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Interactive robots as social partner for communication care

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***Abstract*— Recent research suggests children with autism show certain positive social behaviors while interacting with robots without the presence of peer pressure. This paper explores possible use of interactive robots for interaction with children with autism. Logical artificial intelligence, reasoning about beliefs, desires and intentions (BDI model) serve as a basis to construct a set of scenarios. The present invention also describes a novel real-world motivated learning method. It uses a supervised reinforcement learning approach combined with goal creating. Autonomous agent learns problems in the real world through interaction with the patient. Methods and systems for management of brain and body functions and sensory perception, observing/analyzing, interactive behavior are presented. In one instance, the virtual agent is integrated with a computer-aided system for diagnosis, monitoring, and therapy.**

***Index Terms*— Robotics, BDI, Motivated Learning, Goal creation, Autism therapy, Children with autism, Social robot, Tele communication.**

I. Background & Clinical Significance

All humans learn behaviors in an autonomous open ended manner through lifelong learning. Until now, no robot has this capacity. This is one of the greatest challenges in robotics today as well as the long term goal of the growing field of developmental robotics. This present invention explores a possible method towards such a goal.

Research has shown that children with ASD may be preferentially drawn towards technologically-geared platforms. Rapid progress in technology, especially in the area of robotics, offers tremendous possibilities for innovation in treatment for individuals with Autism Spectrum Disorders (ASD). Considerable attention has been given to what type of robot might be effective, but not as much emphasis has been placed on the best ways to integrate the robot into therapy sessions. There are several open questions such as what the best roles for robots are in therapy, how to best integrate robots into interventions, and who among individuals with ASD are best suited for this approach. We focus on the broad approach of using robots, rather than any one particular target behavior.

With the working hypothesis that children with ASD have an intrinsic interest in technology, robots can be used to elicit pro-social behaviors for therapeutic purpose. Robots can be programmed to respond to child's behavior and provide interesting visual display to encourage a desirable and pro-social behavior from the child.

Besides that, it is also proposed that an environment can be created where the child can practice specific skills with the robot. The aim is to use the robot to teach a skill that the child can learn and imitate and then transfer to interactions with human. The child can repeatedly practice a behavior or social interchange without the presence of peer pressure. Research in this area is still limited and can be improved with the integration of well-established treatment for ASD such as Applied Behavior Analysis (ABA)

Conventional methods of therapy with demonstrated efficacy often relies on the therapeutic rapport between the therapist and child and often face problems in the generalizability of learnt behaviors outside the therapeutic setting. The robot adds to those sessions an element that is intrinsically interesting, engaging and rewarding for the children. In addition, in contrast to one to one session with a therapist, introducing a robot as a medium to learn social skills may alleviate anxiety experienced by some socially withdrawn individuals with ASD and also provide a less intrusive atmosphere of learning [7].

Very little research has been done on what specific cognitive mechanisms might be targeted or affected by robot vs. human interactions. If individuals with ASD fundamentally think about, interact with, and respond to robots differently than humans, it will be necessary to determine how this may affect the generalization of skills. We believe that this work, in combination with work on clinical effectiveness and efficacy, will be mutually informative [3].

II. Objective

The main aim of this study is to test the applicability of using half or full autonomous robot in improving the social skills learning of children with Autism Spectrum Disorders (ASD). We hope to establish improvements in social skills displayed by the child over the sessions they spend interacting

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with the robot. For the long term objectives, we aim to:

1. Using a humanoid robot to augment intervention among children with ASD, does not preclude the role of the human therapist. Provide an additional platform in which children can learn social skills that are embedded in social interaction such as approach, initiation, request, maintenance of interest and termination of interaction.
2. Technology and software should be adapted so that the semi or full autonomous robot can be controlled by the therapist no matter whether the therapist is inside or outside the room. Additionally, studies must not focus purely on behaviors, but also on cognitive processes as well.

I. *METHODOLOGY*

A. *Human Robot Interaction (HRI)*

The aim of classical research in artificial intelligence is to achieve human-like intelligence and cognitive ability, especially in terms of problem solving, planning and so forth. However, some studies proposed that social intelligence is the key for making robot smarter. Hence, research in the field of social robotics or human-robot interaction becomes very crucial. This proves to be a great challenge as the robots need to deal with highly dynamic and stochastic elements inherent in social interaction on top of the normal problems in robotics.

In conventional robotics research, the robots do not need to actively engage with the environment and induce reaction from it. However, social robots are required to initiate contact with human subject, interpret various social signals from the human and react accordingly. In human-robot interaction, any actions by robots may cause an unpredictable reaction from the human which needs to be handled. These two challenges make it difficult for researcher to design social robots with believable and contingent behaviors [5].

As such, the study of human-robot interaction has largely been done using a Wizard of Oz approach [6] instead of a fully autonomous robot. A Wizard of Oz experiment is conducted with a human subject interacting with a robot that he or she believes to be autonomous but is actually being controlled by an unseen operator. The operator will interpret the situation and to the human subject [8].

B. *Human Machine Interface (HMI) - EBART Assessment System*

Emotions, behaviors and Audio Real Time (EBART) assessment system is a real time interface that allows the controller to interact with the child via the robot. EBART assessment system includes modules focusing on social interaction with the child. Areas of skills that may be elicited through the modules may include: conversational skills, social requesting, initiating social interaction and empathy.

A graphical user interface that is simple and intuitive for users to control the robot in real time is developed to integrate the required functionalities of the modules. PyQT is used as a tool to create the interface. The EBART Wizard interface is shown in Fig. 1. It contains different types of human-like motions, emotions, joint attention, four games, audio live streaming and dances that can be chosen by the user.

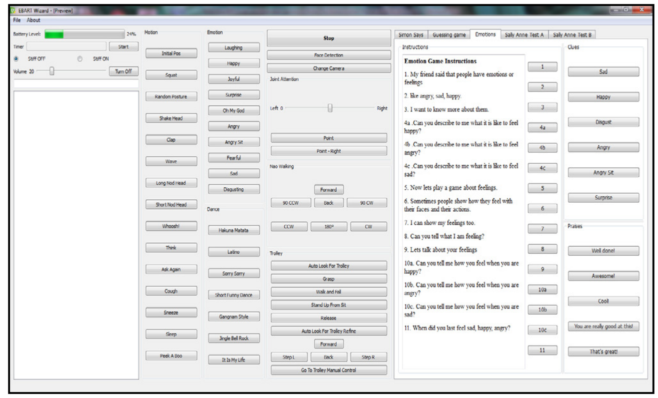


Fig. 1. EBART Wizard interface

The sessions are conducted across two rooms, one with a camera and the other a control room. NAO is placed on a platform across the child seated on a chair in the room with the camera. The height of the chair and the platform are adjusted so that most children will be able to see NAO at eye level. Study team members in the control room observe the interaction session through the camera. Fig. 2 shows the control room used for the study.

Fig. 2. Control room for autism study

The computer in the control room is connected to NAO via wireless network. Live feeds of audio and video are captured by the camera and the microphone on NAO and transmitted to the computer for the controller to manipulate the robot using the EBART Wizard interface.

II. *APPROACH*

A. *BDI Model*

BDI (belief, desire and intention) model acknowledges the primacy of these entities in the practical reasoning process. For our purposes, we merge desire (instant goal) and intention (final goal). To adapt BDI model to our environment, we split the cognitive state into belief and knowledge. The difference between belief and knowledge is that an agent is capable of changing and revising beliefs, but knowledge is only subject to acquisition and cannot contain a false fact. Some mental concepts cannot be formally derived using the basis above.

In this study of human-robot interaction has largely been done using a Wizard of Oz approach [6] instead of a fully autonomous robot. A Wizard of Oz experiment is conducted with a human subject interacting with a robot that he or she believes to be autonomous but is actually being controlled by an unseen operator.

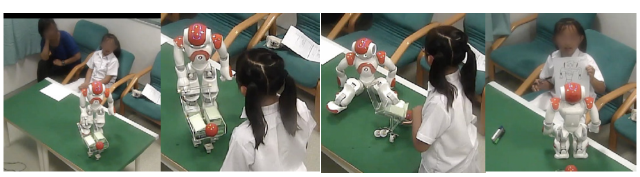
B. *Motivated Learning*

Motivated Learning (ML), the main idea is intrinsic motivations created by learning machines. It is needed base on motivation, goal creation and learning in an embodied agent [2], [4]. Autonomous robot learns problems in real world through interaction with the environment. As a branch of supervised learning, reinforcement learning can maximizes the reward in single value function. However, motivated learning as a combination of Reinforcement Learning (RL) + Goal Creation System (GCS) can dynamically learn better in complex unpredictable environment.

In the environment, every resource discovers by the robot becomes a potential goal and is assigned a value function "level"; GCS establishes new goals and switches robot's activity between them; RL algorithm learns value functions on different levels.

C. *Key Tasks*

We develop behavior-based interaction architecture (BIA) for NAO robot to facilitate the use of the robot in therapy/intervention among children with autism. This behavior- based architecture will integrate an array of NAO's sensory inputs (camera, microphone, sonar, touch sensor) and output devices (speakers, motors) with a set of simple control rules that can execute autonomously and semi-autonomously with human intervention. The semi-autonomous control in BIA will be a critical feature for NAO robot uses in intervention sessions among children with ASD to enable the therapist to have full control of the process. The goal is to carry on a conversation through pre-designed and instant dialogues. The interaction sessions elicit social skills of the child including greetings, elicitation of comfort/ empathy, initiate and maintain conversations etc. Examples of overture from the robot: "Hi, what is your name?"; "Would you like to draw a picture". The robot may engage in a small dance to encourage positive responses from the child.



(a) (b) (c) (d)

Fig. 3. Trolley session
(a) NAO looks for the trolley (b) NAO grasps the trolley
(c) NAO falls down, the typical developing child's empathy is observed (d) Child draws and shows to NAO

Fig. 3 shows a sequence in a session, the girl in the photo is a typical developing child participating in a pre-study technical test. After the robot gets the trolley, the robot falls down when it is turning the trolley. The child is observed for demonstration of empathy during the process.

D. *Model Architecture* and *Learning*

In order to make reinforcement learning practical in real-world scenarios, supervised reinforcement learning offers the possibility of reducing the number of learning steps by avoiding the initial exploration of the state space. This is achieved by providing the robot (work as an agent) with a few correct training examples and using them for off-line training.

We create the training examples by remote control the robot from several random positions to the goal position, while saving state, action and reward information. The off-line training consists of the presentation of the saved action and state vectors (or action sequences) to the robot. Thus, the robot can learn the given action sequences without additional real-world execution of actions.

Since the training examples represent only a reduced subset of possible solutions, we use additional reinforcement learning to safely control the robot around the near-optimal solutions provided by the operator. Especially, we use SARSA learning, which is a classical on-policy algorithm for temporal difference (TD) learning. SARSA does not have major restrictions of convergence, and it can easily be combined with eligibility trace, opposed to Q-learning.

The model has an input layer, which represents the robot's current state, and an output layer, which represents the chosen action. Both layers are fully connected. The number of states, actions and the size of the actions are adjusted empirically as a trade-off between speed and accuracy for each of the tested docking behaviors. The algorithm implementation will be explained using a grid-world example, which offers an intuitive ground and facilitates graphical representation of the modifications.

The navigation problem is modeled as a Markov decision process (MDP) (see Fig. 4). An MDP is defined by a set of states S, a set of actions A, a transition model $P(s'|s,a)$ that specifies the probability of reaching the next state s' by taking action a in state s, a reward model $R(s',s,a)$ that specifies the immediate reward receives when taking action a in state s, and an exploration policy π $(s|a)$, which is a mapping from states to actions.

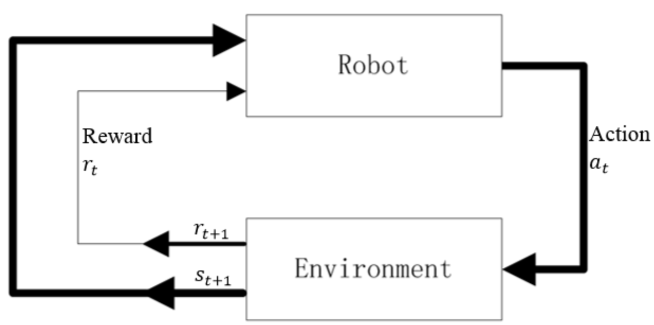


Fig. 4. Markov decision process flow

Considering the two dimensional grid-world example, the state space S is formed by all cells. The goal position is indicated by a red cell and the current robot's position by a black cell. The robot's objective is to reach the rewarded goal position as quickly as possible.

The actions are moving UP, DOWN, LEFT and RIGHT, for clarity, only one connection weight is shown. A move does not depend on the history but only on the policy $\pi(s|a)$, which depends on the learnt network weights W. A binary reward r is used to indicate whether the robot has succeeded or not. The robot is given r = 0 as long as the desired position is not reached. Once the goal position is reached, the robot receives r = 1 and the ‘‘trial’’ is finished.

The learning algorithm is based on SARSA. For each trial the robot is placed at an initial random position within the defined workspace. The robot reads the cell’s coordinates to obtain the internal state activation vector s, with all entries zero except for the entry that corresponds to the world position.

First, to avoid random exploration, a set of training examples are recorded and used for off-line training. The learning algorithm is realized within each trial. However, the selected action is provided by the remote operation data. We refer to this procedure as “supervised reinforcement learning”.

E. Extend BDI Module and goal creation Simulation for Robot Facilitated Autism Therapy

In this experiment, we use goal creation software (GCS) proposed by Starzyk [9] to extend an agent that has to function as our NAO robot. The primary objective of the project is to simulate our Robot to create the goal in dynamic time (which interacts with its environment) using the GCS software. Attached Fig. 5 shows the desire tree designed for session 2.

The Robot has to learn to do various activities related by exploration for a “sense of achievement”. Thus the primary pain of the robot is the “sense of achievement” (pain id (9)). The sense of achievement is high when the robot successfully measures and assesses the behavior and smoothly interacts with child. There are eight externally triggered pains, eight sensory inputs and seven motor actions.

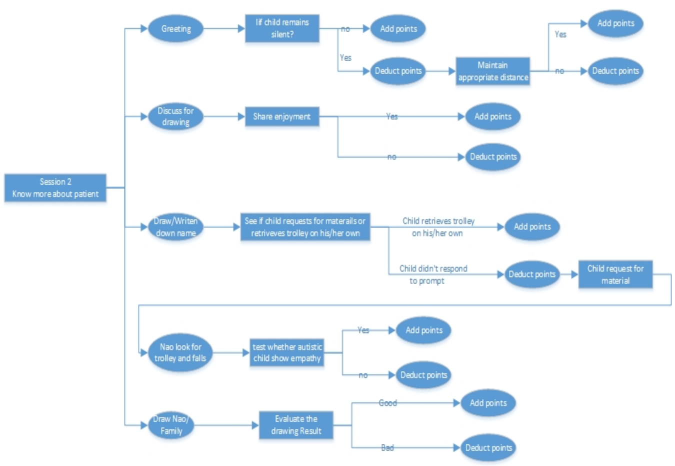


Fig. 5. Desire tree for sessions 2

I. The Goal Map and Valid Actions

Table I provides a map of the valid goals and the pains that are reduced by the valid goals. The robot and environment architectures defined in the Goal creation software are used.

Table I

Pains and the valid actions that reduce particular pains

	Pain	Actions that reduce pain
Externally triggered pains	Lack of interaction	Greeting, Talk about holidays/hobbies, Look for trolley
	Lack of imitate skill	Play simon says game to teach him,
	Lack to stay on topic	Turn taking to the topic which the patient is interested
	Lack of eye contact	Greeting to know more about the patient
	Lack on false belief	Play Sally Anne Task
	Lack of sharing enjoyment	Play drawing, Talk about holidays/hobbies
	Lack of help	Robot look for trolley
	Lack of empathy	Robot look for trolley
Internal primitive pain	Sense of achievement	Dance
Exploratory instinct	Curiosity	

II. NAO’s Parameters

Default values have been assigned to most parameters of NAO. The parameters that have not been assigned the default value or the parameters that have been used for secondary objectives are listed below:

- Number of iterations : 20000
- Pain threshold tp: 0.2
- Maximum increment of the P-G link weight µg : 0.3

Though it would have been interesting to study the effect of the pain threshold for curiosity, number of cycles to remember, and various other parameters, we have refrained from doing so. This is done for two reasons. First, though the effect of each parameter can be predicted analytically based on the GCS document [1]. Second, the parameters that have been chosen above have meaningful and direct impact on the behavior of robot. This facilitates in deriving some meaningful, well defined variations and discussing the observed behavior critically.

III. Environment’s Parameters

All the environment parameters except the resource depletion rate have been assigned the default values. The rate parameters are assigned as below:

- Depletion rate of the “sense of achievement”: tc=10
- Depletion rate of “Sally Anne Task” = tc/2 = 5
- Depletion rate of “Simon Says Game”= tc = 10
- Depletion rate of “Holidays or hobbies”= tc = 10
- Depletion rate of “drawing” = 2tc = 20
- Depletion rate of “trolley”= tc/3 =3.33
- Depletion rate of “Drawing result” = 5tc = 50
- Depletion rate of “Patient focus and look at robot”=tc=10
- Depletion rate of “Different topic” = tc = 10

After 20,000 iterations, the robot must have learnt to adapt to the environment, understand its pains, satisfy its primary concerns (primitive pains), and respond to the situations that may occur in the environment. To study these aspects, we present some quantitative figures generated using GCS.

Here, we intend to study the nature and efficiency of the NAO in learning the goals. For this purpose, we study the goal scatter plot presented in Fig. 6. The green colored data points refer to the goals that actually reduced the pain of NAO. In fact the occurrence of these valid goals can be correlated to the corresponding pain reaching the threshold. Such one-to-one (almost) correspondence can be confirmed by matching the plot of pain and the occurrence of goal.

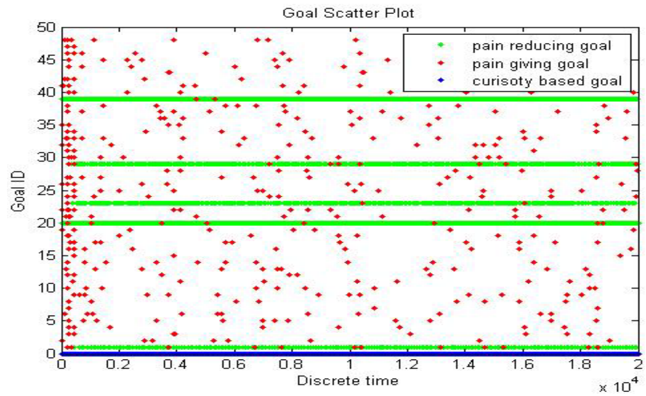


Fig. 6. The goal scatter plot

It is also seen that initially useless actions occur more frequently. However, in later stages, the occurrence of useless actions is greatly reduced. The overall counts of various valid goals, invalid goals and wrong goals are presented in Fig. 7. NAO demonstrates good capability to learn the goals. The total count of invalid action is only a little bit larger than the valid goal with maximum count. In fact, the sum of counts of all valid goals is significantly higher than the count of invalid goals.

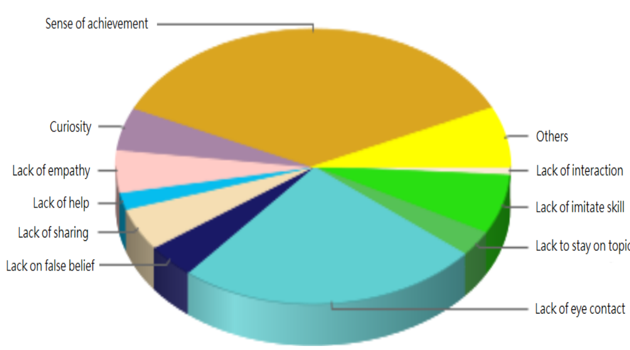


Fig. 7. Action Count Frequency

F. Discussion

The examples above demonstrate the efficacy of the Goal Creation Software in developing complex learning patterns. This is evident from the fact that in order to achieve NAO's primary goal, "sense of achievement", it has been able to identify other meaningful goals and their impact on the environment. It has also been able to reduce the occurrence of various pains as its learning progresses. This indicates that it has adapted to the initially hostile environment and found a balance in it. The frequency of various goals and their choice in a particular iteration show that it has been able to identify most important goal, most often required goal, goal most critical to its primary pain, etc.

In the current scenario, the GCS model is a basic model implementing a crude hierarchy of the goals. Though this basic model itself has various salient features, such a model would mean that NAO is not only motivated for planning its goals and action path, it is also motivated to self-introspect and self-improve.

III. CONCLUSION

The NAO robot aims to act as a social interaction agent. The purpose of using a humanoid robot to augment intervention among children with ASD does not preclude the role of the human therapist. Rather, it is an enhancement to autism intervention. It provides an additional platform in which children can learn social skills that are embedded in social interaction such as approach, initiation, request, and maintenance of interest and termination of interaction. Conventional methods of therapy with demonstrated efficacy often relies on the therapeutic rapport between the therapist and child and often face problems in the generalizability of learnt behaviors outside the therapeutic setting. The robot adds an element that is intrinsically interesting, engaging and rewarding for the children. In contrast to one to one session with a therapist, introducing a robot as a medium to learn social skills may alleviate anxiety experienced by some socially withdrawn individuals with ASD and also provide a less intrusive atmosphere of learning.

In general, the use of robotics for intervention in children with ASD appears to be promising. It would also be interesting to extend the use of this technology to children with other disabilities which share similar overlapping profiles of difficulty in social interaction and communication. For example, children with social anxiety may also benefit from such an application. The programs and specific modules may differ from those used for children with ASD, but additional research in this area could help in laying the groundwork for such an effort. The robot would be an augmentation to the intervention sessions between the therapist and the child with ASD. However, the robot's autonomous capabilities may allow for it to be initiated in community or home-based environments in the future. The NAO robot is only one type of embodiment of the robotic augmentation for autism intervention. The robotic software architecture and the modules that are developed in this project can be mounted on other robotic platforms of similar capability. Hence, with a single hardware, it would pave the way for a new avenue for autism research that would bridge the gap between the families and community and the clinicians in a novel and interactive manner.

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REFERENCES

[1] Pawel Raif, Janusz A. Starzyk, Motivated Learning In Autonomous Systems, *Proceedings of International Joint Conference on Neural Networks*, 2011, pp. 603 – 610.

[2] Diehl, J.J., et al., The clinical use of robots for individuals with Autism Spectrum Disorders: A critical review. *Research in Autism Spectrum Disorders*, 2011.

[3] Min Sung, Yoon Phaik Ooi, Tze Jui Goh, Pavarthy Pathy, Daniel S. S. Fung, Rebecca P. Ang, Alina Chua, Chee Meng Lam, Effects of Cognitive-Behavioral Therapy on Anxiety in Children with Autism Spectrum Disorders: A Randomized Controlled Trial, *Child Psychiatry & Human Development*, 42(6), Dec. 2011 pp. 634–649.

[4] Gillesen, J.C.C., Barakova, E.I., Huskens, B.E.B.M., Feijs, L.M.G., From training to robot behavior: Towards custom scenarios for robotics in training programs for ASD, *2011 IEEE 12th International Conference on Rehabilitation Robotics*: Reaching Users & the Community (ICORR 2011), 2011.

[5] Espinoza, R.R., et al., Child-Robot Interaction in The Wild: Advice to the Aspiring Experimenter, *ICMI'11 Proceedings of the 13th international conference on multimodal interfaces, ACM*, New York 2011, (2011), pp. 335-342.

[6] Ricks, D.J., Colton, M.B., Trends and considerations in robot-assisted autism therapy, *2010 IEEE International Conference on Robotics and Automation (ICRA 2010)*, 2010, pp. 4354-4359.

[7] Giannopulu, I. and G. Pradel, Multimodal interactions in free game play of children with autism and a mobile toy robot, *NeuroRehabilitation*, 27(4), 2010. pp. 305-311.

[8] Boccanfuso, L. and J. O'Kane, Adaptive robot design with hand and face tracking for use in autism therapy, *Social Robotics*, 2010, pp. 265-274.

[9] J. A. Starzyk, Motivation in Embodied Intelligence, *Frontiers in Robotics, Automation and Control*, Oct. 2008, pp. 83-110.