Exploring the Learning Rate of Remote Drivers: A Simulator-Based Study with Realistic Feedback and Delays

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Abstract. Remote driving is emerging as an important backup for automated vehicles, yet the adaptation process and learning rate of remote drivers remain unexplored. In this study, we present a simulator-based experiment designed to evaluate how drivers adapt to remote driving environments characterized by realistic delays and feedback. The experiment employs a high-fidelity driving simulator that replicates real-world remote driving conditions—including motion cueing, steering force, and auditory feedback—while introducing controlled driving feedback delays. Participants navigate a dynamic scenario incorporating changing curvature roads, slalom manoeuvres, lane changes, and parking tasks over 10 training rounds. Both objective performance metrics (e.g., time consumption, lane following deviation, velocity, lateral acceleration) and subjective assessments (e.g., trust, controllability, familiarity, workload) are collected and analysed using repeated measures ANOVA. Results indicate that drivers rapidly adapt to the remote driving environment, achieving stable familiarity and reduced mental workload within the first 4-5 rounds. These findings provide valuable insights for designing effective training protocols and improving remote control tower systems.

Keywords: Teleoperation, learning rate, driver training, driving feedback, remote driver, remote driving learning.

1 Introduction

Automated vehicles have significant progress in research and commercialization in these years, as seen with companies like Waymo in the US [1] and Apollo Go in China [2]. Nevertheless, Remote Control Towers (RCTs) with remote driving capabilities remain essential when automated systems face limitations [3]. Remote driving introduces challenges, such as reduced situational awareness and increased latency, that can compromise performance [4].

Researchers start addressing these issues by enhancing situational awareness [5], reducing latency [6], and developing remote driving assistance systems [7]. However, remote drivers continue to be critical for traffic safety, especially under delayed and low-sensory conditions. While traditional driving training, including traditional vehicles [8] and simulator studies [9, 10], has proven vital for safety. Few studies have examined how remote drivers adapt under these specific constraints. This gap underscores the need to explore the learning process of remote drivers.

Different from traditional driving, remote driving relies on video feeds instead of direct observation, alters auditory and acceleration cues, and suffers from delayed signal transmission [11]. These factors fundamentally change the driving experience and likely affect learning outcomes, including familiarity, performance, training experience, and time efficiency. To investigate these aspects, we conducted a virtual remote driving training experiment using a simulator that replicates real-world delays and provides motion cueing, auditory, and steering force feedback to enhance realism [12].

The main contributions of this study are threefold: (1) assessing the learning rate of remote drivers from various dimensions, such as time consumption and driving velocity, to determine the optimal number of training rounds before formal testing; (2) evaluating the mental and physical workload of remote drivers during training; and (3) examining the effect of training rounds on drivers' subjective learning experiences, including trust and perceived controllability. Detailed results are presented in Section IV.

The remainder of the paper is organized as follows: Section II describes the experimental setup, Section III presents the results and discussion, and Section IV concludes the study.

2 Experimental Setup

2.1 Hardware setup

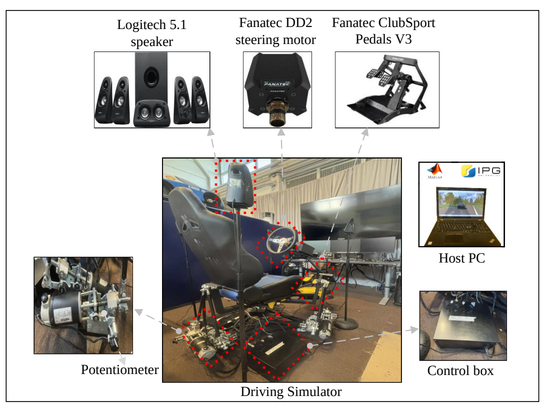

Fig. 1: Experimental platform.

Fig. 1 illustrates the driving simulator's hardware configuration, which replicates a remote driving environment by providing steering force, motion cueing, and auditory feedback. In the virtual remote driving experiment, a 6-DoF Stewart test rig from DoF Reality serves as the driving feedback platform. A ThinkPad workstation with a Core i9 processor runs Matlab/Simulink and IPG CarMaker to simulate the dynamic states of the remote driving vehicle (RDV), while the "Real-time synchronization" block in Simulink ensures the environment runs in real time. Moreover, due to the restricted movement range of the motion platform, the yaw rate and roll rate signals are scaled to 37.5% and 80% of their original values, respectively.

Two delay setups are employed: one uses the baseline delay of the driving simulator, and the other mimics real remote driving delays. Specifically, the visual and auditory render delays are set to 130 ms (with a baseline of around 100 ms), while an extra 200 ms is added to the motion cueing feedback to account for signal transmission and vehicle reaction delays (with a baseline of around 130 ms). Additionally, a single-trip transmission delay of 30 ms simulates the time required for sending driving commands (e.g., steering angle) from the RCT to the vehicle and receiving vehicle state feedback (e.g., yaw rate, pitch rate) back to the RCT. These delays are implemented using the Transport Delay block in Matlab/Simulink, integrated with IPG CarMaker.

2.2 Scenario design

A dynamic scenario (Fig. 2) is designed to evaluate drivers' adaptation and learning rates. The scenario begins with a high-curvature road that transitions into a lower-curvature path, followed by a Slalom maneuver that requires participants to avoid cones, a double lane change maneuver demanding precise control, and concludes with a parking task. Each participant completed 10 rounds of the scenario and provided subjective ratings through a questionnaire after each round, while driving behavior data, including steering angle and throttle engagement are recorded for analysis.

Participants received the following instructions before the test: drive as if it are your own vehicle; maintain the car in the center of the lane during normal driving, near the cones during the slalom but not hit them, and centered between the cones during the lane change; adhere to a maximum speed of 50 km/h; stop in the center of the designated cone box during the parking task; drive quickly yet safely while remaining under the speed limit; and note that successful performance of the task would be rewarded. In order to remind them during training, these notes are also displayed on the boards on the side of the road.

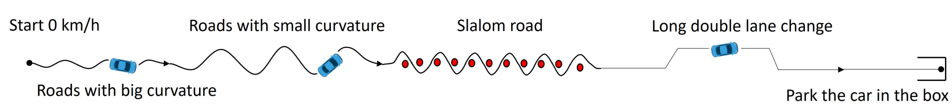

Fig. 2: Driving scenario design.

2.3 Questionnaire design

To address the research objective of investigating how drivers adapt to remote driving, a written questionnaire is compiled (Table I). Various aspects closely related to the research questions, such as trust, motion sickness, controllability, delay perception, and familiarity, are explored using a five-point Likert scale for ratings. In addition, the standard NASA TLX questionnaire is employed to assess the workload of drivers in each round.

2.4 Experimental protocol

The participants are first briefed on the research background related to remote driving. They are then introduced to the driving simulator setup and the driving scenario, while the specific research questions are withheld. Following this, participants are instructed to complete 10 rounds of driving, with an immediate

Table 1: Subjective Assessment Questionnaire.

Trust	1. If this would be a teleoperated car, how much do you trust your ability to drive safely? 1————2—————3————4—————5 Very low trust - Low trust - Neutral - High trust - Very high trust
Motion sickness	2. How strong is your motion sickness, such as nausea, dizziness, discomfort or disorientation? 1————2—————3————4—————5 Not at all - Slightly - Moderately - Strong - Very strong
Controllability	3. How would you rate your level of control over the vehicle? 1————2—————3————4—————5 Very poor - Poor — Neutral —- Good - Excellent
Delay perception	4. How much delay did you perceive during driving? 1————-2—————3————4—————5 Not at all - Small - Neutral —- Big - Very big
Familiarity	5. How familiar are you with the driving, including the scenario, car, and other driving setup? 1————-2—————3————4—————5 Very unfamiliar - Unfamiliar - Neutral —Familiar - Very familiar

questionnaire rating after each round. To mitigate the risk of motion sickness from prolonged simulator use, a short break is provided after the first 5 rounds.

A total of 16 participants take part in the experiment, coming from diverse backgrounds, including PC gaming and racing game experiences. All participants hold a valid passenger car driving license. Among them, 9 participants reported more than 10 hours of PC gaming per week, while 6 participants had over 5 hours of racing game experience per week. Additionally, 86.7% of the participants drive more than 100 km per month in average.

3 Results and discussion

To assess the adaptation and learning rate of remote drivers, both subjective and objective evaluation methods are applied. Specifically, the study examins the following aspects:

1. **Adaptation rate:** The time taken and driving speed in each round are analysed to explore how drivers adapt to the scenario and the driving simulator.
2. **Performance assessment:** Measures such as lane following deviation and the vehicle dynamic index a_y are evaluated to determine the participants' learning progress.
3. **Learning Experience:** Subjective factors, including trust, controllability, and familiarity, are assessed to understand the psychological change of the drivers as the increase of the learning time.
4. **Workload assessment:** Changes in the mental and physical workload of participants are assessed to explore how their demands evolve with increased exposure.

Boxplots are generated to illustrate the outcomes for key metrics, as shown in Fig. 3. In these plots, the mean values are indicated by black squares, with a dashed line connecting them to reveal overall trends. The median is marked by a central black line, while outliers are denoted by a red "+" marker. In addition, the green scatters show the data points for each participant. A larger scatter size indicates that more data points are located at that value, and the number of points is displayed at the center of the scatter

The data analysis begin with the computation of basic descriptive statistics, including the mean value, to highlight primary trends within the dataset. Subsequently, the Statistics Toolbox in Matlab (2020b) is utilized for further analysis. A one-way repeated measures analysis of variance (ANOVA) is conducted to examine the significance among the different feedback modes. Outliers for each round are identified by calculating the 25th and 75th percentiles to determine the interquartile range (IQR); any value falling below Q1 - 1.5×IQR or above Q3 + 1.5×IQR is considered an outlier. The related F and p values are reported in the subsequent section.

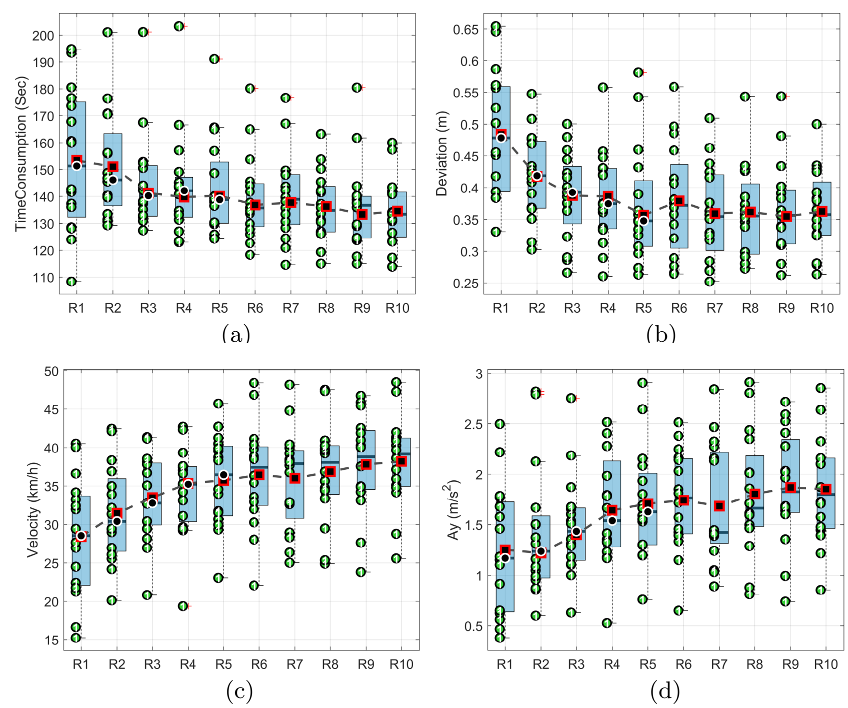

Fig. 3: (a). Time consumption; (b). Lane following deviation; (c). Velocity; (d). Lateral acceleration.

3.1 Driving behaviour analysis

Fig. 3 presents objective data results of driving behavior during the training process, including time consumption, lane-following deviation, RMS velocity and lateral acceleration in the Slalom. Time consumption serves as an index of how quickly drivers adapt to the task. As shown in Fig. 3(a), there is a significant difference across rounds ($F(9, 149) = 3.77, p < 0.001$). The mean time consumption decreases rapidly from 153.4 s in Round 1 to 139.7 s in Round 4, and then more gradually from 139.7 s to 134.5 s by Round 10. This suggests that drivers adapt quickly during the first four rounds, with a slower rate of improvement thereafter, which is likely due to growing familiarity with the driving scenario.

Fig. 3(b) and (c) display the rms value of lane-following deviation ($F(9, 148) = 4.51, p < 0.001$) and Slalom velocity ($F(9, 149) = 3.77, p < 0.001$), respectively.

Lane-following deviation decreases from 0.48 m to 0.36 m in the first five rounds, with minor fluctuations from Round 5, indicating that lane-keeping performance stabilizes after about five rounds of training. In contrast, Slalom velocity continues to increase from Round 1 to Round 10, albeit at a slower rate after Round 5, suggesting that complex maneuvers (e.g., Slalom) require a longer learning period and thus leave more room for performance improvement over time. The lateral acceleration ($Fig.\ 3(d), F(9, 147) = 3.05, p < 0.01$) follows a similar trend to Slalom velocity, since higher speeds under the same maneuver usually lead to larger lateral acceleration.

3.2 Driving experience assessment

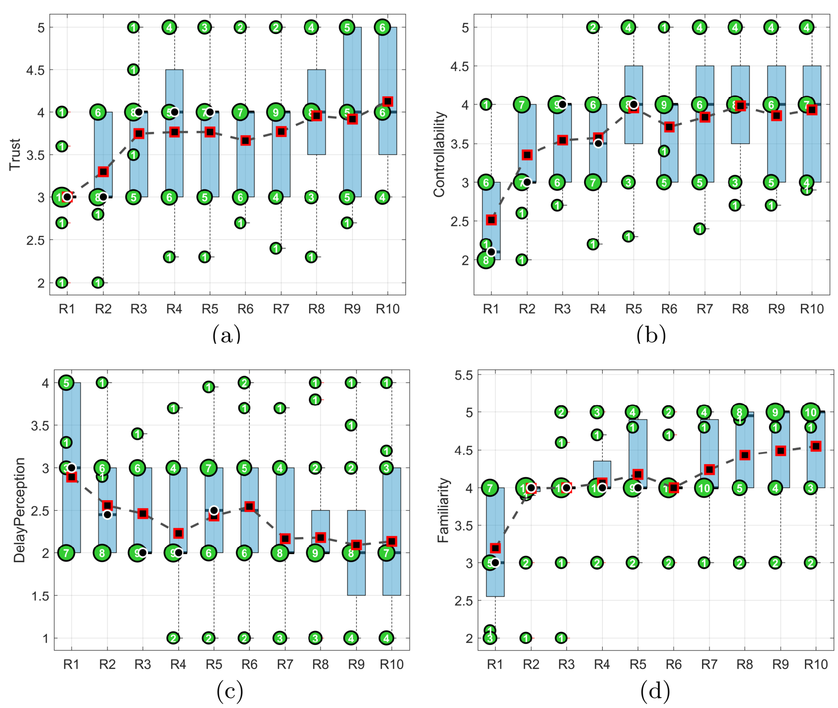

Fig. 4: (a). Trust; (b). Controllability; (c). Delay perception; (d). Familiarity.

Figs. 4 and 5 present subjective ratings of driving experience related to remote driving across various dimensions, including trust, delay perception, and mental workload, etc. Figs. 4(a) and (b) show the drivers' ratings for trust ($F(9, 146) = 2.71$, $p < 0.01$) and controllability ($F(9, 150) = 5.87$, $p < 0.001$), respectively. Both indexes exhibit a similar trend: drivers report slightly lower trust and poorer controllability in the initial round, likely due to unfamiliarity with the scenario and the driving simulator. However, ratings increase sharply in the second and third rounds. The phenomenon is also observed for perceived familiarity in Fig. 4(d) ($F(9, 132) = 6.91$, $p < 0.001$). Thereafter, mean ratings remain relatively stable, although some participants reported the highest levels of trust and familiarity in rounds 9 and 10, indicating that drivers tend to develop higher trust and familiarity with remote driving with more training rounds.

In contrast, delay perception (Fig. 4(c)) shows only a slightly higher rating in the first round compared to subsequent rounds, which may be attributed to initial perceptual errors due to unfamiliarity. ANOVA results reveal no statistically significant differences in delay perception across rounds ($F(9, 145) = 1.64$, $p = 0.1$).

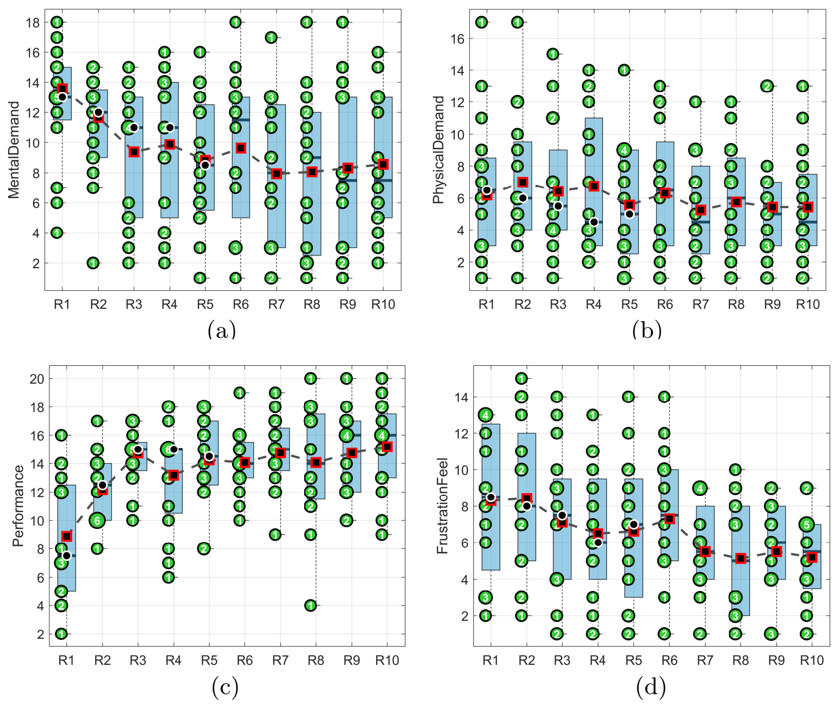

Fig. 5: (a). Mental demand; (b). Physical demand; (c). Self-performance assessment; (d). Frustration feel assessment.

Fig. 5 presents assessments of driving workload based on the NASA TLX questionnaire. Figs. 5(a) and (b) display mental and physical workload, respectively. For mental workload ($F(9, 150) = 1.56$, $p = 0.13$), the mean value of the ratings decrease rapidly from 13.57 to 9.38 in the first three rounds, indicating that drivers' initially high mental workload becomes considerably lower after three rounds of training. Thereafter, the ratings remain low and stable. In contrast, physical workload ($F(9, 149) = 0.40$, $p = 0.93$) shows no significant changes throughout the training process. This may be due to the fact that driving does not require significant physical exertion.

Fig. 5(c) presents self-assessed performance levels ($F(9, 149) = 5.61$, $p < 0.001$). Drivers report a sharp performance improvement in the first three rounds, with ratings increasing from 8.85 to 15, which mirrors the inverse trend observed for mental workload. Subsequently, performance ratings continue to increase slightly. Finally, Fig. 5(d) shows that frustration decreases gradually from 8.5 in Round 1 to 5.2 in Round 10 ($F(9, 150) = 1.92$, $p = 0.05$). A slight increase in frustration in Round 6 may be attributed to a short break after five rounds of driving, but frustration levels decline again in the subsequent rounds.

4 Conclusions

In this paper, a simulator-based remote driving experiment is conducted to investigate how remote drivers adapt to driving. Both objective driving behaviour and subjective learning experience are studied separately. Firstly, the objective results indicate that although the learning process continues after 10 rounds of training, the learning rate in the last 5 rounds is much lower than in the first 5 rounds. This suggests that drivers could almost adapted to the driving task after 5 rounds, although increased familiarity continues to enhance their performance. Secondly, regarding subjective learning experience, participants developed relatively high levels of trust, controllability, and familiarity after just 3 rounds of training; however, these perceptions are further enhanced after 8 rounds. Thirdly, the findings show that drivers achieved mental adaptation to remote driving after 4 rounds of training under the given scenario and setup.

A limitation of this study is that the experiment is conducted in a driving simulator rather than in a real-life remote driving environment due to the cold weather in Sweden. Nevertheless, we aimed to replicate real-life remote driving conditions by matching the delay and driving feedback. Additionally, only one female participated in this study. In the future, we plan to conduct real-life experiments with a more balanced gender representation.

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Informed consent: Informed consent is obtained from all individual participants included in the study.

Ethical approval: All procedures performed in studies involving human participants are in accordance with the ethical standards of the national research committee (Etikprövningsnämnden Dnr: 2020-05020) and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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