Design of a Virtual Reality Driving Environment to Assess Performance of Teenagers with ASD

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Abstract. Autism Spectrum Disorder (ASD) is an extremely common and costly neurodevelopmental disorder. While significant research has been devoted to addressing social communication skill deficits of people with ASD, relatively less attention has been paid to improving their deficits in daily activities such as driving. Only two empirical studies have investigated driving performance in individuals with ASD—both employing proprietary driving simulation software. We designed a novel Virtual Reality (VR) driving simulator so that we could integrate various sensory modules directly into our system as well as to define task-oriented protocols that would not be otherwise possible using commercial software. We conducted a small user study with a group of individuals with ASD and a group of typically developing community controls. We found that our system was capable of distinguishing behavioral patterns between both groups indicating that it is suitable for use in designing a protocol aimed at improving driving performance.

Keywords: Virtual Reality, Autism intervention, Adaptive task, Physiological signals, Eye gaze.

1 Introduction

Autism Spectrum Disorders (ASD) is an extremely common (i.e., 1 in 88 children in the U.S.) and costly neurodevelopmental disorder [1]. While significant research has been devoted to addressing social communication skill deficits of people with ASD [2], relatively less attention has been paid to improving their deficits in daily activities such as driving. Driving is a particularly important skill for individuals with ASD to

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develop because it is often a very important component of optimal adaptive independence and quality of life. Further, it has also been shown in several studies that people with ASD tend to exhibit challenges with driving and in fact may demonstrate behaviors that may lead to unsafe driving practices [3-5]. Sheppard et al. [4] found that when teenagers with ASD were shown video clips of driving scenarios, they were less likely to recognize driving hazards that were social in nature (i.e., involving a person not operating a motor vehicle) than a group of typically developing (TD) controls. In the same study, both groups were found to be equally capable of identifying non-social hazards. Reimer's group [5] conducted a study comparing young adults diagnosed with higher-function autism spectrum disorder (HF-ASD) and a group of TD controls using a driving simulator paradigm where the research team collected performance, eye gaze and physiological signal data from participants. Reimer's study found that the HF-ASD group's gaze tended to be higher in the vertical dimension and further to the right in the horizontal dimension. Although there were no group differences in terms of performance in the simulated driving task, the gaze behavior could indicate dangerous driving behavior in an actual driving scenario. Classen and colleagues [6] also conducted a comparison study using a driving simulator paradigm in which they compared a group of pre-driving teenagers diagnosed with both ASD and attention deficit hyperactivity disorder (ADHD) against a group of TD controls. They found that the ASD-ADHD group demonstrated a higher number of driving errors than the TD group including errors related to lane-maintenance and speed-regulation.

Both of the previously mentioned driving simulation studies utilized proprietary simulation software. One of the major drawbacks of designing a protocol around a commercial driving simulator is that it may not provide access to the source code necessary to embed rules to customize for specific interventions. In addition, a novel simulator allows the creation of a network of sensory modules that can seamlessly interact with the simulator. As a result, we presented the preliminary design of a novel virtual reality (VR) driving environment for autism intervention [7]. In this paper, we build upon our previous work by designing a paradigm capable of assessing and eventually improving the driving skills of teenagers with ASD. We also present the results of a small comparison study between a group of teenagers with ASD and a group of TD controls. The following sections are organized in this way: Section 2 gives an in-depth description of the design of the system that we developed, Section 3 outlines the structure of the experiment, Section 4 highlights our findings and Section 5 concludes the paper with a discussion of our contribution and future work.

2 System Design

Our system is composed of four primary modules that interact over a local area network (LAN): the VR module (the driving simulator), an eye gaze data acquisition module, a physiological signal acquisition module to measure attentive and affective states and a therapist report module. A detailed description of each of these follow. Figure 1 diagrams the system architecture.

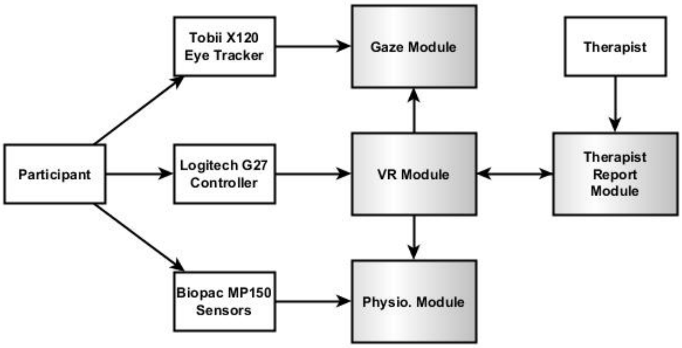

Fig. 1. Driving simulator system architecture

2.1 VR Module

The VR module was modeled as a hierarchical state machine (HSM). Each HSM and low-level finite state machine (FSM) is dedicated to a particular behavior such as monitoring driving errors or establishing network connections with the various sensory modules. Transitions on the top level are preemptive while low-level FSM transitions are either reset-transitions or maintain history.

This study utilized the virtual environment we developed in previous work [7] that was created using the modeling software tools Autodesk Maya and ESRI CityEngine and the game engine Unity. The interactive component of the VR module is modeled as a game with a set of levels with increasing difficulty. Each level contains three assignments (or missions) in which the user must complete a set of eight discretely measureable objectives which we refer to as trials. Trials include scenarios such as decreasing speed in a construction zone, pulling over to the side of the road while emergency vehicles pass and turning left at an intersection when there is oncoming traffic. Trials occurred in a variety of environments including busy city streets and crowded highways.

Users operate the virtual vehicle using a Logitech G27 steering wheel controller and pedal board. The G27 was mounted to a specially designed playseat as seen in Figure 2. Control of the graphical user interface (GUI) was mapped to the device so that users can navigate the menu without using another input device such as a mouse or keyboard. Vehicle controls were logically mapped to the device and a few additional features were added to allow better control of the vehicle. For example, the user can “look around” while stopped at an intersection by simultaneously pressing the brake pedal and rotating the steering wheel in the direction of interest. Additional functionalities included a radio operated by buttons on the steering wheel and turn signals mapped to switches behind the wheel.

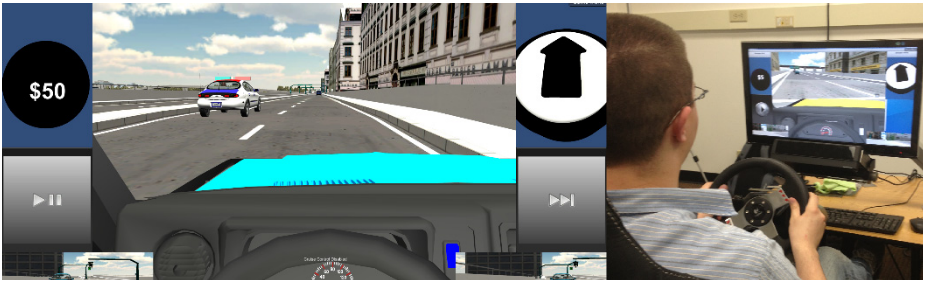

Fig. 2. Driving interface (left) and Logitech G27 and playseat (right)

Fig. 3. Feedback generated from running a red light

The VR module can detect a variety of driving errors and signal a trial failure event whenever a failure is detected. Examples of driving errors that the system can detect include speed-regulation, collision detection, running red lights and stop signs, taking an incorrect turn, driving in the wrong lane, driving on the sidewalk and more. When a failure event is triggered, the system generates feedback based on the circumstances of the failure and this feedback is presented to the user in both text and audio format. For example, Figure 3 shows feedback generated when a user travels through an intersection when it is unsafe to do so. Failure events, as well as other types of events that the system generates, trigger messages to be sent to the various sensory modules in the LAN so that time-synchronized event markers can be logged with the data collected. The VR module logs a large amount of performance data such as vehicle speed, input signals from the G27, position of the vehicle in the environment, trial duration time and details about trial failures.

2.2 Gaze-Acquisition Module

We acquired eye gaze information using a Tobii X120 (www.tobii.com) remote eye tracking device which has a high degree of accuracy and precision [8] and has been effectively used in other studies [9]. We sampled data from the device at a rate of 120 Hz. This data included independent gaze positions of both eyes, composite gaze position, blink rate, and fixation duration for various regions of interest (ROI) in the virtual environment. Examples of ROI that we measured were traffic lights, speedometers, pedestrians and stop signs. This information was logged for offline analysis.

The eye tracker was re-calibrated for each participant according to the specifications of the device manual [8] which required that users be at a distance of approximately 70 cm from the device. We developed a program using the Tobii software development kit (SDK) to perform a nine-point calibration task on a 24 inch monitor (1920 × 1080 px resolution). This program also handled the TCP socket connection with the VR module and calculated fixation durations based on data received from the VR module.

2.3 Physiological Signal-Acquisition Module

Physiological signals were collected using a Biopac MP150 (www.biopac.com) wireless physiological data acquisition system at a sampling rate of 1000 Hz. We measured the following physiological signals from participants: electrocardiogram (ECG), photoplethysmogram (PPG), respiration, electromyogram (EMG), skin temperature and galvanic skin response (GSR). These physiological signals were chosen because they have been shown to indicate a person's levels of engagement and anxiety [10-15]. A program was developed in MATLAB to accumulate and record the signals for offline analysis. This module also handled socket communication to the VR module and recorded event markers received from the VR module when some event occurred.

2.4 Therapist Report Module

The therapist report module was operated by a trained therapist and was not operated by the participant in the driving simulator. The purpose of this module was to record subjective assessment information from a therapist about the affective state of the participant. This module received an event message every two minutes while an assignment was in progress and at that time, the therapist was prompted to input their assessment. At the end of each assignment, whether successfully completed or failed, the therapist was prompted to give an assessment of the appropriateness of the ended assignment's difficulty level. This information was recorded on a nine point Likert scale and logged for offline analysis.

3 Experimental Design

3.1 Participants

We recruited four participants that were diagnosed with an ASD between 13 and 17 years of age (all males) and four TD controls (three males and one female). The mean age of the ASD group participants was 16.87 years (standard deviation: 0.42) and the mean age of participants in the TD group was 15.34 years (standard deviation: 0.94). Each participant completed a driving task that was approximately 90 minutes in length. Participants were reimbursed for their travel and time. The experiment protocol was approved by Vanderbilt University's Institutional Review Board.

3.2 Session Structure

At the start of a session, participants were seated in the driving playseat which was then adjusted for each individual's comfort. Physiological sensors were then placed on the participants' bodies followed by a calibration of the eye tracker. Each participant was shown a short tutorial that explained the vehicle's controls as well as the objectives of the game. Participants then began a three minute practice session in order to become accustomed to the vehicle operation and G27 interface. The main part of the session consisted of two assignments from level four, two from level five and two from level six. Each assignment was required to be attempted in order to progress to the next assignment, but we did not require successful completion of each assignment before moving on to other assignments. Assignments were completed if no more than three trials were failed during an assignment. If more than three trials were failed during an assignment, the assignment was failed and could not be reattempted. A short survey followed each assignment and participants responded to survey questions using the G27 to manipulate the GUI.

4 Results and Discussion

For group comparisons, we utilized two-tailed t-tests. The number of trial failures accumulated during a level was found to be significantly different ($p < 0.05$) between the two groups (Table 1) with the ASD group experiencing a higher number of failures. There was no difference in the time that it took for groups to complete assignments. Table 2 shows that there was an inverse relationship between the number of trial failures per level and level difficulty. This could indicate that the assignments' difficulty levels were not perceived as significantly different and/or the practice with the system from proceeding through the easier levels strongly affected performance.

Table 1. Individual Trial Failures Per Level

ASD Mean	SD	TD Mean	SD	p-value
4.583	2.178	2.833	1.572	0.042

Table 2. Total Group Trial Failures Per Level

Level	ASD	TD
4	22	13
5	19	12
6	14	9

Analysis of the gaze data shows the average vertical and horizontal gaze positions differ between each group. Among the ASD group, the gaze is significantly higher ($p < 0.001$) in the vertical direction (0.92 cm) and towards the right ($p < 0.001$) in the horizontal direction (1.02 cm). These results seem to support results found by Reimer's group [5]. As can be seen in Table 3, the ASD group had a significantly higher skin conductance level (SCL) and skin conductance response rate (SCR) than the TD group. From our previous work [12-13, 15], this may indicate that the participants in the ASD group experienced higher levels of anxiety during the session.

Table 3. Extracted feature means from both groups

Signal features	ASD	TD	p-value
Sympathetic power of ECG (Unit/s^2)	2948.29	2210.83	0.15
Skin conductance level of GSR (μS)	9.59	8.59	< 0.05
Skin conductance response rate of GSR (Response peaks/s)	6.46	2.09	< 0.05

5 Conclusion

We designed a novel driving simulator that can effectively measure driving performance as well as input from several sensory modules. From our user study, we found that the system is sensitive enough to detect significant group differences between individuals with ASD and TD controls. Such differences were present not simply in performance, but the system was able to detect gaze differences in how individuals were processing information within the paradigm. This is the first step towards development of a task aimed at improving the driving performance of teenagers with ASD while making use of online gaze and physiological signals. Our hierarchical state machine model allows for relatively easy modification of the system and addition of new sensory modules which we can utilize in future work to add, for example, an electroencephalography (EEG) sensory module.

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