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Demonstration of a Virtual Reality Driving Simulation Platform

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Abstract

A virtual reality (VR) driving simulation platform has been built for use in addressing multiple research interests. This platform is a VR 3D engine (Unity ©) that provides an immersive driving experience viewed in an HTC Vive © head-mounted display (HMD). To test this platform, we designed a virtual driving scenario based on a real tunnel used by Törnros to perform on-road tests [1] . Data from the platform, including driving speed and lateral lane position, was compared the published on-road tests. The correspondence between the driving simulation and on-road tests is assessed to demonstrate the ability of our platform as a research tool. In addition, the drivers' eye movement data, such as 3D gaze point of regard (POR), will be collected during the test with an Tobii © eye-tracker integrated in the HMD. The data set will be analyzed offline and examined for correlations with driving behaviors in future study.

Introduction

Autonomous driving is rapidly expanding in the auto industry. The advantages brought by self-driving vehicles may positively impact the daily life of humans by relieving traffic jams, reducing travel time, and preventing accidents [2]. The current driverless approaches are based on machine learning from a variety of sensors. Although these approaches are the great deal toward achieving the ultimate goal, a couple of potential issues exist. First, the autonomous driving core, which comprises the environment-perceiving sensors and machine-learning algorithms, require actual driving mileage for training purposes. However, on-road tests present public safety concerns [3]. Second, data collected by sensors is not as efficient as an alert human driver because sensor arrays on autonomous vehicles tend to sample large portions of the visual field uniformly for processing [4]. In contrast, humans have high acuity vision only in a small, central region of vision known as the fovea. Despite that constraint, intelligent gaze behavior supports safe driving over long distances. So, perhaps autonomous vehicles could be more efficient in their information processing if they leveraged human-inspired algorithms to determine where and when to sample the visual environment. Therefore, we believe a driving simulation platform balances the need to collect data on human drivers with the ethical concerns inherent in collecting data during real-world driving [5][6][7][8][9]. Integration of an eye-tracker in the platform will allow exploration of the interaction between human perception and autonomous driving.

Driving simulation software has existed in the market for some time. In our previous study of driving simulation, we utilized commercial driving simulation software [10]. But, we found that limitations in commercial simulation software applications can be significant. First, the license of software is typically based on an annual subscription mode. The subscription cost can be high, making it unaffordable for many researchers. Second, compatible driving hardware is constrained by the commercial software. Using the recommended hardware may be required to ensure compatibility, but this sometimes leads to a situation in which the hardware lacks functionality that is critical for a particular study. Third, many commercial software products can not be customized for a specific research need. The result is that researchers are often constrained by the existing resources. Finally, the latest technologies, such as VR and eye-tracking, are not supported by most of the commercial simulation software [11].

VR is an important technology because it can offer an immersive and more realistic experience that helps to simulate the actual driving experience in the laboratory [12]. VR also avoids the calibration issue that exists screen-based simulators caused by the layout of displays, which can lead to motion sickness in participants [10].

Motivated by these requirements and opportunities, our goal was to prototype a driving simulator platform with the following benefits: 1) low-cost and affordable software and hardware environment; 2) modular and customizable structure; and 3) VR and eye-tracking support. To fulfill these goals, we developed an immersive VR driving simulation platform. "Immersion" and "realism" are hard to quantify. We define realism by the degree to which the simulation is realistic enough to support natural driving behavior. To test the realism of the simulator, we compare the behavior of drivers on a closed real-world driving track, as reported by Törnros [1], with the behavior of drivers in our driving simulator as they navigate a 3D model approximation of the roadway used in the published experiment. Dependent variables include speed control and lateral lane position. In addition, eye movement data, including 3D gaze point of regard (POR), of human drivers during the test is collected by the integrated eye-tracker. These PORs will form the data set of fixation points that will allow exploration of how fixation is assisting human drivers in maintaining speed and lateral position in the future.

This paper is structured by the following sections: Experimental Methods, which describes the instrument, experimental scene, participants, and experimental procedure; Results, which provides the data analysis and discussion; Conclusion and Future Work, which summarizes the study.

Experimental Methods

Instrument

The VR platform is mainly constituted by the components illustrated in Figure 1: 1) Unity 3D engine software [13], 2) HTC Vive Pro Eye with integrated Tobii Eye Tracking © [14], and 3) Logitech G920 steering wheel and pedals [15]. The Unity 3D engine is free for personal and academic use to create virtual scenes. Its system structure not only has powerful built-in functionality but also supports modular plugins or APIs. Unity considers each plugin as an individual functionality carrier, making it highly flexible and accessible to achieve the research goals via plugins. The Unity Store is equipped with thousands of free and price-friendly plugins that are available to be integrated into the platform [13]. The HTC Vive Head Mounted Display (HMD) displays the VR content and coordinates with the Tobii eye tracker. This HMD is 1440 by 1600 pixels per eye. It has 110 degrees field of view and 90 Hz refresh rate. The integrated Tobii eye tracker provides 3D PORs that can be used to identify eye events such as fixations, saccades, and VOR. More specifically, this eye-tracker outputs gaze data with 120Hz frequency and 0.5 to 1.1 degree of accuracy [14]. The Logitech G920 steering system includes a steering wheel with 540 degrees lock-to-lock, and force-adjustable braking and gas pedals. In addition, our platform adopted a gaming PC with the configuration of an i7 3.5GHz CPU, a Nvidia GTX 980 video card, a 32GB ram, and a 1TB SSD. Although this video card is entry-level and inexpensive, it is able to provide sufficient graphic rendering abilities. The total cost of the simulation platform is $\approx \$4,000$. To many researchers, it is a budget friendly platform that is able to perform multiple driving tasks based on customized research interests.

Experimental Scene

The experimental scene in the demonstration test is a virtual recreation of the Ekebergtunnelen tunnel in Oslo, Norway. The virtual tunnel was based on data outlined in Törnros's on-road tests and in measurements derived from Google Street View images of the tunnel [1]. The construction material and detailed design of the tunnel are replicated as closely as possible. Figure 2 reflects the comparison between the virtual tunnel created in Unity and the real tunnel from the top view. The virtual tunnel was modeled in four sections, a straight section, a transition section, a long curve and an exit curve. The straight section is 600 meter (m) long. It is divided into left, middle, and right lanes with widths of 3.25m, 3.5m, and 3.25m, respectively. A short transition section branches the straight route into a long curve and an exit curve. The 550m long curve includes two lanes that are connected with the left and middle straight lanes. These two lanes are both widened to 3.65m. The exit curve is continued from the right lane, which is widened to 3.75m. The posted speed limit in the tunnel is 70 km/h, or 43 mph. The scene details in the tunnel are depicted in Figure 3.

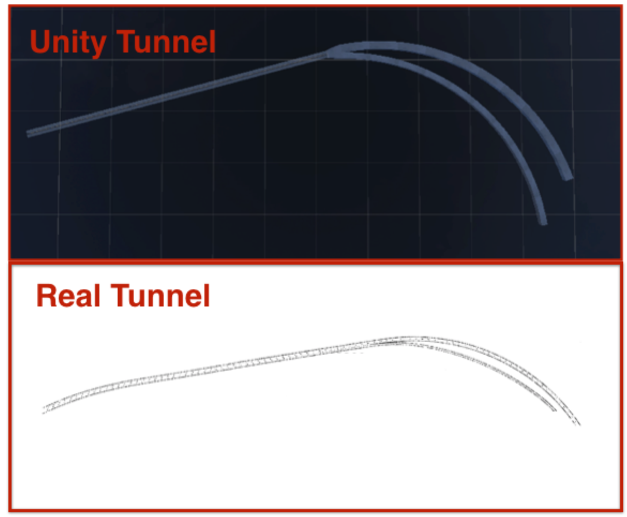

Figure 2: The comparison between the simulated tunnel (top) and the real tunnel (bottom) in top view.

Participants

Törnros's on-road test included twenty participants [1]. We invited the same number of participants (10 M and 10 F) to join our simulation test. All participants were required to hold a valid US driver-license. In addition, we sent a questionnaire to all of the participants to collect information on their annual mileage driven, and any driving accidents. The questionnaire indicates: 1) the median age of participants is 28 (23 - 55); 2) The median annual-mileage is 6000 miles with the range from 2000 to 24000 miles; 3) 18 out of 20 participant have never been involved in a driving

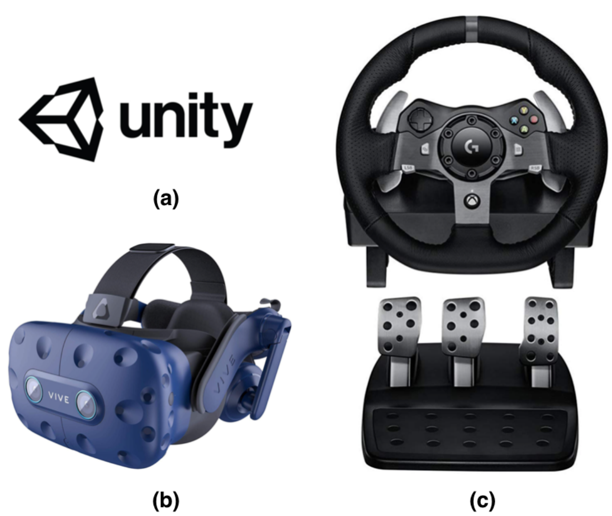

Figure 1: The platform composition: (a) Unity 3D engine [13]; (b) HTC Vive Pro Eye 3D HMD [14]; (c) Logitech G920 driving hardware [15].

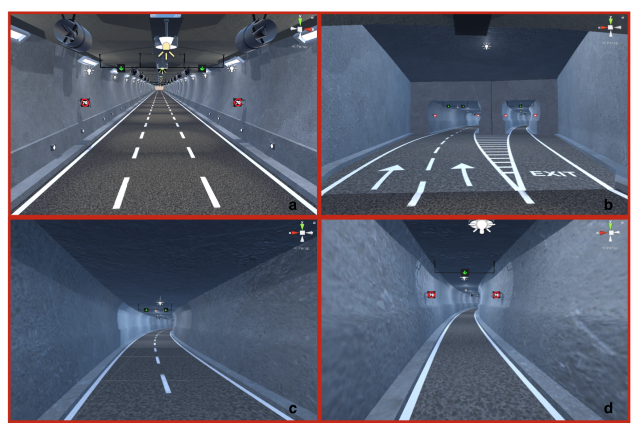

Figure 3: The inside look in the simulated tunnel: (a) the straight section of left, middle, and right lanes with widths of 3.25m, 3.5m, and 3.25m correspondingly; (b) the transition section branches the straight route into a long curve and an exit curve; (c) the long curve lanes connected with left and middle lane, which are both 3.65m; (d) the 3.75m wide exit curve that continues from the right lane.

accident and the remaining participants have 3 driving accidents in total.

Experiment Procedure

participants were required to wear the HMD and sit in the designated seat to execute the driving simulation task. Before performing this task, the HMD setup was customized to the participants, including headset adjustments and eye-tracking calibration. The five point eye-tracking calibration includes one center and four corners of the virtual scene. Participants are required to focus on the corresponding calibration point when it is highlighted. Once the setup was completed, participants were introduced to the experimental content and requirements. Figure 4 shows the first author wearing the HMD in the driving simulator.

The experiment included practice and test sessions. In both sessions, participants were required to take one trial drive in each lane along the forward direction, indicated in Figure 4(a). Once these trials were completed, participants were required to repeat each trial in the reverse direction, as shown in Figure 4(b). To avoid confusion about lanes, we use the same left, middle, and right order in the forward direction to represent the lanes in the reverse direction. During driving, participants were instructed to maintain vehicle position within the lane. Switching lanes was not allowed. Participants were also asked to keep their driving speed to the posted speed limit. Participants were aware of the speed in US and international units. Before beginning the test session, participants completed a practice session. This is to help participants be familiar with the instrument control and driving scene. Törnros' on-road test also included similar practice trials for the same purpose [1]. Furthermore, in order to eliminate the effect of the lane as a factor, participants started in different lanes for each direction in the test. During the whole tests, vehicle on-time position, speed, and 3D gaze PORs were recorded for the further analysis.


Figure 4: The first author wearing the HMD in the driving simulator.

Results

The primary dependent factors in the scene are lateral lane position and speed. The lateral position was measured between the side-line center to the vehicle center. The measurement of the lateral position is taken in the straight section, the right curve, and the left curve individually. In each measurement, lateral position is only collected for the same width lanes. In other words, the vehicle position in the left and right lanes is assessed for the straight section while that in the left and middle lanes is analyzed for the curves. The comparison between real and virtual performance was calculated as the difference between the average lateral lane position in each section for the two conditions. The average speed was computed for the entire driving route including the forward and reverse directions and the final comparison was performed using the average speed between the virtual and actual driving conditions. It should be noted that Törnros did not include the data populations for speed and lateral position analysis. Therefore, this paper qualitatively compares the performance of the simulation platform with the on-road test.

Average Speed

The average speed comparison is shown in Figure 6. In the figure, red represents the simulation outcome and cyan the on-road results. This color code holds true for the rest of comparison figures. On-road test data reflected that the average speed in left and middle lanes similarly tends to be faster than that in the right lane, though the difference is not statistically significant. Our simulated data also reflected this trend, which indicates the good relative validity that lane factor is effective for both on-road and simulation tests, implying that drivers in the real and simulated environments relied on visual references to judge the current speed in addition to the speedometer. Considering looking at ob-

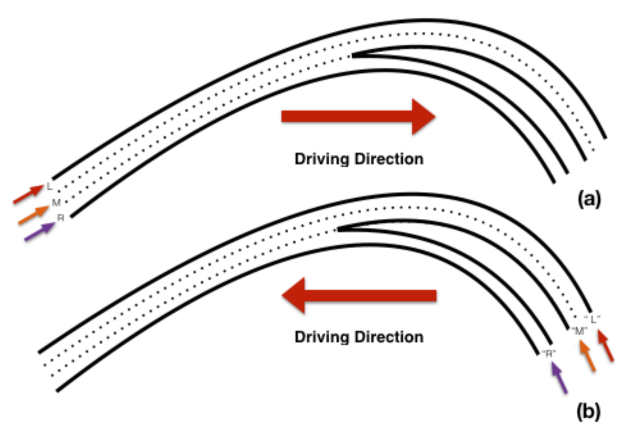

Figure 5: The driving direction diagram in the experiment: (a) the forward driving direction; (b) the reverse driving direction.

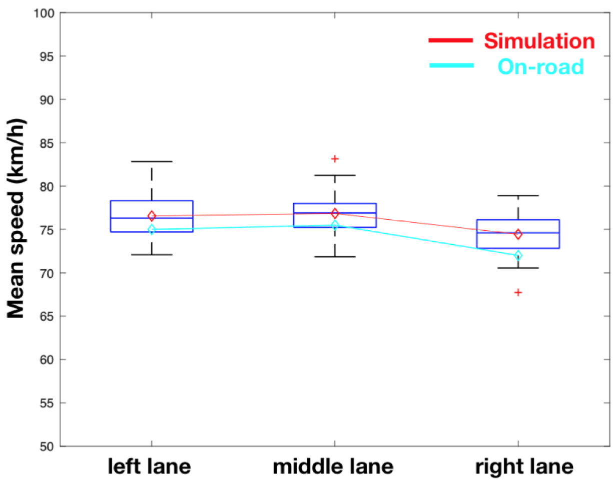

Figure 6: Average speed comparison between driving simulation and on-road tests in left, middle, and right lanes. Red represents the simulated data and cyan exhibits the on-road data.

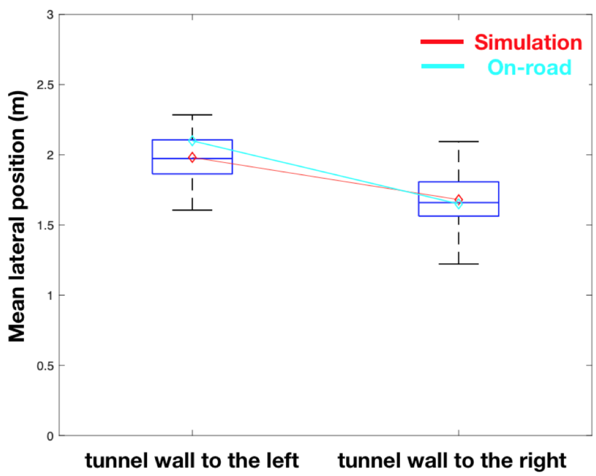

Figure 7: Average lateral position in the straight section between driving simulation and on-road tests in left (tunnel wall to the left), and right (tunnel wall to the right) lanes. Red represents the simulated data and cyan exhibits the on-road data.

jects in the left side is very natural behavior in a left driving country. Drivers are able to have a good reference to avoid running into the wall by just looking at the left wall when driving in the left and middle lane. When drivers drive in the right lane, looking at the right wall is probably not a typical habit. Therefore, drivers may be more cautious and drive more slowly to avoid a potential collision with the wall.

Average Lateral Position in the Straight Section

The comparison of the average lateral position in the straight section is presented in Figure 7. In order not to confuse the definition of the left or right lane in each direction, we use tunnel wall to left to represent the nearest wall on the left side of the driver. Similarly, tunnel wall to right means that the nearest wall is on the right side of driver. Based on the data depicted in the figure, drivers positioned the car closer to the wall in the left lane for the simulation test. This may be because the virtual wall did not impact drivers as strongly as the physical wall. As for the right lane, the average lateral position is roughly the same in the simulated and the on-road tests. Overall, the average lateral position in the straight section is very close to the findings of the on-road test.

Average Lateral Position in Curve Sections

Average lateral position in the curve sections are divided into right and left curve section. Right curve means taking the curve along the forward direction while left curve means taking the curve along the reverse direction. Figure 8 shows the average lateral position in the right curve. Comparing with the on-road test outcome, drivers positioned the vehicle much closer to the left wall and further away from the right wall. The straight section results indicate that it is reasonable for the vehicle to be close to the left wall. However, we did not expect the significant reduction of the lateral position between the vehicle and the left wall in the left lane. It is also unexpected that the vehicle was far from the right wall. This difference from the on-road results led us to take a closer look at the curve in the road. After inspection, we found out that the transition point actually has unnatural curvature, highlighted in the red circle in Figure 9, that shifts both lanes toward the left. Therefore, the variation seen in Figure 8 may be due to this transition section, a difference between the real world and our simulation.

Another clue to support our assumption is the average lateral position in the left curve, which is shown in Figure 10. Without the affection of that difference in the left curve, drivers positioned the vehicle closer to the wall in the left lane of the simulation test. This fact is matching the observation in the straight section. Figure 11 illustrates the left curve scene in details.

Conclusion and Future Work

A VR driving simulation platform has been built for use in addressing multiple research interests. In order to demonstrate the realism of our platform, we quantify the degree to which the simulation is realistic enough to support natural driving behavior. To be specific, we designed a virtual driving scenario based on a real tunnel used by Törnros to perform on-road tests [1]. The collected data from the platform driving simulation, such as driving speed and vehicle lateral position in the lane, showed a similarity with those in on-road tests qualitatively, which suggests the use of our platform as a research tool may be possible.

In the future, we plan to examine the collected eye-tracking data, particularly the 3D PORs, for possible correlations between gaze behavior and driving behaviors. The specific processing includes eye-movement classification (fixation, saccade, and VOR), categories of objects being viewed in driving, and fixation correlation with speed, and lateral position control.

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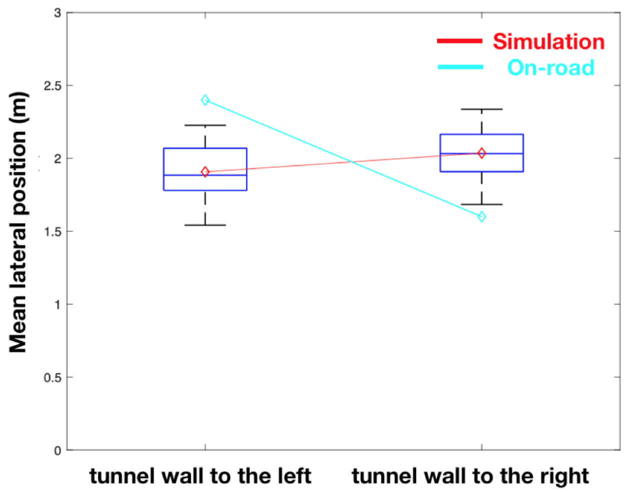

Figure 8: Average lateral position in the right curve between driving simulation and on-road tests in left (tunnel wall to the left), and middle (tunnel wall to the right) lanes. Right curve means taking curve along the forward direction while left curve means taking curve along the reverse direction. Red represents the simulated data and cyan exhibits on-road data.

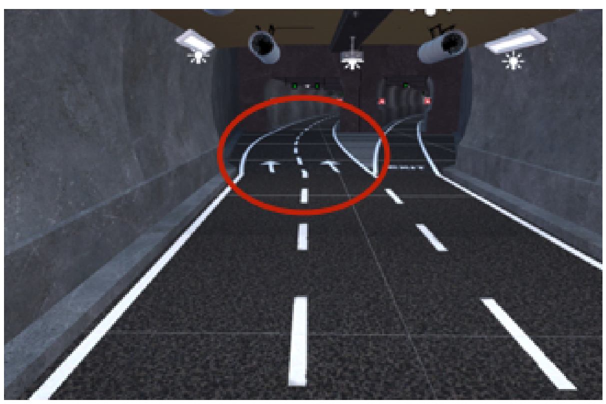

Figure 9: The transition details. Circle highlights the shifted curve lanes.

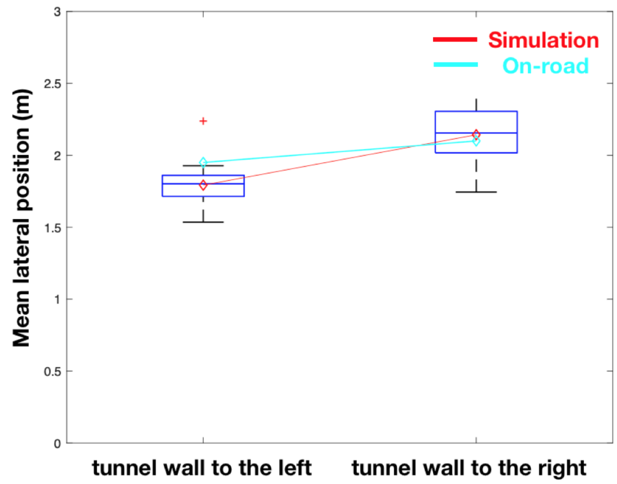

Figure 10: Average lateral position in the left curve between driving simulation and on-road tests in middle (tunnel wall to the left), and left (tunnel wall to the right) lanes. Red represents the simulated data and cyan exhibits the on-road data.

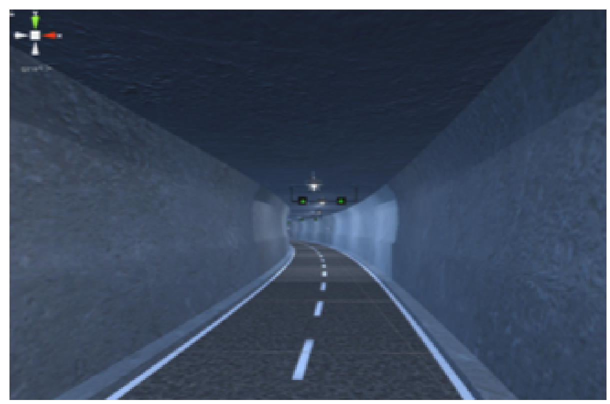

Figure 11: The left curve details.

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