Adaptive and Long-Term Robot-Assisted Autism Therapy for Children with ASC: A Reinforcement Learning System

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ABSTRACT

This work focuses on adaptive robot-assisted autism therapy (RAAT) for children diagnosed with Autism Spectrum Condition (ASC). We aim to conduct a multiple-session RAAT that supports socio-emotional skills and language development. The six blocks of play-based activities target challenging skills and use ABA-based approaches. Our distinction would be the primary focus on reinforcement learning (RL) algorithm that can respond to each child's needs and evaluate learning progress over time to maximize social gains. We will compare the effectiveness of an autonomous RL-based robot against a non-adaptive robot and a control condition. Both quantitative and qualitative observations will be applied to measure how children engage with the robot and what kinds of socio-emotional outcomes they gain across the adaptive and non-adaptive conditions.

CCS CONCEPTS

• Computer systems organization → Robotics; **• Human-centered computing → Field studies**; **• Applied computing**;

KEYWORDS

reinforcement learning, child-robot interaction, robot-assisted autism therapy

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1 INTRODUCTION

Autism therapy should start as early as possible after receiving the clinical diagnosis of Autism Spectrum Condition (ASC). There are a variety of autism treatment options that focus on the development of social learning through commonly known types of treatment: behavioral, developmental, educational, socio-relational, pharmacological, psychological, complementary and alternative [9]. There is no single method that can treat autism, and therefore the main goal of autism therapy is to decrease autistic behavioral patterns to help individuals live a more independent life and build social relationships. While some children make remarkable gains in improving social and communication skills, others make slow or limited progress [12]. Thus, a special focus on those children who do not progress is required.

Our primary focus rests on behavioral treatment which helps children to develop social skills for daily life. We bring this aspect to robot-assisted autism therapy (RAAT) that focuses on developing social, behavioral and emotional learning while interacting with robots in different social environments. This area yet is at the very beginning of development because most studies remain cross-sectional and lack generalization. Social robots are considered to engage children in interactive learning activities that supplement and augment those provided by therapists [16]. However, behavioral research requires large data of children to optimize their learning and currently lacks diverse data from children with ASC due to the small sample size in experimental research [4]. Another related aspect is the extent to which current human-robot interaction (HRI) studies can ensure tailored support and that the shift from teleoperated to autonomous interactions brings challenges in computer-based perception and robot control [20].

Our work aims at using reinforcement learning (RL) to develop socially adaptive robot applications for autism therapy. Reinforcement learning is a subgroup of machine learning in which an agent learns to make decisions by performing actions and receiving rewards or penalties in response to the task outcome[22]. We will conduct a series of long-term and adaptive RAATs that takes into account children's individual characteristics and therapeutic needs to develop long-term adaptation and learning content integrated into standard autism therapy.

2 CURRENT APPLICATIONS OF ADAPTIVE RAAT

Autism therapy commonly offers highly structured and predictive interventions to accommodate learners' needs. Yet, some promising efforts towards adaptive and autonomous systems have been already taken in HRI. Past research shows a greater need for game difficulty personalization to fit each child's skill level and to prevent them from getting demotivated during intervention [21]. For instance, Scasselatti et al. [20] integrated personalization in RAAT by adjusting the difficulty levels of practice games, similar to the personalization of educational content in other smart systems. Over

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a period of one month, they deployed autonomous robots for a total of 127 hours over 279 sessions at the homes of children with ASC. As a result, they found that practicing joint attention with the robot could help children to transfer those skills when interacting with other people.

Affect recognition is another aspect of HRI contribution. Creating deep learning models that can accurately predict a user's state during autism therapy is still a challenge. Some studies address this issue with the help of adaptive systems. For instance, Rudovic et al. [16] developed a personalized deep learning framework, the personalized perception of affect network (PPA-net), that can adapt robot perception of children's affective states and engagement to different cultures and individuals. This multi-modal collects data from unobtrusive sensors and consists of video recordings of facial expressions, body movements, audio data, and physiological data such as heart rate. The framework operates in three steps: sensing, perception and interaction. In their follow-up study [17], the data selection method was found to be effective for new children. This is because it can choose the appropriate data samples that allow the pre-trained engagement classifiers to quickly adapt to the new child. Personalizing the multi-modal model can significantly improve the accuracy of engagement assessment for each child, even when using only a small amount of data. The authors stress that data labeling is both time-consuming and expensive and that it can also be affected by human bias when dealing with multi-modal data. Next up, Clabaugh et al [5] proposed RAAT personalization as a hierarchical human-robot learning framework (hHRL) with five controllers, disclosure, promise, instruction, feedback, and inquiry, to personalize instruction challenge levels and robot feedback as per each user's learning patterns. They validated the framework with 17 children with ASD, aged 3–7 years old, over one month in their homes. The results show that the fully autonomous robot system could personalize its instruction and feedback to each child's needs over time, with improvements in targeted skills and post-intervention retention of content. Considering the past contributions, we will develop our system to match the learning patterns of each child and deploy an affective assessment to detect child engagement and adapt task content.

3 REINFORCEMENT LEARNING FOR RAAT

To optimize engagement and learning, the robots can use RL to track a child's learning patterns and use that information to modify the level of task difficulty. The adaptation might also benefit RL to observe the child's engagement in real time and adapt its social behaviors. For instance, the robot could modify the activity or switch to another if the child works on a challenging and uninteresting task. RL can personalize the learning content to be effective and engaging. The proposed RL-based system adapts to each child's individual characteristics by choosing tasks that children would need to practice and improve targeted skills. The RL algorithm mediates between the robot and the child by collecting task performance data through the internal and external sensors of the system. Additionally, it communicates information to the robots, awaits the response, and then ultimately acts on it to increase user engagement. Some characteristics allow the RL environment to control the therapy autonomously. They include levels of activity difficulty and three arrays of task categories for practice. The task difficulty levels with the corresponding games are grouped into beginner, intermediate and advanced levels. Arrays match new, previously seen and learned activities to record what kinds of tasks should be presented to children during therapy. Depending on the child's profile, the algorithm will identify user engagement and choose the next task.

3.1 Environment

We create our own custom environment based on the OpenAI Gym library. The state space of the environment will have two parts. The first part is the variables that will be static during the full cycle of interaction with one child. These are verbality, age, hyperactivity and autism levels. They are predefined before the interaction. The second part includes variables of the state space that change during the interaction. They contain engagement level/time, completion count, eye Gaze, and others. More detailed information about the variables are written in Section 4.6. The reward for each step of the agent in the environment will be based on these variables. The target state is to have the completion count parameter be equal to 6, which is the number of activity blocks done by the agent with the child. The actions space will be based on six discrete actions. These actions are changing the activity blocks of interaction such as "Imitation", "Emotions", "Turn-taking", "Tactile interaction", "Vocabulary", and "Joint attention". More detailed information about these activity blocks is written in Section 4.3. The policy of the action of the environment will be defined by Deep Q-Network.

3.2 Deep Q-Network Algorithm

We implement the Deep Q-Network (DQN) algorithm model to develop our system. The algorithm suits well to our project implementation because our environment has a relatively simple multi-dimensional state space and discrete action space. In other words, 22 parameters for state space and six actions.

The algorithm will deploy a neural network, made of linear layers, that extracts the feature vectors from the parameters of the state space and calculates the Q-value for each possible action in the action space. The action with the maximum Q-value will be chosen by the agent as the action for a current state. During training, the agent will interact with the environment and will change the Q-function until it finds the most optimal function by minimizing the difference between the predicted and actual Q-value. This will be done by applying Mean Squared Error (MSE) method and the Adam optimizer. [10].

4 METHODS

The work aims at evaluating adaptive RAAT for children with ASC who engaged in behavioral activities tailored to autism subgroups and adapted to children's learning experience. For this purpose, we will carry out long-term intervention with children aged as young as three years old.

4.1 Conditions

There are two conditions: adaptive (RL) and non-adaptive (non-RL) sessions. Additionally, we adopt a between-subject design to compare the two experimental groups with the control condition.

- **RL condition**: sessions containing only adaptive tasks that are chosen by the RL system according to children's performance and engagement.
- **Non-RL condition**: sessions introduced according to fixed order as suggested by a therapist before the intervention.

4.2 Robot

In this study, we used a humanoid NAO robot manufactured by SoftBank Robotics. NAO is the primarily used robot in autism therapy, with nearly one-third of published studies in the past decade [18]. It is an autonomous and programmable robot often used for child-robot interaction research. It has basic modules such as built-in speech recognition, face recognition, display of gestures and body postures, and a text-to-speech engine that enables it to function more naturally.

4.3 Intervention framework

We will refine the previously used activities targeting different individual and social skills, described in detail in our past works [13, 19]. Overall, there will be six blocks of activities with at least three activities per block. They are organized according to particular social skills such as joint attention, imitation, turn-taking, emotion labeling and display, and other core social skills. Each activity will be varied from easy to advanced levels which will be configured based on user performance after each task is introduced. The six activity blocks, namely, "Imitation", "Emotions", "Turn-taking", "Tactile interaction", "Vocabulary", and "Joint attention" follow the ABA-based principles for autism therapy.

Imitation block. It allows a child to act first as imitators, then as initiators of robot movements [6]. The robot calls the child by their names after introducing itself with music. Then, it shows various body movements like walking back and forth and raising and lowering the arms. When the child imitates its movements correctly, the robot rewards them; however, when the child imitates it wrongly, the robot guides or prompts correct imitation. The robot continues to engage the child by saying it now imitates the child's movements. It says goodbye to the child after performing all planned imitation movements.

Emotions block. Individuals in different situations are depicted on matching cards expressing one of the five basic emotions (happiness, sadness, anger, surprise, and fear) in daily contexts [1]. The robot displays all the happiness and sadness expressions with the gesture animation and provides an audio explanation, for example: "How do you think this girl feels when she eats a cake on her birthday?".

Turn-taking block. Two children in pairs play a LEGO construction game with one robot [3]. They must take turns while building, for instance, a house. The robot guides and prompts whenever appropriate over the interaction by asking additional questions: "Can you say what we are building today?" If they cannot find a missing block, the robot would remind him/her to ask for it. The robot would ask the children whose turn comes next while they put blocks one by one.

Joint attention block. The system captures two images on a child's left and right sides as its attention points. The therapist and the robot elicit JA by alternately focusing on the child for one second and then on the image for three seconds [11]. There will be different items on the floor to which the robot turns its gaze throughout the session.

Tactile interaction block. The child controls the robot at the beginning of the game by touching its body parts and finding the various autonomous reactions [15]. When feedback is required, the robot asks the child to try once again to get a correct response (for example, if the child hits the robot in an area not covered by the sensors). Additionally, based on the child's cognitive development, the robot says the child to touch its body parts and also asks the child to describe how it "feels" when it displays a sad or happy expression (e.g. tickling the foot or the torso).

Vocabulary block. The robot and the child are introduced as peers during the first session and are engaged in conversation about sharing personal information like names and ages [2]. The robot first demonstrates some vocabulary-learning flashcards with audio explanations to the children. After the robot, the child has to repeat the phrases while looking at the flashcards. The children would then predict these words when the robot acts out the vocabulary in a game that followed.

4.4 Setup

All experiments occur in a small room without any furniture to maintain non-distractive environment with only sports mats on the floor and walls. One child and one robot sit on the ground to keep eye contact and see each other's behaviors. Two cameras record the child and the room. The robot acts autonomously, in the presence of a researcher in case of any malfunction.

4.5 Procedure

Each child first goes through a habituation phase when they interact with the robot in the presence of their parents/caregivers. Then, they attend a series of 15-minute-long sessions with the robot. On maximum, children will attend 10-20 sessions on alternating days. We employ an ASC therapist to observe the children during interventions. Parents are invited to attend the sessions with their children. The therapist chooses the specific activity for the first session considering parental input and autism-related patterns of children (e.g., sensitivity to sounds). The following activities are introduced according to the RL algorithm that detects each child's responses and performance. The robot continues to choose activities based on how well children handled their previous practice.

4.6 Measures

The behavioral data will be collected from video-based observation, for which we use predefined variables. When video-coding the interactions, we will measure a set of variables we used before [14]. They include: engagement time, eye gaze time, stereotyped behaviors and smiles are calculated relative to the overall time of the session. For example, 3 minutes out of 12 min-session is 25%. Moreover, we will calculate the means of all measures for sessions grouped by different blocks and conditions. There are at least two mean variables for each metric.

- ***Engagement Time*** is the amount of time a child was engaged (scores 4 and 5) relative to an activity duration;
- ***Valence*** is a mean of all valence scores within one activity;

- ***Eye Gaze Time*** is the amount of time a child spent looking at the robot calculated relative to an activity duration;
- ***Affection*** is the duration of actions (kissing, hugging, tender touching, scratching, petting) of a child calculated relative to an activity duration;
- ***Curiosity*** is the frequency of actions (opening, rotating, touching body parts) calculated relative to an activity duration;
- ***Aggression*** is the frequency of actions (pushing, biting, hitting, pulling fingers) calculated relative to an activity duration;
- ***Stereotyped Behaviors*** is the amount of time a child was flapping hands, screaming, and crying that was calculated relative to an activity duration;
- ***Smiles*** is a total number of smiles in each activity;
- ***Words*** is a total number of spoken words in each activity;
- ***Completion Time*** is the amount of time a child spent to complete an activity (only Songs and Dances blocks have this metric);
- ***Completion Count*** is the total number of completed tasks during an activity (only Touch Me, Emotions and Imitation blocks have this metric);
- ***Response Time*** is time measured from the start of the application until the first attempt to respond to the robot (only Touch Me, Songs and Dances blocks use this metric).
- ***Imitation*** is a rating of body movements (arm, neck, torso, feet) on Likert scales from 0 (no action done or completely wrong) to 4 (excellent imitation) [23].
- ***Touch*** is when the child touches any parts of the robot body [6, 7]
- ***Human interaction*** is when the child freely looks or says something to the unknown agent like a researcher during interaction [6]
- ***Turn-taking*** is when a child is able to wait for his/her turn evaluated on a Likert scale where 0- did not wait for his turn, 1- waited for his turn keeping still without interrupting the robot [8].
- ***Emotion recognition*** is a binary scale showing correct/wrong recognition of happy and sad emotions suggested by each situation-based animation (e.g., eating ice cream to show happy emotion) [8].

In this study, we described the RL-based system for RAAT that maintains adaptive learning to augment standard care for children with ASC who have different social and cognitive development, autism background, and language abilities.

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