IEEE Proceedings of 4th International Conference on Intelligent Human Computer Interaction, Kharagpur, India, December 27-29, 2012

A Step Towards an Intelligent Human Computer Interaction: Physiology-based Affect-Recognizer

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***Abstract*. Impairment in social communication skills is one of the core deficits in the children with Autism Spectrum Disorder (ASD). These children are characterized by an inherent inability to express their affective states thereby imposing limitations on traditional self-report and observational methodologies. However physiological signals are continuously available and are arguably not impacted by these difficulties. In recent years several assistive technologies utilizing the benefits of physiology-based systems have been investigated to promote social communication skills in this population. Among these we chose Virtual Reality (VR) as our platform. Investigations in the area of Human Computer Interaction (HCI) have shown that variations in the physiological signals can be evoked by different amounts of presence in the VR environment and the transition from one affective state to another is accompanied by dynamic shift in indicators of Autonomic Nervous System (ANS) activity. The presented work seeks to fuse behavioral viewing pattern and peripheral physiological features with the affective rating. Thus, this is a step towards indicating the potential of such a system to build an intelligent therapist-like affect-recognizer. The preliminary findings of a usability study are promising.**

***Index Terms*—ASD, Virtual Reality, Engagement, Liking, peripheral physiology.**

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental disability that has a debilitating effect in the areas of communication, socialization, cognition, imagination and intuitive thought, which in turn severely inhibits a child's repertoire of interests and social interaction [1]. These children are characterized by communicative impairments (both nonverbal and verbal), particularly regarding expression of affective states, as well as potent vulnerabilities related to meta-cognition [2][3][4]. These challenges place limits on the traditional self-report and observational methodologies (e.g., facial expressions, vocal tone, gestures, and postures [5][6]). However, physiological signals are continuously available and are arguably not directly impacted by these difficulties [7][8][9]. As such, physiological modeling may represent a methodology for gathering rich data despite these impairments. There is a rich history where investigators have used one's peripheral physiological measurements like heart rate (i.e., Cardiovascular (CV)), skin conductance (i.e., Electrodermal Activity (EDA)), muscle contractions (Electromyogram (EMG)), and behavioral viewing pattern quantified by Fixation Duration (FD) to study mental and emotional states (such as engagement, liking, etc.) [7][10].

Researchers in the area of Human Computer Interaction (HCI) have shown that variations in physiological signals can be evoked by different amounts of presence in the virtual environment [11][12], and the transition from one affective state to another is accompanied by dynamic shifts in indicators of Autonomic Nervous System (ANS) activity [13]. In addition, HCI researchers have suggested that one's behavioral viewing pattern characterized by fixation duration is also related to one's cognitive processing [14]. Thus, peripheral physiological data along with one's behavioral viewing pattern may offer an avenue for recognizing aspects of the affect that may be less obvious for humans but more suitable for computers. Different studies have been investigating application of advanced interactive technologies e.g., computer technology [15], virtual reality (VR) environments [16] and robotic systems [17]. Among the different alternative interactive technologies, we chose VR as our platform because it is particularly relevant for children with ASD. The strength of VR for ASD intervention includes malleability, controllability, modifiable sensory stimulation, individualized approach, safety, and potential reduction of problematic aspects of human interaction during initial skill training [18][19]. Harnessing these positive attributes of VR while integrating it with one's behavioral viewing pattern and peripheral physiological signal features for developing intelligent adaptive affect-sensitive system for children with ASD might be critical. Previous research has shown the feasibility of developing VR-based affect-sensitive adaptive system from one's behavioral viewing pattern and eye-physiological signals for children with ASD [20][21] with reliable real time prediction performance. Additionally, there have been investigations reporting the affective implication of one's behavioral viewing pattern [20], eye-physiology [20], and peripheral physiology [22]. However, the joint analysis of behavioral viewing along with peripheral physiological signals while developing VR-based affect-sensitive systems has not been fully investigated. In this paper, we present a new VR-based social communication system for individuals with ASD that can adapt itself to one's affective state (e.g. engagement) predicted from one's behavioral viewing pattern, eye-

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physiology, and performance. In addition, we collected peripheral physiological signals (e.g., CV, EDA, and EMG) of the participants while they interacted with the VR-based social communication scenarios. Also we asked a therapist to rate the participants on what they think on the participants' level of engagement and liking. Subsequently, we performed an offline analysis fusing the behavioral viewing index (i.e., FD), the peripheral physiological indices (i.e., CV, EDA, etc.), and the therapist's rating on the affective states to understand the potential of developing intelligent therapist-like affect recognition mechanisms. Thus, such a system can be a step towards developing a therapist-like intelligent affect-recognizer. In turn such a system can provide a complementary tool in the hands of the therapist for creating interactive intervention paradigms for skill training in core areas of impairment for children with ASD.

The objectives of this work are two-fold, namely, 1) to understand the psycho-physiological response of children with ASD while they interact with the VR-based social communication scenarios and 2) to use intelligent techniques to map the behavioral viewing and the peripheral physiological signals to the affective states (engagement and liking) as rated by the therapist. Here we choose engagement and liking as the target affective states. The engagement of children with ASD is the ground basis for the 'floor-time-therapy' to help them develop relationships and improve their social skills [18]. With "playful" activities during the intervention, the liking of the children (i.e., the enjoyment they experience when interacting with the computer) may create urges to explore and allow prolonged interaction for the children with ASD [23].

This paper is organized as follows: In section II we present the system design. The method used for the usability study is presented in section III. The results and discussions are presented in section IV. Finally, Section V summarizes the contributions of this work and outlines the scope of future research.

II. System Design

The system design can be sub-divided into four main subsystems containing: (i) a VR-based social communication task module, (ii) a real time eye-gaze monitoring module, (iii) peripheral physiological acquisition module integrated with the VR world and (iv) an adaptive response module utilizing a rule-governed affective state prediction mechanism.

A. *Social communication Task module based on the VR environment*

In order to perform socially interactive tasks for the children with ASD, we developed extensive social situations with context relevant backgrounds and avatars using the VR platform (Vizard from Worldviz Llc.) environments. Also for effective bidirectional social communication between the avatars and the participants, we developed several conversation threads. Our social communication task module comprised of task presentation and bidirectional conversation modules.

Task Presentation Module. We developed 24 social task modules with avatars narrating different stories (based on diverse topics of interest to teenagers e.g., favorite sport, favorite film, etc.) to the participants. The voices of the avatars were gathered from teenagers from the regional area. The avatars made pointing gestures and moved dynamically in a context-relevant VR environment. With the avatar narrating his experiences, the VR situation changed with a smooth transition of the background image to display the topic-relevant situation.

Bidirectional Conversation Module. Initially the participant was asked to watch and listen to the avatar narrating a personal story during the VR-based task presentation. At the end of the task presentation, the participant was asked to interact with the avatar. The degree of interaction difficulty was controlled by varying the number of questions a participant needed to ask in order to obtain a desired piece of information from the avatar and the nature of the conversation. The conversation tasks were categorized into Type 1 (low), Type 2 (medium) and Type 3 (high) to control the interaction difficulty. The performance metric of the participant were scored numerically depending on the conversation types. A typical example is shown in Figure 1.

Fig. 1. Snapshot of a bidirectional conversation module

B. *Real-Time Eye-Gaze Monitoring Module*

The system was designed to capture the eye data of a participant interacting with an avatar using eye-tracker goggles (from Arrington Research Inc.). We extracted behavioral viewing pattern index quantized in terms of Fixation Duration (FD).

C. *Peripheral Physiological Signal Acquisition Module*

In the work presented in this paper we fuse the behavioral viewing pattern with peripheral physiological indices (such as cardiovascular, electrodermal, etc.) to gain an in-depth understanding of the relation between these indices and affective states (such as engagement and liking) as rated by the therapist. This system was made capable of capturing event-marked synchronized peripheral physiological responses of the participants while they communicated socially with the avatars. In our present work, we analyzed these signals off-line to show the physiological features which are the most sensitive to the level of engagement and liking of the participants.

We acquired the peripheral physiological signals when a participant interacted with the VR-based social communication tasks. The VR task computer, as shown in Figure 2 was dedicated to the VR-based social communication task. This transmitted task-related event-markers to the parallel port of a Physiological Data Acquisition Module which also collected the peripheral physiological signals of the participants. These signals were then subsequently collected and stored by a physiological data logger computer for offline analysis.

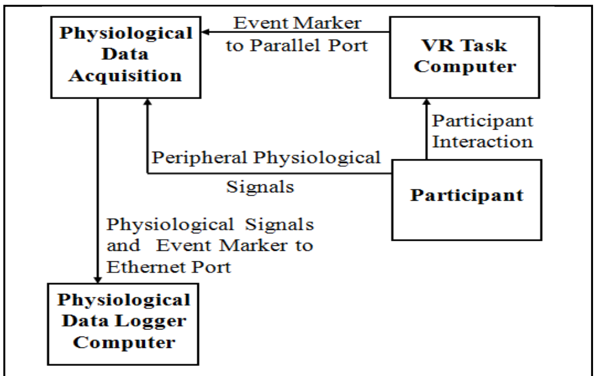

Fig. 2. Physiological Signal Data Acquisition System

D. *Adaptive Response Module*

Here we used task modification strategy based on one's performance metrics alone (Performance-sensitive System (PS)). Additionally we developed an intelligent adaptive response module that switched tasks of different difficulty levels based on the participant's engagement level predicted from the cumulative effect of eye gaze data and performance metric (Engagement System (ES)). We implemented these task modification strategies by using state machine representation [24].

III. EXPERIMENT AND METHODS

A. *Participants*

Eight adolescents with high functioning ASD participated in the experiment. Participants were selected on the basis of their scores on Peabody Picture Vocabulary Test (PPVT) [25], Social Responsive Scale (SRS) [26], Social Communication Questionnaire (SCQ) [27], Autism Diagnostic Observation Schedule (ADOS) [28], Autism Diagnostic Interview-Revised (ADI-R) [29] as presented in the Table I.

B. *Experimental Setup*

The experiment was created using the VR design package.

TABLE I. PARTICIPANT CHARACTERISTICS

	Age	PPVT	SRS T-score	SCQ	ADOS-G (cutoff=7)	ADI-R (cutoff=22)
ASD1	17.58	134	80	12	13	49
ASD2	16.92	110	73	13	7	33
ASD3	14.25	130	89	16	15	34
ASD4	13.83	170	92	14	13	53
ASD5	16.50	92	87	20	-	-
ASD6	18.25	97	63	17	9	49
ASD7	13.00	133	90	10	7	25
ASD8	18.25	97	63	17	9	49

The participants' eye movements were tracked by the Arrington Eye tracker and the peripheral physiological signals were acquired using the Biopac MP150 (from Biopac Inc.) physiological data acquisition system. The therapist watched the participant from the video camera view, whose signal was routed to a television, hidden from the participants' view. The therapist was provided with a separate monitor to view the progress of the VR task. Based on these two observations the therapist rated the affective states of the participants on engagement and liking using a 1-9 scale.

IV. RESULTS AND DISCUSSION

To test the efficacy of our designed system we carried out a small usability study. In this study, we collected and analyzed the data on the peripheral physiological signals, the behavioral viewing pattern and the therapist's ratings on the affective states of the participants when they interacted with the VR-based social situations.

A. *Analysis of Variation in the Participants' Engagement and Liking Level as Rated by the Therapist*

Initial analysis of the Therapist's rating on the engagement and liking levels of the participants while they interacted with the VR-based social communication scenarios revealed that both engagement and liking of participants varied over the rating spectrum.

TABLE II. VARIATIONS IN PARTICIPANTS'ENGAGEMENT LEVEL AS RATED BY THERAPIST [RATING SCALE: 1-9]

	LE	HE
Mean	3.8	6.3
Std. deviation	0.39	0.52
Range	3-7	

Note: LE – Low Engagement [Rating: 1-4]; HE – High Engagement [Rating: 6-9]

TABLE III. VARIATIONS IN PARTICIPANTS' LIKING LEVEL AS RATED BY THERAPIST [RATING SCALE: 1-9]

	LL	HL
Mean	3.6	6.2
Std deviation	0.68	0.62
Range	1-7	

Note: LL – Low Liking [Rating: 1-4]; HL – High Liking [Rating: 6-9]

Though the mean for Low Engagement (LE) and High Engagement (HE) and Low Liking (LL) and High Liking (HL) are very close to 4 and 6 (i.e., very close to upper limit and lower limit of low and high levels respectively) yet the range indicates that the ratings as provided by the therapist were on a wider spectrum (3-7) for engagement and (1-7) for liking.

B. *Analysis of Statistical Significance of the Psycho-physiology based data.*

Further data analysis was carried out to test the statistical significance of various peripheral physiology-based signal and behavioral viewing pattern features. The p-test revealed 14 features (Table IV) as statistically significantly (p-value<0.05) different corresponding to trials rated as eliciting LE and HE.

Additionally a set of 14 features (Table V) were found to be statistically significantly different corresponding to trials rated as eliciting LL and HL among the participants. Thus our analysis indicate a potential of a VR-based social communication system to elicit variations in one's peripheral physiological signal features (e.g., cardiovascular, electrodermal, and electromygram) and viewing pattern (e.g., Fixation Duration (FD)) corresponding to the affective states (e.g., engagement and liking).

TABLE IV. STATISTICALLY SIGNIFICANT FEATURES CORRESPONDING TO LOW ENGAGEMENT (LE) AND HIGH ENGAGEMENT (HE)

	Features Derived	p value
CV	std_ibi_ekg	0.0035
	ptt_mean	0.0015
	ptt_std	0.0001
	ibi_ppg_std	0.0005
	power_VLF	0.0001
	power_para	0.0021
EDA	tonic_slope	0.0317
EMG	cfreq_mean	0.0269
	interblink	0.0126
	blink_amp	0.0115
	zfreq_med	0.0032
	zfreq_mean	0.0301
	zemg_slope	0.0056
VP	FD	0.0252

Note: CV- Cardio-Vascular; EDA- Electrodermal Activity; EMG- Electromyogram; VP- Viewing Pattern (For details on Features, please refer [33]).

TABLE V. STATISTICALLY SIGNIFICANT FEATURES CORRESPONDING TO LOW LIKING (LL) AND HIGH LIKING (HL)

	Features Derived	p value
CV	ptt_mean	0.0024
	ptt_std	0.0001
	ibi_ppg_std	0.0001
	ppg_peak_mean	0.0250
	power_VLF	0.0289
EDA	phasic_mean_amp	0.0144
SKT	temp_slope	0.0001
EMG	cfreq_mean	0.0006
	interblink	0.0002
	zfreq_med	0.0069
	zemg_std	0.0231
	temg_mean	0.0059
	temg_std	0.0053
VP	FD	0.0083

Note: CV- Cardio-Vascular; EDA- Electrodermal Activity; SKT- Skin Temperature; EMA- Electromyogram; VP- Viewing Pattern. (For details on Features, please refer [33]).

It is interesting to note that some statistically significant features were found to be common to both engagement and liking (e.g.,ptt_mean, ptt_std, ibi_ppg_std, power_VLF, cfreq_mean, interblink, zfreq_med and FD).

C. *Understanding the Psycho-physiological Implication*

Having realized the potential of our VR-based social communication system to elicit variations in the participants' peripheral physiological signals and viewing pattern, we wanted to understand the psycho-physiological implication of this data. We performed Pearson Correlation between the statistically significant features and the therapist's rating on the affective states (e.g., engagement and liking) of the participants. The Pearson Correlation between the two variables (feature and therapist's rating on the affective states) reflects the degree to which the variables are related.

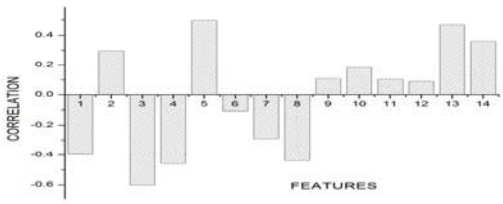

Fig 3. Correlation between Different Features and Therapist's rating on Engagement.

Note: Features 1-std_ibi_ekg, 2-ptt_mean, 3-ptt_std, 4-ibi_ppg_std, 5-power_VLF, 6-power_para, 7-tonic_slope, 8-cfreq_mean, 9-interblink, 10-blink_amp, 11-zfreq_med, 12-zfreq_mean, 13-zemg_slope, and 14-FD.

It can been seen from the Figure 3 that 8 features (namely, cardiovascular (CV), electromyogram (EMG), and viewing pattern (VP)) are positively correlated and 6 features (e.g., CV, EMG, and electrodermal activity (EDA)) are negatively correlated with therapist's rating on engagement.

In the case of liking (Figure 4) 7 features (e.g., CV, EMG and VP) are positively correlated and the rest 7 features CV and EMG) are negatively correlated with therapist's rating on liking.

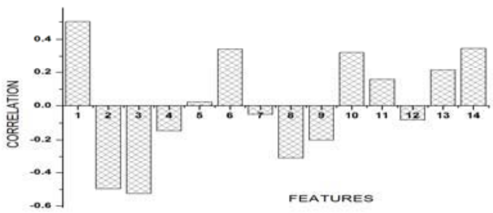

Fig.4 Correlation between Different Features and Therapist's rating on Liking

Note: Features 1-ptt_mean, 2-ptt_std, 3-ibi_ppg_std, 4-ppg_peak_mean, 5-power_VLF, 6-phasic_mean_amp, 7-temp_slope, 8-cfreq_mean, 9-interblink, 10-zfreq_med, 11-zemg_std, 12-temg_mean, 13-temg_std, and 14-FD.

It can be seen from the Figure 5 that all the statistically significant features which were found to be common to engagement and liking are either positively correlated (e.g., ptt_mean, power_VLF, zfreq_med, FD) or negatively correlated (e.g., ptt_std, ibi_ppg_std, cfreq_mean) except interblink, which has opposite correlation, i.e., positive and negative for engagement and liking, respectively.

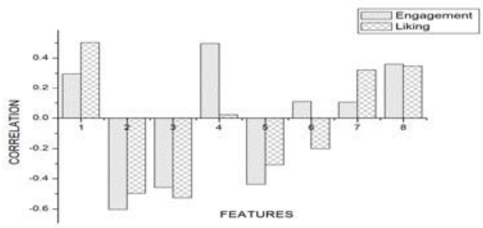

Fig. 5. Comparative analysis of correlation of different features
Note: Features 1-ptt_mean, 2-ptt_std, 3-ibi_ppg_std, 4-power_VLF, 5-cfreq_mean, 6-interblink, 7-zfreq_med, and 8-FD.

The above results show a potential for developing intelligent systems that can adapt itself to one's affective states predicted from one's peripheral physiological signals and behavioral viewing pattern. We planned to test the efficacy of such an affect-recognizer by applying machine learning techniques, such as Support Vector Machine (SVM). SVM has been shown to be the most time and space efficient when compared with other classes of machine learning techniques [30] having many advantages such as its ability to deal with noisy and high-dimensional data [31] that makes it a suitable candidate for physiology-based affect recognition.

D. Utilizing Machine Learning Techniques to Develop Affect-Recognition System

Engagement-Sensitive Affect-recognizer: We applied machine learning techniques such as Support Vector Machine (SVM) to the psycho-physiological data collected in our usability study. Based on the therapist's rating we segregated the data corresponding to the trials rated as eliciting High Engagement (HE) and Low Engagement (LE). The dataset for the 8 participants comprised of 14 significant features (Table IV) corresponding to 17 trials rated as LE and 32 as HE. Here, we used the Leave-One-Out (LOO) and train on the rest approach. By this approach we can improve the quality of estimates by running k-fold cross-validation instead of fixing a training set and a test set [32]. The data were analyzed using different kernels, such as, Linear and Polynomial. The Table VI shows the percentage prediction accuracy for two different kernels for high and low levels of engagement. We observe that the prediction accuracy achieved is better with the polynomial kernel than that with the linear kernel. We know from literature [30] that the prediction accuracy of the SVM depends on the sample size used to train the system. In our usability study we had a limited sample size. We believe that we can achieve better prediction accuracy if we use a larger data sample size.

TABLE VI. PREDICTION ACCURACY FOR ENGAGEMENT WITH DIFFERENT SVM KERNELS

SVM Kernels	Engagement Percent Prediction Accuracy	
	LE	HE
Linear	76.47%	81.25%
Polynomial	76.47%	84.37%

Liking-Sensitive Affect-recognizer: The classification of the psycho-physiological features based on the therapist's rating on liking was also done in the same way as that for engagement. The dataset for the 8 participants comprised of 14 significant features (Table V) corresponding to 51 trials rated as eliciting Low Liking (LL) and 12 trials for the High Liking (HL). The Table VII shows the percentage prediction accuracy for two different kernels for high and low levels of liking. The low prediction accuracy of HL may be due to the fact that our dataset comprised of fewer trials (approximately 25%) rated by the therapist as eliciting HL compared to trials rated by therapist as eliciting LL.

TABLE VII. PREDICTION ACCURACY FOR LIKING WITH DIFFERENT SVM KERNELS

SVM Kernels	Liking Percent Prediction Accuracy	
	LL	HL
Linear	88.24%	50%
Polynomial	94.12%	41.67%

Thus we can say from the Tables VI and VII, that on an average, the polynomial kernel showed higher prediction accuracy than that while using the linear kernel both for engagement and liking.

V. CONCLUSION

In the work presented in this paper, we tried to understand the psycho-physiological response of individuals with ASD when they interacted with a VR-based social communication scenario. Having realized the potential of VR-based systems to cause variations in the participants' peripheral physiological signals and behavioral viewing pattern, we wanted to analyze the efficacy of such a system in developing therapist-like affect-recognizers by using machine learning techniques.

Results from a usability study show the capability of the therapist-like affect recognition system to predict the affective states of the participant from their peripheral physiological features and behavioral viewing pattern. However the system proposed here has some drawbacks.

First, the system (using wired experimental setup) discussed in this paper has been tested with participants with high functioning ASD. This work can be extended to participants with motor deficits by using wireless physiological sensing devices. Also in the present study, the participants presented their responses during bidirectional social conversation by using computer mouse. Such a system can be extended to the low functioning ASD spectrum by introducing speech recognition techniques as a means for the bidirectional conversation.

The current study used the system for the participants from the west. In future, we plan to use the system for participants of the eastern world, which would demand the creation of VR-based social communication with regional languages.

Additionally, our sample size was limited. Further improvement in the SVM based prediction accuracy might be achieved if we have a bigger sample size. The results of the usability study are promising. However, a much larger study must be conducted before such findings can be generalized. Additionally, we acknowledge that the current findings, particularly towards the development of intelligent affect-recognizer, are preliminary and limited in nature. While demonstrating proof-of-concept of the technology, questions about the practicality, efficacy, and ultimate benefit of the use of this and other technological tools for demonstrating clinically significant improvements in terms of ASD impairment remain, which will eventually be addressed by empirical investigation in the future.

ACKNOWLEDGMENTS

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

REFERENCES

[1] APA, 'Diagnostic and statistical manual of mental disorders (4th ed.),Washington, DC: American Pychiatric Association, 1994.

[2] APA. Diagnostic and statistical manual of mental disorders: DSM IV TR American Psychiatric Association., Washington, DC, 2000.

[3] Green, D., Baird, G., Barnett, A. L., Henderson, L., Huber, J., and Henderson, S. E.. The severity and nature of motor impairment in Asperger's syndrome: a comparison with Specific Developmental Disorder of Motor Function. *Journal of Child Psychology and Psychiatry and Allied Disciplines*, 43(5), 655-668, 2002.

[4] Schultz, R. T. Developmental deficits in social perception in autism: the role of the amygdala and fusiform face area. *Int J Dev Neurosci*, 23, 125-141, 2005.

[5] Stelios K and Ioannis P, Statistical Analysis of Human Facial Expressions, *Journal of Information Hiding and Multimedia Signal Processing,* Vol. 1, No. 3, pp. 241-260, July 2010.

[6] Lee, C. M., and Narayanan, S. S. . Toward detecting emotions in spoken dialogs. *IEEE Transactions on Speech and Audio Processing*, 13(2), 293-303,2005.

[7] Ben Shalom, D., Mostofsky, S. H., Hazlett, R. L., Goldberg, M. C., Landa, R. J.,Faran, Y., McLeod, D. R., and Hoehn-Saric, R. . Normal physiological emotions but differences in expression of conscious feelings in children with high-functioning autism. *J Autism Dev Disord*, 36(3), 395-400, 2006.

[8] Groden, J., Goodwin, M. S., Baron, M. G., Groden, G., Velicer, W. F., Lipsitt, L. P., Hofmann, S. G., and Plummer, B. (Assessing Cardiovascular Responses to Stressors in Individuals with Autism Spectrum Disorders. *Focus on Autism and Other Developmental Disabilities*, 20(4), 244-252, 2005.

[9] Toichi, M., and Kamio, Y. . Paradoxical autonomic response to mental tasks in autism. *J Autism Dev Disord*, 33(4), 417-426, 2003.

[10] Lahiri, U., Warren, Z., Sarkar, N. . Design of a Gaze-sensitive Virtual Social Interactive System for Children with Autism. *Transactions on Neural Systems and Rehabilitation Engineering*, 19(4), 443-452, 2011a.

[11] Prendinger, H., Mori, J., and Ishizuka, M. Using human physiology to evaluate subtle expressivity of a virtual quizmaster in a mathematical game. *International Journal of Human-Computer Studies*, 62(2), 231-245, 2005.

[12] Meehan, M., Razzaque, S., Insko, B., Whitton, M., and Brooks, F. P., Jr. Review of four studies on the use of physiological reaction as a measure of presence in stressful virtual environments. *Applied psychophysiology and biofeedback*, 30(3), 239-258, 2005.

[13] Bradley, M. M. Emotion and motivation. *Handbook of Psychophysiology*, J. T. Cacioppo, L. G. Tassinary, and G. Berntson, eds., Cambridge University Press, New York, 602-642, 2000.

[14] Cooke, L. , "Is Eye Tracking the Next Step in Usability Testing?", International Professional Communication Conference, IEEE, pp. 236-242, 2006.

[15] R.W Picard, " Furture Affective Technology for Autism and Emotion Communication,' Philosophical Transcations of the Royal Society B., vol. 364, n0. 1535, pp. 3575-3584, 2009.

[16] S.Parsons, P. Mitchell, & A. Leonard, "The use and understanding of virtual environments by adolescents with austic spectrum disorders," J Autism Dev Disord, vol. 34, no. 4, pp.449-466, 2004.

[17] G. Pioggia, R. Igliozzi, M. Ferro, A. Ahluwalia, F. Muratori, & D. De Rossi, "An android for enhancing social skills and emotion recognition in people with autism.' IEEE Transactions on Neural Systems and Rehab Engg., vol. 13, no. 4, pp. 507-515, 2005.

[18] S. Weider, & S. Greenspan "Can Children with Autism Master the core Deficits and Become Empathetic, Creative, and Reflective?," The J. of Dev. And Learning Disorders, vol. 9, 2005.

[19] Tartaro, A., Cassell, J.: using Virtual Peer Technology as an Intervention for children with Autism. In: Lazar, J.(ed) Towards Universal Usability: Designing Computer Interfaces for Diverse User Populations, UK. John Wiley and Sons, Chichester,2007.

[20] Lahiri, U., Bekele, E., Dohrmann, E., Warren, Z., Sarkar, N. Design of a Virtual Reality based Adaptive Response Technology for Children with Autism Spectrum Disorder. *Affective Computing and Intelligent Interaction* (ACII, 2011), 2011b.

[21] Lahiri, U., Sarkar, M. Adaptive Gaze-Sensitive Virtual Reality based Human-Computer Interaction for Adolescents with ASD. *IASTED, Human-Computer Interaction (HCI, 2012)*, 2012.

[22] Pramila Rani, Nilanjan Sarkar, Changchun Liu, Maintaining Optimal Challenge in Computer Games through Real-Time Physiological Feedback, *In Proceedings of the 11th International Conference on Human Computer Interaction*, pp 184–192, 2005.

[23] Papert, S. "Mindstorms: Children, Computers, and Powerful Ideas," 2nd ed. New York: Basic Books, 1993.

[24] Booth .T, Sequential Machine and Automata Theory, John Wiley and Sons, New York, 1967.

[25] Dunn, LM., Dunn, L.M.: PPVT-III: Peabody Picture Vocabulary Test. Circle Pines. American Guidance Service, Minnesota,1997.

[26] Constantino, J.N.: The Social Responsiveness Scale. W. Psych. Serv., California, 2002.

[27] Rutter, M., Bailey, A., Berument, S., Lord, C., Pickles, A.: Social Communiaction Questionnaire. Western Psychological Services, Los Angeles, 2003.

[28] Lord, C., Risi, S., Lambrecht, L., Cook, E.H., Leventhal, B.L., DiLavore, P.C., Pickles, A., Rutter, M.: The Autism diagonistic observation schedule generic: A standard measure of social and communication deficits associated with the spectrum of autism. J. of Austism and Dev. Dis. 30(3), 205-223, 2000.

[29] Rutter, M., Couteur, A., Le, L.C.: Autsim diagnostic interview revised WPS edition manual. W. Psych. Serv., Los Angeles,2003b.

[30] Rani, P., Liu, C., Sarkar, N., Vanman, E. , An empirical study of machine learning techniques for affect recognition in human-robot interaction. *Pattern Analysis and Applications*, 9(1), 58-69, 2006.

[31] Burges, C. J. C. , A tutorial on Support Vector Machines for pattern recognition. *Data Min Knowl Disc*, 2(2), 121-167, 1998.

[32] Uttama Lahiri, Robert F. Labadie, Changchun Liu, Ramya Balachandran, "A step toward identification of surgical actions in Mastiodectomy," IEEE Transcations on Biomedical Engineering., vol. 57 no. 2 pp. 479-487, 2010.

[33] Rani, P., Liu, C., Sarkar, N.," Human-Robot Interaction Using Affective Cues " *IEEE International Symposium on Robot and Human Interactive Communication* pp. 6-8, 2006.