Physiology-based Intelligent Systems for Individuals with Autism:
Novel Platforms for Autism Intervention and Early Detection

By

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List of Abbreviations

ADOS	Autism Diagnostic Observation Schedule Score
ASD	Autism Spectrum Disorder
BVP	Blood Volume Pressure
CDC	Center for Disease Control and prevention
DDA	Dynamic Difficulty Adjustment
DISCO	Diagnostic Interview for Social and Communication Disorders
ECG	Electrocardiogram
EEG	Electroencephalogram
EDA	Electrodermal Activity
EMG	Electromyogram
ERP	Event-Related Potential
ES	Engagement Sensitive
fMRI	functional Magnetic Resonance Imaging
FSM	Finite State Machine
FSR	Force Sensing Resistor
GSR	Galvanic Skin Response
HR	Heart Rate
HRV	Heart Rate Variability
IBI	Interbeat Interval
IQ	Intelligence Quotient
IRB	Institutional Review Board
LAN	Local Area Network
MADCAP	Multisensory stimulation And data CAPture system
MCDI	MacArthur-Bates Communicative Development Inventories
MSEL	Mullen Scales of Early Learning
PPG	Photoplethysmogram
PS	Performance Sensitive
RSP	Respiration
ROI	Regions of Interest
SCQ	Social Communication Questionnaire
SEQ	Sensory Experiences Questionnaire
SMD	Sensory Modulation Disorder
SRS	Social Responsiveness Scale
SVM	Support Vector Machine
TD	Typically Developing
TSD	Tactile Stimulation Device
TTL	Transistor-Transistor Logic
VABS	Vineland Adaptive Behavior Scales
VDEAR	VR-based Driving Environment with Adaptive Response technology
VR	Virtual Reality

1. Introduction and Background

Autism Spectrum Disorder (ASD) is characterized by social interaction deficits, verbal and non-verbal communication skill deficits, repetitive behaviors, and fixed interests (American Psychiatric Association 2013). The prevalence rate of ASD has consistently risen in recent years to 1 in 59 among children in the US in the latest report by the Center for Disease Control and prevention (CDC) (Baio J Christensen DL, et al. 2018). ASD is associated with high familial and societal cost (M L Ganz 2006; Chasson, Harris, and Neely 2007). Although there is no single agreed upon treatment or known cure for ASD, there is growing consensus that adaptive training and educational intervention programs can improve long-term outcome for individuals with ASD and their families (Buescher et al. 2014). However, many current intervention approaches show limited improvements in functional adaptive skills because traditional skill-based methodologies often failed to systematically match intervention strategies to specific underlying processing deficits associated with targeted skills. Additionally, such intervention approaches may have difficulties creating opportunities for addressing such skills and deficits within and across naturalistic settings in appropriately intensive dosages (Goodwin 2008). In this regard, technological intervention paradigms, including Virtual Reality (VR) platforms, have been suggested as potentially powerful tools for addressing these limits of current intervention paradigms. Moreover, given the limited availability of professionals trained in autism intervention, it is likely that emerging technology will play an important role in providing more accessible and individualized adaptive intervention in the future (Standen and Brown 2005; Tartaro and Cassell 2007; Lahiri et al. 2013). In order to provide individualized adaptive intervention, a human-computer system which has the ability to interpret affective cues, such as engagement or anxiety, can provide much more tailored intervention strategies to people with ASD. Since the affective states can be derived from physiological responses (Sarkar 2002) and with the rapid development of physiological sensor technology and machine learning algorithms in the past decade, it is reliable and promising to document one's physiological profile and use it to derive his/her affective states during intervention process.

While improving the effectiveness of the autism intervention technology is an important way to get better outcomes from the intervention, providing the intervention opportunities in the earliest point could potentially have more impact in practice. Despite the fact that a reliable diagnosis of ASD can be made by the age of 2 years, with many symptoms evident much earlier, most children are not accurately identified with ASD until after age four due to multiple factors, including difficulties in accessing care and a lack of trained providers (Baio J Christensen DL, et al. 2018). Consequently, these children do not receive early intervention in the first years of life, a time period recognized as optimal for enhancing developmental outcomes due to neural plasticity (Veenstra-VanderWeele and Warren 2015). Although the neural basis of complex social and communicative behaviors develops over the course of childhood, brain response to more basic sensory stimuli—e.g., touch, sight, smell—are present much earlier, even during the first few months of life—long before the observable behavioral and communication symptoms of ASD become apparent (Murray et al. 2016). Given that hypo- and hyper-responsiveness to sensory input is a core diagnostic feature of ASD that can cause significant impairment over time (Germani et al. 2014; Weitlauf et al. 2014), recent research (Damiano-Goodwin et al. 2018; Baranek et al. 2018) suggests that children at risk of ASD or other neurodevelopmental disorders may show subtle sensory differences within the first year of life, earlier than ASD can reliably be diagnosed at present, creating an opportunity to identify those children that may benefit from closer developmental monitoring. To date, most of the studies investigating early developmental differences have been focused on single-sensory-modality experimental design, including infant's visual attention or discrete event-related potential (ERP) paradigms related to speech processing, resting state electroencephalogram (EEG) differences, or measures of peripheral physiology in reaction to stimulus (Jones and Klin 2013; Maitre et al. 2013; Fairhurst, Löken, and Grossmann 2014). We believe that investigating multisensory processing differences, which is associated with real-world interaction and learning, could provide richer information for understanding the sensory processing in infancy, and could potentially facilitate early detection of ASD. Collecting multi-dimensional data, such as eye gaze, peripheral physiology, and EEG data, provides the opportunity to use data processing and fusion methods to explore underlying patterns in high dimensional space. Thus, designing a multisensory stimulation and data capture system (MADCAP) is beneficial for the research field in this regard.

1.1 Autism Spectrum Disorder and driving

While substantial effort has been dedicated to improving social skill deficits (White, Keonig, and Scahill 2007), much less research has focused on other daily living tasks that allow for increased independence in adulthood. One critical skill necessary for attaining independence, securing a job, and maintaining social relationships is driving, but it is only recently that researchers have turned their attention towards the issue of driving in the ASD population. In the US, the demographic of 16-19 year old drivers is three times more likely to be involved in a fatal traffic accident than older and presumably more experienced drivers (Centers for Disease Control and Prevention 2012). Over 2,000 teens die each year from highway accidents, and total annual fatalities and injuries for drivers are 35,000 and 2.4 million, respectively (National Highway Traffic Safety Administration 2016). Mounting evidence suggests that learning to drive is particularly difficult for many individuals with ASD due to deficits in attention-shifting, performing sequential tasks, integrating visual-motor responses, and coordinating motor response (Hill 2004; Huang et al. 2012). In addition, lack of confidence—both from the driver with ASD in themselves and the parent of a driver with ASD in their child's driving ability—further exacerbates these concerns. Parent respondents to a survey by Cox et al. (N. Cox et al. 2012) reported that the characteristics associated with ASD exerted a moderately to extremely negative influence on their child's ability to drive safely. Daly et al. (Daly et al. 2014) surveyed licensed driving adults with and without ASD about their driving histories. They found that individuals with ASD reported being older at the age of licensure, spending less time driving, feeling less confident about their driving ability, and experiencing greater number of traffic violations than neurotypical peers. Given that some 1.4 million individuals with ASD are estimated to be driving already—with approximately 60,000 more becoming age-eligible each year—combined with declining conditions on US highways due to the current epidemic of distracted driving, there is an urgent need to develop intelligent driving intervention tools capable of addressing both the performance and processing-level issues of drivers with ASD (Howden and Meyer 2010; N. Cox et al. 2012; Huang et al. 2012; National Highway Traffic Safety Administration 2016). Parents of individuals with ASD suggested having driving-like experiences like driving video games before trying to drive a car is one of the most useful strategies in teaching driving skills (N. Cox et al. 2012). We believe such driving intervention technology provides assistive system which can help individuals with ASD to build confidence toward on-road driving.

Virtual Reality (VR) technology offers promise as an intervention modality for people with ASD because it can provide a controllable, replicable, and safe learning environment (Strickland 1997). Compared to reality, VR creates a less hazardous and more forgiving method for practicing potentially dangerous skills associated with daily life, such as driving. It can also be individualized not only to the general needs of specific learners, but also to their day-to-day levels of engagement.

Several previous studies have examined the generalizability of driving simulators for training real-world driving skills. In a neurotypical population, Shechtman et al. (Shechtman et al. 2009) did not find significant differences in the type or frequency of driving errors when comparing on-road and simulated driving assessments. This suggests that the driving skills learned in driving simulators can be generalized or transferred to the road under the same testing conditions. Reimer et al. (Reimer et al. 2013) assessed driving behaviors in young adults with ASD and found that they displayed a nominally higher and unvaried heart rate compared to controls; they also tended to focus visual attention away from the high stimulus area of the roadway. Other assessment studies have shown that individuals with ASD performed more poorly on selective attention, visual-motor integration (Classen, Monahan, and Wang 2013), increased working memory tasks (S. M. Cox et al. 2016) and predicting time-to-arrival (Sheppard et al. 2016), highlighting the need for systems that can rapidly assess specific types of driver errors and adjust training goals accordingly.

VR-based skill training systems have a demonstrated value for training specific skills in individuals with ASD.

However, a simple performance-based system without appropriate feedback to the user may not be optimal for enhancing and maximizing learning. Managing task difficulty to keep the user optimally challenged is beneficial for designing an effective skill training system. Task difficulty can affect cognitive workload and induce a variety of affective states (Giakoumis et al. 2010). A task which is beyond a user's capability could be overwhelming and may cause anxiety while a task which does not fully utilize the capacity of a user might result in boredom. When people feel anxious or bored, as opposed to engaged, they tend to lose focus on their task, learn less, be less productive and are more likely to make mistakes (Pekrun et al. 2010). Thus, the difficulty of the task should be adjusted to keep the user optimally challenged based on the ability and affective state of the user. As depicted in Fig. 1, keeping the user in the "flow state" will help maintain a positive emotional state during a task by avoiding anxiety and boredom (Nacke and Lindley 2008; Fairclough et al. 2013). When users played Tetris at different levels of difficulty, Chanel et al. found that easy task difficulty was related to boredom and hard task difficulty elicited anxiety, while medium difficulty was associated with engagement (Chanel et al. 2011). This suggests that adjusting task difficulty based on user boredom and anxiety might help him/her become and remain engaged in the task.

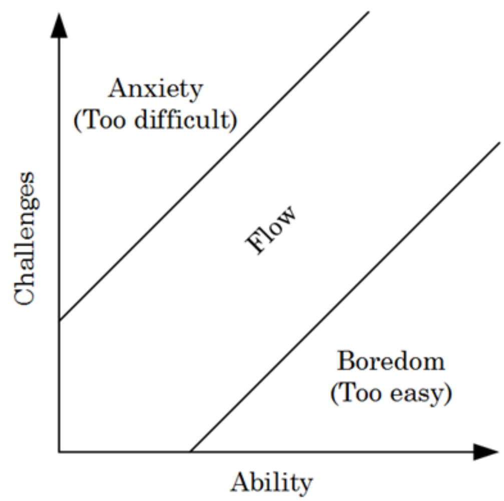

Figure 1: Model of flow

To exploit these benefits, task designers have attempted to keep the user in the flow state by using a mechanism called Dynamic Difficulty Adjustment (DDA), which automatically adjusts task difficulty based on a model of the user's skills (Adams 2008). For example, recent research has shown that game users demonstrate faster gains in performance and feel a greater sense of control when the difficulty adjusts according to their current skill level (Jegers 2007; Stripling et al. 2007; Orvis, Horn, and Belanich 2008). Game users also feel more immersed in game scenarios that adjust the game difficulty according to their current performance, as opposed to those that simply increase the game difficulty over the course of the game (Stripling et al. 2007). Outside of gaming applications, DDA can also be used in applications like human machine interface design to facilitate the progression of the user from novice to expert (Bederson 2004).

Besides these performance metrics, the user's affective states can also be utilized to build a model of the user's skills. These affective states can be derived from physiological responses (Sarkar 2002). Several studies have investigated how these physiological responses impact performance and flow. Compared to strictly performance-based feedback, physiology-based affective state feedback can be more efficient in providing optimal challenge to users, keeping them in a state of flow and improving their performance (Pramila Rani, Sarkar, and Liu 2005; Zhou et al. 2014).

We designed a VR-based driving platform for individuals with ASD that can adapt task difficulty in real-time based not only on task performance, but also on participant engagement. In order to achieve this adaptive system behavior, we developed a closed-loop physiology-based engagement recognition module embedded within a dynamic difficulty adjustment mechanism that controls driving task presentation in the driving platform.

1.2 Autism Spectrum Disorder and early diagnosis

Existing prospective studies of high-risk infant siblings of children with ASD (Sibs-ASD) suggest that sensory differences related to visual processing clearly emerge in the first two years of life (Germani et al. 2014). A growing number of studies have investigated visual attention to faces and other social stimuli in Sibs-ASD, e.g., (Jones and Klin 2013; Sacrey, Bryson, and Zwaigenbaum 2013; Shic, Macari, and Chawarska 2014). For both high- and low-risk infants, most of these studies have described early point-in-time group level similarities on simple performance measurements of visual scanning and preferential looking to core facial features. These studies have also suggested that high-risk infants may show subtle processing differences in the brain-based mechanisms for responding to these stimuli. These subtle processing differences may contribute to neurodevelopmental impairment over time. For example, for those infants who are eventually diagnosed with ASD, attention directed to eyes during infant-directed audiovisual speech initially appears intact but declines from 2 to 6 months of age, a pattern not observed in infants who do not develop ASD (Jones and Klin 2013).

These important findings identify a potentially critical developmental trajectory of decreased visual attention in high-risk infants. However, existing social attention paradigms are limited by their focus on solely audio-visual modalities of early sensory learning. We know that neural mechanisms for processing various sensory inputs, such as tactile, vestibular, and auditory inputs, start to come online prenatally, playing an immediate role in the postnatal social-sensory experiences that lay a foundation for multisensory processing and social learning over time (Lewkowicz, Leo, and Simion 2010). Paradigms using additional sensory processing channels to augment existing visual attention findings may provide more robust methods for detecting actionable neurodevelopmental risk at earlier time points.

One sensory processing channel that could augment existing visual attention work is related to tactile perception, or sense of touch. The sense of touch is widely known for the role it plays in discriminating and identifying external stimuli. For example, by investigating the neural basis of somatosensory remapping in human infancy, Silvia et al. found that the cortical networks underlying the ability to dynamically update the location of a perceived touch across limb movements become functional during the first year of life (Rigato et al. 2014). However, there is growing evidence that the sense of touch has another dimension, also known as “affective touch,” which conveys social information just like what someone sees and hears (Löken and Olausson 2010). Affective touch, which can be described as a comforting, caress-like soft touch (e.g., maternal touch), has been found to impact the “social brain” (Brauer et al. 2016). Previous research has demonstrated that infants are sensitive to affective touch (Fairhurst, Löken, and Grossmann 2014) and that compared to other forms of touch, stroking an infant can not only induce positive emotions but also modulate negative ones (Peláez-Nogueras et al. 1997). In working with adults with ASD, Croy et al. found that they show atypical perception and processing of affective touch. Additionally, the authors hypothesized that the affective touch functionality, which is based on C tactile fiber activation (McGlone, Wessberg, and Olausson 2014), is impaired to some extent in individuals with ASD (Croy et al. 2016). Furthermore, Kaiser et al. demonstrated that in the presence of affective touch stimulus, individuals with ASD exhibit reduced brain activity in social-emotional-related brain regions compared to typically developing (TD) individuals (Kaiser et al. 2015). As such, affective touch represents an identified area of atypical sensory processing related to ASD that can also influence infant response, making it an optimal target for early detection of neurodevelopmental risk.

In order to provide precisely controlled tactile stimulus, an automated mechanism was designed for affective touch and then, integrate it with an audio-visual stimuli presentation system to study multisensory processing of infants at high- and low-risk of ASD. It is difficult to produce skin-to-skin affective touch in laboratory settings. However, an analogous tactile stimulation which is produced by a mechanical source (e.g., soft brushing) is comparable to an affective touch that is manually produced by hand (Triscoli et al. 2013). Previous tactile stimulation work in infants has utilized trained human confederates to administer pleasant social touch via dorsal forearm stroking with Hake brushes at predetermined velocities and forces (Fairhurst, Löken, and Grossmann 2014). Although adequate for documenting generalized physiological responses to the stimulus, this manual control has several limitations: speed and force are not precisely controlled or measured, stroking is hard to coordinate with other stimuli/measurements, and the human presence may confound certain experimental paradigms.

1.3 Atypical sensory processing in toddlers with ASD

As we have developed and tested the MADCAP system, we now have the tool to explore the sensory processing characteristics for toddlers who have been diagnosed with ASD. It is estimated that more than 80% of children with ASD exhibit sensory problems (Ben-Sasson et al. 2009), and hyper- or hyporeactivity to sensory input is now a diagnostic criterion for ASD (American Psychiatric Association 2013). The empirical studies (Rogers and Ozonoff 2005) have demonstrated that the presence of ASD are related to differences in sensory responses, both behavioral and physiological. In terms of investigating sensory responses among toddlers/young children, most of the research focused on parent questionnaire, such as the Sensory Experiences Questionnaire (SEQ) (Baranek et al. 2006), Diagnostic Interview for Social and Communication Disorders (DISCO) (Leekam et al. 2007), and the Sensory Profile (Kientz and Dunn 1997), to collect behavioral data. When we move to the physiological perspective of sensory responses, however, most of the works have been focused on adults with ASD. For example, by working with adults with ASD, Cascio et al. (Cascio et al. 2012) used functional magnetic resonance imaging (fMRI) to investigate responses to tactile stimulation. They found that individuals with ASD tend to show diminished responses to pleasant and neutral stimuli, and exaggerated limbic responses to unpleasant stimuli. Previous physiological evidence also demonstrated that both sympathetic (McIntosh et al. 1999; Schoen et al. 2008) and parasympathetic (Schaaf et al. 2003) impairments in individuals with atypical sensory processing. McIntosh et al. (McIntosh et al. 1999) reported increased sympathetic reactivity and slower habituation as measured by electrodermal activity (EDA) in children with idiopathic Sensory Modulation Disorder (SMD). While EDA is useful for indexing psychological process (e.g., anxiety), it may be more difficult to identify specific brain regions and pathways given its multiple levels of controls. EDA is often used as a general arousal/attention indicator. For example, change in skin conductance level in the absence of a stimulus is an important indicator of an individual's state of arousal and alertness. EDA changes associated with orienting and attention are likely modulated by prefrontal cortical activity. Thus, it is necessary to incorporate EEG measures to provide richer knowledge in terms of physiological response.

As we can see from the aforementioned literatures, existing studies on exploring individual's atypical sensory responses lacks physiological profile in toddlers. Also, most of the studies limited on single sensory channel. As a result, we can utilize the completed MADCAP system to deliver multi-sensory stimuli to toddlers with ASD and their neurotypical peers to investigate the sensory processing differences. In the meanwhile, the system is capable of capturing rich data including peripheral physiology (EDA, PPG), EEG, and eye gaze data. We believe differentiating the physiological and sensory-related behaviors of toddlers with ASD has important implications for understanding sensory processing of ASD, improving diagnostic accuracy and planning appropriate intervention.

1.4 Specific objectives

This dissertation research aims at developing physiology-based intelligent systems for ASD intervention and early detection. The driving intervention system is not only sensitive of user performance but also the user's implicit affective cues inferred from peripheral physiological signals. The system for investigating infants or young children's sensory responses is capable of delivering multi-channel stimuli in a precisely controlled manner and collecting multi-dimensional data in time-synchronized way. The following sections present the specific objectives of each component of this research project and their current status.

Specific Aim 1: Design of a physiology-based adaptive learning architecture for driving skill intervention

Most of the literature (Shechtman et al. 2009; Reimer et al. 2013; Classen, Monahan, and Wang 2013; S. M. Cox et al. 2016; Sheppard et al. 2016) related to driving intervention for ASD focused on assessment of driving performance and comparison between individuals with and without ASD. This project is aimed at developing and testing an adaptive driving simulation platform incorporating physiology-based Dynamic Difficulty Adjustment (DDA) for ASD intervention. The primary objective of this work is to and develop a driving skill training platform that can 1) allow real-time measurement of engagement-related physiological signals while the user takes part in the driving task; 2) predict the user's engagement level based on real-time physiological signals, and 3) alter the task difficulty based on both the user's engagement level and performance metrics. We conducted a preliminary comparison between performance-based driving system and engagement-based driving system. We hypothesized that this engagement-based DDA driving skill training platform 1) would be tolerated by the individuals with ASD, 2) would generate more task engagement, and 3) would result in greater levels of enjoyment for participants when compared to the participants who used only the performance-based DDA modality of the driving skill training platform.

Specific Aim 2: Design of a multisensory delivery and data capture system for investigating sensory processing trajectories

In this project, we present the design, development and preliminary testing of a novel multisensory stimulation and data capture system (MADCAP) for infants and toddlers that delivers multiple sensory stimuli and simultaneously captures multi-dimensional data. In particular, we have developed a novel tactile stimulation device that delivers tactile stimuli to infants with precisely controlled brush stroking speed and force on the skin. The primary objective of this project is to develop the MADCAP system that can 1) delivers multiple sensory stimuli in precisely controlled manner; 2) develop a novel tactile stimulation device to produce affective touch; and 3) testing the tolerability and feasibility of the system among infant participants. Our secondary objective is to 1) design protocol to investigate sensory processing differences between toddlers with ASD and their neurotypical peers; 2) analyze the collected behavioral and physiological data to find the differences, if exist, between the ASD group and the control group; and 3) find the most prominent biomarkers if multiple biomarkers are found.

2. Physiology-based Affect Recognition in a Virtual Reality Driving Environment for Autism Intervention

Abstract

This chapter describes the development of a driving task module and affect recognition models for detecting affective states of teenagers with autism spectrum disorder (ASD). A Virtual Reality (VR) based driving task was designed for affect elicitation. Eight channels of peripheral physiological signals were recorded for affect recognition during driving tasks. A large set of physiological features were extracted based on their correlation with four categories of affective states: engagement, boredom, frustration and enjoyment. In order to get reliable labels for each category of these affective states, a therapist's rating was acquired during driving tasks based on the task progress and audio/video observation. Six well-known machine learning methods were used to develop physiology-based affect recognition models and the results were promising. As an application of this affect modeling, an affect-based adaptive driving task was introduced as future research.

This chapter is organized as follows. In Section 2.1, we provide a brief background on VR-based driving task - the overall system description and how physiology is used to measure the affective states of the participants. This section is followed by a description of the driving task. In Section 2.3, we focus on the physiology-based affect detection system description and results of physiological data analysis. The implication of our results and future work are discussed in the last section.

2.1 System description

The Virtual Reality (VR) based driving system contained a VR module and three subsystems, which were a peripheral physiological data acquisition module, an EEG data acquisition module and an eye tracker module (Figure 2).

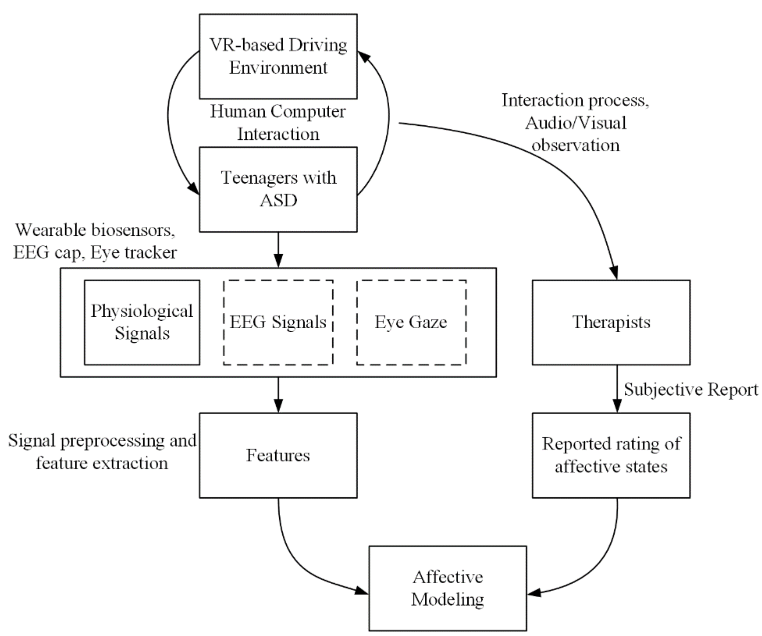

Figure 2: Framework overview of affective computing

The virtual environment was developed via the Unity game engine (www.unity3d.com). Within Unity, we developed a graphical user interface, created behavior for vehicles, pedestrians and traffic lights, designed the driving scenario and embedded traffic rules. Participants interacted with the driving environment by operating a Logitech G27 driving controller that was mounted on a Playseat (www.playseat.com) (Figure 3). The VR system was modeled as a video game with three difficulty levels: easy, medium and hard. Each level contained three assignments. Each assignment had eight trials which were designed in order to improve specific driving skill such as turning, speed-maintenance, merging and following traffic laws. Physiological data, EEG data and eye gaze data were recorded continuously from the beginning of the experiment to the end. A therapist rated the participant's affective states via a custom-designed online rating program. More details of VR module could be found in next chapter.

In this work, we only focused on the physiology-based affect recognition during driving in VR. Four categories of affective states, engagement, enjoyment, frustration, boredom, were chosen because of their importance in driving (Baker et al. 2010) as well as their detectability using peripheral physiological signals (Bradley and Lang 2007; Sarkar 2002; P Rani et al. 2006; Liu Conn, K., Sarkar, N., Stone, W. 2008; Welch Lahiri, U., Liu, C., Weller, R., Sarkar, N., Warren, Z. 2009). Establishing an affect recognition model could lead to the development of an adaptive closed-loop driving skill training system.

2.2 Methods and materials

2.2.1 Experimental setup

The physiological signals were collected using the BIOPAC MP150 physiological data acquisition system (www.biopac.com) with a sampling rate of 1000 Hz. Several physiological signals were investigated. The acquired physiological signals were broadly classified as cardiovascular activities including electrocardiogram (ECG), photoplethysmogram (PPG); electrodermal activities (EDA); electromyogram (EMG) activities from Corrugator Supercilii, Zygomaticus Major, and Upper Trapezius muscles; respiration and skin temperature.

These signals were measured by using light-weight, non-invasive wireless sensors (Figure 3). ECG signal was collected from the chest using two disposable electrodes to record electrical activity generated by the heart muscle. PPG and GSR were measured from toes instead of fingers in order to reduce the motion artifact from driving. EMG was measured by placing surface electrodes on Corrugator Supercilii and Zygomaticus Major and Upper Trapezius muscles. Respiration was used to measure changes in thoracic circumference that occur as a participant breathes. Skin temperature was collected from the upper arm by using a temperature sensor. In addition, an EEG cap and an eye tracker were also used to detect EEG signal and eye gaze in this setup.

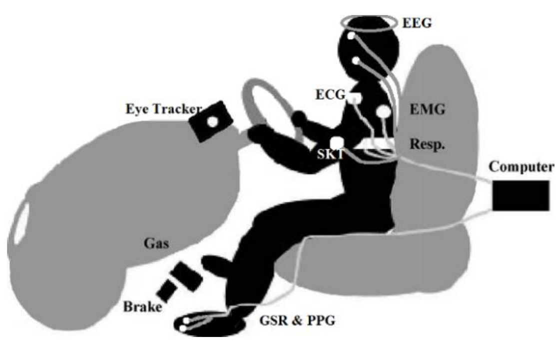

Figure 3: Physiological sensors setup.

A socket-based communication module was developed to transmit task-related (e.g., trial start/stop) event triggers from the virtual driving environment to the Biopac. Physiological signals along with task-related event triggers were sent over an Ethernet link to a physiological data logger computer to enable acquiring and logging of the signals in a time-synchronized manner with the VR-based driving task (Figure 4).

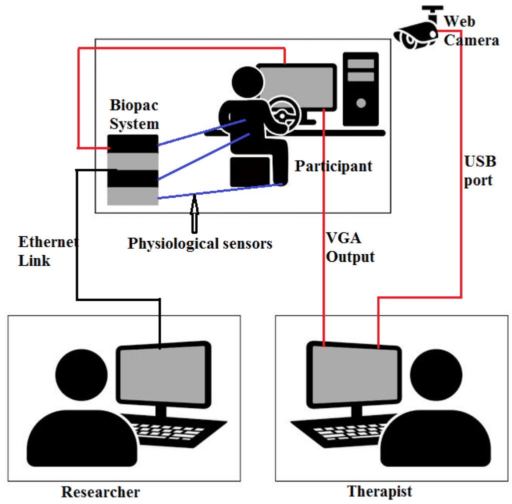

Figure 4: Experimental setup diagram.

2.2.2 Procedure

Each participant completed six sessions in different days. The first and last session were pre- and post- sessions, which contained the exact same assignments. Participants usually completed a single session within approximately 60 minutes. At the start of each session, physiological sensors and EEG cap were placed on a participant's body and the eye tracker was calibrated. Participants watched a short instruction video which explained basic instructions and game controls. After the tutorial, participants were asked to remain calm and relax for three minutes during which physiological, EEG, and eye gaze baseline data were collected. The baseline data were later used to offset environmental variability. Participants also had three minutes' free practice in which there were no pedestrians and no other vehicles in the VR environment. This practice mode allowed participants to familiarize themselves with the game controls and virtual environment.

After the three-minute practice, participants began the first of three assignments. Through the assignment, participants followed the navigation system and tried to obey traffic rules. Disobeying any traffic rules (i.e., running red light) caused a performance failure. In addition, in gaze contingent group, failing to look at a specific region of interest in specific trials (i.e., did not look at speedometer in school zone) also caused a gaze failure. Four failures would cause the assignment end and the game would go back to assignment selection menu. Time duration for each assignment varied from 2 minutes to 5 minutes depending on the participants' performance.

Because of suspected unreliability of self-report of teenagers with ASD, an experienced therapist was involved in the experiment. The therapist was seated next to the experiment room, watching the experiment from the view of two cameras (Fig. 3). The therapist rated the participants' affective states in four categories: engagement, enjoyment, frustration and boredom by using a continuous rating scale from 0 to 9 via an online rating program. For each assignment, an overall rating was given after the assignment. Also, the therapist provided ratings when she felt the participants had obvious affective state changes.

2.2.3 Participants

We have recruited 12 male teenagers with ASD for this phase of the study. While it was not our intention to recruit all male participants, they were recruited randomly through the existing university clinical research registry and happened to be all males. This may partially be due to the fact that ASD prevalence in male population is four times as high as it is for female population (Baio J Christensen DL, et al. 2018). All participants had a clinical diagnosis of ASD from a licensed clinical psychologist as well as cores at or above clinical cutoff on the Autism Diagnostic Observation Schedule (Lord et al. 2000). The Institutional Review Board (IRB) approval was sought and received for conducting the experiment. Ten participants' physiological data were used for this paper because two of them were not able to follow the instructions to get valid physiological data.

Table 1: Participant data.

Participant NO.	Age	IQ	ADOS total raw core	ADOS CSS
ASD01	13.6	--	--	--
ASD02	15.1	80	16	9
ASD03	14.3	86	14	8
ASD04	14.6	99	--	--
ASD05	17.1	118	8	5
ASD06	13.2	108	14	8
ASD08	17.5	125	13	8
ASD09	15.5	117	11	7
ASD10	16.6	88	22	10
ASD12	14.1	--	11	7

Note: ADOS_CSS = Autism Diagnostic Observation Schedule Calibrated Severity Score; IQ = composite score: Differential Ability Scales (General Conceptual Ability) or Wechsler Intelligence Scale for Children (Full Scale IQ).

2.3 Physiological data analysis

In this study, a group model was developed to classify affective states in four categories: engagement, enjoyment, frustration and boredom. A 90-s window was chosen for sampling the continuously-recorded physiological data. The 90-s window was chosen for several reasons: it approximates the time needed for autonomic signal such as skin conductance to recover and it also provides a level of smoothing when the features were extracted. The samples were labeled by the therapist's overall rating for each assignment. The therapist's ratings were mapped into high and low intensity for each category for binary classification.

The recorded physiological signals were preprocessed for feature extraction. First, each signal was filtered using different filters such as high/low pass filter, notch filter etc. to reject outliers and artifacts. The signals were then standardized to be zero mean and unity standard deviation. In addition, baseline wander was removed from the PPG signal before peak detection as this signal is known to be affected by baseline wander.

Several features were extracted for each channel of physiological signal. A brief explanation for all the features are listed in Table 2.

Table 2: Physiological features.

Physiological signal	Feature extracted	Label used	Unit of measurement
Electrocardiogram (ECG/EKG)	Sympathetic power	power_sym	Unit/s^2
	Parasympathetic power	power_para	Unit/s^2
	Very low-frequency power	power_vlf	Unit/s^2
	Ratio of powers	para_vlf para_sym vlf_sym	No unit
	Mean Interbeat Interval (IBI)	mean_ibi_ekg	ms
	Std. of IBI	std_ibi_ekg	Standard deviation(no unit)
Photoplethysmogram (PPG)	Mean and std. of amplitude of the peak values	ppg_peak_mean ppg_peak_std	μV No unit
	Mean and std. of heart rate variability	hrv_mean hrv_std	ms No unit
Electrodermal activity (EDA)	Mean and std. of tonic activity level	SCL_mean SCL_sd	μS μS/s
	Slope of tonic activity	SCL_slope	μS
	Mean and std. of amplitude of skin conductance response (phasic activity)	SCR_mean SCR_sd	 μS
	Rate of phasic activity	SCR_rate	Response peaks/s
	Mean and std. of rise time	tRise_mean tRise_std	
	Mean and std. of recovery time	tHRecovery_mean tHRevovery_sd	
Electromyographic Activity (EMG)	Mean of Corrugator, Zygomaticus and Trapezius activities	Cemg_mean Zemg_mean Temg_mean	μV
	Std. of Corrugator, Zygomaticus and Trapezius activities	Cemg_std Zemg_std Temg_std	No unit
	Slope of Corrugator, Zygomaticus and Trapezius activities	Cemg_slope Zemg_slope Temg_slope	μV/s
	Number of burst activities per minute of Corrugator, Zygomaticus and Trapezius	Cburst_count Zburst_count Tburst_count	/min
	Mean of Corrugator, Zygomaticus and Trapezius burst activities	Cburst_mean Zburst_mean Tburst_mean	mS
	Std. of Corrugator, Zygomaticus and Trapezius burst activities	Cburst_std Zburst_std Tburst_std	No unit
	Mean and Median frequency of		

	Corrugator, Zygomaticus and Trapezius	Cfreq_mean Cfreq_med Zfreq_mean Zfreq_med Tfreq_mean Tfreq_med	Hertz
	Mean of the amplitude of Corrugator, Zygomaticus and Trapezius burst activities	Cburst_amp_mean Zburst_amp_mean Tburst_amp_mean	μV
Respiration (RSP)	Mean amplitude	RSP_mean	No unit
	Std. of amplitude	RSP_std	
	Subband spectral entropy	RSP_subbandSpectralEntropy({1,2,3})	
	Minimum and maximum difference	RSP_minmax_diff	
	Change rate	RSP_rate	
	Power spectrum density	RSP_low_power RSP_high_power RSP_firstOrder_std	
	Std. of Poincare plot geometry	RSP_poincare_SD1 RSP_poincare_SD2	
	Mean and std. of peak valley magnitude	PVM_mean PVM_std	
	Mean and std. of breath per minute	RRI_mean RRI_std	
Peripheral temperature (SKT)	Mean temperature	temp_mean	F
	Slope of temperature	temp_slope	F/s
	Std. of temperature	temp_std	No unit

The Waikato Environment for Knowledge Analysis (WEKA) (Hall et al. 2009), which is recognized as a landmark system in machine learning nowadays, was used to do feature selection and classification in this study. For each category, CorrelationAttributeEval algorithm was used to select features. This algorithm evaluated the value of a feature by measuring the correlation between it and the class. It ranked feature subsets according to a correlation based heuristic evaluation function. The bias of the evaluation function was toward subsets that contain features that were highly correlated with the class and uncorrelated with each other. Irrelevant features were ignored because they would have low correlation with the class. Redundant features were screened out as they would be highly correlated with one or more of the remaining features. Top ten features (Table 3) that had the highest correlations with the classes were chosen for further classification. As we can see from the selected 10 features of each category, PPG, RSP, SCR, EMG_C and EMG_Z are most common for the chosen affective states. This indicates the possibility of using a smaller set of features with a relatively low computational cost for a potential closed-loop system.

As we can see from the selected 10 features of each category, PPG, RSP, SCR, EMG_C and EMG_Z are most common for the chosen affective states. This indicates the possibility of using a smaller set of features with a relatively low computational cost for a potential closed-loop system.

Table 3: Selected features for each category of affective states.

Category	Features selected
Engagement	RSP_subbandSpectralEntropy(1), hrv_mean, SCR_rate, Zemg_mean, RSP_mean, PVM_std, SCL_sd, SCL_slope, Cburst_amp_mean, ppg_peak_mean
Enjoyment	hrv_mean, RSP_mean, ppg_peak_mean, Cburst_count, Cemg_slope, Zburst_count, Temg_slope, PVM_std,Zburst_mean,Cburst_amp_mean
Frustration	Cemg_std, RSP_subbandSpectralEntropy(2), RSP_subbandSpectralEntropy(3), PVM_mean, RSP_firstOrder_std, temp_slope, RSP_std, RRI_std, Zfreq_med, RSP_low_power
Boredom	tRise_sd, hrv_mean, temp_mean, tRise_mean, SCR_sd, SCR_rate, RSP_subbandSpectralEntropy(3), RSP_subbandSpectralEntropy(2), Zfreq_mean, Cburst_count

Table 4: Classifiers and their details

Classifier name	Details
Bayes Network (BN)	SimpleEstimatior estimator and K2 search algorithm were chosen
Naïve Bayes (NB)	Numeric estimator precision values were chosen based on analysis of the training data
Support Vector Machine (SVM)	Radial basis function was chosen with a degree of 3
Multilayer Perceptron (MLP)	HiddenLayers were chosen by using (attribs + classes) / 2, learningRate was 0.3
Random Forest (RF)	The number of trees to be generated was 10, maxDepth was unlimited
J48 Decision Tree (J48)	The minimum number of instances per leaf was 2, 1 of 3 folds data was used for reduced-error pruning

Six different well-known classifiers (Table 4) were used for classification for each category.10-fold group cross validation was used to reduce the overfitting problem. The classification accuracies for each category from different classifiers are shown in Figure 5. The highest accuracy for engagement, enjoyment, frustration and boredom were 77.78%, 79.63%, 79.63% and 81.48%, respectively. These results are comparable to the accuracy of most up-to-date affective computing systems (Tao and Tan 2005; Jerritta et al. 2011).

In this study, we focused on developing a group affective state prediction model instead of model for each individual. In the future, we want to use this group model to provide affective state feedback in a closed-loop system and potentially develop a more efficient driving system to teach teenagers with ASD basic driving skills.

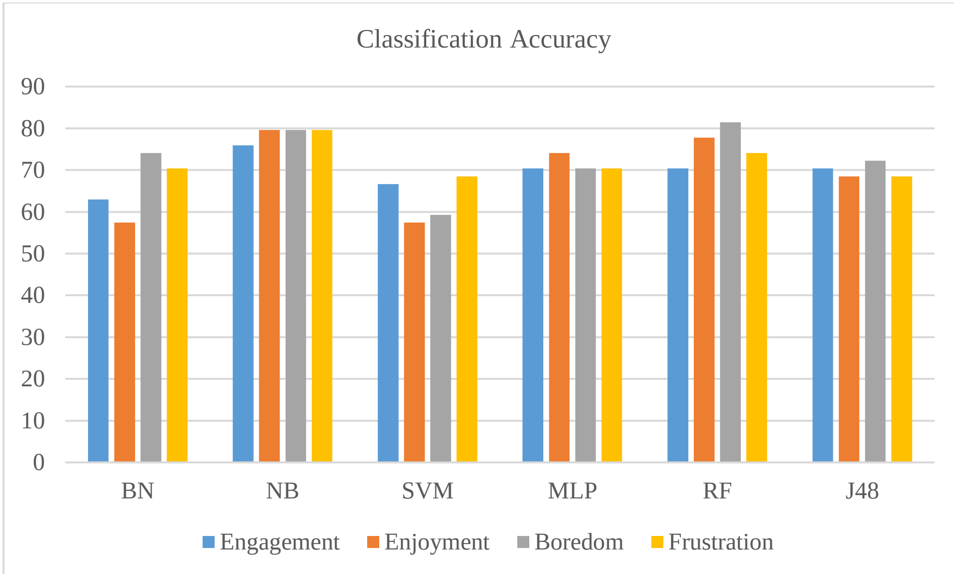

Figure 5: Classification accuracies for each category of affective states.

2.4 Discussion and conclusion

There is a growing consensus that development of computer assistive therapeutic tools can make application of intensive intervention for teenagers with ASD more readily accessible. In recent years, several applications of advanced intervention that address deficit in driving for teenagers with ASD were investigated. However, these application lacked the ability to detect the affective cues of the teenagers, which could be crucial given the affective factors of teenagers with ASD have significant impacts on the intervention practice. In this work, we presented a physiology-based affect recognition framework for teenagers with ASD. Sixty-eight features were extracted from the recorded physiological data. Subsequently 10 features were selected by using CorrelationAttributeEval algorithm to overcome the overfitting problem. Six most commonly used machine leaning algorithms were used to classify four categories of affective states. The developed model could reliably recognize affective states of the children with ASD and provide the basis for physiology-based affect-sensitive driving skill training system.

The affective models discussed in this paper are currently being utilized in a closed-loop driving simulator where the driving difficulty levels are dynamically adjusted based on an individual's engagement level in the hope that such adaptive adjustment will keep the participants optimally challenged and thus will enhance learning. In this dynamic closed-loop system we record three physiological signals from the participants: GSR, PPG and Respiration during driving tasks. The engagement model discussed in this paper was used to detect the participant's engagement level. The engagement level together with driving performance of the participant were fed into a well-defined dynamic difficulty adjustment module to adjust the difficulty level of the driving task. We believe this will keep the participant at optimal levels of challenge and engagement and lead to better driving performance.

Acknowledgement

The authors would like to thank the participants and their families for making this study possible. We also gratefully acknowledge National Science Foundation Grant 0967170 and National Institute of Health Grant 1R01MH091102-01A1 that partially supported the research presented here.

3. Design of a Physiology-based Adaptive Virtual Reality Driving Platform for Individuals with ASD

Abstract

The primary goal of this chapter's work is to design a Virtual Reality (VR) based driving platform for individuals with ASD that can adapt task difficulty in real-time based not only on task performance, but also on participant engagement. We present a closed-loop physiology-based engagement recognition system embedded within a dynamic difficulty adjustment mechanism that controls driving task presentation in the driving platform. We also present results from a small user study of teenagers with ASD to demonstrate the feasibility and tolerability of such a driving platform. Moreover, by utilizing the participants' performance data and physiological data, we provide methods to document the participants' driving performance and engagement level, which makes designing of long-term driving sessions and tracking the users' performance and engagement level over time more accessible. However, a long-term skill learning and skill generalization study is beyond the scope of the current work.

3.1 System design

The proposed VR-based Driving Environment with Adaptive Response technology (VDEAR) is comprised of 1) a VR-based driving task module; 2) a real-time physiological data acquisition module; and 3) an individualized dynamic difficulty adjustment module that embeds a real-time physiology-based engagement prediction mechanism. (Figure 6).

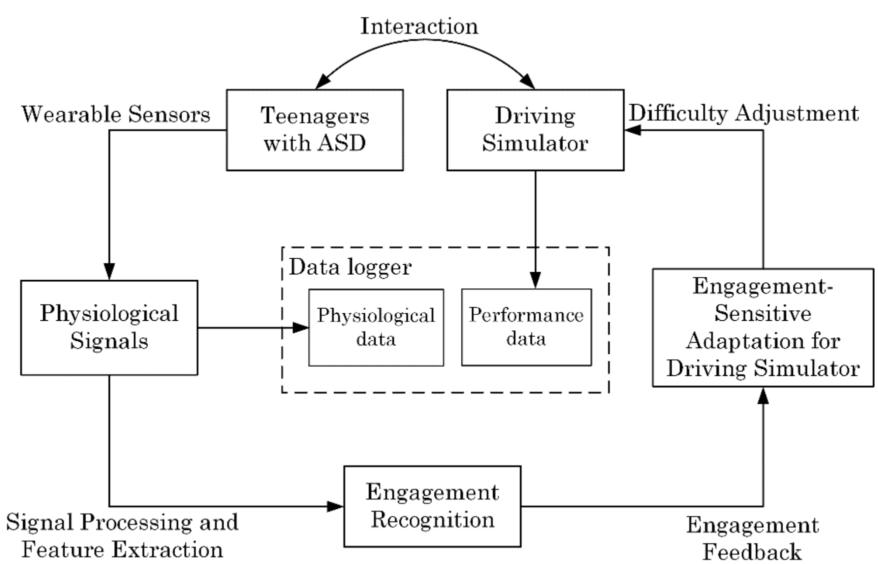

Figure 6: VDEAR system framework overview

3.1.1 VR-based driving environment

We used desktop VR applications because they are accessible, affordable, and potentially minimize cyber sickness – an important consideration for people with ASD, because of their atypical sensory perception (Bellani et al. 2011). Having access to driving simulation software is a prerequisite for developing a driving intervention program. There are a range of high-quality off-the-shelf driving simulation systems that can be used in the assessment of driving behaviors. However, these tools are not suitable for our study because they do not provide access to the source code.

Access to the source code is necessary for designing a closed-loop system that utilizes information from sensors and driving performance.

Figure 7: Driving simulator developed in our lab

As a result, we have utilized a driving simulator that was recently designed in our laboratory (Figure 7). A Logitech G27 steering wheel controller was used to control the virtual agent vehicle in the virtual driving environment. Models in the virtual driving environment, such as traffic lights, stop signs, and vehicles, were developed with the modeling tools ESRI CityEngine (www.esri.com/cityengine) and Autodesk Maya (www.autodesk.com/maya). The game development platform Unity3D (www.unity3d.com), was used to implement the system logic. A total of five difficulty levels were chosen for this adaptive driving environment. These difficulty levels were tested and validated in our previous work (Wade et al. 2014). Two sets of parameters including road conditions and environmental changes were manipulated to produce a range of difficulties. Specifically, to provide different road conditions, we created different slopes of the road (e.g., uphill, downhill, and even road), different road textures (e.g., normal road and raining road), and different turns (e.g., normal turn and sharp turns). When the participants drive through different road conditions, they usually feel the changes of the responsiveness of the brake pedal, the accelerator pedal, and the steering wheel. The environmental changes were manipulated by changing the intensity of light in the environment and the speed of agent vehicles.

The VR system was modeled as a video game consisting of a set number of different trials. Each trial was designed to train a specific driving skill such as speed maintenance, turning, merging, and following traffic laws. At the beginning of each trial, there was a voice-based instruction, such as “Turn right”, “Merge into highway”, “Pass the vehicle in front”, and so on, telling the participant how to progress through a given trial. A directional arrow graphic on the top right side of the screen served to provide navigational information to the participant. Each trial included within it a *critical region* within which the driving performance was monitored to provide “Failure” or “Success” feedback relevant to the content of the trial. For a “Success,” the participant was awarded five points at the same time that congratulatory audio clip was played. The total points were displayed on the top left side of the screen. For a “Fail,” participants were told the reason for their failure, the task was reset to the starting point of this trial’s critical region, and no points were awarded for the failed trial. When the participant’s vehicle was reset to the prior starting point, the system would also give detailed instructions on how to be successful on subsequent attempts, such as, “Stop before the stop sign.”

Performance data, which included the turning angle of the driving wheel, the pressure on the gas and brake pedals, the speed of the vehicle, location of the vehicle, and detailed information of the failure, were logged in both text (.txt) and comma-separated values (.csv) file formats. The sampling frequency of the data were the same as the frame rate of the virtual environment, which was typically 60 Hz. The logged data were used in real-time performance assessment and offline data analysis.

Three-minute performance data were used to assess the user's performance in real time. Performance metrics included number of failures, difference between driver speed and speed limit, steering wheel manipulation pattern (kurtosis and skewness of the values) and gas pedal pressing pattern (mean and kurtosis of the values). We chose these driving features based on feature analysis of the driving data from our previous driving studies that provided the most discriminating information in assessing driving performance (Wade et al. 2015, 2014). Each subcategory of performance metrics has three possible outcomes: Good (worth 3 points), Fair (2 points) and Inadequate (1 points). For example, a participant could score 3 points for gas pedal pressing but only 1 point for steering wheel manipulation. If a participant scored 50% of the maximum possible points within the three-minute performance window, then the overall performance was considered "Good", otherwise, this was considered as "Poor".

3.1.2 Physiological data acquisition module

The physiological data were collected using the BIOPAC MP150 physiological data acquisition system (www.biopac.com) with a sampling rate of 1000 Hz. Using the hardware API provided by BIOPAC, we developed a customized physiological data acquisition program, in which we integrated socket-based communication with the driving program to record event information with automated time stamps (Bian, Wade et al. 2016). In this study, three physiological signals, photoplethysmogram (PPG), galvanic skin response (GSR) and respiration (RSP), were investigated. We chose these signals because they contain important information about the state of one's task engagement as shown in the literature (Picard and Healey 2000; Rainville et al. 2006; Bian et al. 2015). These signals were measured by using light-weight, non-invasive wireless sensors. PPG and GSR were measured from toes of left foot instead of fingers to reduce the interference to the driving wheel manipulation and the motion artifact from driving. PPG measures the blood volume in participant's middle toe. This measurement can also be used to compute the heart rate (HR) by identifying local maxima (i.e., heart beats), and heart rate variability (HRV). Blood pressure and HRV correlate with engagement (Kim and André 2008). GSR provides a measure of the resistance of the skin by positioning two electrodes on the distal phalanges of the index and the ring toe. This resistance decreases with an increase of perspiration, which has been shown to be associated with task engagement (Pecchinend and Smith 1996). Respiration was measured by using a respiration belt tied around the participant's abdomen. Slow respiration is often linked to relaxation while irregular rhythm, quick variations, and cessation of respiration relate with high level of arousal (Rainville et al. 2006).

The physiological signals acquired from BIOPAC were raw signals contaminated by motion artifacts and utility frequency. Thus, signal preprocessing was required before extracting features. First, outliers were removed from GSR, PPG and RSP signals and were interpolated with the mean value of the adjacent data points. A Notch filter with a cutoff frequency 60 Hz was used to remove the 60 Hz utility frequency from these three signals. Notch filter is a band-stop filter with a narrow stopband which can cut the loss of useful frequency component in the process of filtering. Considering different properties of each signal, highpass and lowpass filters with different cutoff frequencies were used as discussed below:

Tonic and phasic components of GSR were decomposed separately from the raw signal. Tonic skin conductance is the baseline level of skin conductance and is generally referred to as skin conductance level (SCL). Phasic skin conductance is the part of the signal that changes when task-related events (e.g., task failure or success) take place. The signal was first filtered by a lowpass filter with a cutoff frequency of 0.5 Hz to remove noise. Then tonic component was acquired by using a highpass filter with a cutoff frequency of 0.05 Hz. Phasic component was then calculated by deducting tonic component from preprocessed signal.

PPG is a low-frequency signal and can easily be contaminated by motion effect. A highpass filter with a cutoff frequency of 1.1Hz and a lowpass filter with a cutoff frequency of 3.6 Hz were used to remove noise.

Respiration is also a low-frequency signal. A highpass filter with a cutoff frequency of 0.05Hz and lowpass filter with a cutoff frequency of 0.35 were used to remove noise.

Note that we recognized noise and motion artifacts by transforming the signals into frequency domains. By doing so, we found that some of the frequency component should not be there for certain signals (e.g., GSR typically should not contain high frequency signal components; a 60 Hz frequency spike within signals usually indicates utility frequency noise). The noise and motion artifacts were removed by using the above mentioned filters to remove the unwanted frequency bands from each signal. The cutoff frequencies of the filters were found empirically and were derived from our specific dataset (as recorded by BIOPAC MP150) and may not be applicable to other datasets, although this process could be replicated using different sample-specific parameters. After outlier removal and filtering, the data were down sampled to 100 Hz. Subsampling can significantly reduce computational time of feature extraction, which is important in a real-time closed-loop system.

3.1.3 Online engagement detection module

Physiological data and engagement ratings from our previous driving experiments (Bian, Wade et al. 2015) were used to build the engagement model. Then the model was used in the current closed-loop system for real-time engagement detection.

In our previous work where participants with ASD were engaged in driving tasks using the VR-based driving simulator (Bian, Wade et al. 2015), 8 channels of physiological signals were examined for offline analysis to build an engagement detection model using machine learning algorithms. Subjective reports of the participants' engagement level from a clinical observer were used as the ground truth (Figure 8). Twenty participants' data from this previous experiments were used to build the engagement model for the current study. Note that the participants for the current study are all different from the participants for the previous study. Each participant finished six sessions in different days and each session lasted about 60 minutes. The physiological data from each session were segmented and labeled using 3-minute window. We chose the 3-minute window for two reasons: 1) physiological signals (especially the GSR signal) are relatively slow, and thus it requires a certain amount of time to reflect the change of affective states; and 2) after consulting with our psychology team, we believe that for this specific driving task, 3-minutes is an appropriate time window for the participant to feel engaged/not engaged with the task for the purposes of using this information to alter the system. Note that this time window can be adjusted based on different tasks, but must be consistent with the time window used to build the engagement model.

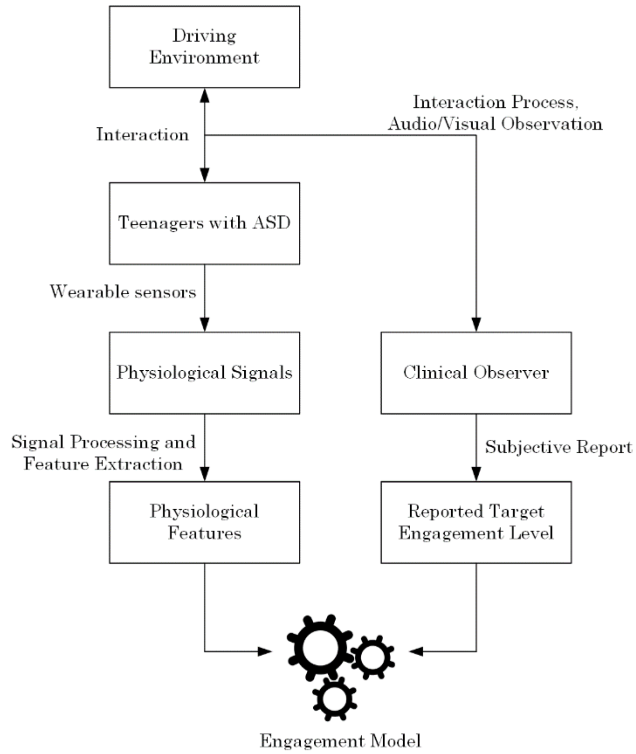

Figure 8: The procedure for building an engagement model based on data from previous driving experiments

In the current study, in order to improve computational speed that is needed for the real-time closed-loop DDA mechanism, we chose only PPG, RSP and GSR signals, the three physiological signals that had the most correlation with engagement to train the engagement detection model. Several features from these three signals were extracted as shown in Table 5.

Table 5: Physiological features used in the engagement model

Physiological signal	Feature	Unit of measurement
Photoplethysmogram (PPG)	Mean of heart rate variability	Ms
	Mean of amplitude of the peak values	μV
Respiration (RSP)	Mean amplitude	No unit
	Standard deviation of amplitude	
	Subband spectral entropy	
	Mean of peak-valley magnitude	
	Standard deviation of peak-valley magnitude	
Galvanic Skin Response (GSR)	Rate of phasic activity	Response peaks/s
	Standard deviation of tonic activity level	No unit
	Slope of tonic activity	μS/s

After feature extraction, several well-known machine learning algorithms, which have shown success in emotion recognition tasks (Jerritta et al. 2011), were explored to build and train an engagement detection model. The engagement detection model produced binary output, which was either “High Engaged” or “Low Engaged”. The Waikato Environment for Knowledge Analysis (WEKA) (Hall et al. 2009) was used to build and compare these models. The machine learning algorithms listed in Table 6 were examined and a group 10-fold cross-validation was used to assess the generalization of the models. Group 10-fold cross-validation was used here to make sure that each fold contains all the samples from one participant. In the end, Random Forest based engagement detection model was chosen since it yielded the greatest accuracy.

Table 6: Classification results by using different machine learning algorithms

Algorithm	Parameters	Accuracy
Multilayer Perceptron	hiddenLayers: 6; learningRate: 0.3; momentum: 0.2	81.94%
Random Forest	maxDepth: unlimited; numTrees: 100	84.72%
Support Vector Machine	kernel: radial basis function; loss: 0.1; degree: 3	80.67%
BayesNet	Estimator: SimpleEstimator; K2 search algroithm	72.95%
NaiveBayes	Numeric estimator precision values were chosen based on analysis of the training data	75.93%
J48 DecisionTree	The minimum number of instances per leaf was 2, 1 of 3 folds data were used for reduced-error pruning	80.37%

Because engagement was elicited in the same context (i.e., the driving simulator task), inter-participant variability was expected to be low (Stemmler, Heldmann et al. 2001). Nevertheless, to further reduce this variability, three minutes of baseline physiological data were collected for each participant at the beginning of the experiment that was used to normalize the data. The driving task program and the engagement detection module communicated via a TCP socket over a local area network (LAN). When defined events (e.g., start/end of a trial, task failure/success) occurred, a JSON (http://www.json.org) string containing a time stamp and event message was sent to the physiological data acquisition module. All event information and physiological data were recorded for offline analysis. Every three minutes, the driving task sent an event to trigger engagement detection. The engagement detection module acquired three minutes of data before this trigger. The three-minute data were preprocessed to remove electrical noise and motion artifacts. After that, the 10 selected features were extracted and baseline features were subtracted from the features to offset environmental and participant differences. Subsequently these features were fed into the previously established model to predict the engagement level. A binary label, “High Engaged” or “Low Engaged”, was sent to the driving task program via the socket which was then utilized by the difficulty adjustment module to make the decision about switching the difficulty levels (Figure 9). By measuring the execution time of the engagement detection code, we observed that the offline analysis for engagement detection took less than 100ms. The data collection resumed immediately after the engagement detection, a minimal enough delay to avoid any problems for our application. The difficulty adjustment process took place in another computer (i.e., in the main task computer) and thus did not cause any delay for the data collection.

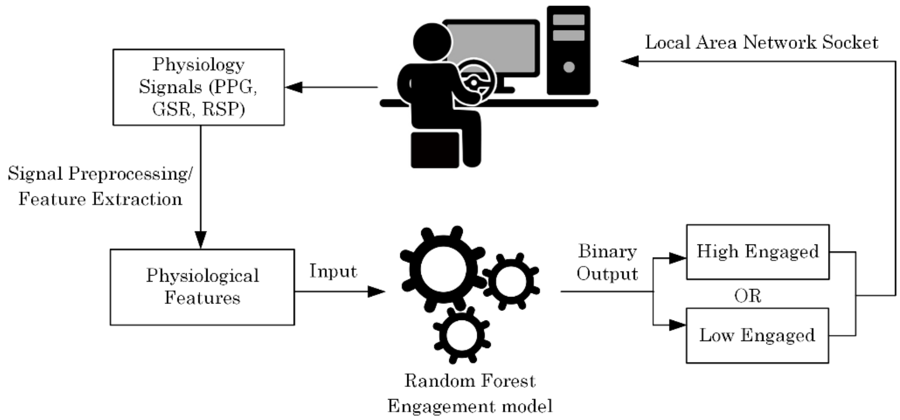

Figure 9: Online engagement detection module diagram

3.1.4 Difficulty adjustment module

We developed two different difficulty adjustment strategies for the proposed driving system. One strategy used only the participant's performance metric to adjust the driving task difficulty, while the other strategy utilized both the participant's performance metric and engagement level to make the adjustment. Within the framework of this study, the independent variable was the difficulty adjustment mechanisms we described below, which was determined before each experiment.

Performance-Sensitive System (PS)

For the PS, a task-switching mechanism adjusts the difficulty states solely based on the participant's performance. When a participant's performance is "Good" (Case 1), the task progression continues step-wise as the task difficulty level increases unless it reaches the most difficult level (Figure 10). On the other hand, if a participant's performance is "Poor" (Case 2), the task progression continues step-wise by decreasing the task difficulty level unless it reaches the easiest level. (Table 7, Algorithm 1)

Table 7: Performance-Sensitive System switching cases

	Performance	Action
Case 1	Good	Increase difficulty
Case 2	Poor	Decrease difficulty

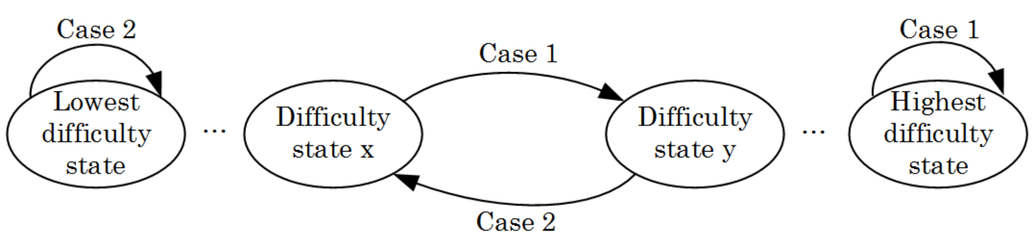

Figure 10: Performance-Sensitive System difficulty switching FSM
(Only draw four difficulty states for simplicity. Assuming difficulty state y is more difficult than x)

ALGORITHM 1. Performance-sensitive Difficulty Switching Action Computation

Input: Participant's performance: *perf*, current difficulty state: *diff_state*
Output: Difficulty switching action

```
repeat every 3-minute:
    if perf == "Good"
        if diff_state reaches highest_diff_state
            stay_the_same;
        else
            increase_difficulty;
        end
    else if perf == "Poor"
        if diff_state reaches lowest_diff_state
            stay_the_same;
        else
            decrease_difficulty;
        end
    end
until task_end;
```

Engagement-Sensitive System (ES)

For the ES, the task difficulty manipulation is not only based on participant's performance but also on his/her engagement level. We fuse the participant's performance metric and engagement level to make the switching decision. In two cases where engagement and performance metrics agree with one another, the switching strategy is straightforward. If a participant is "High Engaged" and his/her performance is "Good", the system increases the difficulty level based on the finite state machine representation (Figure 11). On the other hand, if a participant is "Low Engaged" and his/her performance is "Poor", the system decreases the difficulty level. However, in the other two cases, where engagement and the performance metric do not agree with each other, the switching strategy gives priority to the performance metric. For Case 2, in which engagement is "High" but performance is "Poor", the system recommends decreasing the difficulty level. For Case 3, when a participant is "Low Engaged" but his/her performance is "Good", the difficulty level remains the same and waits until the next trial for potential adjustment. At the next adjustment point, if the participant is still "Low Engaged" and his/her performance is "Good", the system decreases the difficulty level (Table 8, Algorithm 2). While there are alternative interpretations for different cases (refer Section 5), we involved a clinical psychology team to make such decisions and to provide a clear path for subsequent decisions within the learning chain.

Table 8: Engagement-Sensitive System switching cases

	Engagement	Performance	Action
Case 1	High	Good	Increase difficulty
Case 2	High	Poor	Decrease difficulty
Case 3a/3b	Low	Good	Same/Decrease difficulty
Case 4	Low	Poor	Decrease difficulty

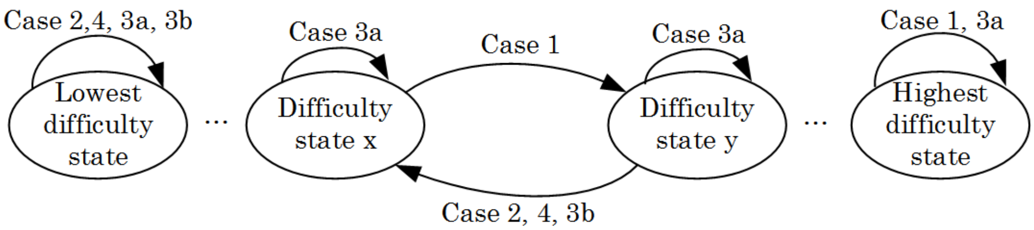

Figure 11: Engagement-Sensitive System difficulty switching FSM
(Only four difficulty states are drawn for simplicity; assuming difficulty state y is more difficult than x)

ALGORITHM 2. Engagement-sensitive Difficulty Switching Action Computation

Input: Participant's performance: *perf*, participant's engagement level: *engage*, current difficulty state: *diff_state*
Output: Difficulty switching action

```
next = False;
repeat every 3-minute:
    if perf == "Good" and engage == "High"
        if diff_state reaches highest_diff_state
            stay_the_same;
        else
            increase_difficulty;
        end
    else if perf == "Poor" and engage == "Low"
        if diff_state reaches lowest_diff_state
            stay_the_same;
        else
            decrease_difficulty;
        end
    else if perf == "Good" and engage == "Low"
        if next == False or diff_state reaches lowest_diff_state
            stay_the_same;
            next = not(next);
        else
            decrease_difficulty;
            next = not(next);
    else if perf == "Poor" and engage == "High"
        if diff_state reaches lowest_diff_state
            stay_the_same;
        else
            decrease_difficulty;
        end
    end
until task_end;
```

3.2 Methods and procedure

3.2.1 Experimental setup

VDEAR was run on a server-grade computer that could provide high-quality graphical rendering, while participants' peripheral physiological signals were acquired and processed in parallel on a separate computer. Both computers communicated over a LAN using socket-based connection. The VR driving task was presented on a 24-inch LCD monitor (at a resolution of 1980×1080). Participants sat on a play seat and interacted with the driving environment using a Logitech G27 driving controller. The experiment was conducted in a laboratory with two rooms separated by a one-way mirror for observation. The researcher sat in the outer room to observe the experiment.

3.2.2 Participants

We recruited 23 teenagers (21 males and 2 females) with ASD for this phase of study. This high number of male participants is in keeping with epidemiological data indicating significantly elevated prevalence for males as compared to females (Centers for Disease Control and Prevention 2014). All participants had a clinical diagnosis of ASD from a licensed clinical psychologist as well as scores at or above clinical cutoff on the Autism Diagnostic Observation Schedule (Table 9) (Lord, Risi et al. 2000). The participants either had a learners' permit or was pursuing a permit. The Institutional Review Board (IRB) approval for conducting the experiment was sought and obtained. In the end, 20 participants' data were used in this study. Three participants (all males) were excluded from the study due to compromised data or equipment failure.

Table 9: The 20 participant profiles from PS and ES groups

Demographic Information	PS Group Mean (SD)	ES Group Mean (SD)	*t*	*p*
Age	15.18 (1.27)	15.19 (1.89)	0.02	0.99
Driving Permit Status	4 (Yes) / 6 (No)	3 (Yes) / 7 (No)	NA	NA
Sex	9M/1F	9M/1F	NA	NA
ADOS New Algorithm Total Raw Score	13.57 (6.37)	12.5 (2.83)	0.41	0.69
ADOS Severity Score	7.71 (1.89)	7.25 (1.39)	0.54	0.60
SRS-2 Total Raw score	100.63 (30.64)	89.89 (31.38)	0.71	0.49
SRS-2 T-score	76.63 (12.16)	72.00 (10.71)	0.83	0.42
SCQ Lifetime Total Score	21.44 (8.47)	15.9 (6.54)	1.58	0.13
IQ	88.6 (23.38)	101.38 (20.21)	1.01	0.34

ADOS = Autism Diagnostic Observation Schedule, it is an instrument for diagnosing and assessing autism.
SRS = Social Responsiveness Scale (Constantino and Gruber 2007), it measures social ability of children from 4 years to 18 years old and is used primary with individuals with ASD.
SCQ = Social Communication Questionnaire (Rutter, Bailey et al. 2003), it is one tool clinicians use when screening an individual for ASD and is a measure for caregivers to complete.
IQ = Intelligence Quotient
NA = Not Applicable

3.2.3 Procedure

The participants were randomly assigned to either PS or ES groups. Each participant visited the lab once and completed a 90-minute session. At the start of the session, physiological sensors were placed on the participant's body by an experienced researcher. Participants watched a tutorial video which discussed basic traffic rules as well as manipulation of the driving interface. After the tutorial, the participant was asked to remain calm and relaxed for three minutes during which baseline physiological data were collected. To get familiar with the driving interface, participants also received three minutes of practice driving in which there were no pedestrians and no other vehicles in the VR environment. After the three-minute practice drive, participants began the driving assignment at medium difficulty. Through the assignment, participants were required to follow the navigation directions and obey traffic rules. Disobeying any traffic rules (i.e., running a red light) resulted in a performance failure. In addition, the system provided instructions and feedback to the individuals regarding performance such that even if one was novice in terms of traffic laws, he/she would be able to follow the rules of the game. Task difficulty was adjusted every 3 minutes in real time. The difficulty adjustment strategy was based on the participant's group assignment. The duration of the assignment was typically between 30 and 40 minutes, depending on the participant's performance. A post-task survey was completed once the participant finished the assignment (Figure 12).

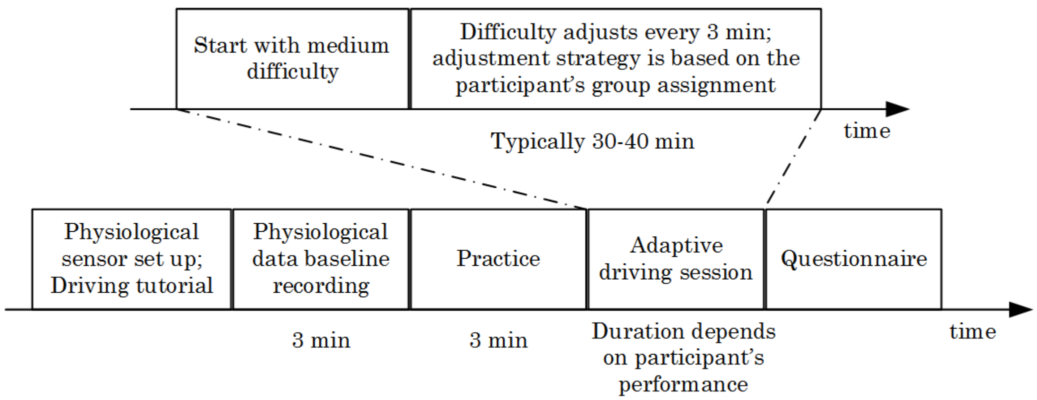

Figure 12: Procedure of the experiment

3.3 Results

3.3.1 Tolerability of the VDEAR system

We excluded the data from three participants because 1) physiological sensors became detached midway through the experiment, resulting in diminished signal quality; 2) the equipment failed thus we terminated the experiment. All participants who completed the study reported that they found VDEAR to be engaging and enjoyable. None felt uncomfortable wearing the physiological sensors. The average duration of the completed driving tasks was 34 minutes (SD=9).

3.3.2 Offline analysis of physiological data

The physiological data (PPG, GSR and respiration signals) were collected from all participants. For those in ES condition, physiological data were used to detect real-time engagement level to help the system determine the appropriate task difficulty level. In addition, we also computed the average engagement level for each group. In order to get a reliable estimate of the average engagement level for each participant, we used a three-minute window size and one-minute step size to segment the physiological data into a certain number of samples. As explained in Section 2.3.1, a number of features were extracted from these data and were normalized using the baseline features. These features were then used as input to the engagement model that we had built earlier. The outputs of the engagement model were the probabilities of two classes: "High Engaged" and "Low Engaged", and the sum of these two probabilities was 1. We used the probabilities of the "High Engaged" class as the engagement index of the participants. Thus, a higher engagement index reflects a higher engagement level.

The average engagement index for each participant was computed using the following equation:

$$\overline{EI} = \frac{\sum EI}{N} \quad (1)$$

where *EI* is the engagement index for each three-minute sample and *N* is the three-minute physiological data sample size for each participant.

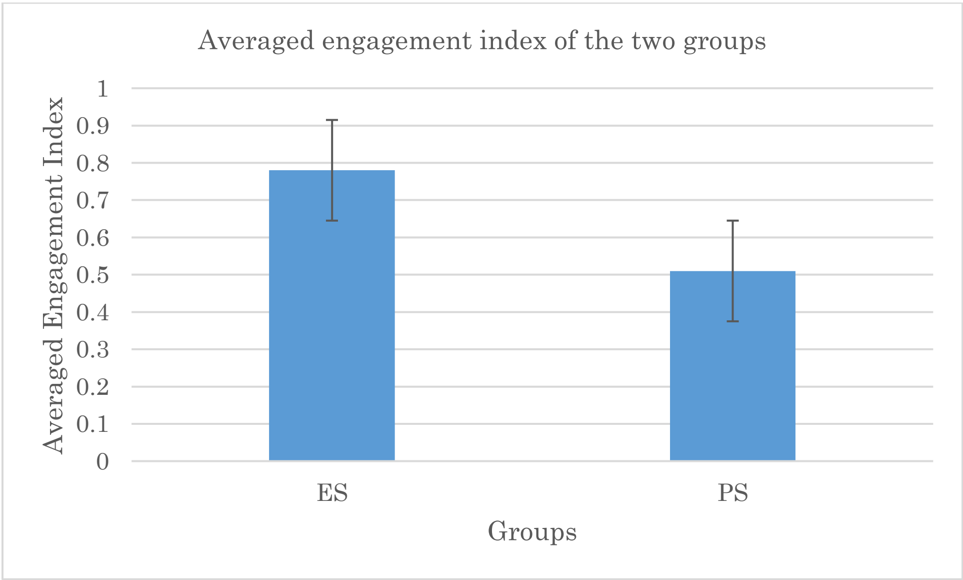

Figure 13: Average engagement index of the two groups

Figure 13 shows the average engagement index for the two groups. The *t* test shows that the average engagement index for the ES group (M = 0.78, SD = 0.18) was statistically significantly higher than the average engagement index for the PS group (M = 0.51, SD = 0.25), (t = -2.46, p = 0.03). We also found a large effect size, Cohen's d = 0.85, for this difference in engagement level.

3.3.3 Performance data analysis

Although the current study was not designed to investigate whether ES-based training was more effective than PS-based training–which will require a systematic long-term user study–we did analyze participants' performance for this study to get a preliminary understanding. We could not use raw performance scores directly to assess the performance of each participant because it is not correct to conclude that two participants with the same raw performance score in different difficulty levels performed equally well. We therefore normalized the raw performance score data by assigning a weight to each difficulty level. The following equation was used to calculate the weight for each difficulty level:

$$w_i = \frac{N_i \times S_{max,i}}{\sum S_{raw,i}} \quad (2)$$

where w_i is the weight, $S_{raw,i}$ is the raw performance score, N_i is the sample size, and $S_{max,i}$ is the maximum possible score, in difficulty level i. The general intuition behind this method is to give greater weight to those levels with lower average raw score because they are more difficult. Then the mean weighted score for each participant was computed by using the following equation:

$$\overline{S} = \frac{\sum w_i S_{raw,i}}{N} \quad (3)$$

where S is the weighted score and N is the sample size for each participant. The mean weighted score for the ES group (M = 12.25, SD = 1.12) was slightly higher than that for the PS group (M = 11.92, SD = 1.24). Although the difference was not statistically significant (t = -0.63, p = 0.53, Cohen's d = 0.28,) an adequately powered study might demonstrate a trend towards better training performance using the ES-based system.

In addition, we explored the distribution of the difficulty levels for both the ES and the PS group. As seen in

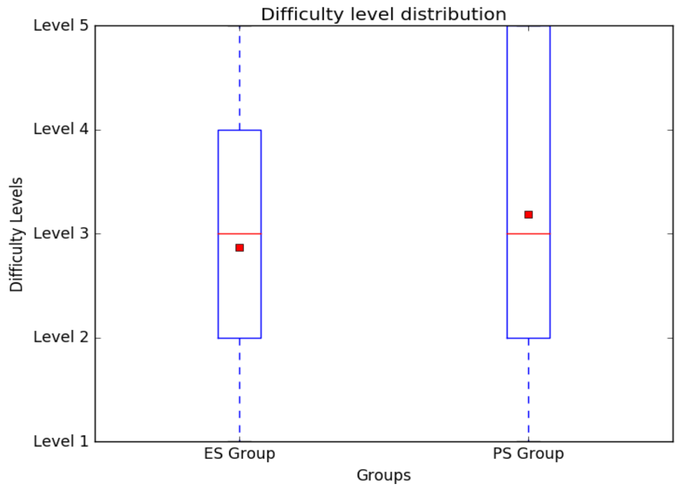

Figure 14, participants in the PS group tended, though not significantly, to progress to a higher difficulty level as compared to those in the ES group (t = -1.79, p = 0.07, Cohen's d = 0.23). This result agrees with the self-report about the overall task difficulty discussed in the following section.

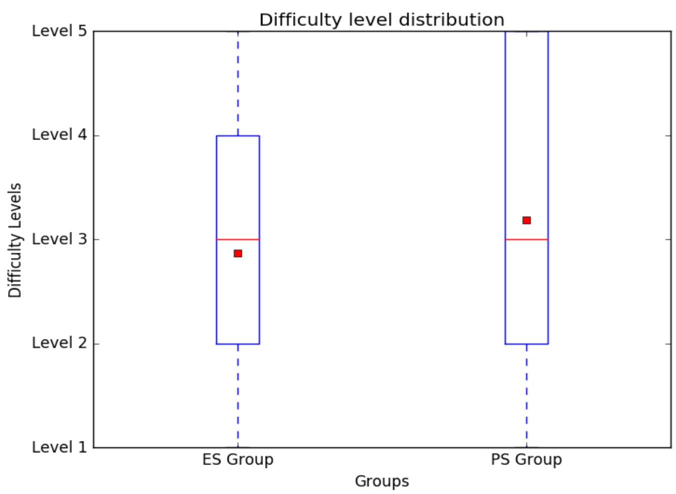

Figure 14: Difficulty level distribution for ES and PS groups

3.3.4 Questionnaire results

A questionnaire evaluating participant responses to the system was designed using a 5-point Likert scale. The questions, the mean values from both groups, t test results and effect size (Cohen's d) are listed in the Table 10.

As seen in Table 7, most of the participants (16 out of 20) from both groups noticed the difficulty adjustment in the driving task. Within those who noticed the difficulty adjustment, participants from ES group liked the difficulty adjustment more. Although other results did not show statistically significant difference, it is interesting to see that ES group reported lower overall difficulty, thought the difficulty adjustment was more helpful than the PS group, experienced less frustration and enjoyed the interaction more. Also, because the driving simulator was designed to be interesting for teenagers on the autism spectrum, and because participants attended only a single training session, the study design did not afford opportunities for variability in boredom levels. As a result, it is not surprising for us to see that both groups reported similar low boredom.

Table 10: Results of questionnaire

Questions	Mean score of ES group	Mean score of PS group	*p*	Cohen's *d*
Overall difficulty of the driving task	3	3.5	0.17	0.66
*Whether noticed difficulty changes?	7 (Yes)/10	9 (Yes)/10	NA	NA
How do you like the difficulty adjustment?	4.4	3.5	**0.005**	1.45
Whether the adjustment is helpful?	4.3	4.1	0.54	0.28
Overall enjoyment	4.3	3.8	0.18	0.62
Overall frustration	1.9	2.3	0.42	0.37
Overall boredom	1.8	1.7	0.81	0.11

*This is a Yes or No question. All the other questions use the 5-Likert scale, 1 means the least and 5 means the most.

3.4 Discussion and conclusion

This work presents the creation and pilot validation of a novel platform, VR-based Driving Environment with Adaptive Response technology (VDEAR), to provide an assistive system for the individuals with ASD to build confidence toward on-road driving. VDEAR capitalizes on the affinity of many people with ASD for technology while also providing for a closed-loop system of data capture, analysis, and system adjustment. Twenty out of 23 participants completed the driving task, and performance data as well as physiological data were properly recorded for offline analysis. All participants who completed the study reported positive experiences with the system. They all tolerated the physiological sensors, an important finding for adolescents with ASD who may have sensory sensitivities to wearable devices.

By feeding the physiological data into the engagement model to detect the average engagement level of each participant, we found that participants in the ES group had statistically significantly higher engagement than participants in the PS group. In addition, participants in the ES group subjectively reported that they liked the difficulty adjustment more than participants in the PS group. This further suggests that the physiology-based DDA mechanism may be more effective at keeping the user in the "flow state" when compared to the performance-based DDA mechanism. No differences were found in performance data, however, with participants in ES group achieving similar performance as participants in PS group. Also, participants in the PS group spent more time in higher difficulty levels in spite of the fact that they were in lower engagement levels. Although we did not expect to observe performance improvement for this one-session study, the ability to document the driving performance as well as engagement level makes designing of long-term driving sessions and assessing users' performance and engagement level over time more feasible using the VDEAR system. We believe that such a system will have the potential to make driver training more accessible to a large number of individuals with ASD.

It can be inferred from the above results that in a one-session study, the physiology-based DDA mechanism could create higher engagement in the participants and result in similar rates of success compared to a performance-only-based DDA. This could be potentially beneficial for long-term driving training programs since the participants will likely be more willing to participate in multiple driving sessions that utilize their engagement feedback, as opposed to the one in which only performance is a factor. While we expect that an engaging and enjoyable training system will foster skill learning, it is beyond the scope of the current work to investigate skill improvement using a longitudinal user study.

This novel driving skill training platform does not rely on the user's input to adjust the system difficulty, which is potentially advantageous because individuals with ASD may not have the self-awareness and cognitive capability to provide such information. Although our system's engagement model must be developed beforehand, in the future we can utilize real-time affective computing methods to update the model to make the system generalizable. Moreover, with the rapid development in the field of wearable and less invasive physiological sensors (e.g., smart watches), this kind of adaptive system, in which a user's affective cues will become easier to implement, will be more reliable and commonplace.

Although the engagement-sensitive adaptive driving task presented in this paper is designed for the ASD population, the presented physiology-based DDA mechanism is independent of the driving environment and thus can be integrated into other gaming or training environments. The engagement information is detected separately and sent to the main program in JSON format over a LAN using standard internet protocols. Once we defined the difficulty switching logic in the game environment, this physiology-based adaptation mechanism can be integrated seamlessly. The following figure (Figure 15) depicts the framework for designing a physiology-based adaptive game environment.

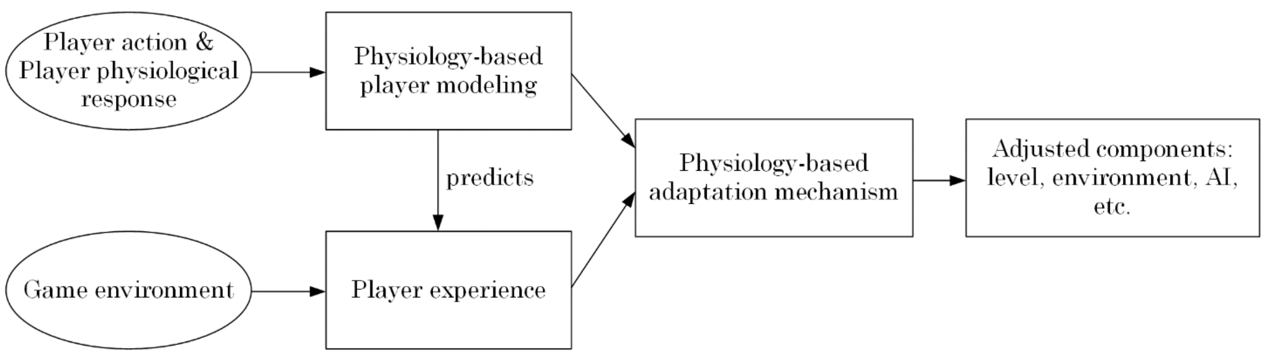

Figure 15: Physiology-based adaptation mechanism in game design

Note that the current work is limited in interpreting and modeling behaviors based on single estimates of both Engagement (E) and Performance (P). It is quite accurate to state that iterations of E and P in their specific combination may be reflective of different learning states (for example low E and Low P could be reflective of boredom or could be reflective of a task that is too challenging). In this capacity, the true value of intelligent, dynamic decision-making systems will come in the form of interpretation of chains of decision and reactions. That is, it becomes clearer to differentiate boredom and challenge if the manipulation hypothesis is not born out in subsequent modeled state. Such delineation and interpretation of sophisticated chains of learning are somewhat beyond the scope of the current work; however, we should mention that these modeling decisions were seen as the best initial hypotheses of manipulation such that an intelligent system could dynamically interpret and discern changes in learning over time. Importantly, we involved a clinical psychology team with requisite experience in Applied Behavior Analysis to inform our initial interpretations regarding potential functions of behavior and decisions that would yield clarity over time. In this context, it was determined that making initial classification decisions on Low E across adequate and low P would provide a clear path for subsequent decisions within the learning chain. Another limitation of the current work is that the engagement measures we used in this work were calculated from the engagement model. In the future an additional measure of engagement will strengthen the work. One threat to the validity of our proposed work is the lack of quantitative measure of participants' driving-related experience before they participated in the study. Different driving-related experience might lead to different confidence levels when completing the driving task. In future work, we will have participants complete a questionnaire about their past driving-related experience. For example, we might want to know whether/how much they have played driving-related video games, whether/how much they have behind-the-wheel driving experience, and so on. Note that we did not observe any performance gains in the ES as compared to the PS in the one-session user study. Driving skill improvement requires greater exposure to training and it is unsurprising not to have observed any gains in just one session. A more systematic longitudinal study will be needed to objectively assess whether ES-based training will result in higher gains in driving skills. What is encouraging, however, is that participants in the ES were found to be significantly more engaged than those in the PS, which may indicate superior compliance among the ES participants in a long-term protocol.

Acknowledgement

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4. A Novel Multisensory Stimulation and Data Capture System (MADCAP) for Investigating Sensory Trajectories in Infancy

Abstract

Sensory processing differences, including responses to auditory, visual, and tactile stimuli, are ideal targets for early detection of neurodevelopmental risks, such as autism spectrum disorder. However, most existing studies focus on the audiovisual paradigm and ignore the sense of touch. In this work, we present a multisensory delivery system that can deliver audio, visual, and tactile stimuli in a controlled manner and capture peripheral physiological, eye gaze and electroencephalographic response data. The novelty of the system is the ability to provide affective touch and integration of tri-modal sensory stimuli. In particular, we have developed a tactile stimulation device that delivers tactile stimuli to infants with precisely controlled brush stroking speed and force on the skin. A usability study of ten 3-20-month-old infants was conducted to investigate the tolerability and feasibility of the system. Results have shown that the system is well tolerated by infants and all the data were collected robustly. This work paves the way for future studies charting the sensory response trajectories in infancy.

This chapter is organized as follows. Section 4.1 presents the system design of MADCAP. Section 4.2 describes the evaluation of the tactile device in terms of both simulation and real device. Section 4.3 presents a usability study to demonstrate the tolerability and feasibility of the system. In the final section, we conclude with a discussion of the results and ideas for future work.

4.1 Multisensory Stimulation and Data Capture System (MADCAP) system design

MADCAP includes three main components: a multisensory stimulation delivery module consisting of auditory, visual, and tactile stimuli, a multi-dimensional data capture module capturing a participant's response, and a supervisory controller module to synchronize the interconnection between the two modules. Figure 16 shows the schematic of the overall system.

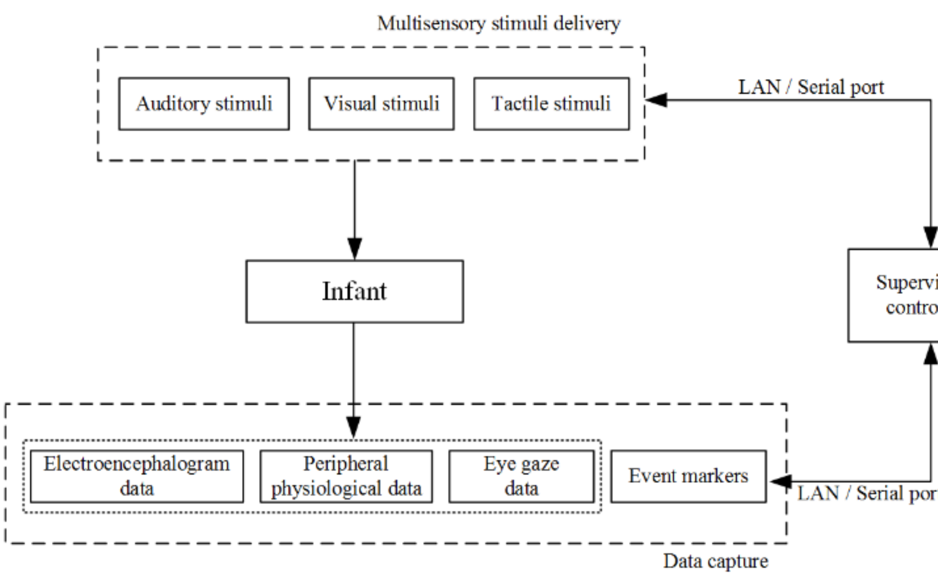

Figure 16: MADCAP system schematic

4.1.1 Multisensory stimulation delivery module

The presented multisensory stimulation delivery module is capable of delivering both synchronized and asynchronized tactile, auditory and visual stimuli to the subjects. While the audio-visual stimuli delivery subsystem is not entirely novel, the tactile stimulation device for affective touch and integration of tri-modal sensory stimuli is novel and is discussed in detail.

A. Tactile stimulation device

In this work, we have developed a tactile stimulation device (TSD) specifically to deliver affective touch to infants at precisely controlled brush speed and force. Since this device is meant for infants, special consideration was given to the size, speed, comfort, and safety of the device, which are described below.

Design overview

TSD is designed to impart affective touch on the dorsal side of the forearm of infants under 24 months of age. The housing of the system needs to provide ample, comfortable space where an infant can place his/her arm to be stroked by a soft brush. In order to determine the overall size of the device, we considered both the arm circumference and arm length for infants under the age of 24 months. The arm circumference median with z-scores of 3 is 18.45 and the average arm length is 13cm (WHO Multicentre Growth Reference; 2007). The compartment that holds the arm should have a variable radius to accommodate different subjects. The brush should have a stroke length longer than the maximum possible forearm length of infants within the target age range.

Brush speed is one of the key variables in creating affective touch. In previous studies, brush stroking speed in the range of 1 cm/s to 10 cm/s was found to be most pleasant and effective in producing affective sensation (Löken, Evert, and Wessberg 2011). We designed our system to cover this speed range with more precision, although if necessary for future work, the speed could be increased.

Comfort is also important for a device used by infants because they may feel frustrated or afraid when their range of motion is restricted (e.g., when an arm is restrained within a mechanical system). As a result, we designed the tactile stimulation device such that an infant can move her arm, along with the device, freely in 3-D space while remaining attached. The design also specifically eliminated sharp edges and rough surfaces. Moving mechanical elements were placed in a space that was out of infants' reach as well as sight.

Based on the above considerations, the TSD was designed and constructed as shown in Figure 17. The device has three compartments from top to bottom. The top compartment contains actuators that control the brush. The middle compartment includes a replaceable soft brush. A force sensing resistor is attached to the bottom of the brush so that the force applied on the arm from the brush can be measured and modulated. The infant's arm rests in the bottom compartment. The infant's forearm is placed into a soft strap to hold it in place and guarantee that the brush will contact the forearm. The device is attached to a gravity compensating articulating arm which gives the infant a certain degree of freedom to move his/her arm while the relative position between the arm and the device remains the same (Figure 18a).

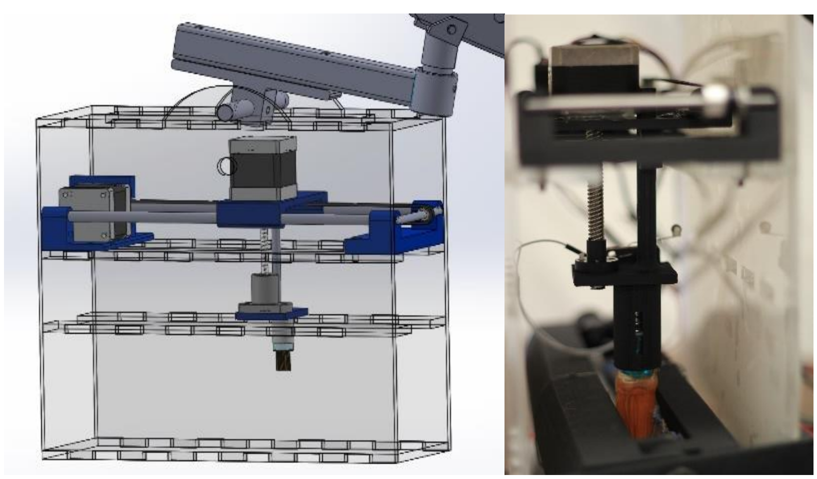

Figure 17: a) A CAD drawing of the mechanism; and b) the fabricated system

Mechanical design

The brushing mechanism has two degrees of freedom, a horizontal motion to move the brush along the length of the forearm and a vertical motion to move the brush up and down to control contact force as shown in Figure 17a. Two stepper motors (NEMA 17) were selected to actuate the brush in both directions. We selected stepper motors because they can provide precise positioning and replicability of movements. Thus, the brushing movement can be precisely controlled and repeated. The stepper motor and its transmission ratio, which controls the horizontal movement, were chosen in such a way that the brush could reach a maximum horizontal speed of 13cm/s, which covered the most effective stroking speed range for affective touch. A lead screw stepper motor was chosen to control the vertical movement of the brushing mechanism. Lead screw converts a turning motion into a linear motion and provides precise positioning, which is suitable for the vertical movement of the brushing mechanism. In the middle compartment, the brush is attached to the device through a Lego brick-type design, so that brushes with various size and material can be attached and detached easily. The brushing force control mechanism lies in the bottom part of the brush, which is discussed in detail in Section *Electronic design and control logic*.

The infant's arm is held inside an arm holder in the bottom compartment. The infant is not able to reach or see any sharp parts like the lead screw or the motors in the upper two compartments. The arm holder was designed and 3D-printed to keep the relative position between the arm and the assembly fixed while the assembly moves in 3D space. The holder could open and close to adapt to the sizes of different subjects. The holder had a gradient radius from 35mm to 40mm to better fit the shape of an arm. Soft cushions were attached to the inner surface of the holder for better comfort (Figure 18b).

As shown in Figure 18a, the assembly described above is hung on a mechanical manipulator (Dectron, USA) such that an infant can move her arm attached to the assembly in the 3-D space. By adjusting the spring inside the rod, the manipulator could compensate for the weight of the assembly as well as for the baby's arm. Thus, the infant could freely move her arm with the attached device.

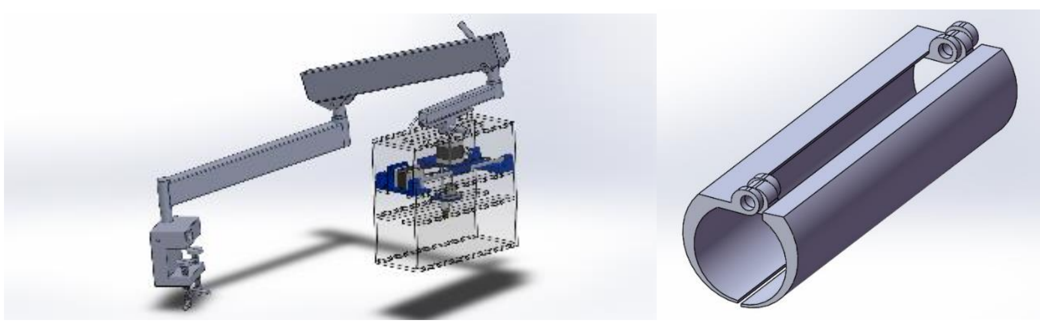

Figure 18: a) The gravity compensated manipulator supporting the weight of device; and b) arm holder

Electronics design and control logic

An Arduino-based microcontroller circuit board (chipKIT uC32) was used to control the two stepper motors because it has a faster processor than the traditional Arduino board, thereby guaranteeing smooth movement of the two stepper motors. We also chose two motor driver boards (EasyDriver) to drive the stepper motors and two limit switches (D2VW-5L2-1HS, Omron) to set up their initial positions. The back and forth motion was controlled in an open-loop manner since the stepper motor was fairly accurate in maintaining speed. The force on the skin was controlled in a closed-loop manner.

The TSD is designed to simulate affective touch by stroking an infant's arm with a soft brush back and forth at a given speed and force. As such, we developed the TSD to receive the control command, including translational speed (v_0), brushing counts (c), and brushing force (f), to perform back and forth stroking based on the Finite State Machine (FSM) shown in Figure 19.

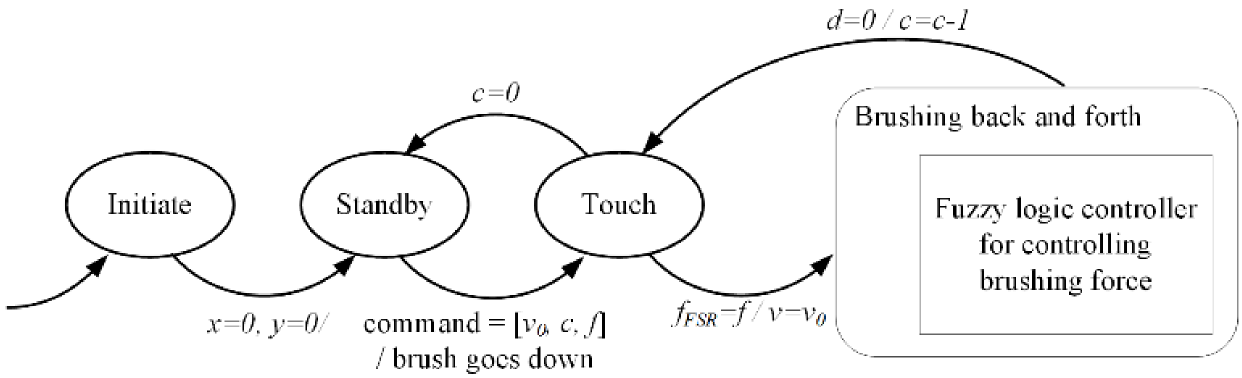

Figure 19: FSM for controlling the horizontal movement of the brush. Where *x* and *y* are the position of the brush in horizontal and vertical directions, respectively, *c* is the brushing count, v_0 is the brushing speed, f is the brushing force, f_{FSR} is the force computed from force sensor, *d* is the horizontal distance of the brush away from the initial position.

Generally, for the TSD, the FSM starts with the "Initiate" state, where the lead screw and the translational stepper motors go up and back, respectively, until both limit switches are triggered to set the initial positions. The FSM then moves into the "Standby" state, waiting for a command. When a valid command comes in, the "Touch" state is triggered, and the brush goes down until the force on the brush reaches the desired value. In the brushing state, the brush strokes the baby's arm back and forth, and the counter subtracts one stroke after each round of stroking. The brush goes back to the "Standby" state once the desired stroke count is completed.

To achieve consistent brushing force and a smooth actuation of the lead screw during the "Brushing back and forth" state, a fuzzy logic controller was implemented. Fuzzy logic control is a natural choice for our application, since instead of applying pressure that varies continuously, we are interested in applying forces to the forearm that can be categorized as "soft", "medium", and "high." Compared to other control methods, fuzzy logic control maintains the variable in a desired range rather than at a specified value. This approach combines regulation algorithms with logical reasoning and reduces mechanical chattering so that the system has a smoother motion and less noise.

In order to apply controlled brushing force on the forearm, allowing the system to control the brush such that it touches the forearm gently and without abrupt force, we implemented a mechanism to measure the contact force as the input of the fuzzy logic controller. The mechanism is illustrated in Figure 20. It contains a brush, a platform connected to the lead screw, an IR-LED, and a force sensing resistor (FSR). The lead screw actuates the brush along the vertical direction based on the output of the fuzzy logic controller. Before the brush touches the forearm, the IR-LED measures the distance between the arm surface and the end of the brush to control the vertical speed towards the arm. The IR-LED has a very accurate linear measurement in the distance range from 2-15cm and it is suitable for this purpose. The end of the brush is connected to the FSR through a spring which is used to avoid the disturbance from tilting during brushing, thereby assuring an exact reading of the normal force. In order to map the sensor analog reading to the normal force, we calibrated the FSR to get the mappings as shown in Figure 21. Gaussian membership functions were used to map the contact force to the five states because they best fit the data with the actual tactual feeling. Thus the fuzzy logic controller has five input and output states. The input states are: None, Soft, Medium, Hard, and Heavy; the output states are: High Speed Down, Low Speed Down, Stop, Low Speed Up and High Speed Up.

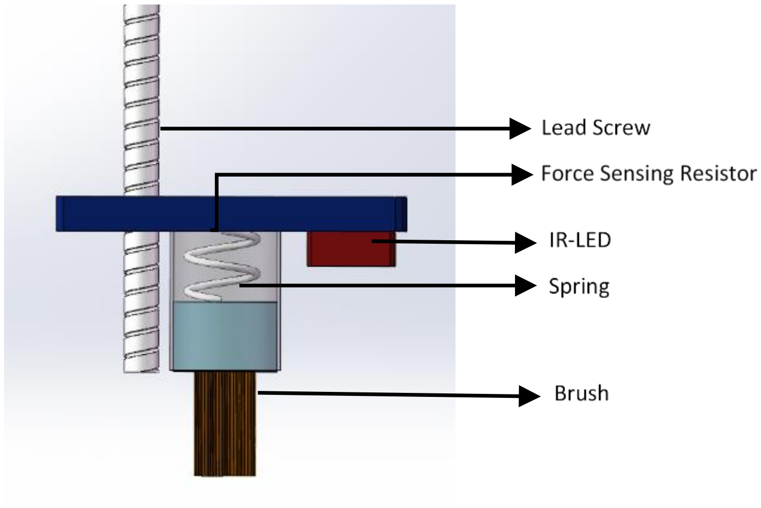

Figure 20: Illustration of the brush and sensors for maintaining consistent brushing force. Force Sensing Resistors (FSR 402, Interlink Electronics) were integrated at the base of the brush to measure the force at the end of the brush. Infrared LED (GP2Y0A51SK0F, Sharp) was used to measure the relative position between brush and the arm.

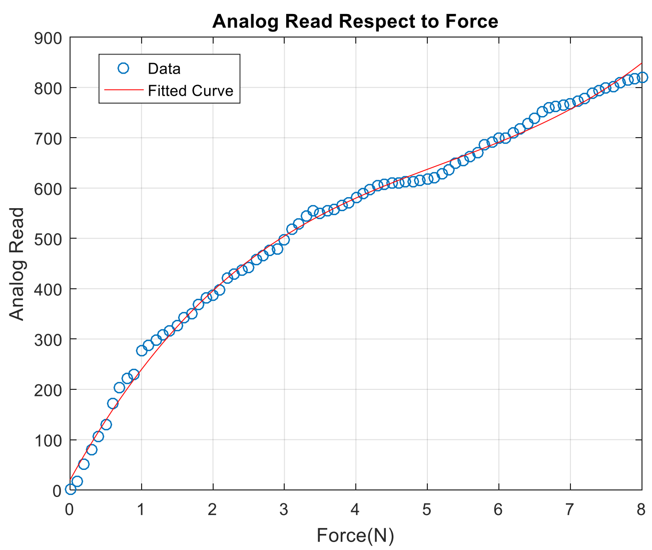

Figure 21: The relationship between readings of the force sensor and actual force upon the sensor

A real-time input is mapped to the state which has the largest membership function value. The membership functions are derived based on real-life experiments, which are plotted in Figure 22. The membership function values, which varies from 0 to 1, indicate the likelihood of an input or output belonging to one state.

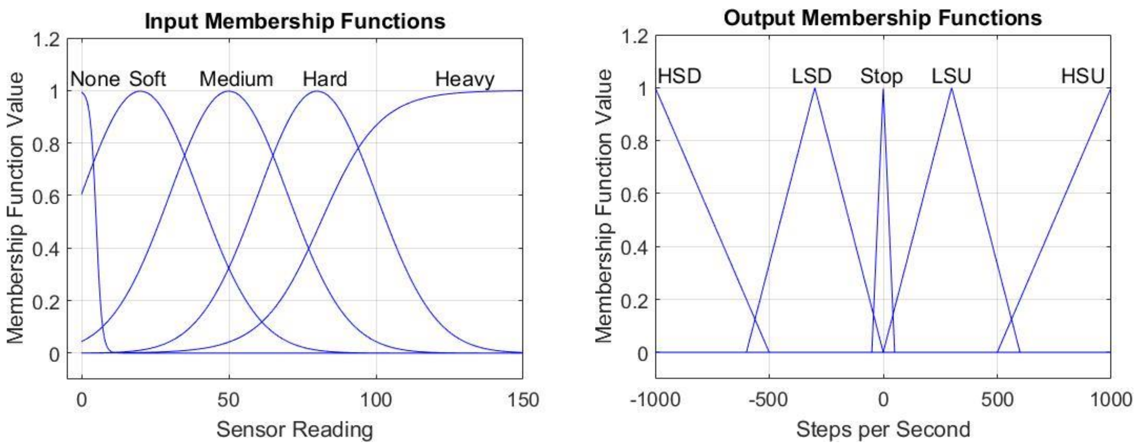

Figure 22: The membership functions of the input and output of the fuzzy controller.
HSD: High Speed Down; LSD: Low Speed Down; LSU: Low Speed Up; HSU: High Speed Up

Fuzzy logic rules generate appropriate output with respect to the input. To maintain different forces of touch, several rules were defined and tested. For example, the rules to produce medium touch are defined as follows:

1. If Pressure is None, then Brush speed is High Speed Down.
2. If Pressure is Soft, then Brush speed is Low Speed Down.
3. If Pressure is Medium, then Brush speed is Stop.
4. If Pressure is Hard, then Brush speed is Low Speed Up.
5. If Pressure is Heavy, then Brush speed is High Speed Up.

These rules generate an appropriate output for real-time inputs to keep the brushing pressure in a desired range.

B. Audiovisual stimulation delivery module

We designed a custom audiovisual stimulation delivery module to present clips of a female adult narrating a short story to the infant in our usability study (Section 4.3.2). This module has the ability to communicate with various other stimulation delivery modules and data capture modules.

Unity (https://unity3d.com) software was used to implement the module. A finite state machine (Figure 23) was used to control the logic of the stimuli presentation. All parameters of the stimuli delivery such as the content of the audiovisual stimuli, the duration of rest between two stimuli, and the dose of the stimuli, could be adjusted easily according to the experimental protocol. In addition, the user-defined event markers, such as start/end experiment and start/end stimulus, were logged into files using the JSON (www.json.org) format.

This audiovisual stimulation delivery module also communicated with the tactile stimulation device via the supervisory controller to ensure that multisensory stimuli were properly synchronized. Furthermore, this module sent the user-defined event markers to the data capture module for later data analysis. We discuss the details of the inter-module communications in Section 4.1.3.

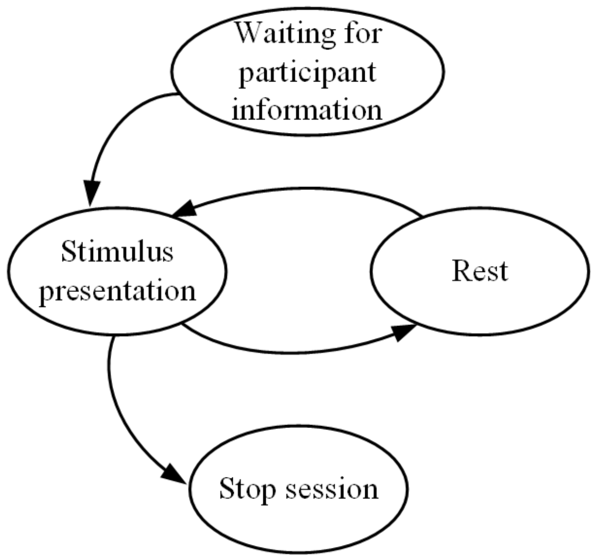

Figure 23: Audiovisual delivery module FSM. The program starts in the “waiting for participant information” state. After the experimenter inputs the participant information, the program starts the “Stimulus presentation” state. The participant has a specified amount of time to rest between two stimuli. After several rounds of stimulus presentation according to the protocol, the program will come to the “Stop session” state and save the data.

4.1.2 Data capture module

MADCAP was designed to track infant eye gaze when they look at audiovisual stimuli. The Tobii X120 eye tracker (Tobii Pro AB), which has a sampling rate of 120 Hz, was used to measure gaze position across defined regions within the audiovisual presentation. The (X, Y) coordinates of the gaze position—(0, 0) for upper left corner—as well as time stamps and event markers were recorded.

The infant’s peripheral physiological data, including blood volume pulse (BVP) and electrodermal activity (EDA), were recorded using the E4 wristband (Empatica Inc.), which is an unobtrusive device suitable for research involving infants. The E4 wristband is worn on the infant’s ankle during recording. The sampling rate for BVP and EDA is 64Hz and 4Hz, respectively. By using the hardware API provided by the E4 wristband, we developed a custom program in C# for the E4 wristband to record time-stamped physiological data within the protocol. The physiological data measured by the E4 wristband were wirelessly streamed to the custom program via Bluetooth.

In addition, electroencephalogram (EEG) data was recorded using a dense-array EEG system (EGI Inc.). EEG was recorded from a 128 channel HydroCel net and the sampling rate was 1000Hz for each channel. All 128 channels were recorded continuously, and event markers were registered via a serial port for off-line segmentation of the data. The vertex electrode was used as a reference, and the data were later re-referenced to an average reference.

4.1.3 Supervisory controller module

As can be seen from the system diagram (Figure 16), the supervisory controller module served as a bridge between the multisensory stimulation delivery and the data capture modules. It played a crucial role in the MADCAP system, making sure that all stimuli were presented in a time-synchronized manner and that data capture was properly controlled based on specific events and time stamps.

The supervisory controller communicates with the tactile stimulation device through the serial port at a baud rate of 9600 bits/second. As depicted in Figure 24, a command is sent to the tactile stimulation device to initiate the brush stroking when a tactile stimulus is needed. The brush stroking does not start immediately because it must first be moved vertically to come into contact with the infant’s arm, as described in Section 4.1.1. As soon as the brush touches the infant’s arm and the force sensor detects the touch, the tactile stimulation device sends a notification message to the supervisory controller. Then the supervisory controller initiates the audiovisual stimulus. In this way, we guarantee the audiovisual and tactile stimuli fire at the same time.

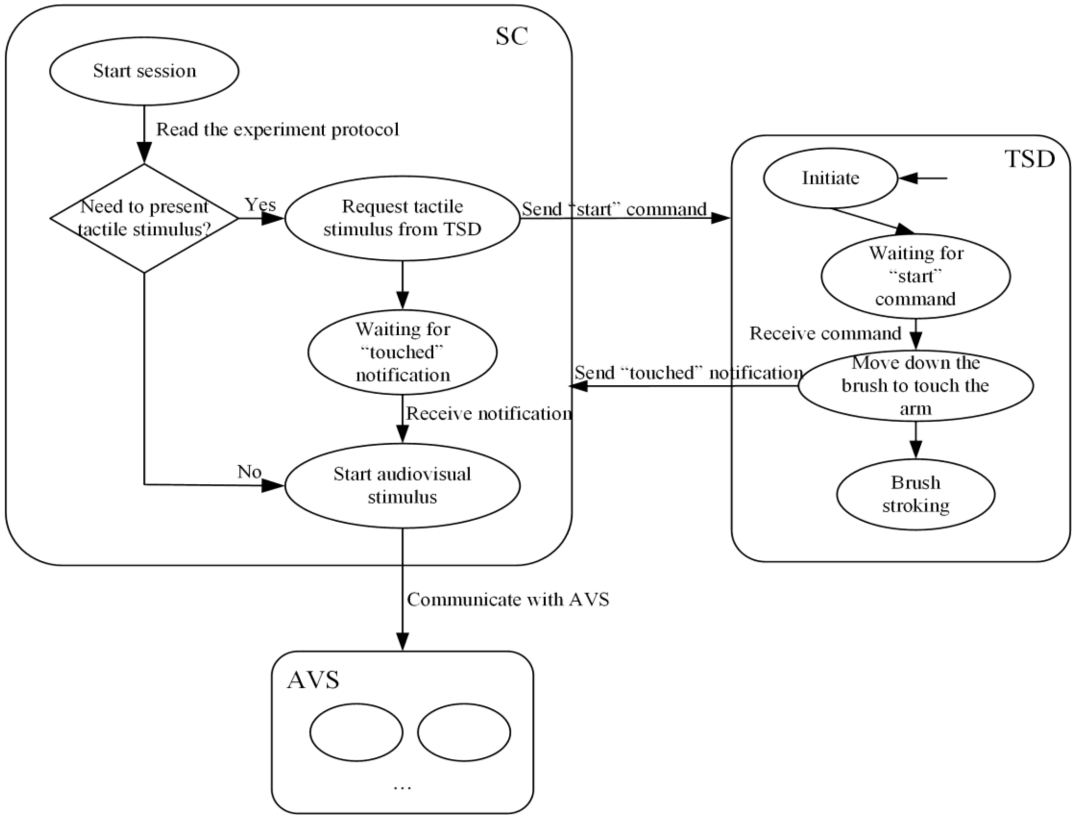

Figure 24: Supervisory controller FSM to synchronize stimuli deliveries.
SC: Supervisory Controller module; TSD: Tactile Stimulation Device; AVS: Audiovisual Stimuli presentation module

The supervisory controller communicates with both the physiological data recording program and the eye gaze data recording program over a TCP/IP based socket in a Local Area Network (LAN). For EEG data recording, event markers are added by inputting Transistor-Transistor Logic (TTL) pulse to the amplifier. We have designed a circuit board which can be controlled by the supervisory controller to generate different kinds of TTL pulse to represent different event markers.

Throughout the experiments, the supervisory controller monitored the stimulation delivery modules. When a user-defined event occurred (e.g., start brush stroking/audiovisual stimulus), the supervisory controller sent an event marker in JSON format to the data capture modules over socket or serial port.

4.2 Tactile stimulation device validation

The TSD was validated in two steps. First, the TSD was validated separately via simulation in MATLAB Simulink. Then we tested the real-world performance of the TSD on adults.

4.2.1 Simulation results

MATLAB Simulink was used to simulate and validate the fuzzy logic controller that maintains the brushing force of the TSD. The basic premise of this simulation is to stroke an uneven surface, much more uneven than a human arm, and to see whether the brushing pressure still stays consistent. Ten Hz Gaussian noise was introduced in the simulation to create realistic situations.

Simulations of the brush stroking under different brushing conditions. The results are shown in Figure 25. The simulation used an extremely wavy arm shape with a peak-to-peak value of 4 cm, which is much greater than the possible variance of arm radius. Figure 25 shows the simulation results of one 10 cm long brush stroke. In the middle point of the stroke (i.e., at 5cm), the brushing pressure changed from Hard to Soft. Figure 25 also shows the brush trajectory. The red curve simulates the shape of the arm and the blue curve is the moving trajectory of the brush. We can see that the blue curve follows the shape of the red curve while keeping a vertical distance lower than the red curve, meaning that the brush bristles were bent. After time 5s, the brushing pressure is automatically adjusted to soft and the vertical distance between the two curves is shorter, meaning that the brush bristles are bent less. The relative position between the red curve and blue curve before and after 5cm point stays relatively constant. In addition, the controller has a short adjustment time of 20 milliseconds, and the relative position stabilizes in a very short time after starting the simulation.

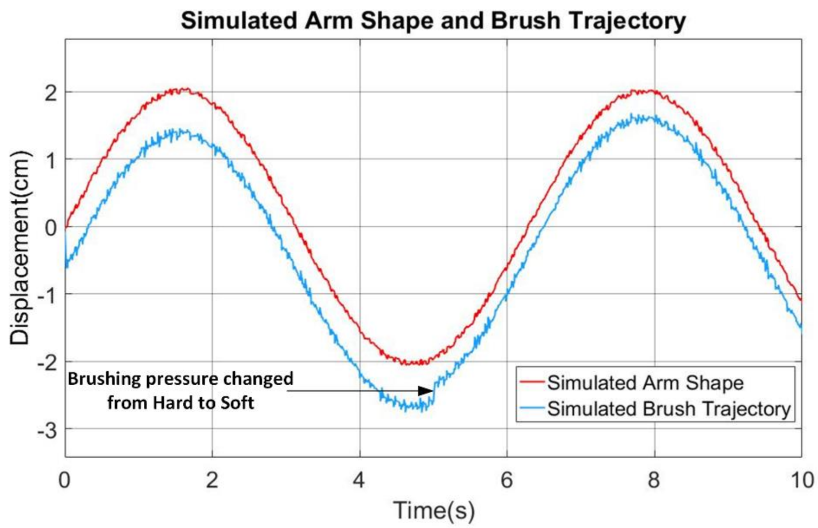

Figure 25: Simulink results.

4.2.2 Real system results

The real system validation was done on the arms of adults without the arm holder (Figure 26), which should be comparable to an infant's arm inside the arm holder, which is only necessary to maintain stillness. The goal of this experiment was to brush back and forth at a speed of 5 cm/s on the arm with a constant force of 0.3N. As can be seen from Figure 26, the brush completed 13 strokes with a constant pressure of 0.3N. It quickly reached the desired force (within 700 milliseconds) and remained within 0.03N of the desired force. The brush shook slightly during the motion, which could be due to the noise in the sensor readings and skin friction. The test subjects reported perceiving consistent brushing force during the stroking procedure.

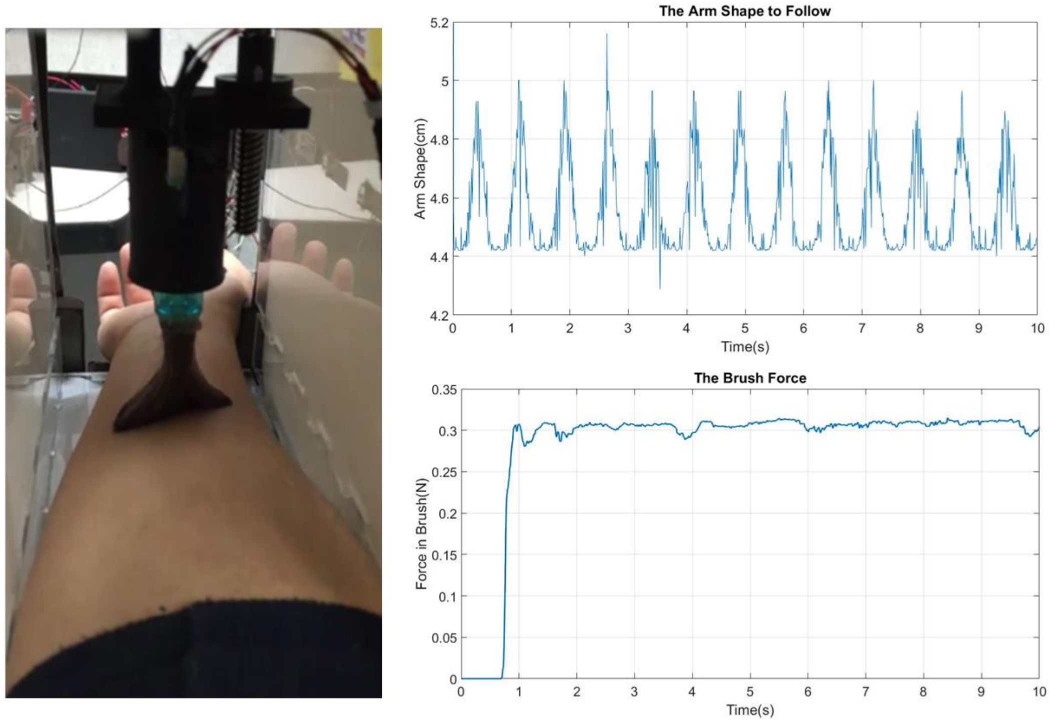

Figure 26: Real system experiment and results.
Left: Brushing test with an adult's arm
Top Right: The simulated arm shape over time; Bottom Right: The brush force recorded by force sensor over time.

4.3 MADCAP usability study

In order to demonstrate the tolerability and feasibility of MADCAP, we tested our integrated audio, visual, and tactile protocol across a sample of 10 infants from 3-20 months of age (5 girls, 5 boys; mean age = 9.75 months, SD = 5.60). The protocol was reviewed and approved by the Institutional Review Board (IRB) at Vanderbilt University. After receiving a thorough explanation of the experiment, parents gave written informed consent for their children's participation.

4.3.1 Experimental setup

Within a sound-attenuated room, the infant was seated in an age-appropriate infant/toddler seat and was positioned 50 cm from the LCD monitor, a video recording device, and an eye tracker. If a parent requested to have the infant on her/his lap or if the infant refused to sit in an infant seat, the parent was permitted to hold the infant in her/his lap but was asked to minimally distract the infant. The Geodesic EEG cap was placed on the infant's head. Then, the infant's left forearm was positioned within the bottom compartment of the tactile stimulation device and was attached using a Velcro strap. The E4 wristband was attached to the right ankle (Figure 27) of the infant. Subsequently, the eye tracker calibration was accomplished by using audio-enabled, animated cartoon pictures. We used 2- or 5-point calibration procedures depending on the infant's age (Gredebäck, Johnson, and von Hofsten 2009). The infants then participated in a single session, lasting approximately 10 minutes, wherein they were exposed to three distinct presentations of audiovisual speech stimuli (each 50s in length) along with affective touch, as described below.

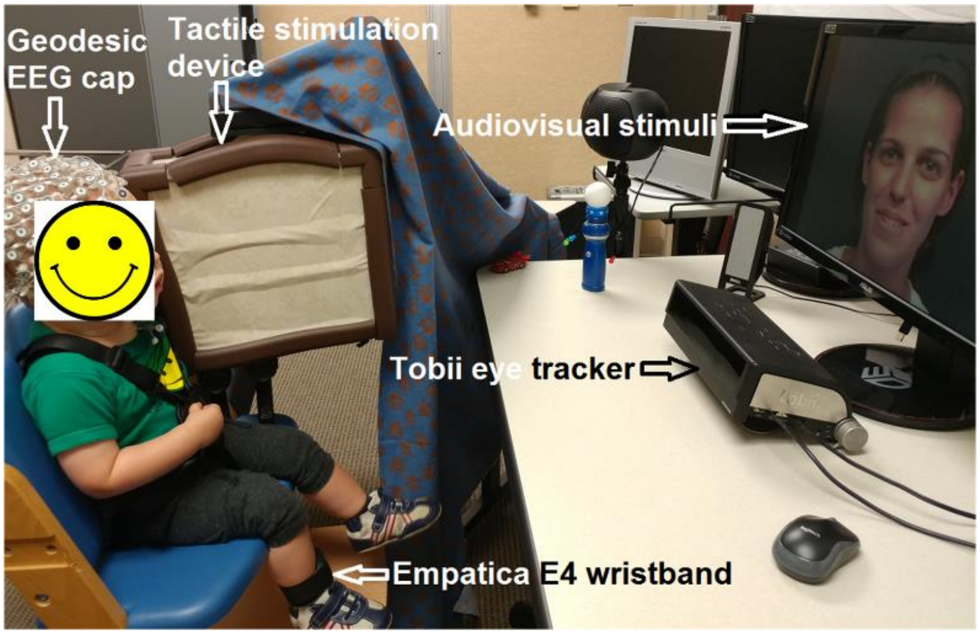

Figure 27: MADCAP experimental setup.

4.3.2 Procedure

The audiovisual speech presentations were the same stimuli utilized by Lewkowicz (Lewkowicz et al. 2015) exploring infant's selective attention to fluent audiovisual speech. Specifically, the stimuli were video clips of an adult female narrating a short story using infant-directed speech produced in three conditions: (a) synchronous, native language (i.e., English), (b) synchronous, non-native language (i.e., Spanish), and (c) asynchronous, native language (with timing of the auditory speech information delayed 500ms). Each audiovisual speech recording was presented with and without concurrent tactile stimulation. In the presence of tactile stimulation, the infant's dorsal forearm was continuously stroked (i.e., back and forth) at a speed of 3cm/s, the pressure around 0.2N, with a soft makeup brush. The brushing length was 10cm. The reason for continuously stroking was to simulate affective touch, which typically happens when the caregiver gently strokes the infant's forearm continuously (McGlone, Wessberg, and Olausson 2014). The stroking speed and pressure were chosen based on existing studies which have shown that gentle touch at medium speed produces the most pleasant effect (Löken, Evert, and Wessberg 2011). The task stimuli were presented in pseudorandom order, and the infant received 10-seconds of rest after each stimulus to reduce sensory habituation. The procedure of the usability study is shown in Figure 28.

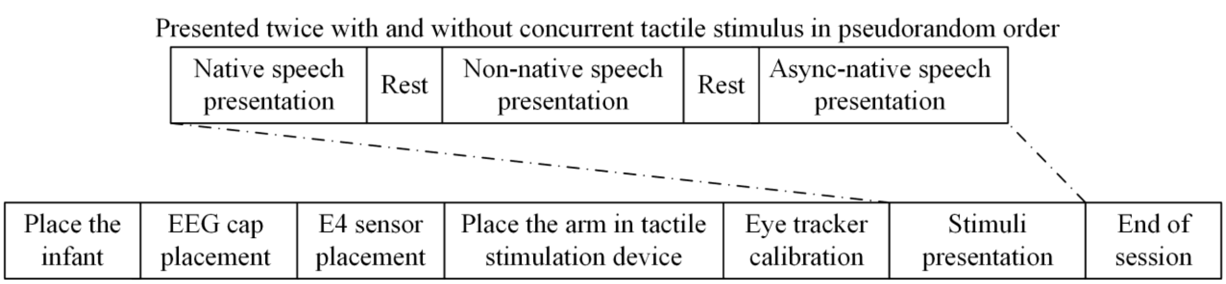

Figure 28: Procedure of the MADCAP usability study.

4.3.3 Usability study results

The target population for MADCAP is infants under the age of two years. Because of the vulnerability of this population as well as their inherent difficulty understanding experimental expectations, establishing tolerability and feasibility is crucial in determining if additional data can be collected robustly.

A. Tolerability and feasibility of the system

Results of this study demonstrated that 7 out of 10 infants completed the whole procedure. Of the three participants who did not complete the session, one could not tolerate the EEG cap. The other two participants, who had smaller arms, pulled their arms out of the tactile device in the middle of the experiments. This indicates that the current design will require modifications in future work in order to comfortably yet effectively restrict the movement of children's arms. Eye gaze data, physiological data, and EEG data were otherwise robustly collected with event markers.

Of note, we found that the rotation of the motor generated a small noise. It started after the computer program sent the command 'start tactile stimulus' and before the tactile stimulus onset. It was caused by the rotation of the lead screw stepper motor. The noise was not loud enough to distract the infants and was greatly reduced after the brush started to stroke the infant's forearm.

B. Data collection

Eye gaze data were collected at a sampling rate of 120Hz. Examining how infants scan social stimuli provides us with valuable information about the distribution of interest and attention. In this study, we defined three Regions of Interest (ROI) surrounding eyes, nose, and mouth regions of the speakers' face (Shic, Macari, and Chawarska 2014) (Figure 29a). From this ROI data, we were able to quantify infants' gaze patterns to the audiovisual speech stimuli. As infants varied in their total looking time to the stimuli, proportion scores (indexing looking time to each ROI/total looking time to the stimulus) were derived for use as primary metrics in future analyses.

Results indicated that, across all the sessions, participants looked at the stimulus screen 27% of the time with gaze toward demarcated ROIs for 57% of this time (Figure 29b.) In terms of coherent and delayed audiovisual stimuli, the participants spent similar percentages of time looking at the ROIs (56% for synchronized audiovisual stimuli and 57% for asynchronized audiovisual stimuli.)

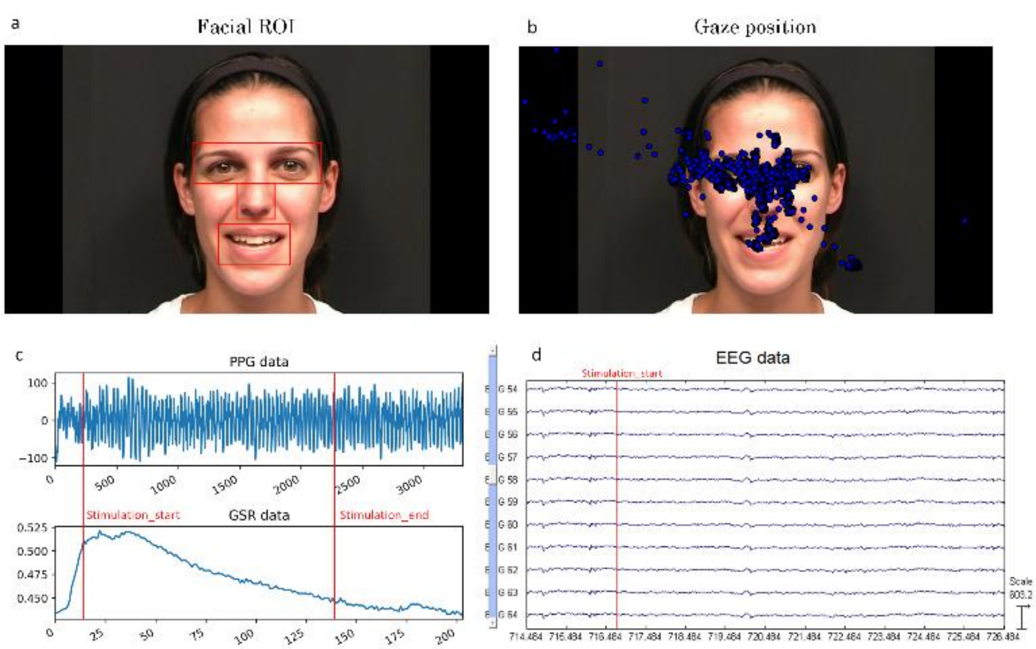

Figure 29: a) Defined ROI in speech stimulus (Lewkowicz and Hansen-Tift n.d.) (this image is shared with permission); b) an example of gaze position for one session; c) An example of peripheral physiological data with event markers; and d) EEG data sample with event marker (only display a subset of the channels).

Peripheral physiological data including PPG and EDA were recorded throughout the whole session. The sampling rates for PPG and EDA are 64Hz and 4Hz, respectively. The data were examined, and multiple features were successfully extracted. Heart rate (HR) was computed by detecting peaks in the PPG signal. Tonic and phasic components of EDA were decomposed separately from the original signal. The tonic component is the baseline level of EDA and is generally referred to as skin conductance level (SCL). The phasic component is the part of the signal that changes when stimuli are presented and is known as skin conductance response (SCR). We documented the average HR and SCR for the participants with the presence of affective touch (HR: 127.02, SCR: 3.5) and without the presence of affective touch (HR: 133.74, SCR: 3.74). Figure 29c shows an example of the recorded physiological data from one trial, which is about 50 seconds. EEG data (Figure 29d) were recorded at the sampling rate of 1000 Hz with event markers. Several common EEG metrics, including oscillatory power in delta, theta, alpha, beta, and gamma bands, were extracted for future data analysis.

4.4 Discussion and conclusion

We have presented evidence for the tolerability and feasibility of a novel multisensory stimuli delivery and data capture system (MADCAP) for infants. To the best of our knowledge, this is the first multisensory stimulation delivery system capable of providing auditory, visual, and precisely-controlled tactile stimuli in a synchronized and asynchronized manner. MADCAP was used to collect the infants' eye gaze, physiological data and EEG data together with user-defined event markers. The tactile stimulation device was validated in a MATLAB Simulink and in real world conditions. The simulation results show that the TSD could produce smooth stroking behavior with consistent brushing force, which means the affective touch could be effectively triggered. Furthermore, a usability study validated the system by demonstrating that: 1) the tactile stimulation device could be precisely controlled in terms of speed, brushing force, and synchronization with other stimuli; 2) infants between 3-20 months old tolerated the system and 10-minute protocol; and 3) the eye gaze, peripheral physiological data, and EEG data could be robustly collected.

We defined three ROIs (areas around eyes, nose, and mouth) of the speech stimulus and computed the infants' normalized attention time in these ROIs. This measurement is important for investigating atypical gaze processing patterns in high-risk infants. The results from physiological data demonstrated that the heart rate and skin conductance response rate were both lower when the affective touch stimulus were presented, indicating a decrease in arousal. Although none of the observed differences reached statistical significance, the results show trends similar to those of earlier work, which revealed that affective touch resulted in infants' arousal decreasing (Fairhurst, Löken, and Grossmann 2014).

This study paves the way for future research into multisensory perception and processing in infancy. This system could be utilized to explore multisensory processing differences between the infants who will and will not develop ASD. Our future work includes conducting a longitudinal study for children from early infancy until the age when they can be clinically diagnosed with ASD. In order to study the early indicators for ASD in infancy, we will examine the rich data captured from our system to explore the sensory processing differences between those infants who develop ASD and those who do not. Furthermore, to facilitate the early diagnosis of ASD, we will use machine learning methods to build models to predict how likely it is that the infant will develop ASD.

Although this work is inspired by the multisensory studies in children with ASD, the MADCAP system can be used in broader applications which require well-controlled stimuli presentation, such as studying the multisensory integration in children with sensory and motor disabilities. In addition, the system can also benefit from providing auditory and visual feedback associated with the spatial position of the tactile stimulator to study the integration of spatially coincident multisensory stimuli. One of the limitations of the system is the cumbersome design of the tactile stimulator. Although most of the infants tolerated the system in the usability study, the intellectual and developmentally delays/disorders, who will be the focus of our future experiments, might be more distressed by the restriction of the stimulator which could introduce confounding factors to the data collection (e.g., it may influence brain responses recorded with EEG.) In the future, we will also work towards the development of a more compact and less cumbersome version of this initial tactile stimulator, which will facilitate the application of this novel technology to infants and young children with or at-risk for neurodevelopmental disorders.

Acknowledgement

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5. Investigating Sensory Processing using MADCAP in Toddlers with ASD: A Step toward Early Diagnosis of ASD

Abstract

The development of the multisensory delivery and data capture (MADCAP) system paves the way for exploring sensory processing differences in terms of physiological responses. With the ability to deliver precisely controlled auditory, visual, and tactile stimuli and collect peripheral physiological, EEG, and eye gaze data, it is promising that we can use this tool to study what biomarkers can be used to differentiate individuals with ASD from their neurotypical peers. This chapter will focus on the system and protocol design for examining sensory processing differences between toddlers with ASD and the typically developing toddlers.

Building on the momentum of the results achieved by the MADCAP pilot study with infants, we improved the system with a new generation of tactile stimulation device. Compared to the previous version, the new tactile stimulation device is more tolerable among the infants and less distractive due to its compact design. While we expect that the toddlers will tend to be more restless than the infants, the new tactile stimulation device will likely be helpful in maintaining a reasonable success rate of the experiments.

In this work, we delivered auditory, visual, and tactile stimuli to the toddlers in both synchronous and asynchronous manner according to the protocol described later. At the same time, we collected physiological responses, including peripheral physiological, EEG, and eye gaze data, and behavioral data via questionnaire from the parent. We believe that there exist important differentiable physiological and sensory-related response patterns in toddlers with ASD that have implications for understanding sensory processing of individuals with ASD, improving diagnostic accuracy and planning appropriate intervention. **We hypothesize that** 1) toddlers with ASD have different response patterns in terms of physiological profiles (e.g., peripheral physiology, eye gaze, and EEG) to multisensory stimuli when compared to the response patterns from the neurotypical toddlers; and 2) features extracted from the data collected by MADCAP system have predictive values in classifying ASD and TD.

5.1 System design

We used the completed and well-validated MADCAP system, as we have described in last chapter, with a second generation of tactile stimulation device. The first generation of the tactile stimulation device was fairly well tolerated across high and low risk samples, but had some limitations (i.e., large, required placing of arm into a chamber, movement restrictions). As such, for the current work, we created a second-generation system ("Soft Brush") optimized for use with infants and toddlers via use of a silicone wrap and tendon-actuated mechanism that can be worn like a sleeve. Soft-Brush consists of three main components (see Figure 30): a silicone wrap, a brushing block, and an actuating mechanism. The lightweight design (combined weight 161 grams) allows children to move their arms much more freely. The unobtrusive silicone wrap has a sleeve-type design that wraps around an infant's forearm and can be quickly secured with Velcro strips. The pressure and velocity are controlled in part via a micro servo (Hitech, HS24BB) integrated to drive the brush, through which we can compute the relative distance between the brush and the skin, which correlates to the brushing pressure. The brush can go 11.5cm and 1cm in horizontal and vertical directions, respectively. The brushing block is able to generate 3-12 cm/s speed range that is optimal for creating affective touch. To reduce the nonlinear friction between the tubes and the tendons, we try to keep the tubes as straight as possible during the experiments in order to achieve smooth brushing, although sufficient smooth motion can be achieved even if the tubes are bent. An Arduino controller controls both the stepper and servo motors. The Arduino connects to a workstation via a serial port to deliver the tactile stimulus synchronously with audio-visual stimulus. The tendons are non-extendable so we can control the brushing velocity through the open-loop speed control of the stepper motor that is precise enough for our application.

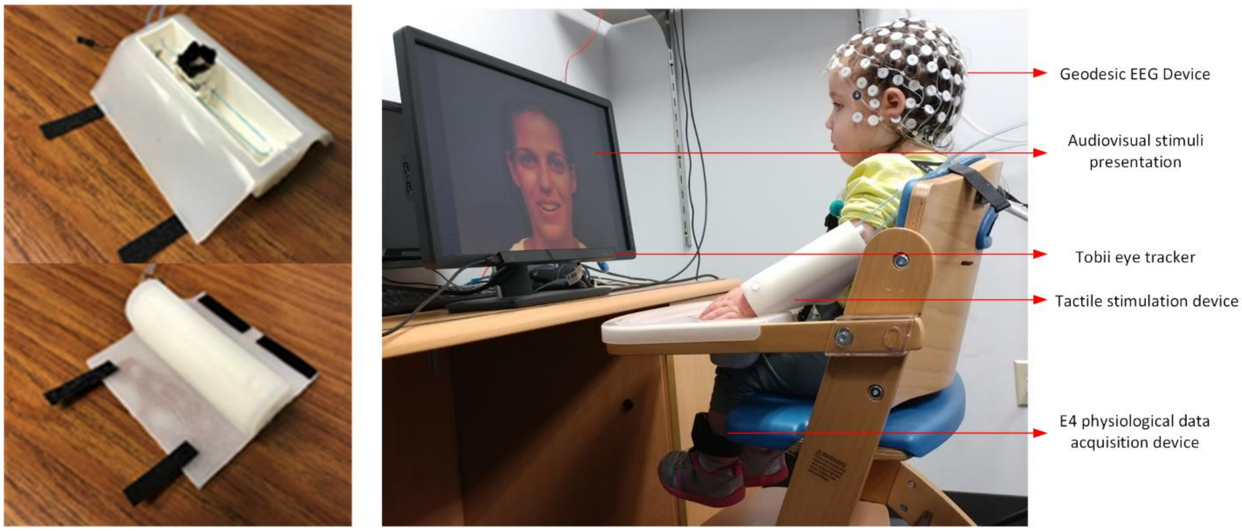

Figure 30: The second generation of tactile stimulation device and the whole system setup

5.2 Methods

5.2.1 Participant

We recruited 17 toddlers aged between 2-5 years with ASD diagnosis and 12 age-matched typically developing controls. Each participant had one visit for this study. The final analyses contained data from 10 participants with ASD and 10 TD controls (Table 11). The details about the system's tolerability is presented in Results Section. The protocol was reviewed and approved by the Institutional Review Board (IRB) at Vanderbilt University. After receiving a thorough explanation of the experiment, parents gave written informed consent for their children's participation.

Table 11: Participant data.

	ASD (N=10)	TD (N=10)
Age (Month)	24-59	19-55
	43.43(11.61)	34.31(11.65)
Gender	8M, 2F	6M, 4F
Visual Receptive T-score*	31.25 (13.59)	47.89 (13.03)
Fine Motor T-score*	29.75 (10.62)	41.67 (12.91)
Receptive Language T-score*	32.13 (13.26)	50.00 (14.85)
Express Language T-score*	31.38 (9.98)	55.56 (14.86)
T-score Sum*	124.5 (43.35)	195.11 (49.63)
ELC standard score*	66.38 (18.22)	98.22 (23.82)

*t test p<0.05

5.2.2 Experimental setup

Within a sound-attenuated room, the infant was seated in an age-appropriate infant/toddler seat and was positioned 50 cm from the LCD monitor, a video recording device, and an eye tracker. If a parent requested to have the participant on her/his lap or if the participant refused to sit in an infant/toddler seat, the parent was permitted to hold the participant in her/his lap but was asked to minimally distract the participant. The Geodesic EEG cap was placed on the participant's head. Then, the participant's left forearm was wrapped by the tactile stimulation device and was secured using a Velcro strap. The E4 wristband was attached to the ankle (Figure 30) of the participant. Subsequently, the eye tracker calibration was accomplished by using audio-enabled, animated cartoon pictures. Before the stimuli were presented to the participants, a three-minute baseline data was collected for peripheral physiology and EEG while the participant was watching a non-social neutral-content video. The participants then participated in a multi-stimuli presentation session, lasting approximately 8 minutes, wherein they were exposed to three distinct presentations of audiovisual speech stimuli (each 50s in length) along with affective touch, as described below. In the end, an ERP session was conducted to explore the event-related potential (ERP) when the participant is exposed to tactile stimulus alone.

5.2.3 Procedure

The experiment consisted of three sessions. First, a three-minute baseline session was conducted to collect baseline peripheral physiological data and EEG data. During this session, the participant watched a non-social neutral-content video to stay in the resting state. In the multi-stimuli presentation session, the participant received the same stimuli presentation as we have described in the last chapter (Chapter 4.3.2). In the third session, the participant watched the same video as we play during the baseline session, which directed the participant's attention to the monitor. In the meanwhile, the tactile stimulation device stroked the participant's forearm once every time and stopped for one second. This one-stroke-and-stop process was repeated for 50 times. At the beginning of each stroke, an event marker was sent to the EEG recording program for ERP analysis. The whole procedure is shown in Figure 31.

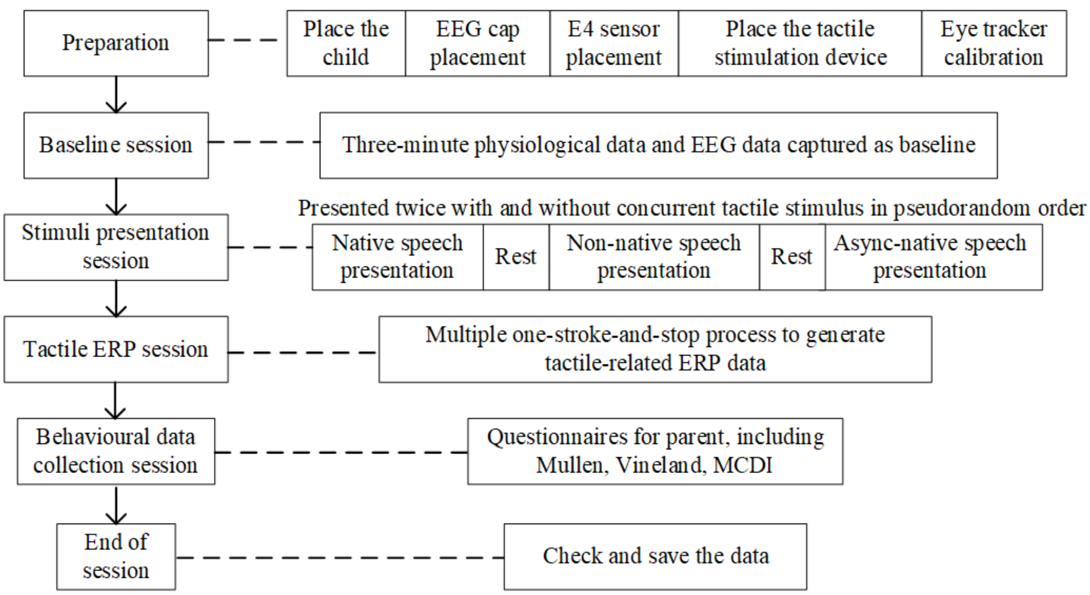

Figure 31: Procedure of the proposed study

5.2.4 Data collection

Throughout the whole sessions, multi-dimensional data were collected with time stamps and event markers. Eye gaze data were collected at the sampling rate of 120Hz. Peripheral physiological data including PPG and EDA were recorded at the sampling rate of 64Hz and 4Hz, respectively. Also, 32-channel EEG data were recorded at the sampling rate of 1000Hz. In baseline session, we collected peripheral physiological data and EEG data. In stimuli presentation session, we collected all the data we mentioned above. In tactile ERP session, only EEG data was collected.

Besides the participants' physiological profile data, we also collected their behavioural data as mentioned below. These are questionnaire-based and reported by the participants' caregivers.

- Mullen Scales of Early Learning (MSEL). The MSEL (Mullen 1995) is a standardized test that assesses development in several domains, including expressive and receptive language, for children birth-68 months.
- MacArthur-Bates Communicative Development Inventories (MCDI). The MCDI (Fenson et al. 2007) is a parent report that assesses early vocabulary and broader spoken language ability.

5.3 Results

5.3.1 Tolerability of the system

Ten out of 12 participants in TD group and 10 out of 17 participants in ASD group were used in the final data analysis. Nine participants' data were excluded from the study due to the following reasons: 1) 5 participants could not tolerate the EEG cap; 2) 3 participants could not sit still, which was required to collect reliable data; and 3) 1 participant's data in TD group was removed because of noticeable developmental delay. The overall compliance rate of toddlers in this study was 72%.

5.3.2 Statistical analyses results

Various features were extracted from EEG data, eye gaze data, and peripheral physiological data (Table 12). Power spectral features extracted from EEG include density of theta, alpha, and beta bands. These band powers are associated with alertness, attention, stimulus and sensory processing and are widely used to measure attention, engagement, emotions, and mental workload. Primary eye gaze features were preferential looking position and fixation duration, both of which have been shown to differentiate children with ASD from their TD peers. We defined Regions of Interest (ROI) around the core features of the face (eyes and mouth) to detect atypical visual processing. We computed the percentage of time an infant examined the ROIs in relation to tactile stimulus presentation. Regarding physiology, we recorded both PPG and EDA in this study. PPG is used as a measure of blood volume pressure (BVP) and to compute heart rate (HR) by identification of local minima and interbeat interval (IBI). Blood pressure and HR variability correlate with defensive reactions pleasantness of stimuli and basic emotions. Electrodermal activity (EDA) is closely linked with psychological concepts of emotion, arousal, and attention.

Table 12: Features extracted from EEG, eye gaze, and peripheral physiology

Signals		Extracted features
Electroencephalography (EEG)	Power spectral features	Delta band (1-4 Hz); Theta band (4-8 Hz); Alpha band (8-13 Hz); Beta band (13-30 Hz) Gamma band (36-44 Hz);
Peripheral Physiological Signals	Photoplethysmogram (PPG)	Mean and Max amplitude of the peak values Mean and Std. of Pulse Transit Time Mean and Std. of IBI
	Electrodermal activity (EDA)	Mean and Slope of tonic activity level Mean and Max amplitude of skin conductance response (phasic activity) Rate of phasic activity
Eye Gaze	Gaze position	Percentage of time the participant examines the ROI of the face

To assess group and condition differences in the above mentioned features, 2×2 two-way repeated-measure ANOVAs were conducted for two independent variables with group (TD, ASD) and condition (with touch, without touch). All analyses are two-tailed and trends are reported if $p < 0.05$. Effect size are reported for all significant and trend analyses with partial eta-squared.

To assess differences in physiological response in group and condition, the percentage of changes from baseline were examined. There was no main effect of group in heart rate variability (HRV) [$F(1,9) = 1.48$, $p = 0.26$, $\eta_P^2 = 0.14$]. However, post hoc analyses indicate that for ASD, the two conditions (with and without touch) did not differ in HRV ($t(9) = 0.59$, $p = 0.50$), but for TD, HRV decreased when touch was presented ($t(9) = 2.31$, $p < 0.05$). There was a main effect of group in skin conductance response rate [$F(1,9) = 1.83$, $p<0.05$, $\eta_P^2 = 0.19$]. Specifically, TD showed greater skin conductance response rate (scr_rate) than ASD. In addition, post hoc analyses show that for ASD, the two condition did not differ in in scr_rate ($t(9) = -0.66$, $p = 0.2$), but for TD, scr_rate increased when touch presented ($t(9) = 2.51$, $p < 0.01$). The results are shown in Figure 32.

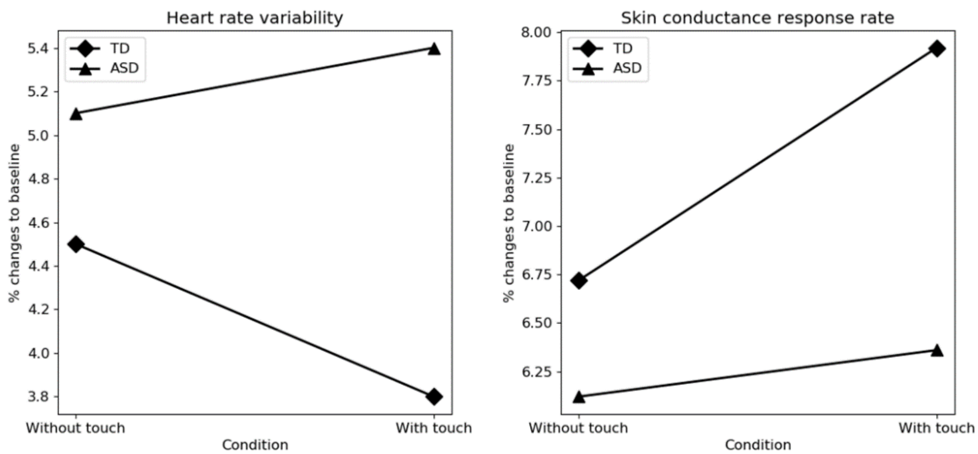

Figure 32: Physiological feature differences in two groups.

Attention to screen measures the percentage of time the participants look at the screen during the session. There was a main effect of group [$F(1,9) = 4.59$, $p<0.05$, $\eta_P^2 = 0.34$]. Overall, TD spent more time looking at the screen than ASD (TD: 0.47, ASD: 0.32). Face, eye, and mouth ROIs were defined as in Figure 33. Attention to face measures the percentage of time the participants look at the face ROI (time spent looking at face ROI divided by time spent looking at screen). There was a main effect of group [$F(1,9) = 1.45$, $p<0.05$, $\eta_P^2 = 0.14$]. TD spent more time looking at the face region than ASD (TD: 0.80, ASD: 0.72). Attention to eye measures the percentage of time the participants look at the eye ROI (time spent looking at eye ROI divided by time spent looking at face ROI). There was a main effect of group [$F(1,9) = 3.3$, $p<0.05$, $\eta_P^2 = 0.27$]. TD group spent more time looking at the eye ROI than ASD (TD: 0.32, ASD: 0.20). Attention to mouth measures the percentage of time the participants look at the mouth ROI (time spent looking at eye ROI divided by time spent looking at face ROI). There was also a main effect of group [$F(1,9) = 3.4$, $p<0.01$, $\eta_P^2 = 0.27$]. Again, TD spent more time looked at the mouth ROI than ASD (TD: 0.31, ASD: 0.21). The aforementioned results are shown in Figure 34.

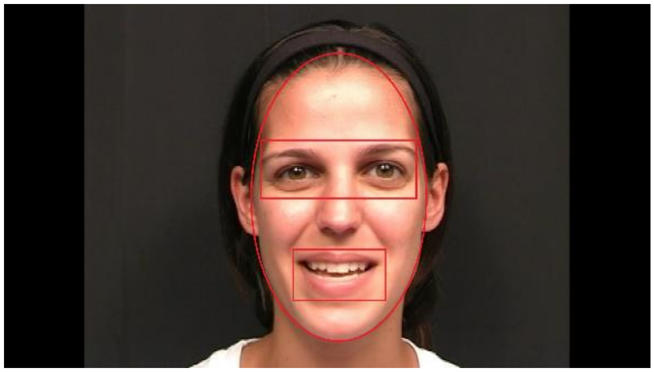

Figure 33: Face, Eye, and mouth ROIs.

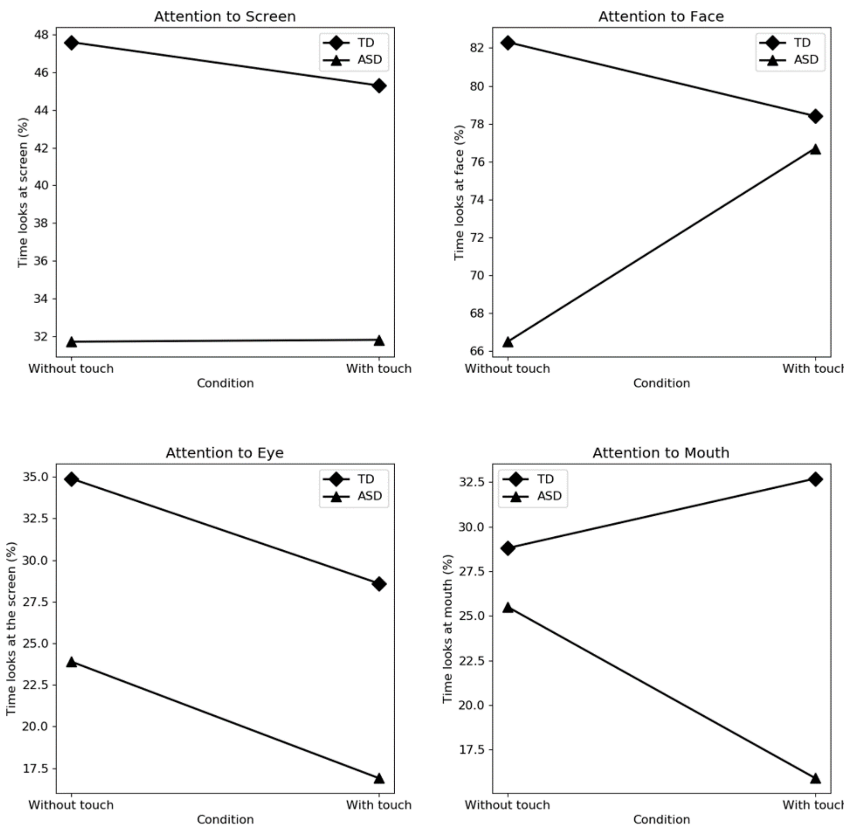

Figure 34: Gaze features differences in two groups.

5.3.3 Machine learning approach

To investigate whether the features extracted from MADCAP data have predictive power to classify ASD and TD, machine learning techniques were implemented. Specifically, features collected by MADCAP system were used to predict the diagnostic results. Furthermore, the participants' behavioural scores were also used for comparison. Machine learning was used to investigate high order nonlinear relationships often overlooked by classical statistical analysis (e.g., t-test, ANOVA).

Four sets of machine learning experiments were run to detect the diagnostic results. The details of the experiments and the overall results are shown in Table 13. To avoid bias in the training and testing samples, also known as overfitting, all experiments were performed using a leave-one-subject-out approach. In this approach, each time one subject's data was used to test the model, the remaining data were used to train the model. Seven most commonly used machine learning algorithms were developed for each set of experiments. For each algorithm, randomized grid search was used to find the optimal hyperparameters. Multiple algorithms were used to ensure that potential differences in prediction results between groups resulted from the data rather than the algorithms. The accuracies for all the algorithms in different experiments are shown in Figure 35.

Table 13: Machine learning experiments.

Machine learning experiments	Data used for developing model	Accuracies (M, SD)
1	MADCAP feature from sessions without affective touch	0.65 (0.07)
2	MADCAP feature from sessions with affective touch	0.68 (0.07)
3	Behavioural scores	0.80 (0.05)
4	Behavioural scores + feature from second run	0.83 (0.05)

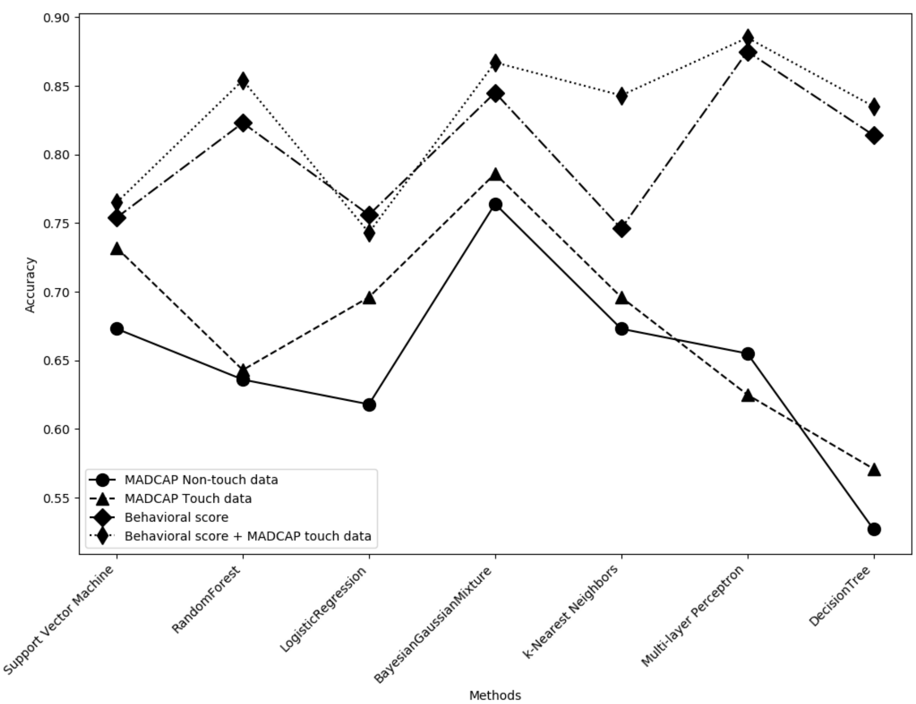

Figure 35: Results of machine learning experiments.

In addition, Random Forest model was used to explore the relative feature importance in MADCAP extracted features. Tree-based algorithms are particularly good at this purpose. It generates a tree-like graph in which each node represents a test on a feature (e.g. percentage of time the infant examines the ROI), each branch represents the outcome of the test and each leaf node represents the class label (decision taking after examining all features). This structure gives us a better understanding of the features extracted from each signal. Also, we can find prominent features from this tree structure since the feature nodes are ordered in such a way that the features which provide more information to the final decision stay closer to the root. The following figure shows the relative importance of the features extracted from MADCAP data, in which higher score means higher importance.

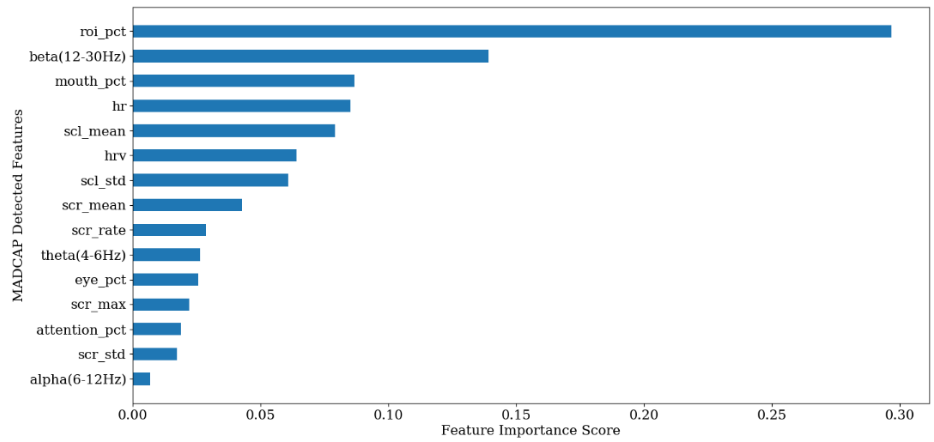

Figure 36: Feature importance.

5.4 Discussion

We conducted a comprehensive assessment of the sensory responses to auditory, visual and tactile stimulation in ASD and match TD, by collecting EEG, peripheral physiological, and eye gaze data. Statistical analyses such as ANOVA and t test were used to explore the group and condition differences. Furthermore, machine learning was used to demonstrate the predictive value of the MADCAP extracted features in detecting ASD.

With respect to peripheral physiological responses, TD participants had overall lower heart rate variability and higher skin conductance response rate, indicating a higher arousal state. Also, a decreased heart rate variability and an increased skin conductance response rate were observed in TD participants when affective touch was presented, however, such trends did not exist in ASD participants. These results indicated sensory processing differences exist in physiological responses, which has the potential to be used as biomarkers in early diagnosis of ASD.

With respect to eye gaze pattern in response to social audiovisual stimuli, overall TD participants spent statistically significant time looking at the screen, the face region, the eye region, and the mouth region of the actress in the video. No differences were observed when affective touch was presented. Some of these findings agree with existing research, which shows that attention to eye declines for infants who are later diagnosed with ASD (Jones and Klin 2013).

Lastly, we turn to the potential role of the MADCAP extracted features in detecting ASD. Four sets of machine learning experiments were run to demonstrate the potential predictive value of these features. First, when affective touch was presented, the models resulted in a higher predictive accuracy, which indicates adding a new channel of stimulation, affective touch, provided additional predictive power. This new channel of stimulation was often overlooked by existing studies. Second, by using sole behavioural scores to predict ASD, higher accuracies were achieved when compared with MADCAP extracted features. This was not surprising because the behavioural scores possibly contain richer information of the participant at certain ages. However, it is interesting to see that the models' accuracies increased further when we added MADCAP extracted features into behavioural scores. These findings demonstrated the predictive value of our features in detecting ASD, which is a step toward diagnosing ASD in their early ages, which current diagnostic methods are not capable of.

Note that the predictive value of this machine learning approach was not extremely valuable here, since at the toddlers' age, reliable diagnosis can be made by clinicians. The value of this process is that it can help us better understand the biomarkers we derived from the physiological profile. And these biomarkers have the potential to be useful in early diagnosis of ASD.

The limitation of this study was the small sample size, but this study is one of the very few, if not only one, to examine the toddlers' sensory processing responses to multisensory stimulation in EEG, peripheral physiological, and eye gaze data.

6. Contributions and Future Work

This chapter briefly describes the potential contributions of this dissertation in terms of technological advancement, advancement in computer-aided intervention in autism research, and benefits for the society. The main contribution of this dissertation is the design, development, and user evaluation of intelligent systems for ASD intervention and early detection. The VR-based Driving Environment with Adaptive Response technology (VDEAR) has the capabilities of adapting to the user in an individualized way which is not possible in a traditional human centric intervention and computer-aided systems that do not integrate implicit cues. The Multisensory stimulation And Data CAPture system (MADCAP) delivers auditory, visual, and tactile stimuli in a precisely controlled manner which had never been done either by human researchers or computer-aided systems. Also, MADCAP captures multi-dimensional physiological data with time stamps and event markers. MADCAP paves the way for researchers to investigate the sensory processing differences between individuals with ASD and their neurotypical peers.

6.1 Technological contribution

The main technological contribution of this dissertation is twofold: VDEAR introduced a physiology-based adaptive intervention architecture for teenagers with ASD, specifically integrated within a virtual reality-based driving training platform; and secondly MADCAP, for the first time, provides a rigorous and precise way for the researchers to document the physiological responses to multisensory stimulation to infants or young children.

Although there are existing works in assessment of driving performance and comparison between individuals with and without ASD, to the best of our knowledge, there is no study incorporating physiology-based adaptive response technology into a driving simulation platform for ASD intervention. VDEAR bridged this gap and developed a driving skill training platform that 1) allows real-time measurement of engagement-related physiological signals while the user takes part in the driving task; 2) predicts user's engagement level based on real-time physiological signals, and 3) alters the task difficulty based on both the user's engagement level and performance metrics. In addition, the physiology-based adaptation mechanism embedded in VDEAR was designed using the premise of Flow Theory (Csikszentmihalyi 1997) and was independent of the driving environment and thus can be integrated into other gaming or training environments. The engagement information was detected separately and sent to the main program in JSON format over a LAN using standard internet protocols. Once we defined the difficulty switching logic in the game environment, this physiology-based adaptation mechanism can be integrated seamlessly.

One of the primary contributions of MADCAP is to design an automated mechanism for affective touch and then, integrate it with an audio-visual stimuli presentation system to study multisensory processing of infants at high- and low-risk of ASD. It is difficult to produce skin-to-skin affective touch in laboratory settings. However, an analogous tactile stimulation which is produced by a mechanical source (e.g., soft brushing) is comparable to an affective touch that is manually produced by hand (Triscoli et al. 2013). Previous tactile stimulation work in infants has utilized trained human confederates to administer pleasant social touch via dorsal forearm stroking with Hake brushes at predetermined velocities and forces (Fairhurst, Löken, and Grossmann 2014). Although adequate for documenting generalized physiological responses to the stimulus, this manual control has several limitations: speed and force are not precisely controlled or measured, stroking is hard to coordinate with other stimuli/measurements, and the human presence may confound certain experimental paradigms. In addition to the design of the tactile stimulation device, the integration of multisensory stimulation within a technological system is entirely novel. To the best of our knowledge, MADCAP is the first multisensory stimulation delivery system capable of providing auditory, visual, and precisely-controlled tactile stimuli in a synchronized and controlled asynchronized manner.

6.2 Societal contribution

With the average lifetime cost of care for individuals of ASD estimated around $3.2 million, average medical expenditures for individuals with ASD 4.1-6.2 times greater than for those without ASD (Michael L Ganz 2007), and with the constant increasing alarming prevalence figures designing more powerful treatments for therapists for the disorder is often considered a public health priority. As the behavioural and pharmacological interventions have somewhat limited effectiveness, finding a more flexible assistive intervention paradigms are of great importance. Also, as we have discussed in Chapter 1, providing the intervention opportunities in the earliest point could potentially have more impact in practice. Thus, technology-based intervention and early detection for ASD hold promise in this respect. The systems developed in this dissertation potentially pave the ways for using intelligent technology for long term intervention and early detection of the disorder. The long-term skill training with the system could potentially and eventually translate into real world skills for individuals with ASD. More importantly, early detection of the disorder could provide the individuals with ASD with early intervention in the first years of life, a time period recognized as optimal for enhancing developmental outcomes due to neural plasticity.

6.3 Future work

One of the future developments of the engagement sensitive driving system is to incorporate more than one emotional state (e.g., adding stress level) to alter the system behaviours. Also, other implicit cues, such as eye gaze or facial expression, could also be beneficial in modelling the user's state. The affect model built in this study was a group model, which might not perform well for some users, especially considering the wide characteristics of ASD. Adding some capabilities to improve the model during the training session in real time could greatly increase the model's accuracy. In addition, a longitudinal study is required to demonstrated the advantages of the proposed system.

MADCAP system demonstrated a novel multisensory platform for researchers in investigating sensory trajectories in infants and the study in toddlers proved the system has the potential to be used as a tool to early diagnose ASD, which is also the inspiration for us to develop this system in the first place. As a result, the very important future work is to carefully design a protocol for longitudinal study based on our current findings. In addition, the tactile device can be further improved to reduce operation noise and mimic the mother's touch as close as possible.

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