2007 IEEE International Conference on
Robotics and Automation
Roma, Italy, 10-14 April 2007

Affect Recognition in Robot Assisted Rehabilitation of Children with Autism Spectrum Disorder*

Changchun Liu[1], Karla Conn[1], Nilanjan Sarkar[2, 1], and Wendy Stone[3]
[1]Department of Electrical Engineering and Computer Science
[2]Department of Mechanical Engineering
[3]Vanderbilt Kennedy Center and Department of Pediatrics
Vanderbilt University, Nashville, TN 37235
Email: nilanjan.sarkar@vanderbilt.edu

Abstract **–This paper presents a novel affect-sensitive human-robot interaction framework for rehabilitation of children with autism spectrum disorder (ASD). The overall aim is to enable the robot to detect and respond to the affective cues of the children in order to help them explore social interaction dynamics in a gradual and adaptive manner. The first part of the proposed framework, namely the 'affect recognition' module is developed in detail in this paper. Two tasks are designed to elicit the affective states of liking, anxiety, and engagement that are considered important in autism rehabilitation. Affective cues are inferred from psychophysiological analysis that uses subjective reports of the affective states from a therapist, a parent, and the child himself/herself. Comprehensive physiological indices are investigated that may correlate with the affective states of children with ASD. A support vector machines based affect recognizer is designed that yielded reliable prediction with approximately 83% success when using the therapist's reports. This is the first time, to our knowledge, such a human-robot interaction framework for autism rehabilitation is proposed. This is also the first time that the affective states of children with ASD have been experimentally detected via physiology-based affect recognition technique.**

Index Terms – Human-robot Interaction, Autism Therapy, Rehabilitation, Physiological Sensing, Affective Computing

I. INTRODUCTION

Autism spectrum disorder (ASD) encompasses a wide variety of symptoms but generally is characterized by impairments in social interaction, social communication, and imagination, along with repetitive behavior patterns [1]. In recent years, there has been a significant increase in the number of children diagnosed with ASD. It is estimated that there are up to two cases of ASD per thousand children. Current resources for children with autism and their families are rare and costly, often involving a trained therapist in one-on-one sessions for a staggering 40 hours-per-week therapy [2].

Therefore one of the challenges is to find appropriate remedial tools and efficient rehabilitation methods for autism therapy. In response to this need, a growing number of studies have been investigating the application of the advanced interactive technologies to autism therapy, namely virtual environments [3], computer technology [4], and robotic systems [5][6].

The work in the area of autism rehabilitation with robots has gained ground only in the last 10 years. 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 [5]. It has been shown 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 [5][7]. A hierarchy of human-robot interaction dynamics with increasing complexity has been proposed in [8]. The robots in autism rehabilitation need to grow and develop along with the children and help them explore the different levels of social interaction dynamics. Michaud and Theberge-Turme 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 [6]. While like all other therapeutic approaches the robotic rehabilitation has the same unsolved generalization problem of how the skills learnt in therapy can be efficiently transferred to the real world, the initial results indicate that robots may hold promise for interventions of children with ASD. Robots can allow simplified but embodied social interaction that is less intimidating or confusing for these children. Robots have 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 [5][7].

While concepts from human-robot interaction (HRI) have been applied to autism rehabilitation in recent years, no work has been done to enable the robot to detect and respond to the affective states of children with ASD during the interaction. On the other hand, affective computing has become the focus of a great deal of attention in the HRI community and it is generally accepted that endowing robots with a degree of emotional intelligence should permit more meaningful and natural human-robot interaction [9][10]. For a robot to be emotionally intelligent it should clearly have a two-fold capability – the ability to display its own emotions [11] and the ability to understand human emotions and

* This work was supported in part by a pilot grant from the Marino Autism Research Institute (MARI) through the Vanderbilt Kennedy Center.

motivations (also referred to as affective states). The primary objective of this research is to address the latter capability for a target population, namely, children with ASD. Specifically we investigate how to augment human-robot interaction to be used in autism rehabilitation 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, we divide the research in two phases: i) to obtain the affect models in Phase I; and ii) to design a robot control architecture that can permit affect sensitiveness in the robot behavior based on the developed affect models in Phase II.

The paper is organized as follows: The proposed human-robot interaction framework for the rehabilitation of children with ASD is presented in Section 2. Section 3 describes the physiological indices used for affect recognition. The learning algorithm employed in this study is briefly described in Section 4. In Section 5, we present cognitive tasks designed for affect elicitation and the experimental setup. This is followed by a detailed results and discussion section (Section 6). Finally, Section 7 summarizes the contributions of the paper and outlines the future directions of this research.

II. Affect sensitive human-robot interaction framework for rehabilitation of children with ASD

The framework has six primary components as illustrated in Fig. 1. The physiological signals from the children with ASD are recorded when they are interacting with the robots. These signals are processed in real time to extract features and determine the affective cues by using the models developed in Phase I. The affect information along with other environmental inputs is used by a controller to decide the next course of action. The database component stores inferred affect and robot behavior for each child with ASD. The child who engages with the robot is then influenced by the robot's action, and the closed-loop interaction cycle begins anew.

The potential impacts brought by the robots that can detect the affective states of a child with ASD and interact with him/her based on such perception could be various. The inferred affective states could be used to determine when to switch among a set of controllers and permissive behavior repertoires that correspond to the different levels of interaction dynamics. For example, when a child has shown pleasure (liking) and little or no anxiety in a game, the introduction of a higher-level task would be appropriate. Within each level of interaction dynamics the affective information of the child with ASD could be used to select the appropriate behavior in order to accommodate the individual preferences. For instance, the behavior that is more interesting for a particular child and more likely to engage him/her could be chosen as his/her 'social feedback'. Playful interaction will be more likely to emerge by addressing a child's affective needs.

In order to achieve affect-sensitive human robot interaction for autism rehabilitation, affective feedbacks are required. In this paper, we focus on the 'affect recognition' module of the framework. There are several modalities such as facial expression, vocal intonation, gestures and postures, and physiology [9][12] that can be utilized to determine the underlying emotion of a person interacting with a robot. We chose physiology to infer affect for children with ASD due to several reasons. Children with ASD generally appear aloof and avoid verbal or non-verbal communications, which poses a limitation on vision and speech based methods. On the other hand, physiological signals are continuously available and are not dependent on overt emotional expression. They offer an avenue for recognizing affect that may be less obvious for humans but more suitable for computers, which can quickly implement signal processing and pattern recognition tools to infer underlying affective states. Even though physiology has been employed to build affect recognizers for typical individuals successfully in several research groups [9][13], the studies of the correlation of the physiological signals and the affective states of people with ASD are relatively few. To our knowledge affect recognition for children with ASD by using comprehensive physiological indices has not been known.

In this work we chose anxiety, engagement, and liking to be the target affective states. Anxiety was selected for two primary reasons. First, anxiety plays an important role in various human-machine interaction tasks that can be related to task performance [13]. Second, anxiety is not simply a frequently co-occurring disorder; in some ways it is also a hallmark of autism [14]. 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 [15]. With 'playful' activities in the learning environments, the liking of the children, i.e., the enjoyment they experience when interacting with the robots, could serve as a 'bonding' between robots and the children with ASD, who are usually withdrawn.

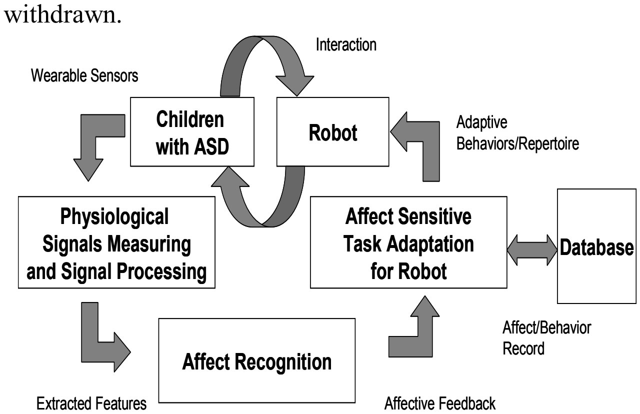

Fig. 1. Framework Overview

The physiological signals we examined were: various features of cardiovascular activity (including inter-beat interval, relative pulse volume, pulse transit time, heart sound, and pre-ejection period), electrodermal activity (tonic and phasic response from skin conductance) and electromyogram (EMG) activity (from corrugator supercilii, zygomaticus, and upper trapezius muscles). We adopt an individual-specific approach where we develop a model for each individual (i.e., we determine the physiological pattern of anxiety for each participant) because of the well-known phenomena of person stereotypy, i.e., within a given context, different individuals express the same emotion with different characteristic response patterns. The physiological signals were recorded when children with ASD participated in the tasks designed for eliciting the target affective states. The input feature set was derived from physiological signals by applying a series of pre-processing and signal analysis techniques. The output set was derived from the subjective reports. Each vector of input features had a corresponding output vector consisting of subjective reports for all the target affective states. This data set was utilized for affect modeling for the children with ASD by using support vector machines (SVM).

III. Physiological Indices

There is good evidence that the physiological activity associated with the affective state can be differentiated and systematically organized. The transition from one affective state to another, for instance, from relaxed to anxious state, is accompanied by dynamic shifts in indicators of Autonomic Nervous System (ANS) activity.

Various signal processing techniques such as Fourier transform, wavelet transform, thresholding, and peak detection were used to derive the relevant features from the physiological signals. The signals are listed in Section 2, and the features are described as follows. Inter beat interval (IBI) is the time interval in milliseconds between two "R" waves in the electrocardiogram (ECG) waveform in millisecond. Power spectral analysis is performed on the IBI data to localize the sympathetic and parasympathetic nervous system activities associated with two frequency bands. The high frequency (HF) 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 (LF) 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 finger tip associated with the pulse cycle, and it provides an index of the relative constriction versus dilation of the blood vessels in the periphery. Pulse transit time (PTT) is the time it takes for the pulse pressure wave to travel from the heart to the periphery, and it 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. 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 consisted of the mean and standard deviation of the 3rd, 4th, and 5th level coefficients of the Daubechies wavelet transform. Bioelectrical impedance analysis (BIA) 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, pre-ejection period (PEP) derived from impedance cardiogram (ICG) and ECG, measures the latency between the onset of electromechanical systole, also measures the onset of left-ventricular ejection, 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. It is also a valuable source of blink information and helps us 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. All these features are used to build the affect recognizer to infer the underlying affective state of a child showing this response.

IV. Machine Learning Method Applied

Determining the intensity 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 (high/low).

SVM, pioneered by Vapnik [16], is an excellent tool for classification. Its appeal lies in its strong association with statistical learning theory as it approximates 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. The SVM approach is able to deal with noisy data and overfitting by allowing for some misclassifications on the training set. This makes it particularly suitable for affect recognition because the physiology data is noisy and the training set size is often small. It has been used to build affect recognizers for typical individuals in our previous work [17]. Another important advantage of SVM is the transformation of the learning task to the quadratic programming problem. For this type of optimization there exist many effective learning algorithms, leading 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. In this work, kernel function RBF (Radial Basis Function) often delivered better performance and was applied. Ten-fold cross-validation was used to determine the final parameters of the classifier.

V. Experiment

In this section we describe in detail the tasks designed for affect elicitation, the participants, and the experimental setup.

A. Tasks for Affect Elicitation

Two PC based tasks were designed to invoke varying intensities of the following three affective states: anxiety, engagement, and liking, in the participants. Physiological data from participants were collected during the experiment. The tasks chosen were solving anagrams and playing "Pong". In our previous work [10], we have shown that the affect models built using these two human-computer interaction tasks could be successfully used to determine affect prediction in a human-robot interaction task for typical individuals. Various parameters of the tasks were manipulated to elicit the required affective responses. For example, a series of extremely difficult anagrams will usually cause dislike, and an optimal mix of solvable and difficult anagrams tends to result in engagement. Likewise, a Pong game with very high ball speed will cause anxiety at times. In the Pong game the adjusted parameters for eliciting affective states include: ball speed and size, paddle speed and size, sluggish or over-responsive keyboard, random keyboard response, and the level of the computer opponent player. The relative difficulties of various trial configurations were established through pilot work.

B. Participants

Three subjects within the age range of 13 to 15 volunteered to participate in the experiments with the consent of their guardians. Each of them had a diagnosis on the autism spectrum, either autistic disorder, Asperger's Syndrome, or pervasive developmental disorder not otherwise specified (PDD-NOS), according to their medical records. Due to the nature of the tasks, the following were considered when choosing the participants: i) having minimum competency level of age-appropriate language and cognitive skills (i.e., "high functioning") and ii) not having any history of mental retardation. Each child with ASD underwent the Peabody Picture Vocabulary Test III (PPVT-III) to assess cognitive function. The PPVT-III is a measure of single-word receptive vocabulary that is often used as a proxy for intelligence testing [18]. Inclusion in our study was characterized as obtaining a standard score of 80 or above on the PPVT-III measure. Monetary compensation was given for the children's voluntary participation. Table 1 shows the characteristics of three children who participated in the experiments.

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

C. Experimental Setup

The objective of the experiment was to elicit varying intensities of emotional states in participants as they performed computer-based tasks. On the first visit, participants completed the PPVT-III measurement to determine a standardized measure of receptive vocabulary and eligibility for the experiments. After initial briefing regarding the computer tasks, physiological sensors of a Biopac system [19] were attached to the participant's body. A three-minute baseline recording was done that was later used to offset day-variability. Subjects were asked to relax in a seated position and read age-appropriate leisure material. Each session lasted about an hour and consisted of a set (10-15) of either 3-minute epochs for anagram tasks or up to 4-minute epochs for Pong tasks. Each epoch was followed by subjective report questions rated on an eight-point Likert scale. In order to gain perspective from different sources and enhance the reliability of the subjective report, a therapist with experience in working with children with ASD and a parent of the participant were also involved in the study, who may best know the participant. We video recorded the sessions to cross-reference observations made during the experiment. 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 monitor. 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 game progressed on the separate computer monitor. After each epoch, they also answered the questions about how they thought the participant was feeling during the finished epoch on an eight-point Likert scale. These three sets of reports, from the therapist, a parent, and the participant, were used as the possible reference points to link the objective physiological data to the participant's affective state. Each child took part in six sessions – three one-hour sessions of solving anagrams and three one-hour sessions of playing Pong – on six different days. These tasks spanned a period of two months. During the tasks, the participant's physiology was monitored with the help of wearable biofeedback sensors and Biopac data acquisition system. The digitally sampled sensor information was sent to the computer using an Ethernet cable. For each participant, the data that comprised both the objective physiological information and subjective reports on affective states was collected. Each data set consisted of 54 input features and 3 output features (arousal of anxiety, engagement, and liking) from the therapist, the parent, and the participant. Each output state was partitioned such that 1-4 was labelled low and 5-8 was labelled high. Each data set contained approximately 85 epochs.

VI. RESULTS AND DISCUSSION

One of the prime challenges of this work is attaining reliable subjective reports. Researchers have been reluctant to trust the response of adolescents on self-reports [20]. In this study, one should be especially wary of the dependability of self-reports from children with ASD, who may be inattentive and exhibit poor self-awareness. In order to overcome this difficulty, a therapist and a parent were involved and were fully exposed to the experiment process in real time by using the approaches described in the experimental setup. Their reports about how they thought the participant was feeling were collected after each epoch.

To measure the amount of agreement among the different reporters/coders, the kappa statistic was used. The kappa coefficient (K) measures pair-wise agreement among a set of reporters making category judgments, correcting for expected chance agreement. When there is complete agreement, then K=1; whereas, when there is no agreement other than which would be expected by chance, then K = 0.

TABLE II
KAPPA STATISTICS FOR TARGET AFFECT STATES

Child ID	Pair	Liking	Anxiety	Engage	Mean
A	T/P	0.566	0.831	0.494	0.631
	T/C	-0.084	0.343	0.205	0.154
	P/C	0.25	0.332	0.133	0.239
B	T/P	0.585	0.634	0.708	0.642
	T/C	0.575	0.561	0.512	0.549
	P/C	0.488	0.537	0.536	0.520
C	T/P	0.753	0.352	0.551	0.552
	T/C	0.675	0.350	0.525	0.517
	P/C	0.475	0.450	0.525	0.483

The results of the values of kappa statistic, K, for the target affective states are shown in Table 2. From the results, we can see that the agreement between the therapist and the parent (T/P) shows the largest mean of the kappa statistic values among three possible pairs for each child. Note that this agreement is substantial for Child A and Child B and moderate for Child C. Such results might stem from the fact that it could be difficult for the therapist/parent to distinguish certain emotions for a particular child with ASD, such as the case for the anxiety level of Child C. In the experiment, Child A's ratings for liking, anxiety, and engagement were almost constant which resulted in lower kappa statistic values for the therapist and child pair (T/C) and the parent and child pair (P/C) than those of Child B and Child C. This may be due to the fact that the spectrum developmental disorder for children with autism manifests different abilities to recognize and report their emotions. Although lack of agreement with adults does not necessarily mean that the self-report of children with ASD is not dependable. However, given the fact that therapists' judgement based on their expertise is the state-of-the-art in most autism therapy approaches, and the fact that there is a reasonably high agreement between the therapist and the parents for all of the three children, the subjective report of the therapist was used as the reference points linking the objective physiological data to the children's affective state. In order to make the subjective reports more consistent, the same therapist was involved in all of the experiments. This choice allows for building a therapist-like affect recognizer. Once the affect modelling is completed, the recognizer will be capable of inferring the affective state of the child with ASD from the physiological signals in real-time even when the therapist is not available.

Fig. 2 shows a comparison of the therapist's average ratings for liking, anxiety, and engagement when the children with ASD play easy or difficult epochs. When averaged across participants, liking decreased, anxiety increased and engagement decreased with increasing task difficulty. Table 3 shows the correlation analysis between the reported affective states and the task difficulty level. For each set of the 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. There is strong positive correlation between anxiety and difficulty. There is also negative correlation between liking and difficulty, and engagement and difficulty. Liking is strongly positively correlated with engagement and negatively correlated with anxiety. There is also a weak correlation between the level of reported anxiety and engagement. The results presented in Fig. 2 and Table 3 average the data across all children. However, when each child is examined individually, different trends could arise. For example, for Child A, the anxiety is positively correlated with the engagement (Pearson correlation =0.453, p=0.0002), while for the two other children anxiety negatively correlated with the engagement (Pearson correlation =-0.503, p=0.0001, and Pearson correlation =-0.394, p=0.0004 respectively), which revealed the diverse personal characteristics of the children with ASD.

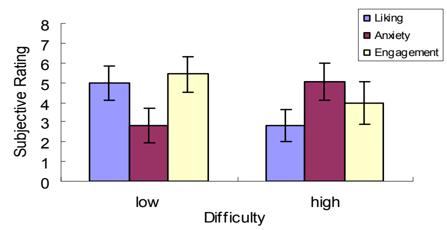

Fig. 2. Rated Average Affect Response from Therapist's Reports

TABLE III
RESULTS OF CORRELATION ANALYSIS FROM THERAPIST'S REPORTS

	Liking	Anxiety	Engage	Difficulty
Liking	1	-0.605	0.838	-0.685
Anxiety		1	-0.291	0.774
Engage			1	-0.416
Difficulty				1

The performance of the developed affect recognizer in classifying unknown instances is shown in Fig. 3. The cross-validation method, 'leave-one-out', was used. The affect recognizer produced high recognition accuracies for each target affective state of each participant. The average correct classification accuracies across all participants were - 85.23% for liking, 80.16% for anxiety, and 83.63% for engagement. This was promising considering that this task was challenging in two respects: (i) the reports were collected from the therapist who was observing the children with ASD engaged in real-life computer tasks as opposed to having typical adults capable of differentiating and reporting their own affective states and (ii) varying levels of arousal of any given affective state (for instance, low and high anxiety) were identified instead of determining discrete emotions (for instance, anger, joy, sadness, etc.). Determining the difference in arousal level in one affective state is more subtle than distinguishing between two discrete affective states. With post-hoc analysis, we found generally the prediction accuracy tends to be higher when the therapist and the parent agree more on the subjective reports about how they thought the participant was feeling during the finished epoch. As shown in Table 4, the Kappa statistic of therapist and parent is positively correlated with the prediction accuracy of the developed affect recognizer (Pearson correlation = 0.7423, p= 0.022). In this experiment, the Kappa statistic could indicate whether it is relatively easy or difficult to differentiate the affective states of a child by observation. The prediction accuracy is likely to improve if the therapist interacts with a particular child with ASD for a significant amount of time and attains more knowledge of his/her affective expression before making the reports regarding the presented interaction tasks.

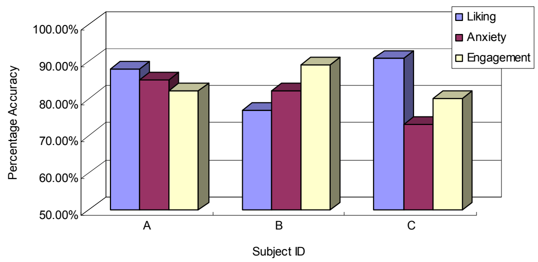

Fig. 3. Classification Accuracy of the Affect Recognizer

TABLE IV
THERAPIST-PARENT KAPPA STATISTICS AND PREDICTION ACCURACY

Child ID		Liking	Anxiety	Engage
A	Kappa Statistics (T/P)	0.566	0.831	0.494
	Prediction Accuracy (%)	87.8%	85.4%	81.7%
B	Kappa Statistics (T/P)	0.585	0.634	0.708
	Prediction Accuracy (%)	76.8%	81.7%	89.0%
C	Kappa Statistics (T/P)	0.753	0.352	0.551
	Prediction Accuracy (%)	91.1%	73.4%	80.2%

VII. CONCLUSIONS AND FUTURE WORK

We have proposed a novel framework for affect-sensitive human-robot interaction in the rehabilitation of children with ASD. A robot that is capable of detecting and responding to affective cues could help the children with ASD explore the social interaction dynamics in a gradual and adaptive manner. In this paper, the module 'affect recognition' of the framework was investigated in detail. We have designed and implemented two tasks – solving anagrams and playing Pong – to elicit the affective states of liking, anxiety, and engagement for children with ASD. In order 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 analysed. We investigated comprehensive physiological indices that may correlate with the affective states of children with ASD. We have experimentally demonstrated that it is viable to detect the affective states of children with ASD via physiology-based affect recognition. A SVM based affect recognizer yielded reliable prediction with approximately 83% success when using the therapist's reports.

Future work will involve completing the Phase I experiments with several more children with ASD. We would also like to design social interaction experiments with robots interacting with these children. We will investigate in Phase II how to augment the autism therapy by having a robot respond appropriately to the inferred affects based on the affect recognizer described here.

ACKNOWLEDGMENT

The authors gratefully acknowledge the staff at the Vanderbilt Kennedy Center and all the parents and children who participated in the presented research.

REFERENCES

[1] *APA. DSM-IV Diagnostic and Statistical Manual of Mental Disorders*, 4th ed., Washington DC: American Psychiatric Association, 1994.
[2] L. Tarkan, "Autism therapy is called effective, but rare," *New York Times*, Oct. 22nd, 2002.
[3] S. Parsons, P. Mitchell and A. Leonard, "The use and understanding of virtual environments by adolescents with autistic spectrum disorders", *Journal of Autism and Developmental Disorders,* vol. 34, pp. 449-466, 2004.
[4] K. Blocher and R. W. Picard, "Affective social quest: emotion recognition therapy for autistic children," *Socially Intelligent Agents - creating relationships with computers and robots*, K. Dautenhahn, A. Bond, L. Canamero and B. Edmonds, Ed., Kluwer Academic Publishers, Netherlands, ch. 16, 2002.
[5] K. Dautenhahn and I. Werry, "Towards interactive robots in autism therapy: background, motivation and challenges." *Pragmatics and Cognition*, vol. 12, no.1, pp. 1–35, 2004.
[6] F. Michaud, and C. Theberge-Turmel, "Mobile robotic toys and autism", *Socially Intelligent Agents - Creating Relationships with Computers and Robots*, K. Dautenhahn, A. Bond, L. Canamero and B. Edmonds, Ed., Kluwer Academic Publishers, pp. 125-132, 2002.
[7] B. Robins, P. Dickerson, P. Stribling and K. Dautenhahn, "Robot-mediated joint attention in children with autism: A case study in robot-human interaction," *Interaction Studies*, vol. 5, pp. 161–198, 2004.
[8] K. Dautenhahn, I. Werry, "Issues of robot-human interaction dynamics in the rehabilitation of children with autism," *The 6th International Conference on the Simulation of Adaptive Behavior*, France, pp. 519–528, 2000.
[9] R. Picard, E. Vyzas, and J. Healy, "Toward machine emotional intelligence: analysis of affective psychological states," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, no. 10, pp. 1175-1191, 2001.
[10] C. Liu, P. Rani, N. Sarkar, "Human-Robot interaction using affective cues", *The 15th IEEE International Symposium on Robot and Human Interactive Communication - ROMAN 2006*, United Kingdom, 2006.
[11] T. Fong, I. Nourbakhsh, and K. Dautenhahn, "A survey of socially interactive robots," *Robotics and Autonomous Systems*, vol. 42, pp. 143-166, 2003.
[12] R. Cowie, E, Douglas-Cowie, N. Tsapatsoulis, G. Votsis, S. Kollias, W. Fellenz, J. G. Taylor, "Emotion recognition in human-computer interaction," *IEEE Signal processing magazine*, vol.18, no.2, pp. 32-80, Jan 2001.
[13] P. Rani, N. Sarkar, C. Smith, and L. Kirby, "Anxiety detecting robotic systems – towards implicit human-Robot collaboration," *Robotica*, vol. 22, no. 1, pp. 85-95, 2004.
[14] A. Gillott, F. Furniss, A. Walter, "Anxiety in high-functioning children with autism," Autism, vol. 5, no. 3, pp. 277-286, 2001.
[15] New Jersey Autism Program Quality Indicators (2004): Available: http://specialedlaw.blogs.com/home/files/autism.pdf.
[16] V. Vapnik, Statistical Learning Theory, New York: Wiley, 1998.
[17] Rani, P., Liu, C., Sarkar, N., "An empirical study of machine learning techniques for affect recognition in human-robot interaction," *Pattern Analysis and Applications Journal*, vol. 9, no. 1, pp. 58-69, 2006.
[18] M. D. Lloyd and M. D. Leota, *Peabody Picture Vocabulary Test--Third Edition (PPVT-III)*, American Guidance Service, 1997.
[19] http://www.biopac.com/
[20] R. A. Barkley, *Attention deficit hyperactivity disorder: A handbook for diagnosis and treatment*, 2nd ed., New York: Guilford Press, 1998.