in-vehicle performance is significantly better,

TABLE 7. Results of statistical analysis with Wilcoxon for the questionnaires about immersion and telepresence, confidence and control and overall driving experience.

Question	Motion vs. Normal		No Motion vs. Normal		Motion vs. No Motion	
	W	p	W	p	W	p
IMM_01	210	< 0.001	210	< 0.001	44	0.942
IMM_02	171	< 0.001	210	< 0.001	60.5	1
IMM_03	210	< 0.001	171	< 0.001	42.5	0.317
IMM_04	210	< 0.001	210	< 0.001	63	0.882
IMM_05	210	< 0.001	210	< 0.001	60	0.437
IMM_06	210	< 0.001	210	< 0.001	108	0.310
IMM_07	187	< 0.001	190	< 0.001	85.5	0.131
IMM_08	210	< 0.001	171	< 0.001	40	0.258
IMM_09	120	< 0.001	190	< 0.001	56	0.835
IMM_10	210	< 0.001	190	< 0.001	25	0.496
C&C_1	190	< 0.001	210	< 0.001	53.5	0.451
C&C_2	210	< 0.001	210	< 0.001	29	0.449
C&C_3	210	< 0.001	190	< 0.001	39.5	0.685
C&C_4	3	< 0.001	8.5	< 0.001	36.5	0.375
C&C_5	12	0.001	13.5	0.001	36	0.830
ODE_1	190	< 0.001	171	< 0.001	42	0.830
ODE_2	190	< 0.001	190	< 0.001	8	0.080
ODE_3	14	0.005	13	0.024	28	0.152
ODE_4	105	< 0.001	136	< 0.001	35	0.110
ODE_5	190	< 0.001	190	< 0.001	37	0.331
ODE_6	205.5	< 0.001	179.5	< 0.001	25	0.824
ODE_7	124	0.003	153	< 0.001	66	0.034

Note. IMM_X = Immersion and telepresence questionnaire, C&C_X = Confidence and control questionnaire, ODE_X = Overall driving experience questionnaire. X represents the number of the item that can be found in .

showing less deviation from this reference line. However, the more conservative strategy of keeping greater distances to the obstacle in the remote driving conditions could be related to two aspects. First, participants applied more caution and took less risks with regards to passing the obstacle in remote driving as they might have lacked confidence and a sense of control. Second, the limited lateral perception, as illustrated by the driving experience questionnaire, may have prompted them to keep a greater distance to the obstacle. Thus, remote driving can be considered inferior to in-vehicle driving regarding the assessment of distances to objects in order to avoid them. The braking task did show significant differences in performance, with participants stopping further from the designated stopping line during remote driving compared to in-vehicle driving. This suggests that the remote drivers' perception of longitudinal distance was compromised, likely due to the camera view's location and perspective. This shows the importance of camera positioning and the need for visual feedback that supports accurate depth perception when designing remote driving systems.

The findings presented in this section do not confirm the hypothesis (H2) that motion feedback significantly enhances task-specific driving performance and decreases the gap to in-vehicle driving, as no notable improvements were observed.

D. LIMITATIONS

This study faced limitations that may have affected the findings. The first limitation is the latency in the system. This is one of the biggest challenges in remote driving and can cause a delay in the control of the vehicle. The main source of the latency is the connectivity between the vehicle and the RDS. The lack of a stable connection also causes inconsistencies in the video quality, which might have affected the results by distorting the isolated impact of motion feedback on the findings. In addition, the control system of the vehicle adds an extra delay in case of erratic steering behavior. Another limitation is the physical limitations of the workspace of the motion platform, constraining its ability to fully replicate real-world motions in all conditions, specifically under longer continuous maneuvers in the same direction. Meanwhile, these results were only explored for low-velocity scenarios and there might be differences in medium- and high-velocity scenarios with other road users also involved. Hence, our findings might be system and scenario specific, and further research is required to generalize them to other scenarios, particularly those at higher speeds, and different systems.

VII. CONCLUSION

This study evaluated the impact of motion feedback on remote driving performance and experience compared to in-vehicle driving performance and experience during low-velocity scenarios. The aim of the study was to determine whether additional motion feedback is redundant in such scenarios, decrease the design costs for the RDS. The results demonstrate that while remote driving performance and experience are significantly worse than in-vehicle driving, the inclusion of motion feedback does not lead to measurable improvements in either performance or experience in remote driving. The findings suggest that motion feedback, in its current form, may not be necessary for low-velocity scenarios. This supports that a simplified Remote Driving Station (RDS) without motion feedback could suffice for these scenarios, leading to significant decrease of the cost for the remote driving station. This can allow the wider and faster adoption of remote driving in low-velocity scenarios (e.g., parking lots, logistics hubs, areas with restricted access and industrial zones, etc.). Additionally the results also show that there is still a big gap between remote driving and in-vehicle driving. Remaining challenges include: reduced situation awareness, impaired depth perception and increased workload. This highlights the need for more comprehensive research towards remote driving from both a technical and human factors perspective.

APPENDIX
QUESTIONNAIRES
A. OVERALL DRIVING EXPERIENCE

1) What was your overall assessment of your driving experience? (5-point: very bad - very good).
2) Did the driving feel realistic? (5-point: very unrealistic - very realistic).
3) How much attention did you pay to your driving? (5-point: no attention - full attention).
4) How present did you feel in the environment you drove in? (3-point: not there - fully there).
5) How well did you sense the vehicle speed? (5-point: very bad - very good).
6) How well did you predict the vehicle speed? (5-point: very bad - very good).
7) How well did you sense and recognize the road surface? (5-point: very bad - very good).

B. IMMERSION AND TELEPRESENCE

All items in this questionnaire were answered on a 7-point Likert scale, from: 1 = "strongly disagree" to 7 = "strongly agree".

1) My perception of the lateral distances was always good.
2) My perception of the longitudinal distances was always good.
3) I always trusted the system.
4) The vehicle reacted immediately to my commands.
5) My interaction with the environment was always natural.
6) The interaction feels realistic.
7) I always had a good overview of the environment.
8) I was able to handle the system from the beginning very well.
9) The control method was intuitive, and I could always focus on the driving task.
10) I was always in full control over the vehicle.

C. CONFIDENCE AND CONTROL

All items in this questionnaire were answered on a 7-point Likert scale, from: 1 = "strongly disagree" to 7 = "strongly agree".

1) I had good control over the vehicle.
2) I felt confident in my ability to drive the vehicle safely.
3) I was comfortable driving the vehicle.
4) Driving the for a long distance would make me tired.
5) I had to apply a lot of physical effort to get the vehicle to go where I wanted.

D. MOTION FEEDBACK QUESTIONNAIRE

All items in this questionnaire were answered on a 7-point Likert scale, from: 1 = "strongly disagree" to 7 = "strongly agree".

1) The motion feedback helps judge the state of the vehicle.
2) The driving experience is more realistic when there is motion feedback.
3) The motion helps in perceiving the road surface.

E. STATISTICAL ANALYSIS OF SUBJECTIVE DATA

The complete results of our statistical analysis on the subjective data are presented in Table 7.

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