Online Affect Detection and Robot Behavior Adaptation for Intervention of Children With Autism

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***Abstract*—Investigation into robot-assisted intervention for children with autism spectrum disorder (ASD) has gained momentum in recent years. Therapists 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, a robot must also be able to understand the affective needs of these children—an ability that the current robot-assisted ASD intervention systems lack—to achieve effective interaction that addresses the role of affective states in human–robot interaction and intervention practice. In this paper, we present a physiology-based affect-inference mechanism for robot-assisted intervention where the robot can detect the affective states of a child with ASD as discerned by a therapist and adapt its behaviors accordingly. This paper is the first step toward developing "understanding" robots for use in future ASD intervention. Experimental results with six children with ASD from a proof-of-concept experiment (i.e., a robot-based basketball game) are presented. The robot learned the individual liking level of each child with regard to the game configuration and selected appropriate behaviors to present the task at his/her preferred liking level. Results show that the robot automatically predicted individual liking level in real time with 81.1% accuracy. This is the first time, to our knowledge, that the affective states of children with ASD have been detected via a physiology-based affect recognition technique in real time. This is also the first time that the impact of affect-sensitive closed-loop interaction between a robot and a child with ASD has been demonstrated experimentally.**

***Index Terms*—Autism intervention, closed-loop human–robot interaction (HRI), physiological sensing.**

I. Introduction

AUTISM is a neurodevelopmental disorder characterized by core deficits in social interaction, social communication, and imagination [1]. Emerging research suggests prevalence rates as high as approximately 1 in 150 for the broad autism spectrum [2]. While there is at present no single accepted intervention, treatment, or known cure for autism spectrum disorders (ASDs), there is growing consensus that intensive behavioral and educational intervention programs can significantly improve long-term outcomes for individuals and their families [3]. Despite the urgent need and societal import of intensive treatment [4], appropriate intervention resources for children with ASD and their families are often extremely costly when accessible [5]. Therefore, an important new direction for research on ASD is the identification and development of assistive intervention tools that can make application of intensive treatment more readily accessible.

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 [6], virtual reality environments [7], and robotic systems [8]–[13]. Initial results indicate that robots may hold promise for rehabilitation of children with ASD. Dautenhahn and Werry [8] have explored how a robot can become a playmate that might serve a therapeutic role for children with autism in the Aurora project. Research suggested that robots can allow simplified but embodied social interaction that is less intimidating or confusing for children with ASD [8]. Michaud and Theberge-Turmel [9] investigated the impact of robot design on the interactions with children and emphasized that systems need to be versatile enough to adapt to the varying needs of different children. Pioggia *et al.* [10] developed an interactive life-like facial display system for enhancing emotion recognition in individuals with ASD. Robots have also been used to teach basic social interaction skills using turn-taking and imitation games, and the use of robots as social mediators and as objects of shared attention can encourage interaction with peers and adults [8], [11], [12]. Robotic technology poses 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 [13]. By employing human–robot interaction (HRI) technologies, robot-based therapeutic tools can partially automate the time-consuming, routine behavioral therapy sessions and may allow intensive intervention to be conducted at home [8].

Even though there is increasing research in robot-assisted autism intervention, the authors found no published studies that specifically addressed how to automatically detect and respond

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to affective cues of children with ASD. We believe that such ability could be critical given the importance of human affective information in HRI [14], [15] and the significant impacts of the affective factors of children with ASD on the intervention practice [16]. Common in autism intervention, therapists who work with children with ASD continuously monitor affective cues of the children in order to make appropriate decisions about adaptations to their intervention 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" [16]. Children with autism are particularly vulnerable to anxiety and intolerant of feelings of frustration, which requires a therapist to plan tasks at an appropriate level of difficulty [17]. The engagement of children with ASD is the ground basis for the "floor-time therapy" to help them develop relationships and improve their social and communication skills [18].

The potential impacts brought by a robot that can detect the affective states of a child with ASD and interact with him/her based on such perception could be various. Interesting activities could be chosen to retain the child's attention when the detected engagement level is low. Complex social stimuli, sophisticated interactions, and unpredictable situations could be gradually but automatically introduced when the robot recognizes that the child is comfortable or not anxious at a certain level of interaction dynamics for a reasonably long period of time. A therapist could use the child's affective records to analyze the therapeutic approach. With the record of the activities and the consequent emotional changes in a child, a robot could learn individual affective characteristics over time, and thus, could adapt the ways it responds to the needs of different children.

The primary objective of the current research is to investigate how to augment HRI to be used in autism intervention by endowing the robot with the ability to recognize and respond to the affective states of a child with ASD. In order to achieve this objective, the research is divided into two phases. Phase I represents the development of affective models through psychophysiological analysis, which includes designing cognitive tasks for affect-elicitation, deriving physiological features via signal processing, and developing affective models using machine learning techniques. Phase II is characterized by the investigation of affect sensitivity during the closed-loop interaction between a child with ASD and the robot. A proof-of-concept experiment was designed wherein a robot learns individual preferences based on the predicted liking level of the children with ASD as discerned by the therapist and selects an appropriate behavior accordingly.

The paper is organized as follows. The scope and rationale of this paper is presented in Section II. Section III describes our proposed framework for automatically detecting and responding to affective cues of children with ASD in the HRI, as well as the experimental design. This description is followed by the detailed results and discussion in Section IV. Finally, Section V summarizes the contributions of the paper and outlines possible future directions of this research.

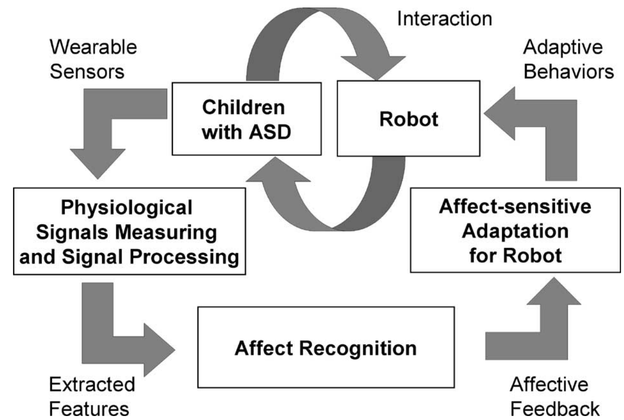

Fig. 1. Framework overview.

II. Scope and Rationale

The overview of the affect-sensitive closed-loop interaction between a child with ASD and a robot is presented in Fig. 1. The physiological signals from the children with ASD are recorded when they are interacting with the robot. These signals are processed in real time to extract features, which are fed as input into the models developed in Phase I. The models determine the perceived affective cues and return this information as an output. The affective information, along with other environmental inputs, is used by a controller to decide the next course of action for the robot. The child who engages with the robot is then influenced by the robot's behavior, and the closed-loop interaction cycle begins anew.

HRIs are characterized by explicit as well as implicit channels of communication with presumed underlying affective states [15]. There are several modalities such as facial expression [19], vocal intonation [20], gestures [21], and physiology [22]–[24] that can be utilized to evaluate the affective states. In this paper, we chose to create affective models based on physiological data for several reasons. Children with ASD often have communicative impairments (both nonverbal and verbal), particularly regarding the expression of affective states [1]. These vulnerabilities place limits on traditional conversational and observational methodologies; however, physiological signals are continuously available and are not necessarily directly impacted by these difficulties [25]. 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, evidence shows that the transition from one affective state to another is accompanied by dynamic shifts in indicators of autonomic nervous system activity [26]. In our previous paper, we successfully developed affective models from physiological signals for typical adults with reliable prediction performance [27]–[29]. Even though, in recent years, physiology has been successfully employed to build affect recognizers for typical individuals in several research groups [22]–[24], the studies on the correlation of the physiological signals and the affective states of people with ASD are relatively few [25], [30]. To our knowledge, real-time physiology-based affect recognition for children with ASD has not been known.

An important question when estimating human affective response is how to operationalize the affective states. Although much existing research on affective modeling categorizes affective states into "basic emotions," there is no consensus on a set of basic emotions among the researchers [31]. This fact implies that pragmatic choices are required to select target affective states for a given application [31]. In this paper, we chose anxiety, engagement, and liking to be the target affective states. Anxiety was chosen for two primary reasons. First, anxiety plays an important role in various human–machine interaction tasks that can be related to task performance [32]. Second, anxiety is not simply a frequently co-occurring disorder; in some ways, it may also be a hallmark of autism [25], [33]. Engagement, defined as "sustained attention to an activity or person," has been regarded as one of the key factors for children with ASD to make substantial gains in academic, communication, and social domains [34]. With "playful" activities during the intervention, the liking of the children (i.e., the enjoyment they experience when interacting with the robot) may create the urge to explore and allow prolonged interaction for the children with ASD, who are susceptible to being withdrawn [8].

Notably, evidence shows that several affective states could co-occur at different arousal levels [35], and different individuals could express the same emotion with different characteristic response patterns under the same contexts (i.e., phenomenon of person stereotypy) [36]. The novelty of the presented affective modeling is that it is individual-specific to accommodate the differences encountered in emotional expression, and it consists of an array of recognizers—each of which determines the intensity of one target affective state for each individual. In this paper, a therapist observed the experiments (described in Section III-B2) and provided subjective reports based on expertise in inferring presumable underlying affective states from the observable behaviors of children with ASD. The therapist's reports on perceived intensity of the affective states of a child and the extracted physiological indexes (described in Section III-B4) were employed to develop *therapist-like* affect recognizers that predict high/low levels of anxiety, engagement, and liking for each child with ASD.

Once affective modeling was completed in Phase I, the therapist-like recognizers equipped the robot with the capability to detect the affective states of the children with ASD in real time from online-extracted physiological features, which could be utilized in future interventions even when a therapist is not available. As stated in [37], it is important to have robots maintain characteristics of adaptability when applied to autism intervention. In Phase II, we designed and implemented a proof-of-concept experiment [robot-based basketball (RBB)] wherein a robot adapts its behaviors in real time according to the preference of a child with ASD, inferred from the interaction experience and the predicted consequent liking level. This is the first time, to our knowledge, that the feasibility and the impact of affect-sensitive closed-loop interaction between a robot and a child with ASD have been demonstrated experimentally. While the results are achieved in a nonsocial interaction task, it is expected that the real-time affect recognition and response system described in this paper will provide a basis for future research into developing robot-assisted intervention tools to help children with ASD explore social interaction dynamics in an affect-sensitive and adaptive manner.

TABLE I
CHARACTERISTICS OF PARTICIPANTS

Child ID	Gender	Age	Diagnosis	PPVT-III Score
A	Male	15	Autistic Disorder	99
B	Male	15	Asperger's Syndrome	80
C	Male	13	Autistic Disorder	81
D	Male	14	PDD-NOS	92
E	Male	16	PDD-NOS	93
F	Female	14	PDD-NOS	83

III. Experimental Investigation

A. *Participants*

Six participants within the age range of 13–16 years volunteered to partake in the experiments with the consent of their parents. Each of the participants had a diagnosis on the autism spectrum, either autistic disorder, Asperger's syndrome, or pervasive developmental disorder not otherwise specified, according to their medical records. Due to the nature of the tasks, the following were considered when choosing the participants: 1) having a minimum competency level of age-appropriate language and cognitive skills and 2) not having any history of mental retardation. Each child with ASD was given the Peabody Picture Vocabulary Test III (PPVT-III) [38] to screen cognitive function. Inclusion in our study was characterized as obtaining a standard score of 80 or above on the PPVT-III measure. The approval of the Institutional Review Board was sought and received for conducting experiments. Table I shows the characteristics of the participants in the experiments.

B. *Phase I—Affective Modeling*

While the eventual goal is to develop affect-sensitive HRI, we built the affective models using physiological data gathered from two human–computer interaction tasks. Our previous paper [29] showed that affective models built through human–computer interaction tasks could be successfully employed to achieve affect recognition in HRI for typical individuals. This observation suggests that it is possible to broaden the domain of tasks for affective modeling, thus reducing the habituation effect due to continuous exposure to the same robotic system.

1) Task Design: Two computer-based cognitive tasks were designed to evoke varying intensities of the following three affective states: anxiety, engagement, and liking, from the participants. Physiological data from participants were collected during the experiment. The two tasks consisted of an anagram-solving task and a Pong-playing task. The anagram-solving task has been previously employed to explore relationships between both electrodermal and cardiovascular activity with anxiety [39]. Affective responses were manipulated in this task by presenting

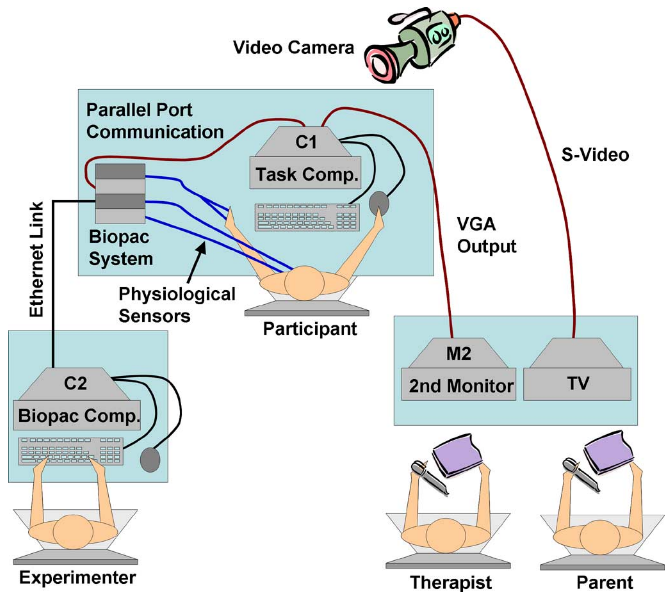

Fig. 2. Experimental setup for affective modeling tasks.

the participant with anagrams of varying difficulty levels, as established through pilot work. A long series of trivially easy anagrams caused less engagement. An optimal mix of solvable and difficult anagrams caused liking and engagement at times. Unsolvable or extremely difficult anagrams and giving time deadlines generated anxiety.

The Pong task involved the participant playing a variant of the classic video game "Pong." This game has been used previously by researchers to study anxiety, performance, and gender differences [32]. Various parameters of the game were manipulated to elicit the required affective responses. These parameters included ball speed and size, paddle speed and size, sluggish or overresponsive keyboard, random keyboard response, and the level of the computer opponent player. Low speeds and large sizes of the ball and paddle made games less engaging after a while; whereas ball and paddle movements at high speeds along with smaller sizes of the two made the game engaging. Very high speeds caused anxiety at times. Playing against a moderate-level computer player usually generated liking. The task configurations were established through pilot work.

Each task sequence was subdivided into a series of discrete trials/epochs that were bounded by the subjective affective state assessments. These assessments were collected using a battery of five questions regarding the three target affective states and the perceived difficulty and performance rated on an 8-point Likert scale where 1 indicated the lowest level and 8 indicated the maximum level. Each participant took part in six sessions—three 1-h sessions of solving anagrams and three 1-h sessions of playing Pong—on six different days.

2) Experimental Setup: Fig. 2 shows the setup for the experiment. A child with ASD was involved in the cognitive tasks on computer C1 while his/her physiological data were acquired via wearable biofeedback sensors and the Biopac system (www.biopac.com). After being amplified and digitized, physiological signals were transferred from the Biopac transducers to C2 through an Ethernet link at 1000 Hz and stored. Because of the suspected unreliability of the subjective self-reports from children with ASD, a therapist with experience in working with children with ASD and a parent of the participant were also involved in the study. The signal from the video camera was routed to a television, and the signal from the participant's computer screen where the task was presented was routed to a separate computer monitor M2. The therapist and a parent were seated at the back of the experiment room, watching the experiment from the view of the video camera and observing how the task progressed on the separate monitor.

3) Experimental Procedure: On the first visit, participants completed the PPVT-III measurement to determine eligibility for the experiments. After initial briefing regarding the tasks, physiological sensors from a Biopac system were attached to the participant's body. Participants were asked to relax in a seated position and read age-appropriate leisure material while a 3-min baseline recording was performed, which was later used to offset day-variability. Each session lasted about an hour and consisted of a set (13–15) of either 3-min epochs for anagram tasks or up to 4-min epochs for Pong tasks. Each epoch was followed by subjective report questions rated on an 8-point Likert scale. After each epoch, the therapist and the parent also answered the questions about how they thought the participant was feeling during the finished epoch on an 8-point Likert scale. These three sets of reports were used as the possible reference points to link the objective physiological measures to the participant's affective state.

4) Physiological Indexes for Affective Modeling: There is good evidence that the physiological activity associated with affective states can be differentiated and systematically organized [26]. Cardiovascular and electromyogram (EMG) activities have been used to examine positive and negative affective states of people [40], [41]. Blood pulse volume amplitude and sympathetic activity have been shown to be associated with task engagement [42]. The relationships between both electrodermal and cardiovascular activities with anxiety were investigated in [39] and [43]. The correlation between physiological responses and underlying affective states was employed in this paper to develop affective models for children with ASD. The physiological signals examined were features of cardiovascular activity [including interbeat interval (IBI), relative pulse volume, pulse transit time (PTT), heart sound, and preejection period (PEP)], electrodermal activity (tonic and phasic response from skin conductance), and EMG activity (from corrugator supercilii, zygomaticus, and upper trapezius muscles). These signals were selected because they are likely to demonstrate variability as a function of the targeted affective states, and also they can be measured noninvasively, and are relatively resistant to movement artifacts [36].

The physiological signals examined in this paper along with the features derived from each signal are described in Table II. Signal processing techniques such as the Fourier transform, wavelet transform, thresholding, and peak detection were used to derive the relevant features from the physiological signals. IBI is the time interval between two "R" waves in the ECG waveform. Power spectral analysis is performed on the IBI data

TABLE II
PHYSIOLOGICAL INDEXES

Physiological Signals	Features Derived	Label Used	Unit of Measurement
Cardiac activity	Sympathetic power (from ECG)	Sym	Unit/Square Second
	Parasympathetic power (from ECG)	Para	Unit/Square Second
	Very Low Frequency Power (from ECG)	VLF	Unit/Square Second
	Ratio of powers	Sym Para Para VLF Sym VLF	No unit
	Mean IBI	IBI ECGmean	Milliseconds
	Std. of IBI	IBI ECGstd	Standard Deviation
	Mean amplitude of the peak values of the PPG signal (Photoplethysmogram)	PPG Peakmean	Micro Volts
	Standard deviation (Std.) of the peak values of the PPG signal	PPG Peakstd	Standard Deviation
	Mean Pulse Transit Time	PTTmean	Milliseconds
Heart Sound	Mean of the 3rd, 4th, and 5th level coefficients of the Daubechies wavelet transform of heart sound signal	Mean d3 Mean d4 Mean d5	No unit
	Standard deviation of the 3rd, 4th, and 5th level coefficients of the Daubechies wavelet transform of heart sound signal	Std d3 Std d4 Std d5	No unit
Bioimpedance	Mean Pre-Ejection Period	PEPmean	Milliseconds
	Mean IBI	IBI ICGmean	Milliseconds
Electrodermal activity	Mean tonic activity level	Tonicmean	Micro-Siemens
	Slope of tonic activity	Tonicslope	Micro-Siemens /Second
	Mean amplitude of skin conductance response (phasic activity)	Phasicmean	Micro-Siemens
	Maximum amplitude of skin conductance response (phasic activity)	Phasicmax	Micro-Siemens
	Rate of phasic activity	Phasicrate	Response peaks/Second
Electromyographic activity	Mean of Corrugator Supercilii activity	Cormean	Micro Volts
	Std. of Corrugator Supercilii activity	Corstd	Standard Deviation
	Slope of Corrugator Supercilii activity	Corslope	Micro Volts/Second
	Mean Interbeat Interval of blink activity	IBI Blinkmean	Milliseconds
	Std. of Interbeat Interval of blink activity	IBI Blinkstd	Standard Deviation
	Mean amplitude of blink activity	Amp Blinkmean	Micro Volts
	Standard deviation of blink activity	Blinkstd	Standard Deviation
	Mean of Zygomaticus Major activity	Zygmean	Micro Volts
	Std. of Zygomaticus Major activity	Zygstd	Standard Deviation
	Slope of Zygomaticus Major activity	Zygslope	Micro Volts/Second
	Mean of Upper Trapezius activity	Trapmean	Micro Volts
	Std. of Upper Trapezius activity	Trapstd	Standard Deviation
	Slope of Upper Trapezius activity	Trapslope	Micro Volts/Second
	Mean and Median frequency of Corrugator, Zygomaticus, and Trapezius	Zfreqmean Cfreqmedian Tfreqmean	Hertz
Temperature	Mean temperature	Tempmean	Degree Centigrade
	Slope of temperature	Tempslope	Degree Centigrade/Second
	Std. of temperature	Tempstd	Standard Deviation

to localize the sympathetic and parasympathetic nervous system activities associated with two frequency bands. The high-frequency component (0.15–0.4 Hz; which corresponds to the rate of normal respiration) measures the influence of the vagus nerve in modulating the sinoatrial node and is associated with parasympathetic nervous system activity. The low-frequency component (0.04–0.15 Hz) provides an index of sympathetic effects on the heart. Photoplethysmograph (PPG) signal measures changes in the volume of blood in the fingertip associated with the pulse cycle and provides an index of the relative constriction versus dilation of the blood vessels in the periphery. PTT is the time it takes for the pulse pressure wave to travel from the heart to the periphery. PTT is estimated by computing the time between systole at the heart (as indicated by the R-wave of the ECG) and the peak of the pulse wave reaching the peripheral site where PPG is being measured. The heart sound signal measures sounds generated during each heartbeat. These sounds are produced by blood turbulence primarily due to the closing of the valves within the heart. The features extracted from the heart sound signal consist of the mean and standard deviation of the third-, fourth-, and fifth-level coefficients of the Daubechies wavelet transform. Bioelectrical impedance analysis measures the impedance or opposition to the flow of an electric current through the body fluids contained mainly in the lean and fat tissue. A common variable in recent psychophysiology research, PEP measures the latency between the onset of electromechanical systole and the onset of left-ventricular ejection. PEP is derived from impedance cardiogram and ECG and is most heavily influenced by sympathetic innervation of the heart. Electrodermal activity consists of two main components—tonic response and phasic response. Tonic skin conductance refers to the ongoing or the baseline level of skin conductance in the absence of any particular discrete environmental events. Phasic skin conductance refers to the event-related changes that occur, caused by a momentary increase in skin conductance (resembling a peak). The EMG signal from corrugator supercilii muscle (eyebrow) captures a person's frown and detects the tension in that region. This EMG signal is also a valuable source of blink information and helps determine the blink rate. The EMG signal from the zygomaticus major muscle captures the muscle movements while smiling. Upper trapezius muscle activity measures the tension in the shoulders, one of the most common sites in the body for developing stress.

5) Support Vector Machine (SVM)-Based Affective Modeling: Determining the intensity (e.g., high/low) of a particular affective state from the physiological response resembles a classification problem where the attributes are the physiological features and the target function is the degree of arousal. Our earlier paper [27] compared the efficacy of several machine learning algorithms to recognize the affective states from the physiological signals of typical individuals and found that SVMs gave the highest classification accuracy. In this paper, SVM was employed to determine the underlying affective state of a child with ASD given a set of physiological features. Details of the theory and learning methods of SVM can be found in [44] and are briefly described in Appendix A.

As illustrated in Fig. 3, each participant had a dataset comprising both the objective physiological features and corresponding subjective reports on arousal level of target affective states from the therapist, the parent, and the participant. The physiological features were extracted by using the approaches described in Section III-B4. Each subjective report was normalized to [0, 1] and then discretized such that 0–0.50 was labeled as low level and 0.51–1 was labeled as high level. All three affective states were partitioned separately so that there were two levels for each affective state. Each dataset contained approximately 85 epochs. The multiple subjective reports were analyzed, and one was chosen as the possible reference point to link the physiological measures to the participant's affective state. For example, a therapist-like affect recognizer can be developed when the therapist's reports are used. An SVM-based recognizer was trained

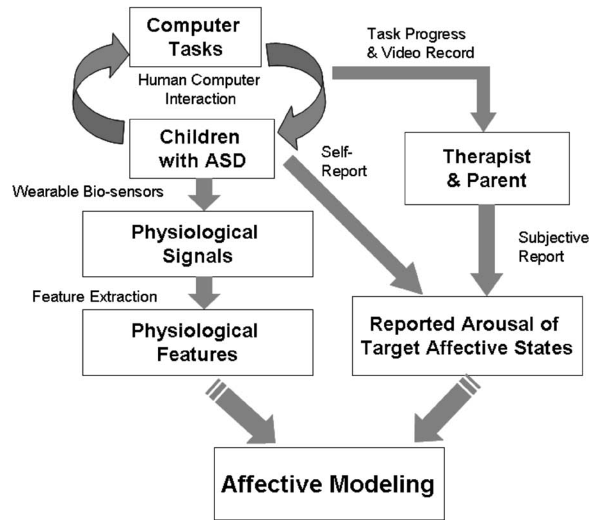

Fig. 3. Overview of affective modeling.

on each individual's dataset for each target affective state. In this paper, in order to deal with the nonlinearly separable data, soft margin classifiers with slack variables were used to find a hyperplane with less restriction [44]. Radial basis function was selected as the kennel function because it often delivers better performance [45]. A tenfold cross validation was used to determine the kernel and regularization parameters of the recognizer.

Once affective modeling is accomplished, the affect recognizers can accept as input the physiological features extracted online and produce as output the probable level of the target affective state of a child with ASD while interacting with a robot. In the design for the HRI task in Phase II, adequate measures were taken to avoid physical effort from overwhelming the physiological response.

C. Phase II—Closed-Loop HRI

1) Task Design: A closed-loop HRI task, "RBB," was designed. The main objective was twofold: 1) to enable the robot to learn the preference of the children with ASD implicitly using physiology-based affective models as well as select appropriate behaviors accordingly and 2) to observe the effects of such affective sensitivity in the closed-loop interaction between the children with ASD and the robot.

The affective model developed in Phase I is capable of predicting the intensity of liking, anxiety, and engagement simultaneously. However, to designate a specific objective for the experiment in Phase II without compromising its proof-of-concept purpose, one of the three target affective states was chosen to be detected and responded to by the robot in real time. As has been emphasized in [8], the liking of the children (i.e., the enjoyment they experience when interacting with a robot) is a goal as desirable as skill learning for autism intervention. Therefore, liking was chosen as the affective state around which to modify the robot's behaviors in Phase II.

In the RBB task, an undersized basketball hoop was attached to the end-effector of a robotic manipulator, which could move the hoop in different directions (as shown in Fig. 4) with different

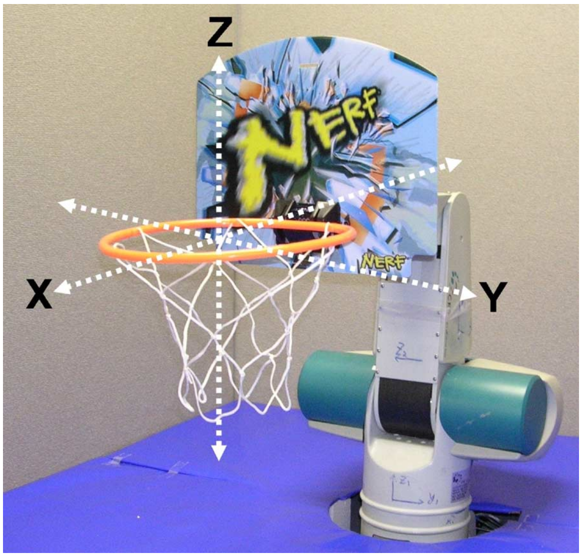

Fig. 4. X-, Y-, and Z-directions for behaviors used in RBB.

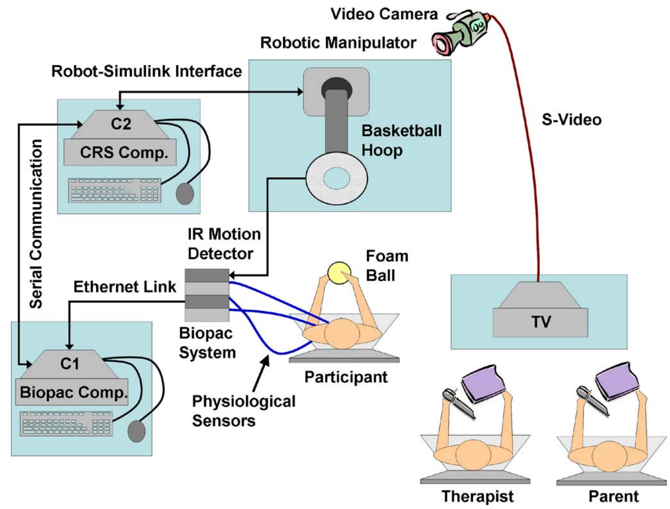

Fig. 5. Experimental setup for robot basketball.

TABLE III
ROBOT BEHAVIORS

Behavior ID	Motion Direction	Speed (sec/period)	Threshold (shots/epoch)	Background Music
1	X	8	12	Serene
2	Y	4	20	Lively
3	Z	2	30	Irregular

speeds. The children were instructed to shoot a required number of baskets into the moving hoop within a given time. Three robot behaviors were designed, as shown in Table III. For example, in behavior 1, the robot moves toward and away from the participant (i.e., in the X-direction) at a slow speed with soft background music, and the shooting requirement for successful baskets is relatively low. The parameter configurations were determined based on a pilot study to attain varied impacts on affective experience for different behaviors. From this pilot study, the averaged performance of participants for a given behavior was compiled and analyzed. The threshold of shooting requirement (TSR) was defined as 10% lower than the average performance. At the end of each epoch, the participant's performance was rated as excellent (baskets $\geq \lfloor 1.2\text{TSR} \rfloor$), above average ($\lfloor 0.8\text{TSR} \rfloor \leq$ baskets $< \lfloor 1.2\text{TSR} \rfloor$), or below average (baskets $< \lfloor 0.8\text{TSR} \rfloor$). Behavior transitions occurred between but not within epochs. As such, each robot behavior extended for the length of an epoch (1.5 min in duration) to have the participant fully exposed to the impact of that behavior.

Each of the six participants took part in two robot basketball sessions (RBB1 and RBB2). In RBB1 (nonaffect-based), the robot selected its behavior randomly (i.e., without any regard to the liking information of the participant), and the presentation of each type of behavior was evenly distributed. This session was designed for two purposes: 1) to explore the state space and action space of the QV-learning algorithm used in RBB2 for behavior adaptation (described in Section III-C4) and 2) to validate that the different robot behaviors have distinguishable impact on the child's level of liking. In RBB2 (liking-based), the robot continues to learn the child's individual preference and selects the desirable behavior based on interaction experiences (i.e., records of robot behavior and the consequent liking level of a participant predicted by the affective model). The idea is to investigate whether the robot can automatically choose the most liked behavior of each participant as observed from RBB1 by means of physiology-based affective model and QV-learning.

2) Experimental Setup: The real-time implementation of the RBB system is shown in Fig. 5. The setup included a 5-degree-of-freedom robot manipulator (CRS Catalyst-5 System) with a small basketball hoop attached to its end-effector. Two sets of IR transmitter and receiver pairs were attached to the hoop to detect small, soft foam balls going through the hoop. The setup also included the biological feedback equipment (Biopac system) that collected the participant's physiological signals and the digital output from the IR sensors. The Biopac system was connected to a PC (C1) that

1) acquired physiological signals from the Biopac system and extracted physiological features online;
2) predicted the probable liking level by using the affective model developed in Phase I;
3) acquired IR data through the analog input channels of the Biopac system;
4) ran a QV-learning algorithm that learns the participant's preference and chooses the robot's next behavior accordingly.

Computer C1 was connected serially to the CRS computer (C2), which ran Simulink software. The behavior switch triggers were transmitted from C1 to C2 via an RS232 link. The commands to control the robot's various joints were transmitted from C2 to the robot. There was a communication protocol established between C1 and C2 that ensured that the beginning and end of the basketball task was appropriately synchronized with the physiological data acquisition on C1. As in Phase I tasks, the therapist and a parent were also involved, watching the experiment from the TV that was connected to a video camera.

3) Experimental Procedure: Each basketball session (RBB1 or RBB2) was approximately 1-h long and included 27 min of active HRI (i.e., 18 epochs of 1.5 min each). The remaining time was spent attaching sensors, guiding a short practice, taking a baseline recording, collecting subjective reports, and pausing for scheduled breaks. During the experiment, the participant was asked to take a break after every four epochs and the participant could request a break whenever he/she desired one. During each basketball epoch, the participant received commands and performance assessments from prerecorded dialogue via a speech program running on C1 and the interaction proceeded as follows.

1) The participant was notified of the goal (i.e., TSR).
2) A start command instructed the participant to start shooting baskets.
3) Once the epoch started, the participant was given voice feedback every 30 s regarding the number of baskets remaining and the time available.
4) A stop command instructed the participant to stop shooting baskets, which ended the epoch.
5) At the end of each epoch, the participant's performance was rated and relayed to him/her as excellent, above average, or below average.

Each epoch was followed by subjective reports that took 30–60 s to collect. The subjective assessment procedure was the same as the protocol used in the affective modeling tasks in Phase I. After the subjective report was complete, the next epoch would begin. To prevent habituation, a time interval of at least seven days between any two RBB sessions was enforced.

4) Affect-Sensitive Behavior Adaptation in Closed-Loop HRI: We defined the state, action, state transition, and reward functions so that the affect-sensitive robot behavior adaptation problem could be solved using the *QV*-learning algorithm, as described in [46] and Appendix B.

The set of states consisted of three robot behaviors, as described in Table III. In every state, the robot has three possible actions (1/2/3) that correspond to choosing behavior 1, 2, or 3, respectively, for the next time step (i.e., next epoch). Each robot behavior persists for one full epoch and the state/behavior transition occurs only at the end of an epoch. The detection of consequent affective cues (i.e., the real-time prediction of the liking level for the next epoch) was used to evaluate the desirability of a certain action. To have the robot adapt to a child's individual preference, a reward function was defined based on the predicted liking level. If the consequent liking level was recognized as high, the contributing action was interpreted as positive and a reward was granted ($r = 1$); otherwise the robot received a punishment ($r = -1$). *QV*-learning uses this reward function to have the robot learn how to select the behavior that was expected to result in a high liking level, and therefore, positively influenced the actual affective (e.g., liking) experience of the child.

RBB1 enables state and action exploration where the behavior-switching actions are chosen randomly, with the number of visits to each state evenly distributed. The V-function and Q-function are updated using (3) and (4) from Appendix B. After RBB1, the subjective reports are analyzed to examine the impacts of different behaviors on each participant's preference. In RBB2, the robot starts from a nonpreferred behavior/state and continues the learning process by using (3) and (4). A greedy action selection mechanism is used to choose the behavior-switching action with the highest Q-value.

Because of the limited number of states and actions in this proof-of-concept experiment, a tabular representation is used for the V-function and the Q-function. To prevent a certain action and/or state from being overly dominant and to counteract the habituation effect, the values of $Q(s, a)$ and $V(s)$ are bounded by using the reward or punishment encountered in the interaction. The parameters in (3) and (4) are chosen as $\alpha = 0.8$ and $\gamma = 0.9$. Before RBB1 begins, the initial values in the V-table and the Q-table are set to 0.

IV. Results and Discussion

In this section, we present both the Phase I results of physiology-based affective modeling for children with ASD and Phase II results of the affect-sensitive closed-loop interaction between children with ASD and the robot.

A. Affect Detection

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 in [31] and [47], 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. 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 generally regarded as an effective way to evaluate the affective responses. As a result, subjective report is widely used for affective modeling and endowing an intelligent system with the recognition abilities similar to those of the reporters [15], [21]. One of the prime challenges of this paper is to attain reliable subjective reports. Researchers are generally reluctant to trust the response of adolescents on self-report [48]. In this study, 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 [49]. Therefore, in order to overcome this difficulty, reports on how a therapist and a parent thought the participant was feeling based on his/her observed behaviors were collected after each epoch.

To measure the amount of agreement among the different reporters, the κ-statistic was used [50]. The κ-coefficient measures pairwise agreement among a set of reporters making category judgments, correcting for expected chance agreement. When there is a complete agreement, then $\kappa = 1$; whereas, when there is no agreement other than that which would be expected by chance, then $\kappa = 0$.

It was observed that the agreement between the therapist and parent showed the largest κ-statistic values (mean $= 0.62$) among the three possible pairs for each child ($p < 0.05$, paired

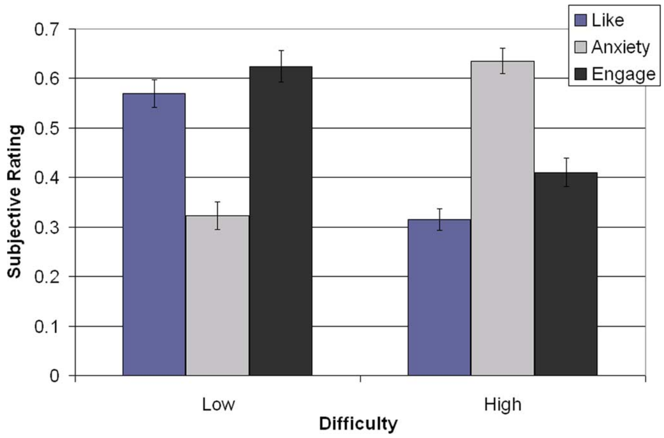

Fig. 6. Rated average affect response from therapist's reports.

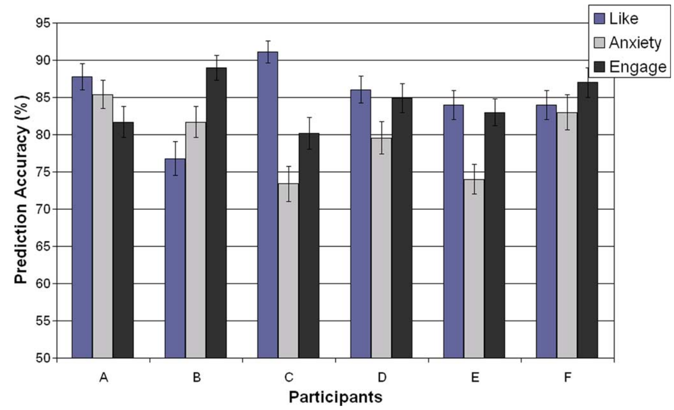

Fig. 7. Classification accuracy of the affect recognizer.

TABLE IV
RESULTS OF CORRELATION ANALYSIS FROM THERAPIST'S REPORTS

	Anxiety	Engage	Difficulty
Liking	-0.521	0.885	-0.616
Anxiety		-0.401	0.731
Engage			-0.486

t-test). The means of the κ-statistic values between the children and either the therapist or the parent were relatively small (0.37 and 0.40, respectively). Lack of agreement with adults does not necessarily mean that the self-reports of children with ASD are not dependable; however, given the objective of this study is to develop an affect-sensitive robotic system for autism intervention where the therapists' judgment based on their expertise is the state-of-the-art and the fact that there is a reasonably high agreement between the therapist and the parents for all of the six children, the subjective reports of the therapist were used as the reference points linking the objective physiological data to the children's affective state. To make the subjective reports more consistent, the same therapist was involved in all of the experiments. This choice allowed for building a *therapist-like* affective model. In the rest of the paper, unless otherwise specified, we will use the term liking, anxiety, and engagement to imply the target affective states as discerned by the therapist.

Fig. 6 shows a comparison of the therapist's average ratings for liking, anxiety, and engagement when the children with ASD played easy or difficult epochs in the Phase I computer games. When averaged across all participants, liking decreased, anxiety increased, and engagement decreased with increasing task difficulty. Table IV shows the correlation analysis between the reported affective states and the task difficulty. For each set of variables, the probability value (p-value) was computed from a two-side t-test. Due to the large sample size (approximately 85 epochs for each participant), the p-value for all correlations was less than 0.005. Through point biserial correlation analysis, it was found that difficulty is strongly positively correlated with anxiety and negatively correlated with liking and engagement. By examining Pearson's correlation coefficients, it was observed that there is a strong positive correlation between liking and engagement and a negative correlation between liking and anxiety, and there also exists a weak correlation between the reported anxiety and engagement. The results in Fig. 6 and Table IV present the results across all the children. However, when each child is examined individually, different trends could arise. For example, for child A, anxiety is positively correlated with engagement (Pearson's correlation $= 0.45$); for child F, no significant correlation is observed (Pearson's correlation $= -0.15$, $p > 0.05$); while for the four other children (B, C, D, and E), anxiety negatively correlated with engagement (Pearson's correlation equals -0.50, -0.39, -0.61, and -0.58, respectively), which revealed diverse affective characteristics of the children with ASD.

The performance of the developed affective model for each child is shown in Fig. 7. The cross-validation method, "leave-one-out," was used. The affective model produced high recognition accuracies for each target affective state of each participant. The average correct prediction accuracies across all participants were 85.0% for liking, 79.5% for anxiety, and 84.3% for engagement. This was promising considering that this task was challenging in two respects: 1) the reports were collected from the therapist who was observing the children with ASD as opposed to having typical adults capable of differentiating and reporting their own affective states and 2) varying levels of arousal of any given affective state (e.g., low/high anxiety) were identified instead of determining discrete emotions (e.g., anger, joy, sadness, etc.). Determining the difference in arousal level in one affective state is more subtle than distinguishing between two discrete affective states. In order to explore the effects of reducing the number of physiological signals and the possibility of achieving more economical modeling, we examined the performance of the affect recognizers when cardiovascular, electrodermal,[1] and EMG activities, and their combinations were used for affective modeling separately. It was observed that the EMG signal is less discriminatory than cardiovascular and electrodermal activities (with prediction accuracy of 69.7%, 73.5%, and 73.0%, respectively). While no combination surpassed the prediction

[1]Peripheral temperature has relatively few features derived, as shown in Table II, and was not examined independently. Instead, it was studied conjunctively with the electrodermal activity, both of which were acquired from the nondominant hand of a participant.

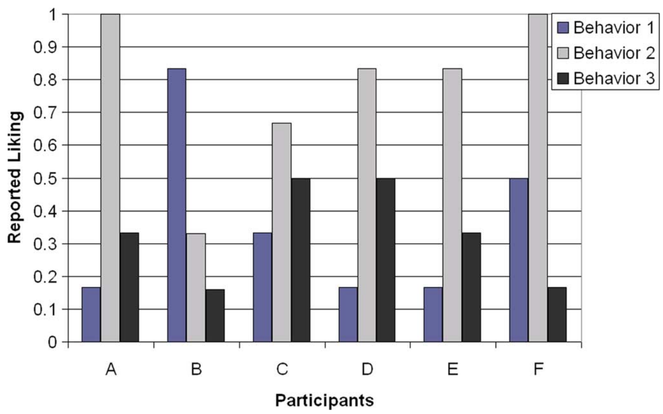

Fig. 8. Mean liking level for different behaviors in RBB1.

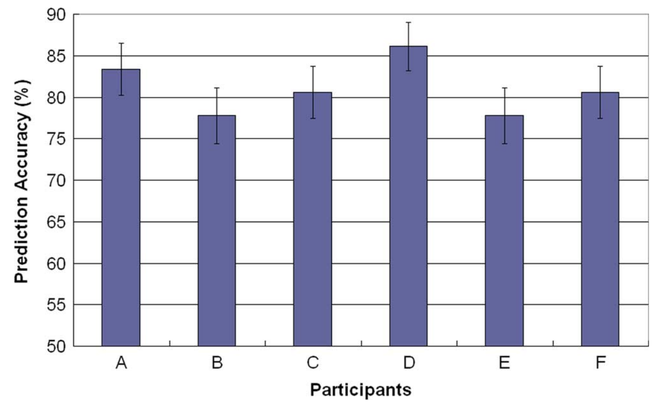

Fig. 9. Real-time classification accuracy of liking.

accuracy achieved when all signals were used (82.9%), the results suggested that it may be possible to selectively reduce the set of signals and obtain nearly-as-good performance (e.g., using a combination of cardiovascular and electrodermal signals yielded 78.7% prediction accuracy).

B. Affect Adaptation in RBB Task

The six children with ASD who completed the Phase I experiments also took part in the robot basketball task. The results described here are based on the RBB1 (nonaffect-based) and RBB2 (liking-based) tasks.

First, we present results to validate that 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. Fig. 8 shows the average labeled liking level for each behavior as reported by the therapist in RBB1. The difference of the impact is significant for five children (participants A, B, D, E, and F) and moderate for participant C. 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 are 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. For example, 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 robot-assisted autism intervention. Playful interaction will be more likely to emerge by addressing a child's preference.

Second, the predictive accuracy of how closely the real-time physiology-based quantitative measures of liking, as obtained from affective models developed in Phase I, matched with that of the subjective rating of liking made by the therapist during Phase II is presented in Fig. 9. The average predictive accuracy across all the participants was approximately 81.1%. The highest was 86.1% for child D and the lowest was 77.8% for child B and child E. Note that the affective model was evaluated based on physiological data obtained online from a real-time application for children with ASD. However, this prediction accuracy is comparable to the results achieved through offline analysis for typical individuals [22], [27].

TABLE V
PROPORTION OF DIFFERENT BEHAVIORS PERFORMED IN RBB2

Child ID	Most-Liked Behavior		Moderate-Liked Behavior		Least-Liked Behavior	
	ID	Proportion	ID	Proportion	ID	Proportion
A	2	82.4%	3	11.8%	1	5.8%
B	1	70.6%	2	17.7%	3	11.7%
C	2	58.8%	3	23.5%	1	17.7%
D	2	76.5%	3	11.8%	1	11.7%
E	2	76.5%	3	17.6%	1	5.9%
F	2	70.6%	1	17.7%	3	11.7%

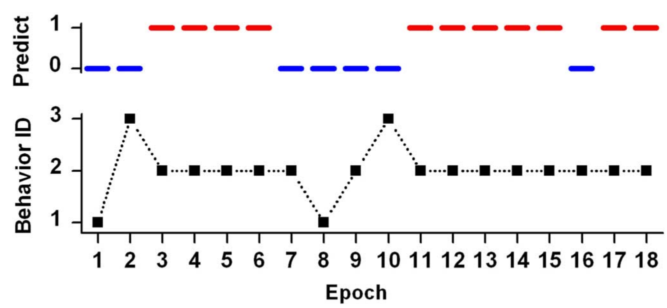

Fig. 10. Behavior selected by affect-sensitive robot in RBB2 for child A.

Third, we present results about robot behavior adaptation and investigate its impact on the interaction between the children with ASD and the robot. Table V shows the percentages of different behaviors that were chosen in the RBB2 session for each participant. The robot learned the individual's preference and selected the most preferred behavior with high probability for all the participants. Averaged across all participants, the most preferred, moderately preferred, and least preferred behaviors were chosen to be 72.5%, 16.7%, and 10.8% of the time, respectively. The preference of a behavior was defined by the reported liking level in RBB1, as shown in Fig. 8. To understand these results more clearly, we describe an individual case. Fig. 10 shows the affect-sensitive behavior adaptation in RBB2

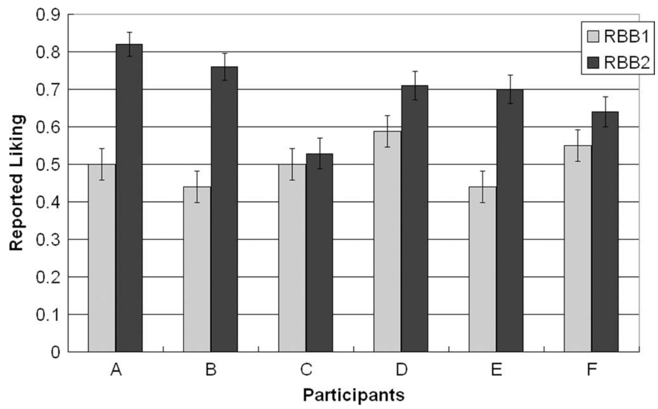

Fig. 11. Subjective liking as reported by therapist.

for child A, who prefers behavior 2 most (refer to Fig. 8). The real-time predicted liking level (i.e., high/low) is denoted by "H" or "L." The robot starts in a nonpreferred behavior (behavior 1) and then explores other behaviors before settling on the most preferred behavior (behavior 2) where the liking level is high (as confirmed by the affective model prediction as well as the therapist's subjective report). After a considerable time interacting with behavior 2 (e.g., epoch 7), the participant appears not to enjoy this behavior as much as before. The affective model detects this change and returns negative rewards. The QV-learning algorithm updates its state/action space and directs the robot to switch behaviors. However, after exploring other behaviors, the robot eventually finds that behavior 2 is the most preferred by child A (e.g., epoch 11) and continues the interaction using this behavior. At epoch 16, even though the predicted liking level is low, due to high frequent positive rewards received for behavior 2, the robot checks the updated Q-function and remains at this behavior. There could be several reasons why less-preferred behaviors were chosen in RBB2. The learned behavior selection policy might not have been optimal after the exploration in RBB1, and the QV-learning algorithm continued the learning process in RBB2. Another reason could be that the affective model is not 100% accurate and may return false reward/punishment, which may have given the robot imperfect instruction for behavior switches. Habituation to the most preferred behavior during RBB2 could also be a factor that might have contributed to temporary changes in preference that led the robot to choose other behaviors.

In Table V, the robot chose a less-preferred behavior more often for child C than for other participants. As can be seen in Fig. 8, child C does not show differences of liking among the three behaviors as significantly as the other children. This instance of less-distinct preference could result in more inconsistent rewards/punishments and the robot switching behaviors more frequently. However, despite the aforementioned possible reasons for choosing less-preferred behaviors, Table V and Fig. 10 show that the robot is capable of identifying and selecting the preferred behavior automatically in most of the epochs for all participants, and thus, positively influencing the subjective liking level of the children with ASD (as shown in Fig. 11).

In Fig. 11, we present results to demonstrate that active monitoring of participants' liking and automatically selecting the preferred behavior allowed children with ASD to maintain high liking levels. The average labeled liking levels of the participants as reported by the therapist during the two sessions were compared. The agreement between the therapist and the parent on the subjective liking level is substantial for both RBB sessions and has a larger κ-statistic value (0.71) than that of the other two possible reporter pairs (0.39 for the therapist and children and 0.43 for the parent and children). The lighter bars in Fig. 11 indicate the liking level during the RBB1 session (i.e., when the robot selected behaviors randomly), and the darker bars show the liking level during the RBB2 session (i.e., when robot learned the individual preference and chose the appropriate behavior accordingly). It can be seen that for all participants, liking level was maintained, and for five of the six children, liking level increased. There was no significant increase for child C during the liking-based session as compared to the nonaffect-based session. As mentioned earlier, the impact of the different robot behaviors on the liking level of child C is not as significant as that of the others, which may impede the robot in finding the preferred behavior and hence impede the robot in effectively influencing the subjective liking level positively. Note that RBB1 presents a typically balanced interaction with equal numbers of most preferred, moderately preferred, and least preferred epochs and the comparisons in Fig. 11 are not between liking-based sessions and sessions of least preferred epochs. In order 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 liking-based sessions and nonaffect-based 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.

V. Conclusion and Future Work

There is increasing consensus in the autism community that development of assistive tools that exploit advanced technology will likely make the application of intensive intervention for children with ASD more readily accessible. In recent years, robotic technology has been investigated in order to facilitate and/or partially automate the existing behavioral intervention that addresses specific deficits associated with autism. However, the current robot-assisted intervention tools for children with ASD do not possess the ability to decipher affective cues from the children, which could be critical given that the affective factors of children with ASD have significant impacts on the intervention practice. In this paper, we have proposed a novel framework for affect-sensitive HRI where the robot can implicitly detect the affective states of the children with ASD as discerned by the therapist and respond to it accordingly.

The presented affective modeling methodology could allow the recognition of affective states of children with ASD from physiological signals in real time and provide the basis for future robot-assisted affect-sensitive interactive autism intervention. In Phase I, two cognitive tasks—solving anagrams and playing Pong—have been designed to elicit the affective states of liking, anxiety, and engagement for children with ASD. To have reliable reference points to link the physiological data to the affective states, the reports from the child, the therapist, and the parent were collected and analyzed. A large set of physiological indexes have been investigated to determine their correlation with the affective states of the children with ASD. We have experimentally demonstrated that it is viable to detect the affective states of children with ASD via a physiology-based affect recognition mechanism. An SVM-based affective model yielded reliable prediction with a success rate of 82.9% when using the therapist's reports.

In order to investigate the affect-sensitive closed-loop interaction between the children with ASD and the robot, we designed a proof-of-concept task, RBB, and developed an experimental system for its real-time implementation and verification. The real-time prediction of liking level of the children with ASD was accomplished with an average accuracy of 81.1%. The robot learned individual preferences of the children with ASD over time based on the interaction experience and the predicted liking level, and hence, automatically selected the most preferred behavior, on average, 72.5% of the time. We have observed that such affect-sensitive robot behavior adaptation has led to an increase in reported liking level of the children with ASD. This is the first time, to our knowledge, that the affective states of children with ASD have been detected via a physiology-based affect recognition technique in real time. This is also the first time that the impact of affect-sensitive closed-loop interaction between a robot and children with ASD has been demonstrated experimentally.

In order to account for the phenomenon of person-stereotypy and the diverse affective characteristics of the children with ASD, we employed an individual-specific approach for affective modeling. An intensive study was preformed based on a large sample size of observations (approximately 85 epochs over 6 h) for each of the six children with ASD. The time spent collecting the training data for affective modeling can be justified by the current ASD intervention practices [5]. However, note that the methodology for inducing, gathering, and modeling the experimental data is not dependent on the participants. The consistently reliable prediction accuracy for each participant demonstrated that it was feasible to model the affective states of children with ASD via psychophysiological analysis.

The presented research 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. But given the rapid progress in wearable computing with small, noninvasive sensors and wireless communication, e.g., physiological sensing clothing and accessories [51], we believe that physiology-based affect recognition can be appropriate and useful for the application of interactive autism intervention. None of the participants in this study had any objection to wearing the physiological sensors.

Future research will involve designing socially directed interaction experiments with robots interacting with children with ASD. Specifically, we plan to integrate the real-time affect recognition and response system described here with a life-like android face developed by Hanson Robotics (www.hansonrobotics.com), which can produce accurate examples of common facial expressions that convey affective states. This affective information could be used as a feedback for empathy exercises to help children recognize their own emotions. Enhancements on the intervention process could also be envisioned. For instance, the robot could exhibit interesting behaviors to retain the child's attention when it detects that his/her liking level is low. Additionally, besides liking, anxiety and engagement are also considered important in autism intervention practice (as described in Sections I and II). For example, anxiety is considered "as both a possible consequence of, and a possible cause of, aspects of the behavior of children with autism" [33]. While the affective model developed in this paper is capable of predicting the intensity of liking, anxiety, and engagement simultaneously, more sophisticated behavior adaptation mechanisms would be demanded to incorporate multiple inferred affective cues and account for other intervention information of interests, such as the intervention goals, historical records, and contextual inputs. We will investigate fast and robust learning mechanisms that would permit a robot's adaptive response in the more complex HRI tasks and allow the affect-sensitive robot to be adopted in the future autism intervention.

Appendix

A. Pattern Recognition Using SVMs

SVM, pioneered by Vapnik [44], is an excellent tool for classification [45]. Its appeal lies in its strong association with statistical learning theory as it approximates the structural risk minimization principle. Good generalization performance can be achieved by maximizing the margin, where margin is defined as the sum of the distances of the hyperplane from the nearest data points of each of the two classes. SVM is a linear machine working in a high k-dimensional feature space formed by an implicit embedding of n-dimensional input data X into a k-dimensional feature space ($k > n$) through the use of a nonlinear mapping $\phi(X)$. This allows for the use of linear algebra and geometry to separate the data, which is normally only separable with nonlinear rules in the input space. The problem of finding a linear classifier for given data points with known class labels can be described as finding a separating hyperplane $W^T\varphi(X)$ that satisfies

$$y_i(W^T\varphi(X_i)) = y_i\left(\sum_{j=1}^{k} w_j\phi_j(X_i) + w_0\right) \geq 1 - \xi_i \qquad (1)$$

where N represents the number of training data pairs (X_i, y_i) indexed by $i = 1, 2, \ldots, N$, $y_i \in \{+1, -1\}$ represents the class label, $\varphi(X) = [\phi_0(X), \phi_1(X), \ldots, \phi_k(X)]^T$ is the mapped feature vector $[\phi_0(X) = 1]$, and $W = [w_0, w_1, \ldots, w_k]$ is the weight vector of the network. The nonnegative slack variable ξ_i generalizes the linear classifier with soft margin to deal with nonlinearly separable problems.

All operations in learning and testing modes are done in SVM using a so-called kernel function defined as $K(X_i, X) = \varphi^T(X_i)\varphi(X)$ [44]. The kernel function allows for efficient computation of inner products directly in the feature space and circumvents the difficulty of specifying the nonlinear mapping explicitly. One distinctive fact about the SVM is that the learning task is reduced to a dual quadratic programming problem by introducing the Lagrange multipliers α_i [44]

$$\text{Maximize}$$
$$Q(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j K(X_i, X_j)$$
$$\text{subject to} \sum_{i=1}^{N} \alpha_i y_i = 0 \quad \text{and} \quad 0 \le \alpha_i \le C \tag{2}$$

where C is a user-defined regularization parameter that determines the balance between the complexity of the network characterized by the weight vector W and the error of classification of data. The corresponding α_i multipliers are nonzero only for the support vectors (i.e., the training points nearest to the hyperplane). The SVM approach is able to deal with noisy data and overfitting by allowing for some misclassifications on the training set [45]. This characteristic makes it particularly suitable for affect recognition because the physiology data are noisy and the training set size is often small. Another important feature of the SVM is that the quadratic programming leads in all cases to the global minimum of the cost function. With the kernel representation, SVM provides an efficient technique that can tackle the difficult, high-dimensional affect recognition problem.

B. Behavior Adaptation Using QV-Learning

QV-learning [46], a variant of the standard reinforcement learning algorithm Q-learning [52], was applied to achieve the affect-sensitive behavior adaptation. *QV*-learning keeps track of both a *Q*-function and a V-function. The Q-function represents the utility value $Q(s, a)$ for every possible pair of state s and action a. The V-function indicates the utility value $V(s)$ for each state s. The state value $V(s_t)$ and Q-value $Q(s_t, a_t)$ at step t are updated after each experience (s_t, a_t, r_t, s_{t+1}) by

$$V(s_t) := V(s_t) + \alpha(r_t + \gamma V(s_{t+1}) - V(s_t)) \tag{3}$$
$$Q(s_t, a_t) := Q(s_t, a_t) + \alpha(r_t + \gamma V(s_{t+1}) - Q(s_t, a_t)) \tag{4}$$

where r_t is the received reward that measures the desirability of the action a_t when it is applied on state s_t and causes the system to evolve to state s_{t+1}. The difference between (4) and the conventional Q-learning rule is that *QV*-learning uses V-values learned in (3) and is not defined solely in terms of Q-values. Since $V(s)$ is updated more often than $Q(s, a)$, *QV*-learning may permit a fast learning process [46] and enable the robot to efficiently find a behavior selection policy during HRI.

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