Investigating Remote Driving over the LTE Network

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ABSTRACT
Remote driving brings human operators with sophisticated perceptual and cognitive skills into an over-the-network control loop, with the hope of addressing the challenging aspects of vehicular autonomy based exclusively on artificial intelligence (AI). This paper studies the human behavior in a remote driving setup, i.e., how human remote drivers perform and assess their workload under the state-of-the-art network conditions. To explore this, we build a scaled remote driving prototype and conduct a controlled human study with varying network delays based on current commercial LTE network technology. The study demonstrates that remote driving over LTE is not immediately feasible, primarily caused by network delay variability rather than delay magnitude. In addition, our findings indicate that the negative effects of remote driving over LTE can be mitigated by a video frame arrangement strategy that regulates delay magnitude to achieve a smoother display.

Author Keywords
Remote driving; feedback delay; human-vehicle interaction.

CCS Concepts
•Human-centered computing → Empirical studies in HCI;
•Computer systems organization → External interfaces for robotics;

INTRODUCTION
Beyond the development of fully autonomous vehicles based on AI [14, 22], many research efforts focus on unmanned driving through teleoperation. This process is referred to here as "remote driving", where a human remote driver indirectly perceives the vehicle's environment or controls the vehicle through telecommunication networks. Several automobile companies and research institutes have built remotely driven cars and some of them are targeted to be controlled from miles away [4, 21, 29], for driving on real roads [20, 6, 29, 15]. It is argued that remote driving reduces the equipment investment required by fully computerized autonomy [32, 4, 15]. More importantly, computerized driving environment perception and path planning correspond to daunting AI tasks, which may cause failures in fully autonomous systems [5, 16]. Including a human in the control loop increases reliability and effectiveness when dealing with complex situations [4, 6, 15].

There is some research in remote driving system aspects, such as mechanical control [4, 20] and path planning [27, 26], but less on the visual display aspect. Existing work in this area mainly focuses on the presentation and augmentation of each frame that is received from the remotely driven vehicle [9, 25, 24, 41]. Nevertheless, the arrangement of the frames, i.e., the timestamps of presenting the delayed frames, is largely ignored. Since the magnitude and the pattern (e.g., variable or stable) of the feedback delay influence remote human driver's driving performance [40, 11, 37], properly arranging the frames in the timeline is a key point in the display design of remote driving systems under the current network condition.

In this paper, remote driving human behaviors *under the state-of-the-art commercial network condition (i.e., LTE)* are studied. Since the feedback delay over LTE networks is a random variable, we investigate two visual information display arrangement strategies: (i) presenting display frames to a remote driver as soon as the frames arrive to minimize the delay magnitude, or (ii) smoothing the display by adding additional delay when necessary to the received frame to mitigate the delay variance, i.e., postponing each frame with the max possible delay. Specifically, we build a remote driving platform and use it to quantitatively study human drivers' performance and their self-reported workload assessment of remote driving under various delays based on LTE networks. The results demonstrate that the major challenge that causes the degradation of the remote driver's driving performance is the variability of feedback delay. Moreover, the second visual information display arrangement strategy, i.e., eliminating the delay variance of the display frames by adding additional delay, mitigates the negative effect of feedback delay incurred by LTE networks.

RELATED WORK
Prior studies have revealed that human's remote driving performances are strongly dependent on the magnitude and variance of the feedback delay [8]. Small constant delays (e.g. $<$170 ms) are found to have mild influences on the remote driving performance [8], while driving performances are substantially affected when the delay exceeds 700 ms [12]. In particular, when the delays go beyond one second, the effective real-time interactions through teleoperation are largely restricted [40]. These findings are also confirmed by the model recently built between driving performance degradation and constant time delay [42]. Variable delays are believed to have a worse im-

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(a) RC Car (b) Remote Control Station (c) Test Track

Figure 1. Remote driving prototype and test track.

pact on the driving performance than constant delays [34, 12]. However, prior studies only compared the variable delay and the constant delay of the same magnitude [34, 12]. Moreover, depending on various variability patterns, small variances (<=0.5) have controversial effects on the teleoperation performance (i.e., significant impact in [12] but insignificant in [34]). While prior studies choose delay values subjectively, our study tests human's remote driving performances based on the delay learned from real LTE network measurements. More importantly, our study compares the remote driving performance under variable delays to that under constant but longer delays, implying that a UI design that mitigates delay variance at the expense of increased magnitude reduces the challenges perceived by the remote driver.

Display interface design is an important research issue for remote driving. Prior studies have looked into the field of view (FoV) [20], the augmentation of display frames, e.g. including the safety zoom [41] or the prediction of vehicle position [9, 25, 12] in the display scene, and the incorporation of virtual reality interface [24]. Nevertheless, these studies focus on the form or the content displayed in each frame, without touching the frame arrangement problem studied in this paper.

HUMAN PERFORMANCE AND PERCEPTION STUDY

In this section, we conduct controlled experiments in which participants control a scaled remote driving prototype in a lab environment. The network delay is manually controlled to simulate the measured delay in the LTE network.

Prototype System

For a more realistic driving perception, we put together a 1/10 scale car as our basic experiment platform (shown in Figure 1(a)) as opposed to utilizing driving simulators. Inspired by the ABR project [36], the speed and steering of the car are controlled by an IOIO micro-controller board, which accepts the remote driving commands. An Android smartphone works as the on-board Internet access point, connecting to a remote driving station via cellular networks or WiFi. Three cameras are mounted on the scaled car, where one front-facing camera and two side cameras represent the front windshield view and side mirrors of a real car, respectively. Each camera provides an 85-degree horizontal and 70-degree vertical FoV.

The remote driving station is built on a commodity computer with 8GB memory and an Intel i7-3520 dual-core processor. It consists of three monitors (arrangement shown in Fig.1(b)). The video caught by the front-facing on-board camera is displayed on a 24-inch monitor with a 178-degree horizontal/vertical FoV. The video frames from the two side cameras are connected to two 17-inch monitors that have a 170-degree horizontal and 160-degree vertical FoV. Based on video frames displayed on the monitors, a remote driver controls the car using a Logitech G27 racing wheel controller.

In the lab environment, we connect the driving station and the car to a private TP-Link N600 router using an Ethernet cable and WiFi, respectively. To emulate various network settings, the routing rules were manipulated such that the packets between the remote control station and the remotely driven car must first go through a WANem [2] virtual machine, where various additional delays can be inserted.

Emulate LTE Network

The network communication incurs additional feedback delays, which cause the performance degradation of remote driving. Based on prior studies, a local Internet (i.e., distance < 1000 mile) can provide at least 4 Mbps bandwidth and less than 16 ms RTT (Round Trip Time) [35]. Moreover, LTE wireless networks cover over 99.4% of the U.S. population in 2014 [19], providing around 16.02 Mbps download and 7.43 Mbps upload bandwidth [38, 28] with the mean RTT ranging from 75 ms to 83 ms [18]. Based on the statistics, remote driving over regional Internet and LTE networks could expect a network delay of 100 ms for video transmission in 720p quality (based on the frame bit rate of Youtube [1]).

To simulate remote driving under the LTE network, we also collected real data in a field test, modeled the data and generated the random delays. During the field test, the remote driving prototype was mounted on a real car that traveled around a university campus for 22 miles. While traveling, the prototype continuously captured 240p video frames and transmitted them to the remote driving station over a tier 1 LTE network. Each frame was about 10 kB and was sent using UDP. Upon receiving each frame, the server immediately replied with an ACK message to measure the RTT at the remote driving prototype. The measured RTT values ranged from 56 ms to 358 ms, with the mean value and standard deviation of 97.73 ms and 47.47 ms, respectively. Based on the test results and the empirical study of NetEm in [30], we found that a Pareto distribution with the mean value of 95 ms and jitter of 55 ms in WANem best modeled the delay in LTE.

Participants and Procedure

We recruited eleven volunteers, aged 21 to 36 (median 28) to participate in the experiment. Participants were asked to operate the remote driving prototype and drive through a scaled test track (shown in Figure 1(c)). The test track was built to simulate a 400-meter lap with the speed limit of 30 km/h and the standard 3.6-meter lane width (as suggested by US Federal Highway Administration). To match the 1/10 scaled car, the test track and speed limit were accordingly scaled down by 10 times. Note that the curves were considerably sharper than regular streets: the radius of each curve was 3/4 of the safety value suggested by the American Association of State Highway and Transportation Officials [3] in the left half of the track and 1/2 in the right half track; no straight sections were included to reduce the length of the course.

Before the experiments, participants were trained to drive the prototype until they reported that they were familiar with the device. During the experiments, they iterated among the no-delay setting, the simulated LTE setting (random-delay), and the max-delay setting in a random order and in each setting they drove five laps. The max-delay setting used a constant delay of 358 ms, the highest value observed in our field test. Note that, the random-delay setting corresponds to presenting the frames as soon as they are received. In contrast, the max-delay setting essentially corresponds to postponing the presentation of each video frame by the max possible delay compared to the frame's capture timestamp to smooth the display. Assuming the received frames are marked with their timestamps, the max-delay arrangement can always be realized even if the frame's arrival time at the remote driving station is affected by the random network latency. The no-delay experiment is included as the baseline (the oracle case).

Participants were notified before the experiments that both the time elapsed per lap and the number of cross-lane errors would be recorded to evaluate their performances but staying within the lane should be their first priority. While driving, participants perceived the driving environment only through the video stream and the range finder readings (i.e., distance to obstacles) and they were not told of the value of the delay. After each experiment, participants were required to submit a subjective questionnaire using the NASA Task Loading Index [23], reporting their self-perceived workload in six dimensions, including mental demand, physical demand, temporal demand, performance, effort, and frustration. They were also instructed that the workload of real driving should be used as the baseline with score 10 in each dimension.

Results

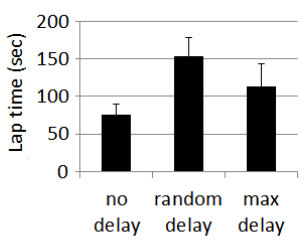

Figure 2. Mean and standard deviation of lap time.

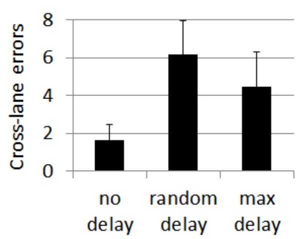

Figure 3. Mean and standard deviation of cross-lane errors.

Fig. 2 and Fig. 3 illustrate the mean and standard deviation of the time taken per lap and that of the number of cross-lane errors per lap under different experiment settings. Repeated measures ANOVA shows significant differences between the three experiments in both the time taken per lap ($F_{2,20} = 65.28, p < 0.0001$) and the number of errors per lap ($F_{2,20} = 60.59, p < 0.0001$). The result from the no-delay experiment is the best among the three experiments. However, variable delays cast enormous difficulty on remote driving: The random-delay experiment shows doubled average time and tripled cross-lane errors comparing to the no-delay experiment. In the max-delay experiment, where the magnitude of the delay is over two times higher than the mean value of random delay, the average lap time and cross-lane errors are only 1.5 times and 2 times as high as the values from the no-delay experiment, respectively. The significant differences in the

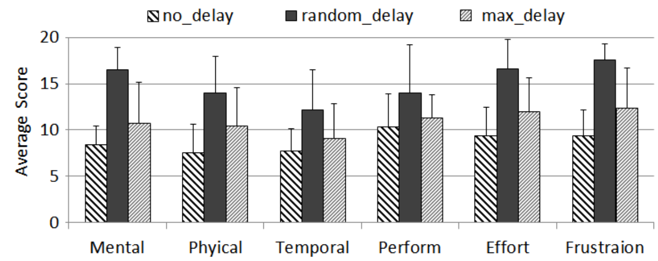

Figure 4. Mean and standard deviation of self-reported workload in different experiments.

overall effect under various settings are also consolidated by the pairwise comparison results (presented in Table 1).

Fig. 4 illustrates the self-reported workload of remote driving under different delay conditions. Repeated measures ANOVA shows that three experiments have significant differences on participants' mental ($F_{2,20} = 41.18, p < 0.0001$), physical ($F_{2,20} = 15.52, p < 0.0001$), temporal ($F_{2,20} = 8.86, p = 0.0018$), effort requirements ($F_{2,20} = 24.54, p < 0.001$) and incurred frustration ($F_{2,20} = 36.56, p < 0.0001$). These five dimensions follow the same pattern: the no-delay experiment is the least demanding, followed by the max-delay experiment, and finally the random-delay experiment is the hardest. In particular, the difficulty of remote driving in a simulated LTE environment is almost two times as hard as driving without network delays in the mental, physical, effort and frustration dimensions. Interestingly, for the self-rated performance, the repeated measures are marginally significant ($F_{2,20} = 3.24, p = 0.0604$). Post hoc analysis on the pairwise comparison consolidates the overall effect results (shown in Table 1): while the random-delay experiment is significantly or near-significantly different from the no-delay experiment ($p = 0.0238$) and the max-delay experiment ($p = 0.0816$) in self-rated performance, the max-delay experiment has no significant differences from the no-delay experiment ($p = 0.5478$).

We conduct a post hoc power analysis for the overall effect using G*power [17] and find that the power ranges from 94.6% to 99.5% ($\alpha = 0.05$) for all measurements except for the self-reported performance (power = 47.0%).

DISCUSSION

Feasibility and the Major Barrier The results show that pure remote driving is still questionable over the current network if no compensations are added to deal with the delay. While remote driving with no-delay shows moderate demands in driver's mental, physical, temporal, effort, and frustration, the demands in all these dimensions are substantially boosted in the random-delay experiment. The performance measured by the lap travel time and the cross-lane error also demonstrate large degradations caused by the random delay.

Comparing the results from the random-delay experiment and the max-delay experiment, we believe that it is the variability of the network delay rather than the magnitude that primarily cause the performance degradation. Even though the max delay is over three times as high as the mean of random delays, when participants are confronted with not the max delay but

Pairwise comparison	Lap time	Cross-lane errors	Mental	Physical	Temporal	Performance	Effort	Frustration
no delay vs. random delay	-77.8	-4.5	-8.0	-6.5	-4.5	-3.6	-7.2	-8.2
no delay vs. max delay	-37.9	-2.7	-2.3	-2.9	-1.4†	-0.9§	-2.6	-3.0
random delay vs. max delay	39.9	1.8	5.7	3.5	3.1	2.7‡	4.5	5.2

Note: All estimates have $p < 0.05$ except for values labeled by †(p=0.2231), §(p=0.5478) and ‡(p=0.0816).

Table 1. Pairwise differences of least squares means for various measurements.

the random delay, they are uncertain "whether their driving commands have taken effect" and "where the car really is compared to what is seen through the video". Moreover, it is only reported under random delay that some of the participants tend to be irritated or start to adapt a stop-and-go pattern to control the car, which according to prior work happens only when the constant delay exceeds one second [8, 10].

Human Adaptation A particularly interesting observation is found in the max-delay experiment: although both the lap driving time and the cross-lane errors increase, the self-reported performance and temporal requirement are not significantly different from that in the no-delay experiment. By looking into the time cost and errors committed per lap, we find that participants' driving time first increases and then decreases, while the cross-lane errors keep dropping. This is because most drivers conceive that "remote driving in the max-delay experiment is as easy as in the no-delay experiment by just viewing the video". Consequently, they drive fast in the beginning laps but make much more errors than their expectation. After they recognize this, the self-adaptation initiates and the participants finally can finish a lap with only slightly longer time and a little increased cross-lane error count, compared to the no-delay experiment. As a result, participants are satisfied with their performance. Self-adaptation incurs increased self-reported workload. However, in most dimensions, the demand is slightly higher than the baseline (i.e., no-delay). In contrast, in the random-delay experiment, though participants try even harder to adapt to the varying delay, they still cannot manage the remote diving to a satisfactory level at last. Therefore, all six dimensions have increased value in the self-report survey. Moreover, the driving time and the cross-lane error count are high in all laps in the random-delay experiment.

Display Frame Arrangement for Remote Driving While pure teleoperation relying on real-time feedback (e.g., video) is not ready over the current network, there is high potential if proper visual information display arrangement techniques are applied. In the max-delay experiment, we completely eliminate the delay variability by shifting every video frame using the largest possible delay. This method significantly improves both the driving performance and the demands to the remote driver. Based on the latest network research, e.g., [33, 7], there is a high potential that the realtime network delay can be predicted. Since previous studies suggest that reducing frame rate has weaker negative impacts on vehicle teleoperation [8, 13], we can design smarter frame arrangement algorithms by balancing the magnitude and the variability of network delay in LTE networks. The new method is likely to achieve even more benefits than the method we use in the max-delay experiment. The suggested arrangement method can also be combined with other methods, such as predictive displays [12, 39] and adding semi-autonomy [31], to improve the user experience of remote driving. However, compared with predictive display and adding autonomy, our method works in the signal processing level and does not need to deal with complex computer vision and path planning problems. Thus it is easier to implement.

Limitations In the current study, we use a scaled car as the testing platform, which may have different driving perceptions than a full-size car. Moreover, due to the space limitation on the scaled car, we implement the remote driving platform with simple hardware, e.g. cameras with limited FoV. We acknowledge that both above factors may affect the participants' driving performance during the experiment. However, since all three settings are conducted using the same platform, we believe the comparison results regarding the two visual information display arrangement strategies still hold when remotely driving a real car. We plan to validate and extend the findings using real autonomous cars on real road settings.

CONCLUSION AND FUTURE WORK

This paper conducts a human study to evaluate two visual information display arrangement strategies, through which a driver remotely controls a car via indirect vision over LTE networks. The result shows that the immediate feasibility of remote driving over LTE is hindered primarily by the high variability of the network delay. Two main implications for future remote driving systems are drawn from the result: (i) Properly trading off the timeliness (i.e. increasing delay of some frame) or frame rate while achieving a smooth driving environment perception may work as a compensation method in the signal processing level, in parallel with other high-level compensation methods. (ii) While reducing the absolute network delay is useful, enabling stable and predictive delay under LTE networks has even higher priority for remote driving systems.

For future work, we plan to conduct multiple test runs to assess the learning effect and study the human reactions when introducing sudden incidents from the varying network latency setups. In addition, the trade-off function between the delay magnitude and variability will also be explored to direct the UI design in future remote driving systems.

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