Affective Computing and Interaction:

Psychological, Cognitive and Neuroscientific Perspectives

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Chapter 15

Affect-Sensitive Computing and Autism

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ABSTRACT

This chapter covers the application of affective computing using a physiological approach to children with Autism Spectrum Disorders (ASD) during human-computer interaction (HCI) and human-robot interaction (HRI). Investigation into technology-assisted intervention for children with ASD has gained momentum in recent years. Clinicians involved in interventions must overcome the communication impairments generally exhibited by children with ASD by adeptly inferring the affective cues of the children to adjust the intervention accordingly. Similarly, an intelligent system, such as a computer or robot, must also be able to understand the affective needs of these children - an ability that the current technology-assisted ASD intervention systems lack - to achieve effective interaction that addresses the role of affective states in HCI, HRI, and intervention practice.

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INTRODUCTION

Autism is a neurodevelopmental disorder characterized by core deficits in social interaction, social communication, and imagination (American Psychiatric Association, 2000). These characteristics often vary significantly in combination and severity, within and across individuals, as well as over time. Research suggests prevalence rates of autism has increased in the last 2 decades from 1 in 10000 to as high as approximately 1 in 110 for the broad autism spectrum (CDC, 2009). While, at present, there is no single universally accepted intervention, treatment, or known cure for Autism Spectrum Disorders (ASD) (NRC, 2001; Sherer and Schreibman, 2005); there is an increasing consensus that intensive behavioral and educational intervention programs can significantly improve long term outcomes for individuals and their families (Cohen et al., 2006; Rogers, 2000).

Affective cues are indicators, external or internal, of the manifestations of emotions and feelings experienced in a given environment. This research utilizes and merges recent technological advances in the areas of (i) robotics, (ii) virtual reality (VR), (iii) physiological signal processing, (iv) machine learning techniques, and (v) adaptive response technology in an attempt to create an intelligent system for understanding various physiological aspects of social communication in children with ASD. The individual, familial, and societal impact associated with the presumed core social impairments of children with ASD is enormous. Thus, there is a need to better understand the underlying mechanisms and processes associated with these deficits as well as develop intelligent systems that can be used to create optimal intervention strategies.

In response to this need, a growing number of studies have been investigating the application of advanced interactive technologies to address core deficits related to autism, namely computer technology (Bernard-Opitz et al., 2001; Moore et al., 2000; Swettenham, 1996), virtual reality environments (Parsons et al., 2004; Strickland et al., 1996; Tartaro and Cassell, 2007), and robotic systems (Dautenhahn and Werry, 2004; Kozima et al., 2009; Michaud and Theberge-Turmel, 2002; Pioggia et al., 2005; Scassellati, 2005). Computer- and VR-based intervention may provide a simplified but exploratory interaction environment for children with ASD (Moore et al., 2000; Parsons et al., 2004; Strickland et al., 1996). Robots have been used to interact with children with ASD in common imitation tasks and can serve as social mediators to facilitate interaction with other children and caregivers (Dautenhahn and Werry, 2004; Kozima et al., 2009). In the rest of the chapter, the term "computer" is used to imply both computer- and robot-assisted ASD interventions.

Even though there is increasing research in technology-assisted autism intervention, there is a paucity of published studies that specifically address how to automatically detect and respond to affective cues of children with ASD. Such ability could be critical given the importance of human affective information in HCI (Picard, 1997; Prendinger et al., 2005) and HRI (Fong et al., 2003) and the significant impacts of the affective factors of children with ASD on the intervention practice (Ernsperger, 2003; Seip, 1996; Wieder and Greenspan, 2005). A computer that can detect the affective states of a child with ASD and interact with him/her based on such perception could have a wide range of potential impacts. Interesting activities likely to retain the child's attention could be chosen when a low level of engagement is detected. Complex social stimuli, sophisticated interactions, and unpredictable situations could be gradually, but automatically, introduced when the computer recognizes that the child is comfortable or not anxious at a certain level of interaction dynamics for a reasonably long period of time. A clinician could use the history of the child's affective information to analyze the effects of the intervention approach. With the record of the activities and the consequent emotional changes in a child, a computer could learn individual preferences and affective characteristics over time using machine-learning techniques and thus could alter the manner in which it responds to the needs of different children. This chapter presents the results of investigations which assess what effects there are on physiological response for children with ASD during performance-oriented and socially-oriented tasks. The ability to detect the physiological processes that are a part of impairments in social communication may prove an important tool for understanding the physiological mechanisms that underlie the presumed core impairments associated with ASD.

BACKGROUND

Physiology for Affect Recognition of Children with ASD

There are several modalities such as facial expression (Bartlett et al., 2003), vocal intonation (Lee and Narayanan, 2005), gestures and postures (Asha et al., 2005; Kleinsmith et al., 2005), and physiology (Kulic and Croft, 2007; Mandryk et al., 2006; Nasoz et al., 2004; Rani et al., 2004) that can be utilized to evaluate the affective states of individuals interacting with computer. This work evaluates affective states based on physiological data for several reasons. Children with ASD often have communicative impairments (both nonverbal and verbal), particularly regarding expression of affective states (American Psychiatric Association, 2000; Green et al., 2002; Schultz, 2005). These vulnerabilities place limits on computerized affective modeling based on traditional conversational and observational methodologies. For example, video has been used to teach children with ASD to recognize facial expressions and emotions of *others* (Stokes, 2000), but no published studies were found that used visual recognition through video to autonomously determine the affective states of people with ASD. A facial recognition algorithm could be designed to detect certain expressions but would have to accommodate when expressions are abnormal (e.g., smiling under mild pain, etc.) or lack variability (Schultz, 2005). Physiological signals, however, are continuously available and are not necessarily directly impacted by these difficulties (Ben Shalom et al., 2006; Groden et al., 2005; Toichi and Kamio, 2003). As such, physiological modeling may represent a methodology for gathering rich data despite the potential communicative impairments of children with ASD. In addition, physiological data may offer an avenue for recognizing aspects of affect that may be less obvious for humans but more suitable for computers by using signal processing and pattern recognition tools. Furthermore, there is evidence that the transition from one affective state to another state is accompanied by dynamic shifts in indicators of Autonomic Nervous System activity (Bradley, 2000). More than one physiological signal, judged as a favorable approach (Bethel et al., 2007), is examined in this research, and the set of signals consists of various cardiovascular, electrodermal, electromyographic, and skin temperature signals, all of which have been extensively investigated in psychophysiology literature (Bradley, 2000).

One of the prime challenges of this work is attaining reliable subjective reports. There have been reports that adolescents could be better sources of information than adults when it comes to measuring some psychiatric symptoms (Cantwell et al., 1997), but researchers are generally reluctant to trust the responses of adolescents on self-reports (Barkley, 1998). One should be especially wary of the dependability of self-reports from children with ASD, who may have deficits in processing (i.e., identifying and describing) their own emotions (Hill et al., 2004). While there have been some criticisms on the use of subjective report (i.e., self-assessment or the reports collected from observers) and its effect on possibly forcing the determination of emotions, the subjective report is by and large regarded as an effective way to evaluate affective responses. Due to the unresolved debate on the definition of emotion (e.g., objective entities or socially constructed labels), researchers in affective computing often face difficulties obtaining the ground truth to label the natural emotion data accordingly. As suggested by Cowie et al. (2001) and Pantic and Rothkrantz (2003), the immediate implication of such a controversy is that pragmatic choices (e.g., application and user-profiled choices) must be made to develop an automatic affect recognizer. As a result, subjective report is widely used for affective modeling and endowing a computer with the recognition abilities similar to those of the reporters (Picard, 1997; Silva et al., 2006).

An important question when estimating human affective response is how to operationalize the affective state. Although much existing research on affective modeling categorizes physiological signal data into "basic emotions," there is no consensus on a set of basic emotions among the researchers (Cowie et al., 2001). This fact implies that practical choices are required to select target affective states for a given application. Anxiety, engagement, and enjoyment/liking are chosen as the possible target affective states in our work. Anxiety is chosen for two primary reasons. First, anxiety plays an important role in various human-machine interaction tasks that can be related to task performance (Brown et al., 1997). Second, anxiety frequently co-occurs with ASD and plays an important role in the behavior difficulties of children with autism (Gillott et al., 2001). Engagement, meaning sustained attention to an activity or person (NRC, 2001), has been regarded as one of the key factors for children with ASD to make substantial gains in academic, communication, and social domains (Ruble and Robson, 2006). With playful activities during the intervention, the liking of the children (i.e., the enjoyment they experience when interacting with the computer) may create urges to explore and allow prolonged interaction for the children with ASD, who are susceptible to being withdrawn (Dautenhahn and Werry, 2004; Papert, 1993).

Literature in the human factors and psychophysiology fields provide a rich history in support of physiology methodologies for studying stress (Groden et al., 2005; Zhai et al., 2005), engagement (Pecchinenda and Smith, 1996), operator workload (Kramer et al., 1987), mental effort (Vicente et al., 1987), and other similar mental states based on physiological measures such as those derived from electromyogram (EMG), galvanic skin response (GSR; i.e., skin conductance), heart rate variability (HRV), and blink rates. Meehan et al. (2005) reported that changes in physiological activity are evoked by different amounts of presence in stressful VR environments. Prendinger et al. (2005) demonstrated that the measurement of GSR and EMG can be used to discriminate a user's instantaneous change in levels of anxiety due to sympathetic versus unconcerned reactions from a life-like virtual teacher. In general, it is expected that higher physiological activity levels can be associated with greater stress levels (Smith, 1989). Therefore, developing intelligent systems for exploration of physiological signals and the target affective states of anxiety, engagement, and enjoyment/liking that may be associated with core social deficits for children with ASD is both scientifically valid and technologically feasible.

Technology in the Treatment of ASD

Interventions often focus on social communication, including social-problem solving and social skills training, so that participants can gain experience and exposure to various situations representative of everyday living. The ultimate goal of such interventions is for some generalization of these skills to carry over into real-life situations. A growing number of studies have been exploring the application of interactive technologies for future use in interventions to address the social deficits of children with ASD. Initial results indicate that such technologies hold promise as a potential alternative intervention approach with broad accessibility. Various software packages and VR environments have been developed and applied to address specific deficits associated with autism, e.g., understanding of false belief (Swettenham, 1996), attention (Trepagnier et al., 2006), social problem-solving (Bernard-Opitz et al., 2001), and social conventions (Parsons et al., 2005). Research on applying robotics to ASD intervention has suggested that robots can allow simplified but embodied social interaction that is less intimidating or confusing for children with ASD (Robins et al., 2005). By employing HCI and HRI technologies, interactive intervention tools can partially automate the time-consuming, routine behavioral intervention sessions and may allow intensive intervention to be conducted at home (Dautenhahn and Werry, 2004). For the purpose of employing an affect-sensitive intelligent system, computers or robots could be the mode of technology for assisted ASD interventions.

Dautenhahn and colleagues have explored how a robot can become a playmate that might serve a therapeutic role for children with autism in the Aurora project. Dautenhahn et al. (2003) emphasize the importance of robot adaptability in autism rehabilitation. Research showed that children with ASD are engaged more with an autonomous robot in the "reactive" mode than with an inanimate toy or a robot showing rigid, repetitive, non-interactive behavior (Dautenhahn and Werry, 2004). Michaud and Theberge-Turmel (2002) investigated the impact of robot design on the interactions with children with ASD and pointed out that systems need to be versatile enough to adapt to the varying needs of different children. Pioggia et al. (2005) developed an interactive life-like facial display system for enhancing emotion recognition in people with ASD. Robotic technologies pose the advantage of furnishing robust systems that can support multimodal interaction and provide a repeatable, standardized stimulus while quantitatively recording and monitoring the performance progress of the children with ASD to facilitate autism intervention assessment and diagnosis (Scassellati, 2005).

There are numerous reasons why a VR-based intervention system may be particularly relevant for children with ASD. The strength of VR technology for ASD intervention includes malleability, controllability, reduced sensory stimuli, individualized approach, safety, and a reduction of human interaction during initial skill training (Strickland, 1997). VR does not necessarily include direct human-to-human interaction, which may work well for an initial intervention to remove the difficulties common in ASD related to mere human interaction that is part of a typical intervention setting involving a child and a clinician (Chen and Bernard-Opitz, 1993; Tartaro and Cassell, 2007). However, VR should not be considered an isolating agent, because dyadic communication accomplished between a child and a VR environment can lead into triadic communication including a clinician, caregiver, or peer and in due course potentially accomplish the intervention goals of developing social communication skills between the child with ASD and another person (Bernard-Opitz et al., 2001). Furthermore, the main sensory output of VR is auditory and visual, which may represent a reduction of information from a real-world setting but also represents a full description of a setting without need for imagined components (Sherman and Craig, 2003; Strickland, 1997). Individuals with ASD can improve their learning skills related to a situation if the proposed setting can be manifested in a physical or visual manner (Kerr and Durkin, 2004). Since VR mimics real environments in terms of imagery and contexts, it may allow for efficient generalization of skills from the VR environment to the real world (Cromby et al., 1996). However, since limited social insight and social cognition are vulnerabilities that are often part of the core deficits associated with ASD, individuals may lack the skills to envision abstract concepts or changes to situations on their own. Virtual environments can easily change the attributes of, add, or remove objects in ways that may not be possible in a real-world setting but could be valuable to teach abstract concepts. Therefore, VR can offer the benefit of representing abstract concepts through visual means (e.g., thought bubbles with text descriptions of a virtual character's thoughts) and seamlessly allows for changes to the environment (e.g., changing the color of a ball or making a table disappear) that may be difficult or even impossible to accomplish in a real-world setting (Sherman and Craig, 2003; Strickland, 1997). Furthermore, the highly variable nature autism in terms of individual symptoms means an individual approach is appropriate, and computers can accommodate individualized treatment (Strickland, 1997). The highly versatile VR environment can illustrate scenarios which can be changed to accommodate various situations that may not be feasible in a given therapeutic setting because of space limitations, resource deficits, safety concerns, etc. (Parsons and Mitchell, 2002). Therefore, VR represents a medium well-suited for creating interactive intervention paradigms for skill training in the core areas of impairment for children with ASD (i.e., social interaction, social communication, and imagination). However, to date the capability of VR technology has not been fully explored to examine the factors that lead to difficulties in impairments such as social communication, which could be critical in designing an efficient intervention plan.

Consensus statements from both the American Academy of Pediatrics (Myers et al., 2007) and the National Resource Council (NRC, 2001) underscore that effective intervention for children with ASD includes: provision of intensive intervention, individual instruction tailored to the qualities of the child, promotion of a generalization of skills, and incorporation of a high degree of structure/organization. Despite the urgent need and societal import of intensive treatment (Rutter, 2006), appropriate intervention resources for children with ASD and their families are often difficult to access and extremely costly when accessible (Jacobson et al., 1998; Sharpe and Baker, 2007; Tarkan, 2002). Therefore, an important direction for research on ASD is the identification and development of intelligent systems that can make application of effective intensive treatment more readily accessible and cost effective (Parsons and Mitchell, 2002; Rogers, 2000). In addition, with trained professional resource limitations, there is potential for emerging technology to play a significant role in providing more accessible intensive individualized intervention (Goodwin, 2008). VR has shown the capacity to ease the burden, both time and effort, of trained clinicians in an intervention process as well as the potential to allow untrained personnel (e.g., parents or peers) to aid a participant in the intervention (Standen and Brown, 2005), thereby offering the facility of providing cost and time effective and readily accessible intervention. As such, the future creation of a VR-assisted affect-sensitive intelligent system, with a potential of individualized intervention, for autism intervention could meet all of the core components of effective intervention while at the same time increasing the ability of the intervention provider to systematically control and promote intervention related skills.

Affective cues are insights into the emotions and behaviors of children with ASD. The ability to utilize the power of these cues may permit a smooth, natural, and more productive interaction process (Gilleade et al., 2005; Kapoor et al., 2001; Picard, 1997; Prendinger et al., 2005), especially considering the core social and communicative vulnerabilities that limit individuals with ASD to accurately self-identify affective experiences (Hill et al., 2004). Common in autism intervention, clinicians who work with children with ASD intensively monitor affective cues of the children in order to make appropriate decisions about adaptations to their intervention and reinforcement strategies. For example, "likes and dislikes chart" is recommended to record the children's preferred activities and/or sensory stimuli during interventions that could be used as reinforcers and/

or "alternative behaviors" (Seip, 1996). Children with autism are particularly vulnerable to anxiety and intolerant of feelings of frustration, which requires a clinician to plan tasks at an appropriate level of difficulty (Ernsperger, 2003). The engagement of children with ASD is the ground basis for the "floor-time therapy" to help them develop relationships and improve their social skills (Wieder and Greenspan, 2005). Given the importance of affective cues in ASD intervention practice (Ernsperger, 2003; Seip, 1996; Wieder and Greenspan, 2005), using affective information as a means of implicit and bidirectional communication may be critical for allowing a computer to respond to a child's affective states. The design of affect-sensitive interaction, an area known as affective computing, is an increasingly important discipline within the HCI and HRI communities (Picard, 1997). However, to date little work has been done to explore this approach for technology-assisted intervention of individuals with ASD. Furthermore, *no existing technology specifically addresses how to autonomously detect and flexibly respond to affective cues of children with ASD within an intervention paradigm* (Bernard-Opitz et al., 2001; Dautenhahn and Werry, 2004; Kozima et al., 2009; Michaud and Theberge-Turmel, 2002; Mitchell et al., 2007; Parsons et al., 2005; Pioggia et al., 2005; Scassellati. 2005; Strickland, 1997; Swettenham, 1996; Tartaro and Cassell, 2007; Trepagnier et al., 2006). The primary contribution of the research covered in this chapter is to address this deficiency. The research develops HCI technologies capable of eliciting affective changes in individuals with ASD. We investigate how to augment HRI to be used in affect-sensitive interaction by endowing the technology with the ability to recognize and flexibly respond to the affective states of a child with ASD based on his/her physiological responses. The research also assesses the efficacy of measuring affect in VR.

COMPLETED RESEARCH ON AFFECT-SENSITIVE COMPUTING AND AUTISM

We briefly present our results to demonstrate the feasibility as well as the likelihood of success of applying affect-sensitive computing to individuals with ASD.

Affective Modeling and Closed-Loop Affect-Sensitive Interaction for Children with ASD During Non-Social Tasks

In Phase I of this study (Liu et al., 2008a) six participants (ages 13-16) with ASD completed two computer-based tasks (i.e., Anagram game, Pong) wherein changes in task difficulty evoked varying intensities of three target operationalized affective states: liking, anxiety, and engagement. Affective modeling based on initial simultaneous clinical observation, performance characteristic/evaluation, and physiological data produced affect-recognition capabilities with predictive accuracies averaging around 82.9% in future performance. In Phase II (Liu et al., 2008b), a robot-based basketball (RBB) task was designed wherein a robotic arm with a basketball hoop attached to its end-effector learned individual preferences based on the predicted liking level of children with ASD and selected an appropriate behavior in real-time. Each participant completed two sessions RBB1 (non-affect-sensitive) and RBB2 (affect-sensitive). The results showed that the three different behaviors of the robot had distinguishable impacts on the liking level of the children with ASD. To reduce the bias of validation, in RBB1 the robot selects behaviors randomly and the occurrence of each behavior is evenly distributed. Average labeled liking level for each behavior as reported by the therapist in RBB1 showed differences between behaviors and individual preferences of each child. The difference of the impact on liking of each robot behavior was significant for five of the six children and moderate for one child. By performing two-way ANOVA analysis on the behavior (i.e., most-preferred, moderately-preferred, and least-preferred behavior) and participant, it was found that the differences of reported liking for different behaviors were statistically significant ($p < 0.05$), whereas no significant effect due to different participants was observed.

Furthermore, it was also observed that different children with ASD may have different preferences for the robot's behaviors. These results demonstrated that it is important to have a robot learn the individual's preference and adapt to it automatically, which may allow a more tailored and affect-sensitive interaction between children with ASD and the robot. When a robot learns that a certain behavior is liked more by a particular child, it can choose that behavior as his/her "social feedback" or "reinforcer" in a robot-assisted individualized affect-sensitive autism intervention.

In the closed-loop affect-sensitive session, RBB2, the robot autonomously selected the desirable behavior based on interaction experiences (i.e., the consequent liking level of a participant predicted by the individual affective model developed in Phase I). To determine the effects of the session type and participant on the reported liking, a two-way ANOVA test was performed. The null hypothesis that there is no change in liking level between affect-sensitive sessions and non-affect-sensitive sessions could be rejected at the 99.5% confidence level. Additionally, no significant impact due to different participants was observed. This was an important result as the robot continued learning and utilizing the information regarding the probable liking level of children with ASD to adjust its behaviors. This ability enables the robot to adapt its behavior selection policy in real time and hence keeps the participant in a higher liking level. *These results suggest that endowing an affect-sensitive adaptive system with the ability to recognize and respond to the affective states of a child with ASD based on physiological information could be a viable means for autism intervention.*

Affective Reactions to Manipulation of Social Parameters in VR

This study examined affective and physiological variation in response to manipulated social parameters (e.g., eye gaze and social distance) during social interaction in VR for both children with ASD and typically developing (TD) children. Experiments have been completed for 7 pairs of children with ASD and TD (age 13-17 years) matched on age, gender, and reciprocal verbal ability. Social interactions were designed using VIZARD VR toolkit software to project virtual human characters (i.e., avatars) who displayed different eye gaze patterns and stood at different distances while telling personal stories to the participants. We measured physiological responses and collected reports from an observing therapist on the levels of affective states (i.e., anxiety and engagement) for each participant who completed two 1.5-hour sessions. The social parameters of interest, eye gaze and social distance, were examined in a 4x2 design, presented in a random order based on a Latin Squares design to account for sequencing and order effects. Four types of eye gaze dictated the percentage of time an avatar looked at the participant. These were tagged as *direct*, *averted*, *normal while speaking*, and *flip of normal* (Argyle and Cook, 1976; Colburn et al., 2000). Two types of social distance, termed *invasive* (1.5ft away) and *decorum* (4.5ft away), characterized the distance between the avatar and the participant (Schneiderman and Ewens, 1971). Figure 1 shows two examples of the avatars. Other social parameters, such as facial expression and vocal tone were kept as neutral as possible. Efforts were made to minimize reactions due solely to viewing an avatar by choosing the 10 most-neutral avatars based on a survey of 20 participants. Therefore, affective rating and physiological reactions during the experiment could

Figure 1. Snapshot of an avatar displaying straight gaze at the invasive distance (left) and an avatar standing at the decorum distance and looking to her right in an averted gaze (right)

be reasonably expected to be related to change in eye gaze and/or social distance and not due to viewing the avatar alone.

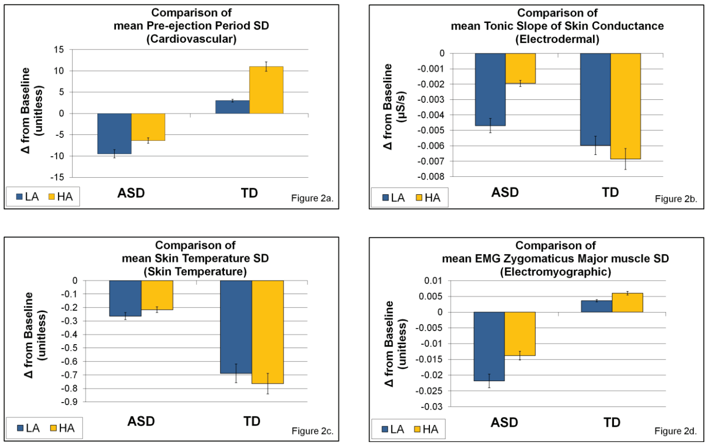
Analysis of the subjective rating by the therapist revealed that manipulation of social parameters created affective changes in the participants (Table 1). The reported anxiety group mean was higher and the engagement group mean was lower for ASD than for the matched TD group, which is consistent with observations of social deficits of ASD children. The standard deviation (SD) for the ASD group was higher for both anxiety and engagement reports than that of the TD group. This result implied that the ASD group was more susceptible than the TD group to manipulation of social parameters in the VR trials. In addition, the range of subjective rating (9-point scale) was higher for the ASD group than the TD group on both affective states. *Thus, the results implied that our VR-based social interaction system was capable of creating affective changes among the participants*.

A set of 53 extracted physiological indices were analyzed to determine the extent of physiological responses occurring during the VR-based social interaction. A detailed description of the sensor placement, signal processing, and routines used to extract the physiological indices from the raw signals can be found in our previous work (Liu et al., 2008a). Figure 2a.-d. shows a sample of results of physiological indices in response to effect of varying eye gaze with anxiety, and Figure 3a.-d.shows the same sample of physiological indices from effect of varying eye gaze with engagement. The variation of social interaction within the VR trials generated statistically significant physiological changes (^{3} 90% confidence) in each of four major physiological categories – cardiovascular (ECG), electrodermal (EDA), skin temperature (ST), and electromyographic (EMG) – corresponding to both reported low anxiety (LA) and high anxiety (HA) states as well as low engagement (LE) and high engagement (HE) states. *Thus, the physiological indices are a viable means to differentiate among the ASD and TD groups.*

Table 1. Affective Intensity (full range [1-9]) Reported by Therapist

	Anxiety			**Engagement**		
Group	Mean	SD	Range	Mean	SD	Range
ASD (N=7)	4.9	1.7	8	4.7	1.6	8
TD (N=7)	4.4	1.4	6	5.1	1.4	7

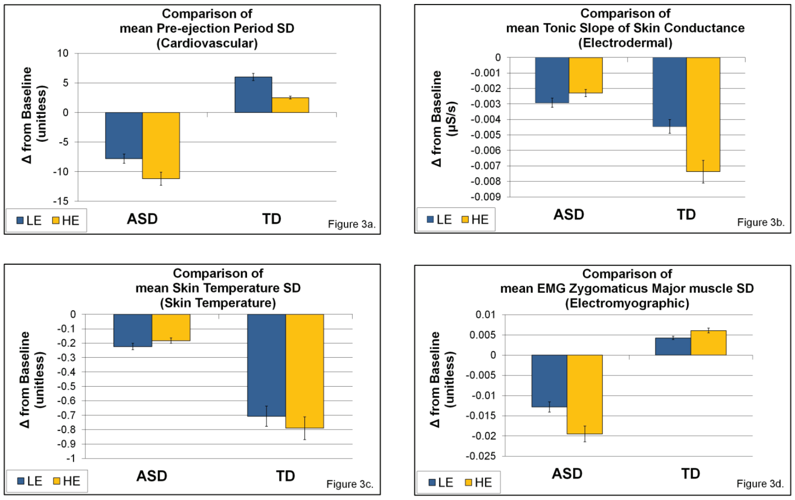
Figure 2. Shown are the changes from baseline in physiological indices corresponding to Low Anxiety (LA) and High Anxiety (HA) states for the ASD and TD groups in response to variation of the avatar's eye gaze. Significant differences are evident between groups for physiological indices extracted from cardiovascular signals (a), electrodermal signals (b), skin temperature signals (c), and electomyographic signals (d)



FUTURE RESEARCH DIRECTIONS

To address the core deficits of children with ASD in social communication in complex interactions, effective dynamic adjustment mechanisms would be demanded to incorporate multiple factors of interests such as affective and behavioral (e.g., attentive) cues, intervention goals, and task measures. As discussed earlier, expert therapists attempt to adeptly infer the affective cues ex-

Figure 3. Shown are the changes from baseline in physiological indices corresponding to Low Engagement (LE) and High Engagement (HE) states for the ASD and TD groups in response to variation of the avatar's eye gaze. Significant differences are evident between groups for physiological indices extracted from cardiovascular signals (a), electrodermal signals (b), skin temperature signals (c), and electomyographic signals (d)



hibited by the children with ASD to adjust the intervention process (Ernsperger, 2003; Seip, 1996; Wieder and Greenspan, 2005). Therefore, a technology-assisted ASD intervention system must also be able to understand and respond to the affective needs of these children - an ability that the current ASD intervention systems lack - to achieve effective interaction leading to efficient intervention.

The physiology-based affect-sensitive technology described here could be employed to develop new intervention paradigms, which could promote interventions for individuals with ASD that are practical, widely available, and specific to the unique strengths and vulnerabilities of individuals with ASD. With further integration, a VR and physiological profiling system could be effective for use in developing and adapting controlled environments that help individuals explore social interaction dynamics gradually but automatically (i.e., introducing the aspects of social communication that are more challenging based on physiological data). Future work may include a reduction of the verbal components in the cognitive tasks which would allow application to the broader ASD population. Also, the research could benefit from exploring and merging other types of signals and features proven useful in affective computing, such as pupil diameter from eye-tracking data, with the current set of physiological signals. These ideas are currently being explored by researchers in our laboratory.

Note that the presented work requires physiological sensing that has its own limitations. For example, one needs to wear physiological sensors, and use of such sensors could be restrictive under certain circumstances. However, none of the participants in our studies had any objection in wearing the physiological sensors. Similar observations were achieved by Conati et al. (2003) that suggested concerns for intrusiveness of physiological sensors could be lessened for children in a game-like environment. Given the rapid progress in wearable computing with small, non-invasive sensors and wireless communication, physiological sensors can be worn in a wireless manner such as in physiological sensing clothing and accessories (Picard, 1997; Wijesiriwardana et al., 2004), which could alleviate possible constraints on experimental design. Physiology-based affect recognition can be appropriate and useful for the application of interactive autism intervention and could be used conjunctively with other modalities (e.g., facial expression, vocal intonation, etc.) to allow flexible and robust affective modeling for children with ASD.

Future work may also involve designing socially-directed interaction experiments with embodied robots interacting with children with ASD. For example, the real-time affect recognition and response system described here could be integrated with a life-like android face developed by Hanson Robotics (hansonrobotics.com), which can produce accurate examples of common facial expressions that convey affective states. This affective information could be used as feedback for empathy exercises to help children with ASD recognize their own emotions.

CONCLUSION

There is increasing consensus that development of assistive therapeutic tools can make application of intensive intervention for children with ASD more readily accessible. In recent years, various applications of advanced interactive technologies have been investigated to facilitate and/or partially automate the existing behavioral intervention that addresses specific deficits associated with autism. However, the current technology-assisted therapeutic tools for children with ASD do not possess the ability of deciphering the affective cues of the children, which could be critical given that the affective factors of children with ASD have significant impacts on the intervention practice.

A physiology-based affective modeling framework for children with ASD was presented. The developed model could allow the recognition of affective states of the child with ASD from the physiological signals in real time and provide the basis for computer-based affect-sensitive interactive autism intervention. How to augment the interactive autism intervention was investigated by having a robot respond appropriately to the inferred level of a target affective state based on the affective model. VR-based intervention tools that address the social communication deficits of children with ASD were also developed and evaluated.

The impact of an intelligent system built on a computer-, robot-, or VR-based platform that can detect the affective states of a child with ASD and interact with him/her based on such perception could be transformative. Such a system could feasibly allow the manipulation and exacerbation of salient characteristics of interactions in a highly flexible environment that could potentially scaffold skills while minimizing potentially negative consequences. Thus, having a methodology that can objectively identify and predict social engagement as well optimal levels of affective arousal in a manner targeted to the specific child would represent a powerful intervention platform that addresses a serious potent barrier to the treatment of children with ASD.

Ultimately, continued exploration of this research could demonstrate the utility of affect-computing systems and physiologically-based affect recognition to address fundamental gaps in existing intervention paradigms designed to remediate clinically impairing social difficulties within an ASD population. Not only is the potential application of this technology particularly promising to this population, but demonstration of such a tool may hold even greater import in future extension of this methodology to individuals with ASD and other developmental disabilities wherein intellectual disabilities and communication limits are even more challenging.

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