1-1-2018

Studying Facial Expression Recognition and Imitation Ability of Children with Autism Spectrum Disorder in Interaction with a Social Robot

Farzaneh Askari
University of Denver

Studying Facial Expression Recognition and Imitation Ability of Children with Autism Spectrum Disorder in Interaction with a Social Robot

Abstract

Children with Autism Spectrum Disorder (ASD) experience limited abilities in recognizing non-verbal elements of social interactions such as facial expressions [1]. They also show deficiencies in imitating facial expressions in social situations. In this Master thesis, we focus on studying the ability of children with ASD in recognizing facial expressions and imitating the expressions using a rear-projected expressive humanoid robot, called Ryan. Recent studies show that social robots such as Ryan have great potential for autism therapy. We designed and developed three studies, first to evaluate the ability of children with ASD in recognizing facial expressions that are presented to them with different methods (i.e. robot versus video), and second to determine the effect of various methods on the facial expression imitation performance of children with ASD using Reinforcement Learning (RL).

In the first study, we compared the facial expression recognition ability of children with ASD with Typically Developing (TD) children using Ryan. Overall, the results did not show a significant difference between the performance of the ASD and groups in expression recognition. The study revealed the significant effect of increasing the expression intensity level on the expression recognition accuracy. The study also revealed both groups perform significantly worse in recognizing fear and disgust expressions.

The second study focused on the effect of context on the facial expression recognition ability of children with ASD compared to their TD peers. The result of this study showed a higher general performance of TD children compared to the ASD group. Within the TD group, fear and in the ASD group sadness were recognized with the lowest accuracy compared to the average accuracy of other expressions. The result of this study did not show any difference between groups; however, we found that there is a significant effect of different background categories in both groups. It means, we found a significant higher recognition accuracy for the negative backgrounds compared to positive backgrounds in 20% intensity for the fear and sadness expressions.

In the third study, we designed an active learning method using RL algorithm to identify and adapt based on the individual differences in expression imitation in response to different conditions. We implemented the RL to first, identify the effective imitation method based on individual's performance and preference; and second, to make an online adaptation and adjustment based on the effective method for each individual. The result of this study showed that the active learning method could successfully identify and adjust the session based on participant's strength and preference. The results also showed that each participant responded differently to each method in general and for each expression.

Document Type

Thesis

Degree Name

M.S.

Department

Computer Engineering

First Advisor

Mohammad Mahoor, Ph.D.

Second Advisor
Timothy Sweeny

Third Advisor
Matthew Rutherford

Keywords
Adaptive human robot interaction, Autism spectrum disorder, Facial expression recognition, Social assistant robots

Subject Categories
Behavior and Behavior Mechanisms | Computer Engineering | Early Childhood Education | Educational Technology | Robotics

Studying Facial Expression Recognition and Imitation Ability of Children with Autism Spectrum Disorder in Interaction with a Social Robot

---

A Thesis

Presented to

the Faculty of the Daniel Felix Ritchie School of Engineering and Computer Science

University of Denver

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

---

by

Farzaneh Askari

November 2018

Advisor: Dr. Mohammad Mahoor

Author: Farzaneh Askari
Title: Studying Facial Expression Recognition and Imitation Ability of Children with Autism Spectrum Disorder in Interaction with a Social Robot
Advisor: Dr. Mohammad Mahoor
Degree Date: November 2018

Abstract

Children with Autism Spectrum Disorder (ASD) experience limited abilities in recognizing non-verbal elements of social interactions such as facial expressions [1]. They also show deficiencies in imitating facial expressions in social situations. In this Master thesis, we focus on studying the ability of children with ASD in recognizing facial expressions and imitating the expressions using a rear-projected expressive humanoid robot, called Ryan. Recent studies show that social robots such as Ryan have great potential for autism therapy. We designed and developed three studies, first to evaluate the ability of children with ASD in recognizing facial expressions that are presented to them with different methods (i.e. robot versus video), and second to determine the effect of various methods on the facial expression imitation performance of children with ASD using Reinforcement Learning (RL).

In the first study, we compared the facial expression recognition ability of children with ASD with Typically Developing (TD) children using Ryan. Overall, the results did not show a significant difference between the performance of the ASD and groups in expression recognition. The study revealed the significant effect of increasing the expression intensity level on the expression recognition accuracy.

The study also revealed both groups perform significantly worse in recognizing fear and disgust expressions.

The second study focused on the effect of context on the facial expression recognition ability of children with ASD compared to their TD peers. The result of this study showed a higher general performance of TD children compared to the ASD group. Within the TD group, fear and in the ASD group sadness were recognized with the lowest accuracy compared to the average accuracy of other expressions. The result of this study did not show any difference between groups; however, we found that there is a significant effect of different background categories in both groups. It means, we found a significant higher recognition accuracy for the negative backgrounds compared to positive backgrounds in 20% intensity for the fear and sadness expressions.

In the third study, we designed an active learning method using RL algorithm to identify and adapt based on the individual differences in expression imitation in response to different conditions. We implemented the RL to first, identify the effective imitation method based on individual's performance and preference; and second, to make an online adaptation and adjustment based on the effective method for each individual. The result of this study showed that the active learning method could successfully identify and adjust the session based on participant's strength and preference. The results also showed that each participant responded differently to each method in general and for each expression.

Acknowledgments

I would like to acknowledge my advisor Dr. Mohammad Mahoor, for the opportunity and support. During my master studies he kindly provided all the required resources and supports to provide a good environment to conduct my research. This research was supported by NSF grants (IIS-1450933 and CNS-1427872).

I would also like to acknowledge Dr. Timothy Sweeny from the department of psychology, as my defense committee chair and for his insight and contribution on the psychological aspects of my research. I would like to thank Dr. Matthew Rutherford, my defense committee member, for his great input on my thesis that helped me to develop it further.

I had the opportunity to work in the *Computer Vision and Social Robotics lab* at the University of Denver. I would like to thank my colleagues and lab mates who helped me with the experiment design and in conducting research. I am thankful to all the families and children that participated in our study.

Last but not least, I thank my family and friends for their support and encouragement during my studies. I dedicate this dissertation to my family members and friends.

Table of Contents

Abstract ii

Acknowledgement iv

List of Figures vii

Chapter 1 Introduction 1
- 1.1 Autism Spectrum Disorder (ASD) 1
- 1.2 Socially Assistive Robotics 2
- 1.3 The Role of Socially Assistive Robots in Autism Research 3
- 1.4 Adaptive Human Robot Interaction 4
- 1.5 Research Problems and Thesis Contributions 5
- 1.6 Organization 6

Chapter 2 Background and Literature Review 8
- 2.1 Expression Recognition in Children with ASD using SAR 8
- 2.2 Rear-Projected Robots 10
  - 2.2.1 Ryan Companionbot 11
- 2.3 Expression Recognition within Social Context 12
- 2.4 Expression Imitation in Children with ASD 14
- 2.5 Adaptive Socially Assistive Robotic 15

Chapter 3 Studying Facial Expression Recognition Using Rear-Projected 17
- 3.1 Methods 17
- 3.2 Result and Discussion 20

Chapter 4 A Study on the Effect of Thematic Background on the Facial Expression Recognition of Children with Autism Spectrum Disorder 26
- 4.1Methods 26
- 4.2 Results and Discussion 32

Chapter 5 Toward Adaptive Socially Assistive Robots for children with Autism Using Reinforcement Learning 37
- 5.1 Reinforcement Learning 39
- 5.2 Methods and Parameters 43
  - 5.2.1 Facial Expression Imitation Materials 43

5.2.2 Reinforcement Learning Algorithm Parameters 45
5.3 Results and Discussion 48

Chapter 6 Conclusion and Future Work Direction 56
6.1. Conclusion 56
6.2. Future Work Direction 60

Bibliography 62

List of Figures

Figure 3-1 Left) Ryan Companionbot robot Right) Expressions demonstrated by Ryan with 100% intensity (Top from left to right: anger, disgust, fear. Bottom from left to right: happiness, sadness, surprise) 18
Figure 3-2 Room setup of the experiment protocol 19
Figure 3-3 The average group accuracy is shown for both ASD (blue), TD (yellow), and the average of both groups (green). Each bar represents the average of the group for that specific expression. Error bars are standard errors 22
Figure 3-4 The average group accuracy is shown for both ASD (blue), TD (yellow), and the average of both groups in different intensity levels 23
Figure 3-5 Confusion matrix for the recognition of six basic expressions by ASD group. Rows are ground truth and columns are recognized expressions by ASD participants 23
Figure 3-6 Confusion matrix for the recognition of six basic expressions by the TD control group. Rows indicate ground truth and columns indicate the proportion of expression categorizations made by TD participants 24

Figure 4-1 Basic facial expression. Left to right) anger, disgust, fear, happiness, sadness, surprise 27
Figure 4-2 Happiness facial expression with intensity levels of (left to right) 20%, 40%, 60%, 80% and 100% 28
Figure 4-3 Top) Positive backgrounds. Middle) Neutral Backgrounds Bottom) Negative backgrounds 29
Figure 4-4 First frame of each video integrated with different Backgrounds 29
Figure 4-5 Left) Ryan Companionbot. Right) The Experimental Setup 31
Figure 4-6 The average recognition accuracy for is shown for both ASD (blue) and TD (orange) for each expression. Each bar represents the average of the group for that specific expression. Error bars are standard errors 33
Figure 4-7 Confusion matrix for the recognition of six basic expressions by ASD group. Rows are ground truth and columns

are recognized expressions by ASD participants 34
Figure 4-8 Confusion matrix for the recognition of six basic expressions by TD group. Rows are ground truth and columns are recognized expressions by TD participants 34
Figure 4-9 The average recognition accuracy is shown for both ASD (blue), TD (yellow) and average of both groups (green) in each intensity 34
Figure 4-10 The average recognition accuracy for each category of background images 35
Figure 4-11 The recognition accuracy for each background category in different intensity levels 35
Figure 4-12 The recognition accuracy for each background category and each of the expressions in 20% intensity levels 36

Figure 5-1 Four basic facial expression. Left to right) disgust, fear, happiness, sadness 44
Figure 5-2 Expression demonstrated by Ryan. Left to right) disgust, fear, happiness, sadness 44
Figure 5-3 The accumulative average state-action value function (Q-function) subject A (left) subject B (right) 49
Figure 5-4 The accumulative average state-action value function (Q-function) for each expression 50
Figure 5-5 Policy adjustment for each expression based on the gained reward, Subject A (left) subject B (right) 52
Figure 5-6 Imitation scores for each expression, Subject A (left) subject B (right) 55

Chapter 1 Introduction

1.1 Autism Spectrum Disorder (ASD)

By the definition from *The Diagnostic and Statistical Manual of Mental* communication, social skills, and the presence of restricted, repetitive patterns of behavior. ASD symptoms appears at different times. In some children the symptoms become evident by lack of progress and in others may be a loss of previously developed skills [3]. There are symptoms that lead to earlier identification such as, an absence of intentional communicative response, an absence of coordinated gaze, effect, and voice during interaction with others and atypical social interest, and engagement [4].

There have been many studies to identify the cause of ASD. However, the studies could not conclusively implicate any one factor as the major cause. Although, studies confirmed that ASD is a pervasive disorder with lifelong symptoms [1]; young children with ASD who receive early age applied behavior analytic (ABA) interventions can acquire the social and communication skills later in life [1].

Facial expressions are one of the key elements of social interactions and communications. A deficit in recognizing facial expressions prevent the formation of effective social interactions. Although, facial expression recognition and emotion perception are not main parts of ASD definition, the idea of children with ASD suffer from emotion recognition deficiency is presumed [5][6]. On the other hand, there are studies [7][8] that doubt the idea of general deficiency in facial expression recognition in children with ASD, instead, they suggest that children with ASD may perform worse than their TD peers in recognizing some facial expressions and emotions.

Studies suggest that difficulties with imitation tasks appear in children with ASD as young as 24 months of age [9]. There are different ideas on a general imitation deficiency in children with ASD. Some studies claim a significant difference in imitation skill of children with ASD compared to their TD peers [10]; however, there are other studies casting doubt on the idea of general imitation deficiency in children with ASD [11].

A study by Ingersoll [12] focuses on social aspect of imitation skill and its role in developing social skills. according to this study, the imitation skill serves as two distinct functions in early childhood that are learning function and social function. The study suggests, a disruption in social use of imitation skill in early childhood have considerable impact on social and communication skill later in life.

1.2 Socially Assistive Robotics

Initially, Assistive Robotics (AR) has referred to robots that assisted people with physical disabilities through physical interaction [13]. On the other hand, Fong [14] used the term Socially Interactive Robotics (SIR) for the first time to describe robots with the main tasks of social interactions. Socially Assistive Robotics (SAR) are considered as combination of AR and SIR, that is defined as robots that assist human by providing certain terms of social interactions [13].

The difference between SIR and SAR is the ultimate goal of interaction. in SIR the robot's goal it to create effective interaction for the sake of interaction; however, in SAR the robot creates the effective interaction with a human to achieve specific goals such as rehabilitation, learning, etc. [13]. Studies have shown that SAR can serve as an effective tool in therapy sessions for individuals that suffer from cognitive and behavioral disorders. They can provide efficient assistant to teach certain types of skills [15].

Socially assistive robots can address various applications and needs. They can serve as companion for elderly people to reduce stress and depression. While the robots are not replacements for human, they can provide tutoring services for children. Studies showed that effectiveness of socially assistive robots in post-surgery rehabilitation of adult and children by providing regular exercise instructions [16] or story-telling [17] and companionship [13]. As mentioned above, the socially assistive robots can be used to assist individuals with cognitive disorders. For example, they have been used as social agents and facilitators for children with ASD to practice social skills [18], monitor their social interactions with other peers [19] and to encourage emotional expressions.

1.3 The Role of Socially Assistive Robots in Autism Research

As previously discussed, children with ASD exhibit deficiencies in social interaction and communication. One reason for this deficiency is that in a social scene, children with ASD seem to pay more attention to objects in the scene rather than human, and human bodies rather than their faces [20]; which result to loosing social cues and fail to effectively communicate. similarly, studies [21] showed that individual with ASD are more successful in understanding social cues in less complex stimuli (i.e. scenes with single social cues).

Additionally, Baron-Kohen is one of his studies [22] states:

> “The hyper-systemizing theory of autism proposes that the systemizing mechanism is set too high in people with autism. As a result, they can only cope with highly lawful systems, and cannot cope with systems of high variance or change (such as the social world of other minds). They appear ‘change-resistant’ “.

Summing up these two characteristics of individuals with ASD, interacting with robots is more predictive and systemized with less social cues compared to real social situations. Therefore, individuals with ASD exhibit comfort and interest toward robots [23]. In fact, robots are able to simulate social situations without complicity and unpredictability of daily social interactions. As a result the field of SAR has been widely studied [24].

1.4 Adaptive Human Robot Interaction

One of the recent fields of studies in social robotic is the adaptive human robot interaction using RL. In despite of many studies with pre-programmed and structured human robot interaction scenarios there are researches working on active robot learning or human robot interaction that consider inputs from human to integrate with a RL method. In some of these studies a machine learns by observing human behavior [25] [26] [27]; other studies focused on how machines can learn and adapt using human’s instruction [28] [29] or by interacting [30] with human during the learning process.

A study [31] that focused on different aspects of active learning in human robot interaction, presented three interaction modes which enable a robot to actively learn. The three modes are different in when they make queries. The first mode, made query every turn, the second made query under certain circumstances and the last made query only when explicitly asked by human. Although, each of the modes seemed to have their advantages and disadvantages, they were preferable to passive supervised learning mode in terms of performance and human subject preference.

The use of adaptive social robots for behavioral therapy of children with ASD has receive of many attentions. Researches showed that children with ASD show interest toward the robots; however, there is a question that if it is the appearance of the robot that affects the social behavior of a child with ASD or its behavior. A study [32] by Feil-Seifer et al. demonstrated it is the behavior of the social robot that affects social behavior of a child with ASD, by designing an autonomous robot-assisted behavior intervention using a control architecture.

1.5 Research Problems and Thesis Contributions

The objectives of this thesis are:

1. To study the facial expression recognition ability of children with ASD in comparison with TD children using Ryan, a rear-projected humanoid robot.
2. To study the effect of context on facial expression recognition of children with ASD compared to TD children.
3. To design an adaptive human robot interaction using RL to determine ASD individuals' differences in imitating a sequence of expressions in different conditions and adjust the interaction based on them.

To answer the questions above, we designed three studies and executed them on a group of participants. For the first study, we used Ryan companionbot to produce six basic facial expressions [33] with different intensities. The expressions were displayed to 12 children (i.e. 6 ASD and 6 TD) and we analyzed the data using ANOVA analysis. For more details see chapter 3. In the second study, we produced custom videos of facial expressions with integrated thematic backgrounds, as the simplified context, to examine the effect of backgrounds on facial expression recognition. The stimuli set was then displayed to 12 children (i.e. 6 ASD and 6 TD). We analyzed the result using ANOVA analysis. For more details see Chapter 4. Finally, in the last study, we designed an adaptive human robot interaction session using RL; during the session four facial expressions (i.e. disgust, fear, happiness and sadness) were presented to participants with three different methods (i.e. image, video, and robot). Two ASD participants were asked to imitate the displayed expressions. The goal of the session was to detect each participant's strength and preference using the algorithm and adjust the session based on each participant's effective method. For more details see Chapter 5.

1.6 Organization

The thesis is organized as follow: Chapter 2 presents literature review of the existing studies on the field of SAR, facial expression recognition in children with ASD and active learning in social robotics using RL methods. Chapter 3 focuses on studying the facial expression recognition ability of children with ASD using Ryan. the effect of thematic background on facial expression recognition is discussed in Chapter 4. Chapter 5 discusses the findings of an active learning human robot interaction session focused on facial expression imitation. And finally, Chapter 6 concludes the thesis and provides some directions for future studies.

Chapter 2 Background and Literature Review

2.1 Expression Recognition in Children with ASD using SAR

Studies have demonstrated that children with ASD exhibit less anxiety and more comfort toward technology and robots [23]. Therefore, the field of Socially Assistive Robotics (SAR) has been widely studied [24]. There are many socially assistive robots with expressive face to target and improve the facial expression recognition ability in children with ASD. They are capable of expressing realistic facial expressions as well as engaging children in social interaction without causing much anxiety and complexity for them. Some of them such as FACE [34] and Zeno [35] can demonstrate nearly realistic human facial expressions. On the other hand, some socially assistive robots such as KASPAR [36] and Tito [37] have more simplified faces to reduce sensory overload.

There have been many studies in using SAR as a tool to teach social skills and emotion recognition to children with ASD. Keepon is a non-humanoid robot with snowman-like body made of silicon rub, which can express excitement, pleasure and fear emotions with body movement [38]. A study with a three year old girl autistic girl and a group of twenty-five TD children in the age range of one to three, showed the success of Keepon to improve some of the social skills such as eye contact, joint attention, emotional expression, and turn-taking in both groups after several intervention sessions with Keepon [39].

Another study used FACE [34], a female android robot. The robot's face is made of skin-like silicon rubber, which enables the robot to show six basic expressions (i.e. anger, disgust, fear, happiness, sadness, and surprise). FACE has been used in [40] to target emotional behavior. The study included four subjects with high functioning autistic individuals in the range of seven to twenty-years-old. All subjects demonstrated improvement in emotional behavior at the end of the intervention sessions. Additionally, participants showed a spontaneous ability of imitating the head movements and facial expressions of the robot.

Another example of using humanoid robots to teach social skills to autistic children, is a study using KASPAR [36], which is a child-size male robot with active arms, hands, and head. KASPAR can open and close its mouth and eyes. In another study [41] KASPAR is used as a therapeutic tool for a 16-year-old boy, who was diagnosed with severe autism and could not tolerate other children. The intervention sessions improved his skills such as imitation, eye contact, joint attention, and turn-taking. Besides, the child showed interest toward the robot's eyes, eye lids and face. This interest led to the child later touching his own face and eyes as well as those of his therapist.

Recent studies [42][43] used Zeno R50 [35], which is a child-size male robot with active arms and legs, and the ability to express six basic facial expressions. Zeno R-50 provides more realistic expressions than other facially expressive robots such as KASPAR, but less realistic than FACE. The study aimed to compare expression recognition ability of ASD children with those of TD children. The study did not find any general deficiencies in expression recognition between groups, except for fear.

2.2 Rear-Projected Robots

Although robots with nearly realistic expressive faces are considered as important achievements, they still suffer from several limitations. First, once the mechanical platforms are built, they are fixed and cannot be modified. Second, large numbers of actuators in the robots' face make them expensive and difficult to maintain. Finally, in the long term, some of the actuators either completely fail or weaken so the expressions are not as intense and recognizable.

A good solution for the problems mentioned above is rear-projected robots, which have received much attention recently [44][45]. Rear-projected robotic heads consist of a neck mechanism, a face-shaped translucent mask and a projector that projects a computer graphic avatar onto the mask. The computer graphic avatar is produced using character animation technologies. Compared to android robots, rear-projected robots are less expensive more flexible, and feature low power consumption and fast reaction time. Dome robot [46] is one of the rear-projected robots that uses a cartoonish animated face projected on a dome-shaped mask. Dome robot lacks a realistic human face. Another example of rear-projected robots is the Lighthead robotic face [47] which projects a more realistic animation onto a face-shaped translucent mask. Al Moubayed et al. presented Furhat [44], a human-like light-projected robot that uses computer animation to demonstrate facial expressions and a mirror to produce a side projection-angle which results in a larger form factor.

2.2.1 Ryan Companionbot

Ryan is a rear-projected humanoid robot developed at DreamFace Technologies, which is based on the Expressionbot [45]. It is created by using character animation technologies to show 3D avatar models that produce natural speech and facial expressions. The animated face model is then projected onto a face-shaped translucent mask. This design is not only an effective alternative to overcome many of the limitations with the mechanical-expressive face design, it also provides flexibility to redesign and customize facial expressions, from simplistic non-sophisticated expressions to nearly realistic human like expressions.

The 3D models of six universal basic expressions (i.e. anger, disgust, fear, happiness, sadness, and surprise) were designed in Maya based on the Facial Action Coding System (FACS) [48]. For example, sadness involves Inner Brow Raiser (AU 1), Brow Lowerer (AU 4) and Lip Corner Depressor (AU 15) and happiness involves Cheek Raiser (AU 6) and Lip Corner Puller (AU 12).

Ryan is an emotive robot with an expressive face and accurate visual speech. This robotic platform has been used in a number of other studies to interact with autistic children [49], TD adults [50] and older adults with dementia and/or depression [51]. Since Ryan is equipped with key elements of social communication such as facial expression, gaze, spoken dialogue and visual speech, it is capable of natural face-to-face communication.

2.3 Expression Recognition within Social Context

Most of the studies on facial expression recognition use static images; however, a study [52] that examined the effect of videos with different durations (i.e. 4 s, 2 s and 1 s long) showed that all emotional and non-emotional expressions were recognized better when seen on dynamic faces versus static pictures. Additionally, in real life most expressions happen under dynamic visual conditions; therefore, in this study we used video of facial expressions.

For individuals with ASD, the real social world is full of challenges and ambiguities; the explicit and narrow experimental tasks considerably minimize these ambiguities which results in findings that might not accurately describe the difficulties individuals with ASD face every day. Consequently, there need to be experiments with conditions closer to daily social situations. One opportunity is to add thematic (situational/ meaningful) backgrounds and objects to the experiment materials (e.g. images, videos) of facial expression recognition studies. Below we review some of the studies that consider the more realistic experimental setups and their findings.

There are studies that put more emphasis on facial expression recognition ability within a social context. One of these studies [21] focused on the recognition of complex emotions within a social context. There were 23 children with ASD and 24 children in the control group. They were asked to watch twenty-seven short scenes (i.e. 6-30 s long) of movies. The movies involved the expression of complex emotions. After each clip the children were asked to label the expressions of one of the people in the scene. They were provided with the choice of four emotion labels. The results of this study show that children with ASD perform worse than their TD peers in average. They also show that children with ASD perform as well as the TD group in single cue scenes but perform worse when the scenes contain multiple cues. It shows children with ASD fail to use multimodal socio-emotional information, which happens very frequently in daily life.

In another study conducted by Klin et al. [20], 15 participants with ASD and 15 TD participants were asked to watch five digitized clips from a movie. The demonstrated social interactions in the movie were socially complicated, simulating the social situations that individuals with ASD will face in daily life. The sessions were recorded and then the visual fixations were measured using eye-tracking technology. The result of this study showed individuals with ASD paid attention to the objects (e.g., a vase on the table) in the scene more than TD individuals did, correlated with the social impairment (i.e. children with more social impairments paid more attention to objects rather than facial expressions). Although, the fixation time on the objects was small relative to fixation time on the face and body, the paper does not find it surprising given that their videotape clips were chosen to minimize inanimate distraction. The paper suggests further studies with more attractive backgrounds.

As suggested by studies [20][53] Limited activity monitoring in toddlers with autism spectrum disorder., in a social scene, children with ASD lose part of the important social cues and features as they pay attention to non-social objects. Lee et. al in a study [54] created Clip-based videos that are half-static and half-dynamic videos of social situations. In these videos, the surrounding objects are static and blurred, which requires less visual attention than fully dynamic videos and the children focus more on the facial expression without losing the social context of the facial expression. Six children with ASD were recruited for this study. The videos were used as intervention material during multiple sessions. The results of this study show some improvements in facial expression recognition and emotion judgement. The study concluded that limiting the amount of information from surrounding areas in a social scene with specific close-up cues can help an individual with ASD to better understand emotions and facial expressions. This study is another confirmation of the fact that in a normal social scene, individuals with ASD tend to pay more attention to non-social objects rather than social cues such as facial expressions.

2.4 Expression Imitation in Children with ASD

Children use the imitation skills to learn from their environment [55]. There are different ideas on a general imitation deficiency in children with ASD. Some studies claim a significant difference in imitation skill of children with ASD compared to their TD peers [10]; however, there are other studies casting doubt on the idea of general imitation deficiency in children with ASD [11]. A study [20] by Ingersoll focused on two different aspects of imitation that are social function and learning function. Through a social use of imitation skill children interact with their caregivers through games and learn communication and social skill. The study concludes, a disruption in social use of imitation skill in early childhood have considerable impact on social and communication skill later in life.

Socially assistive robots have been used in studying imitation skills of children with ASD. A study [37] focused on effect of a mobile robot on facilitating reciprocal interaction such as imitative play. The goal of this work was to address the question that a robot, which more predictable and less complex than human can improve social interaction and imitative plays in children with ASD. The study found that forms of shared conventions such as imitation of body movements are higher with two children paired with a human mediator which can be explained by the limited motion capabilities of the robot. Additionally, it showed children paired with robot, showed more shared attention such as visual contact and physical proximity in all types of imitation plays including facial expressions. It shows the interaction with a robot with appealing characteristics has benefits for children with ASD.

2.5 Adaptive Socially Assistive Robotic

One of the recent filed of studies in use of SAR for children with ASD is to design adaptive interaction and intervention sessions. A study [39] studied the use of three different interaction modes of a social robot with human. The three modes are different in when they made queries. The first mode, made query every turn, the second made query under certain circumstances and the last made query only when explicitly asked by human. Although, each of the modes seemed to have their advantages and disadvantages, they were preferable to passive supervised learning mode in terms of performance and human subject preference.

A study [56] proposed an adaption mechanism for robot behavior based on RL to improve the quality of human robot interaction. The robot will read the body signals such as repositioning body and averting gaze from a human partner and adjust the gaze, distance and the interaction speed based on that information. In this study, the occurrence of body signals were the inputs for the policy gradient RL algorithm (PGRL). The PGRL algorithm minimizes the reward by changing the policy, which in turn determines the robot's behavior. 15 subjects between the age of 20 to 35 participated in one 30-minute session to interact with robot. the results showed for most of the subjects the parameters (e.g. distance and interaction speed) converged to the each of the subject's preferences within 15 to 20 minutes. The study showed the robot could adapt to individual preferences for most of the subjects in the experiment. It concluded that a robot can adapt its behavior parameters to individuals by PGRL method.

Another study [57] examined whether a social robot can learn how to employ different social behaviors to achieve interactional goals from a task-oriented interaction from a human user. In this study, pre-defined high-level behaviors such as guiding attention, motivating, or providing positive feedback are mapped into low-level behaviors such as directed gaze, specific gestures, or verbal utterances. Low-level behaviors that are executable by the social robot allow for parameterization in accord with the desired high-level behaviors. They used Q-learning to adapt this mapping based on the direct reward from the robot experiences through the interaction with the human user. The setup was implemented within a memory game with the robot head Furhat as an assistant. They learning-based assistance condition with the random behavior condition. The results showed the participants in learning-based condition can solve the memory game faster because better assistance from the robot compared to the random behavior mood.

Chapter 3 Studying Facial Expression Recognition Using Rear-Projected

In this pilot study, we used Ryan Companionbot, a rear-projected humanoid robot developed by DreamFace technologies, to evaluate the facial expression recognition ability of ASD children compared to TD children. Our first hypothesis is that ASD children will perform worse than the TD control group on average. Our second hypothesis is that both groups will show a higher expression recognition accuracy as the intensity of Ryan's facial expressions increase. Our third hypothesis is that both groups will perform worse in recognizing negative expressions (i.e. anger, disgust, and fear) comparing to other expressions, as suggested by some studies [58]. Finally, we predict that Ryan's facial expressions will be, overall, comprehensible and recognizable with high average accuracy for children in both groups.

3.1 Methods

In this pilot study, Ryan demonstrated a sequence of facial expressions. The set consisted of six basic facial expressions (i.e. anger, disgust, fear, happiness, sadness, and surprise) and four different intensities (i.e. 25%, 50%, 75%, and 100%) for each of the expressions (total of 24 trials). We determined each expression intensity based on the number of frames between neutral and 100% intensity of that specific expression [33]. (e.g. for 25% intensity, number of frames between neutral and 100% intensity were divided by 4). Each expression started from a neutral state and progressed to a desired expression at a certain intensity level. For each participant, the expression demonstration started with the lowest intensity (i.e. 25%). In each intensity level, the expressions were shown randomly. The intensity increased to the next level after all the trials were completed for the current intensity level. After showing each expression, Ryan resumed demonstrating the final intensity and waited for the children's response. When the children were ready to answer, they verbally gave their answer to Ryan and the researcher recorded the response. Figure 3-1 shows Ryan and six basic expressions demonstrated on its face with 100% intensity.

Fig 3-1 Left) Ryan Companionbot robot [31,32]. Right) Expressions demonstrated by Ryan with 100% intensity (Top from left to right: anger, disgust, fear. Bottom from left to right: happiness, sadness, surprise)

Before the experiment started, children were introduced to the whole experiment setup including the robot and different expressions. They could choose one of the seven choices available for each expression. Choices included six basic expressions and neutral. Although no neutral expression was included in the expression set, the children could choose neutral if the expression was ambiguous due to low intensity. The researcher made sure each of the choices was understandable for the children. Children had the choices printed on a paper in front of them during the session. At times when the children were indecisive about their guess, we took the final guess as the official decision/answer.

The experiment was conducted in the social robotics laboratory at the University of Denver where an IRB approval was obtained, and all the children's parents signed a consent form. The study was presented to each child in a room with the presence of Ryan and a research assistant. We asked each participant to sit on a chair in front of Ryan. Each time the researcher made sure that Ryan's face is in the same height as the children's face. Figure 3-2 shows the room setup.

Fig 3-2. Room setup of the experiment protocol

Twelve children between the ages of 8 and 16 were recruited for the study. Six were classified as high functioning autistic by medical diagnosis (Age *M*=11.1, *SD*=3.27) (one female and five male) and six as typically developing children (Age *M*=11.1, *SD*=3.12) (six male). In accepting high functioning ASD participants, we insured that a doctor or psychiatrist formally diagnosed the children. Additionally, Autism Diagnosis Observation Schedule (ADOS) [59] examinations were performed by clinical psychologist collaborators in the Department of Psychology at the University of Denver to reassure that all the ASD participants met the threshold score for ASD diagnosis. As for the control group, neuro-typical children who had never been diagnosed with any kind of developmental or social disorder were recruited. Neuro-typical siblings of children with ASD were excluded from the study to ensure clear separation between the TD-control and ASD group.

Additionally, all the children's parents were asked to fill *the Social Responsiveness Scale™ (SRS™)* questionnaire, as a complementary assessment to the ADOS. According to the SRS diagnostic manual, a T-score between 60 and 75 indicates deficiencies in social skills that are associated with mild (high functioning) to moderate Autism Spectrum condition and a score above 76 indicates presence of deficiencies in social skills that are strongly associated with a clinical diagnosis of Autistic Disorder or Asperger's Disorder [60]. Of our six ASD participants, SRS scores were available for five of them. Comparing the scores for ASD participants (M=66.4, SD=7.38) with TD control group (M=40, SD=2.09) showed a significant difference ($t(5) = 7.75$, $P<0.001$) between the two groups.

3.2 Results and Discussions

Overall, we did not find a significant difference between the performances (average recognition accuracy) of the ASD (M=0.71, SD=0.15) and TD (M=0.73, SD=0.17) groups in expression recognition. We ran a 3-way mixed ANOVA on recognition accuracy as the independent variable and group (ASD vs. TD), expression (anger, disgust, fear, happiness, sadness and surprise) and intensity (25%, 50%, 75% and

100%) as dependent variables. The results revealed significant main effects of intensity [F(3,240) = 9.7, P<0.0001] and expression [F(5,240) = 6.5, P<0.0001] with no main effect of group. The three-way interactions between these factors was not significant, nor were the interactions between intensity and group, or between expression and the group.

The ANOVA analysis showed the main effects of expression and intensity but did not show any interaction between these factors by groups. We thus examine these factors in greater depth below, regardless of group. Figure 3-3 shows the recognition accuracy for each expression. The average recognition accuracy was lower for disgust and fear expressions. Our analysis shows that both groups performed significantly worse in recognizing disgust (*M*=0.5, *SD*=0.3) versus the average of other expressions (*M*=0.76, *SD*=0.15) (*t*(16) = -2.7, *P*=0.008). Also, the average performance of groups in recognizing fear (*M*=0.54, *SD*=0.38) was significantly lower compared to the average of other expressions (*M*=0.75, *SD*=0.14) (*t*(14) = -1.8, *P*=0.04).

Figure 3-4 demonstrates the effect of increasing the intensity on recognition accuracy. Our analysis shows that increasing the intensity from 25% to 50% had a significant effect on recognition accuracy. The recognition accuracy with the 25% intensity (M=0.5, SD=0.26) was significantly lower than the accuracy with 50% intensity (M=0.72, SD=0.22) (t(11) = -3.75, P=0.001). Additionally, the recognition accuracy with the 75% intensity (M=0.83, SD=0.14) was significantly higher than the accuracy with the 50% intensity (t(11) = -2.34, P=0.019). We did not find any significant effect of the intensity increment on recognition accuracy from 75% to 100%.

Figure 3-5 and 3-6 show the confusion tables for the ASD participants and TD group, respectively. The figures compare the ability of both groups to recognize expressions and reveal how the demonstrated expressions by Ryan are recognizable by children. It can be seen that disgust and fear are more often mistaken with other expressions.

In general, we did not find a general impairment in the ASD group for recognizing facial expressions of emotion. This could have occurred for several reasons. First, the sample size was small in each group. Second, since all the participants in this study were children with high functioning autism, they had higher levels of cognitive abilities. Thus, it is reasonable that they performed close to their TD peers. However, as mentioned before, the emotion recognition findings in ASD have been inconsistent and there are many studies [15,16] that disagree with any general expression recognition deficiency in ASD children.

Fig 3-3 The average group accuracy is shown for both ASD (blue), TD (yellow), and the average of both groups (green). Each bar represents the average of the group for that specific expression. Error bars are standard errors.

Although we did not find differences between groups, both groups showed significantly lower performance in recognizing disgust and fear expressions. This is consistent with some evidence that people with ASD may have particular deficits recognizing negative basic emotions [29]. For instance, studies have shown lower accuracy in recognizing fear [36,37] and disgust [38]. We found impairment in recognizing fear and disgust in both groups.

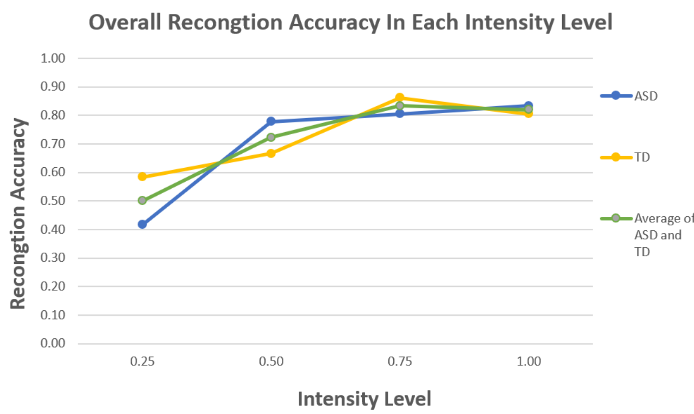


Fig 3-4 The average group accuracy is shown for both ASD (blue), TD (yellow), and the average of both groups in different intensity levels.

ASD	Neutral	Anger	Digust	Fear	Happiness	Sad	Surprise
Anger	0.13	**0.79**	0	0	0	0.08	0
Digust	0.04	0.33	**0.42**	0.08	0	0.08	0.04
Fear	0.17	0	0.04	**0.5**	0	0.29	0
Happiness	0.04	0	0	0	**0.92**	0	0.04
Sad	0.17	0	0	0	0	**0.83**	0
Surprise	0.08	0	0	0.04	0.04	0.04	**0.79**

Fig 3-5. Confusion matrix for the recognition of six basic expressions by ASD group. Rows are ground truth and columns are recognized expressions by ASD participants.

TD	Neutral	Anger	Digust	Fear	Happiness	Sad	Surprise
Anger	0.12	**0.88**	0	0	0	0	0
Digust	0.08	0.21	**0.58**	0.04	0.04	0	0.04
Fear	0.04	0	0.04	**0.58**	0.13	0.13	0.08
Happiness	0.08	0	0.04	0	**0.75**	0	0.13
Sad	0.17	0	0	0.04	0	**0.79**	0
Surprise	0.17	0	0.04	0	0	0	**0.79**

Fig 3-6. Confusion matrix for the recognition of six basic expressions by the TD control group. Rows indicate ground truth and columns indicate the proportion of expression categorizations made by TD participants.

Moreover, there was a significant effect of increasing the intensity on the average recognition accuracy. The effect remained significant as the intensity increased up to 75%. Since no interaction was found between expressions and intensity, it can be concluded that all the expressions demonstrated by Ryan are recognized with 80% accuracy and higher when the expression intensity level reaches 75% and higher.

Finally, Fig. 3 and Fig. 4 show that the recognition rates for most of the expressions are better in higher intensities, and in lower intensities such as 25% which is difficult to recognize the expression, Ryan was successful to effectively conveying the expressions. Fig. 5. shows that in the ASD group, disgust was often mistaken with anger. This low recognition accuracy might be due to inherent deficiency of ASD children in recognizing negative expressions as shown by other studies [37]; however, we did not find any difference between ASD and TD group in recognizing disgust. In general, the only expressions with low recognition accuracies are disgust and fear; besides, according to previous studies [36-38], children are expected to show lower recognition in these expressions. Therefore, Ryan can successfully demonstrate facial expressions and convey facial social cues to children.

Anecdotally, all the children in both groups showed an acceptance toward Ryan when being first introduced to the robot, which confirms that Ryan is an effective tool to be used in future studies of SAR for children diagnosed with autism.

Chapter 4 A Study on the Effect of Thematic Background on Facial Expression Recognition in Children with Autism Spectrum Disorder

In this study, our first hypothesis is that ASD children will generally perform worse than the TD control group in the expression recognition task, especially in negative expressions compared to other studies. Our second hypothesis is that both groups will show higher expression recognition accuracy as the intensity increases. Our third hypothesis is that the recognition accuracy will be higher for matching expression-background combinations (e.g. happiness combined with positive backgrounds) and lower for non-matching combinations (e.g. happiness combined with negative backgrounds) in the ASD group. This means, as suggested by studies [20][53] we expect the participant in the ASD group will attend to the background more than the facial expression; whereas the TD group will ignore the background and focus on the task. Finally, we expect the effect of the background to be more visible in lower intensities.

4.1 Methods

The raw videos of six basic facial expressions were obtained from the MMI facial expression dataset [61]. The videos were then properly cropped and scaled. Figure 4-1 shows the last frame of each facial expression video. The expressions in these videos are demonstrated with 100% intensity level. To create different intensity levels, for each expression, the repetitive neutral frames before the expressions were deleted, as well as the repetitive frames after the expression reached the maximum intensity. Then the number of remaining frames were divided by five to create five levels of intensity (i.e. 20%, 40%, 60%, 80% and 100%). To have the same length for all the videos (i.e. 3 s), neutral and maximum intensity frames were added to the beginning and the end of each video, respectively. Figure 4-2 shows the last frame of happiness with different intensity levels.

Fig 4-1. Basic facial expression. Left to right) anger, disgust, fear, happiness, sadness, surprise [61]

We intended to use different emotionally stimulating images as background images for the facial expressions. It was important for us not to have any other human or facial expressions in the background images to avoid confusion or distraction from the main facial expression in the videos. We also made sure that all the pictures were appropriate for children. We chose the backgrounds from a large scale dataset for image emotion recognition [62] by You et al. and other internet websites. In the dataset, the pictures are categorized in eight emotion categories (i.e. amusement, awe, contentment, excitement, anger, disgust, fear and sadness); however, for our study we did not use these labels. Instead, we categorized the selected images as positive, neutral and negative categories.

Initially 76 images were selected. 10 adults between the age of 23 to 35 were asked to label each picture as negative, positive or neutral and provide a scale between -10 to 10 with -10 as the most negative, 0 neutral and 10 the most positive. Then the z-scores from each participant were compared and three top pictures with the highest rating in each category were chosen. Figure 4-3 shows all the selected pictures and their categories.

Fig 4-2. Happiness facial expression with intensity levels of (left to right) 20%, 40%, 60%, 80% and 100% [61]

In this step, all the videos of six facial expressions (i.e. anger, disgust, fear, happiness, sadness and surprise) with five intensity levels were integrated with each of the nine backgrounds using video editing software. In integrating the videos with the background images, we tried to keep a balance between the size and brightness of the foreground and the background. Figure 4-4 demonstrate the first frame (neutral) of all the video expressions integrated with all the backgrounds.

In this study Ryan was the only assistant present in the experiment room with the participants. We created a remote-control software to control the robot from the observation room. This software follows a scripted scenario and sends commands to the robot to conduct the experiment. This software is also able to show a video/image on the screen in front of the robot. The work by Abdollahi [51] contains more details on the hardware and software of the robot.

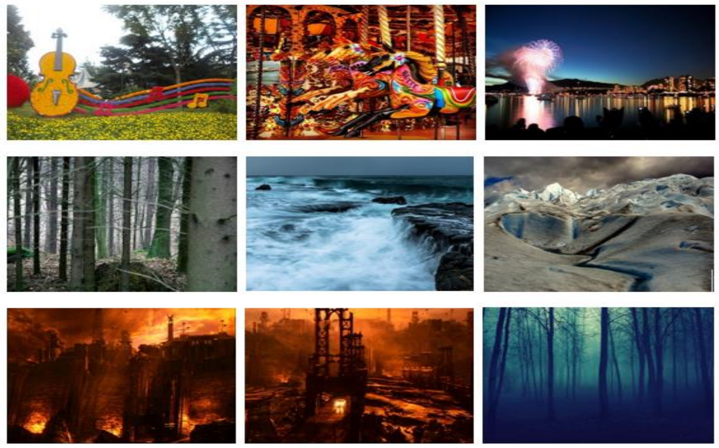


Fig 4-3. Top) Positive backgrounds. Middle) Neutral backgrounds
Bottom) Negative backgrounds [1]

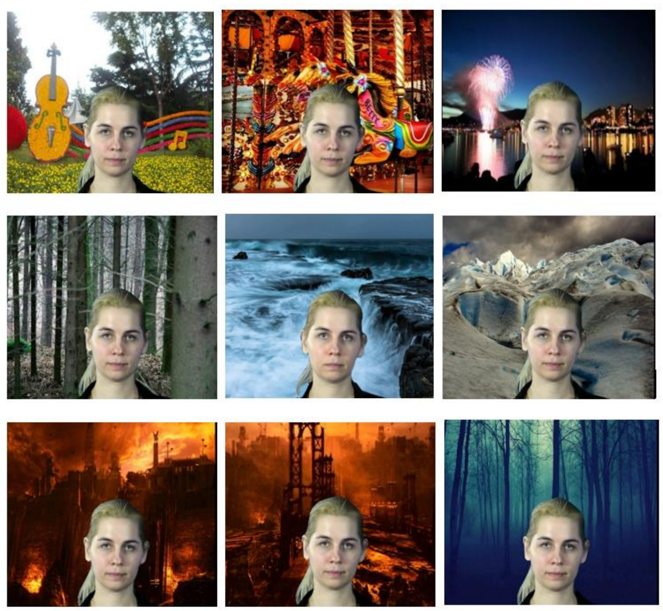


Fig 4-4. First frame of each video integrated with different backgrounds

[1] top right: https://www.scoop.it/t/greeting-cards-quotes/?&tag=Canada+Day+Fireworks
Bottom left and middle: https://wall.alphacoders.com/
Bottom right: https://www.aray.gr/katoxirosi-pneymatiko-dikaiomato-vivlio

Ryan followed a scripted scenario controlled by a researcher in the control room. The research assistant also had the ability to interrupt the scripted conversation and add extra sentences to provide a more natural and flexible experiment for the children. Ryan started the session with a brief self-introduction and by asking some easy questions (e.g. what is your favorite color?) to decrease the participants anxiety and make them feel comfortable with the robot and the environment. Then Ryan explained the study structure and details. The participants had a list of six basic expressions in front of them. Ryan asked each participant to read the expressions out-loud and made sure they knew the meaning of all the expressions. After we confirmed that all the explanations were clear for the participants, Ryan practiced a few tests with them and then the participants continued the rest of the study.

The study took about 60 to 75 mins for each participant. There were six blocks, each block included 45 videos. Participants could take a break between each block. During the study if the participants seemed less motivated and focused, Ryan would have a conversation with them about their different hobbies, as the study was paused. Ryan also encouraged them with positive and motivating phrases. If any one of the participants seemed tired (especially younger children) we would randomly skip one or two blocks to make the experiment shorter for them.

An IRB approval was obtained for this study and all the participants and their parents signed a consent form. The study was conducted in the social robotics laboratory at the University of Denver. We asked each participant to sit on a chair in front of a screen and the robot. Figure 4-5 (right) shows the room setup.

Twelve children 7-15 years old were recruited for the study. Six of them were diagnosed with high function autism by medical diagnosis (Age M=11.54, SD=2.19) (one female and five males) and the other six were typically developing children (Age M=10.34, SD=3.09) (two females and four males).

Fig 4-5. Left) Ryan Companionbot. Right) The Experimental Setup

Additionally, all the children's parents filled out the Social Responsiveness Scale™ (SRS™) questionnaire. According to the SRS diagnostic manual, a T-score above 76 indicates presence of deficiencies in social skills that are strongly associate with a clinical diagnosis of Autism Spectrum Disorder and a score between 60 and 75 indicates deficiencies in social skills that are associated with mild (i.e. high functioning) to moderate ASD [60]. The difference between scores for ASD participants (M=78.83, VAR=183.36) and TD control group (M=45.83, VAR=28.16) was significantly different (t (7) = 5.55, P=0.0004).

4.2 Results and Discussions

We ran a 4-way independent ANOVA on recognition accuracy as the dependent variable and group (ASD vs. TD), expression (anger, disgust, fear, happiness, sadness and surprise), intensity (20%, 40%, 60%, 80% and 100%) and background category (negative, neutral and positive) as the independent variables.

In terms of the main effect, the results showed significant main effects of group [$F(1,2316) = 47.76$, $P<0.001$], expression [$F(5,2316) = 88.38$, $P<0.001$], intensity [$F(4,2316) = 30.82$, $P<0.001$] and category [$F(2,2316) = 3.351$, $P = 0.035$]. The results also revealed the significant two-way interactions of intensity*category [$F\ (8,2316) = 2.27$, $P = 0.02$], group*expression [$F\ (5,2316) = 15.26$, $P < 0.001$] and expression*intensity [$F\ (20,2316) = 7.50$, $P < 0.001$]. The three-way interaction between expression*intensity*category was also significant [$F\ (40,2316) = 1.77$, $P = 0.002$].

Figure 4-6 shows the effect of expressions and groups. Looking at the graph and following by two-way ANOVA on recognition accuracy as the dependent variable and group and expressions as independent variables, the groups are different in overall performance with TD ($M=0.84$, $VAR = 0.028$) group performing better than ASD group ($M=0.76$, $VAR=0.067$) ($F(1,70) = 4.24$, $P=0.04$). Additionally, for the TD group, fear, and for the ASD group, sadness, seem to have the lowest accuracy compared to the other expressions. A T-test revealed a significant difference between the recognition accuracy of fear ($M=0.69$, $VAR=0.026$) and the average of other expressions ($M=0.87$, $VAR=0.005$) ($t(6) = -2.42$, $P=0.02$) in the TD group; and a significant difference between the recognition accuracy of sadness ($M=0.51$, $VAR=0.092$) and the average of other expressions (M=0.81, VAR=0.012) (t(6) = -2.27, P=0.03) in the ASD group. Figure 4-7 and 4-8 show the confusion matrix for ASD and TD groups respectively.

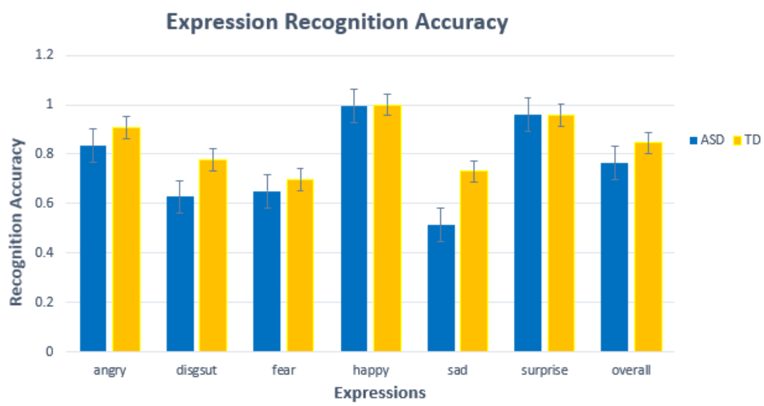


Fig 4-6. The average recognition accuracy for is shown for both ASD (blue) and TD (orange) for each expression. Each bar represents the average of the group for that specific expression. Error bars are standard errors.

Figure 4-9 demonstrates the effect of intensity on expression recognition accuracy. Both groups showed significant improvement in recognition accuracy when the intensity increased from 20% (M=0.67, VAR=0.14) to 40% (M=0.81, VAR=0.092) (t (71) = -3.69, P=0.0002).

ASD	Anger	Disgust	Fear	Happiness	Sadness	Surprise
Anger	**0.83**	0.05	0.01	0	0.08	0.02
Disgust	0.31	**0.63**	0	0	0.04	0.01
Fear	0.02	0.12	**0.65**	0	0.18	0.03
Happiness	0	0	0	**1.00**	0	0
Sadness	0.06	0.16	0.25	0	**0.51**	0.01
Surprise	0.01	0	0.03	0	0	**0.96**

Fig 4-7. Confusion matrix for the recognition of six basic expressions by ASD group. Rows are ground truth and columns are recognized expressions by ASD participants.

TD	Anger	Disgust	Fear	Happiness	Sadness	Surprise
Anger	**0.91**	0.05	0.01	0.00	0.01	0.03
Disgust	0.15	**0.78**	0.04	0.02	0.00	0.02
Fear	0.04	0.06	**0.70**	0.00	0.18	0.02
Happiness	0.00	0.00	0.00	**1.00**	0.00	0.00
Sadness	0.04	0.05	0.17	0.00	**0.73**	0.01
Surprise	0.00	0.00	0.04	0.00	0.00	**0.96**

Fig 4-8. Confusion matrix for the recognition of six basic expressions by TD group. Rows are ground truth and columns are recognized expressions by TD participants.

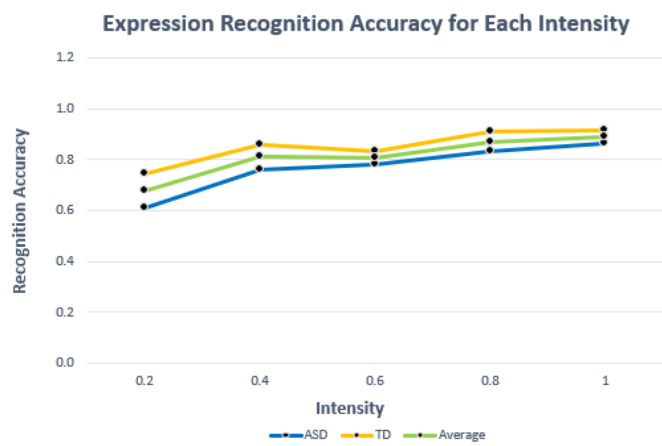


Fig 4-9. The average recognition accuracy is shown for both ASD (blue), TD (yellow) and average of both groups (green) in each intensity.

As mentioned earlier, the ANOVA analysis showed the main effect of the background category and its interaction with all the variables except the group factor, which means both groups had the same pattern of performance depending on the background category. Therefore, for further analysis of the effect of background we did not separate the groups. Figure 4-10 shows the main effect of category. Running the T-test, there is a significant difference between the recognition accuracy of videos with negative (M=0.83, VAR=0.008) and positive (M=0.77, VAR=0.014) (t (11) = 3.09, P=0.005) backgrounds.

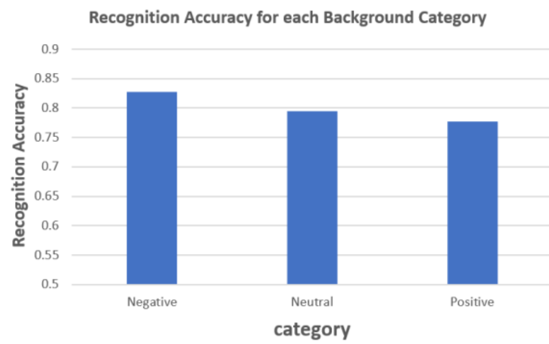


Fig4-10. The average recognition accuracy for each category of background images.

To find the point where the significant effect of category lays within the three-way interaction of category*intensity*expression, we first broke down the analysis by studying the effect of category on each intensity. Figure 4-11 demonstrates the effect of category in each intensity. Running a T-test, the only considerable effect of background was found in 20% intensity, in which the recognition accuracy for the negative background (M=0.75, VAR=0.135) was significantly higher than for the positive background (M=0.58, VAR=0.199) (t (119) = 2.40, P=0.008). Therefore, we studied the effect of background with 20% intensity on each of the expressions. Fig. 10 shows the graph of the recognition accuracy for each of the expressions with different background categories with 20% intensity.

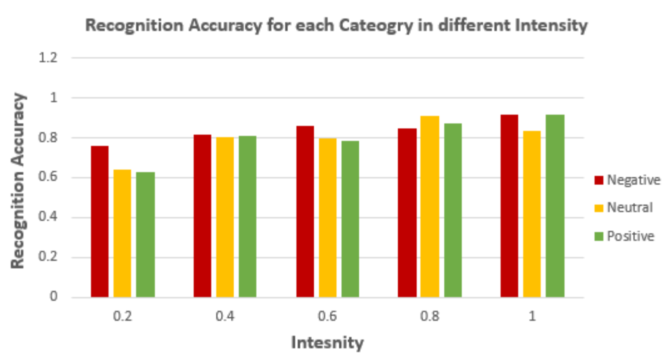


Fig 4-11. The recognition accuracy for each background category in different intensity levels.

Figure 4-12 suggests that the difference lays within the fear and sadness expressions. T-test analyses confirmed that for the sadness expression the recognition accuracy of videos with negative backgrounds (M=0.652, VAR=0.12) was significantly higher than for videos with the positive backgrounds (M=0.257, VAR=0.15) (t (20) = 2.60, P=0.008).

The same effect was found for the videos of fear expression between the negative (M=0.696, VAR=0.16) and positive backgrounds (M=0.125, VAR=0.035) (t (14) = 4.25, P=0.00039).

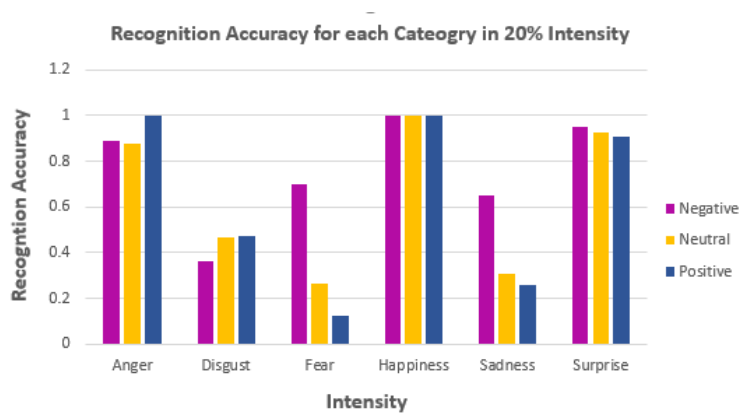


Fig 4-12. The recognition accuracy for each background category and each of the expressions in 20% intensity levels.

Chapter 5 Toward Adaptive Socially Assistive Robotic for Children with Autism Using Reinforcement Learning

SAR has received many attentions in the field of Autism research [24] because children with ASD show interest and comfort toward the robots [23]. In this field, social robots serve different purposes. In some studies they appear as a guide or facilitator to engage children in a study or a therapy session and encourage them to interact and focus throughout the session, normally in these studies the instructions are presented by a human teacher or a computer software [63]. While in other studies robots are used as the main teacher or therapist and convey the lessons and materials such as language learning applications and they are expected to be able to replace a human tutor [64][65]. Generally, such tutoring systems are expected to adapt to the students' input and their needs, to provide help in form of hints or instructions as a human teacher or therapist would do. There is another category of studies that use robots as a tool to present the experiment or game materials. An example of these studies is using robot to evaluate facial expression recognition or imitation ability of children with ASD [49] or using the robots to run intervention sessions for children with ASD to improve their social skills [66].

A common factor in this last category of social robot studies or generally most of the studies in facial expression is participants are exposed to one method out of all the possible methods. For example, in a facial expression recognition study, the facial expressions can be presented to participants in the form of images, videos or using a humanoid robot with realistic [34] or simplified [36] expressive face. Normally each of these methods lead to different conclusions, for example there are different discussions on facial expression recognition baseline of children with ASD, or more importantly the outcome of the intervention sessions might be different using each of the available methods.

Consequently, in this pilot study we designed an adaptive human robot interaction session, using RL, in which the participants were exposed to different sets of stimuli that were four basic facial expressions (i.e. happiness, sadness, disgust and fear) with three different methods (i.e. images, videos and robots). Our main goal was to explore whether we can customize the session based on individual's performance and preference in response to different methods of presenting facial expressions within an adaptive human robot interaction session using RL. To accomplish this task, we first observed whether presenting the facial expressions with different methods result to different facial expression imitation response from children with ASD. Second, we explored if there is one method that results to the best facial expression imitation response for all the expressions., and third, to explore whether the effective method is the same among all individuals or it is different for each individual. Fourth, if the adaptive algorithm can find the most effective method in terms of performance and preference for each individual and is able to adjust and customize the session for each individual based on the feedbacks from the participant and the researcher.

There are books and papers that explain about the theory of RL and its methods. In the next chapter we review RL using some of these resources [67][68].

5.1 Reinforcement Learning (RL)

In RL, an agent tries to maximize the accumulated reward by interacting with its environment over its lifetime. Most of the time, the tasks run in episodes, which means the task is restarted after the end of each episode. In this setting the learning agent tries to maximize the total reward per episode. For the non-episodic or continuous tasks either the average reward over the whole lifetime or a discounted return is considered. In RL problems, the learning agent and its environment are modeled being in a ***state*** (***$s \in S$)*** and can perform ***actions ($a \in A$)***. Each of these variables can be discrete, continuous and multi-dimensional. The states contain all the information related to current situation and will be sued to predict future states. The actions are the choices made by the agent, based on the states. ***Rewards (R)*** are basis for evaluating the choices. In RL everything inside the agent is completely known and controllable by the agent; everything outside may or may not be completely known. A ***policy (л)*** is a stochastic rule, by which the agent selects actions as a function of states.

As discussed above, the goal of RL is to find a mapping from states to actions, called policy, that picks actions in given states maximizing the cumulative expected reward. The ***return*** is the function of future rewards that the agent seeks to maximize. It has several different definitions depending on the nature of the tasks and whether there needs to be any ***discount*** for the delayed rewards. There are several ways to define a return function. One of the most conventional return functions is defined as below:

$$R_t = \sum_{k=0}^{T} \gamma^k r_{t+k+1} \quad (5.1.1)$$

where, R_t is the return, r_t is the reward at the step t and γ is a number between 0 and 1 as the discount factor, with the possibility of $T = \infty$ or γ =1 (but not both).

The RL agent needs to discover the relations between the states, actions and the rewards. Therefore, exploration is required. In contrast to supervised learning, the learner must first discover its environment and is not told the optimal actions needed to be taken. To gain information about the states, actions, rewards and their relations, the agent needs to explore previously unused actions or the actions that is not certain about. The algorithm needs to decide if it should stick to actions with high reward or to explore and possibly discover new state-action pairs with higher reward. The problem is commonly known as the ***exploration-exploitation trade-off***.

Almost all the RL algorithms are based on estimating ***value functions*** of states or state-action pairs. Value functions are defined with respect to particular policies. Value of a state under a policy, denoted as $V^{л}(s)$, is the expected return when starting in s and following л thereafter. $V^{л}(s)$ is defined as below:

$$V^{л}(s) = E_{л}\{R_t \mid s_t = s\} = E_{л}\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} | s_t = s\} \quad (5.1.2)$$

where $E_{л}\{\,\}$ is the expected value when the agent follows policy л. We call $V^{л}$ the ***state-value function*** for policy л. Similarly, we define the value of taking action a in state s under a policy л, denoted $Q^{л}(s, a)$, as the expected return taking action a from state s and following policy л thereafter. $Q^{л}$ is called ***action-value function***:

$$Q^{л}(s, a) = E_{л}\{R_t \mid s_t = s, a_t = a\} = E_{л}\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} | s_t = s, a_t = a\} \quad (5.1.3)$$

Both of these functions can be estimated from the experience. The ***optimal value function*** is the largest expected return assigned to a state or state-action pair by a given policy. Any policy that its value function is optimal is an ***optimal policy***.

There are variety of methods in RL algorithms are based on value function that attempt to estimate the optimal value function for state or state-action pair. These methods can be classified into three classes: 1) Dynamic Programming-based methods 2) Monte-Carlo methods and 3) Temporal Difference learning such as Q-Learning and State, Action, Reward, State, Action (SARSA).

Dynamic programming methods require a model of the reward function to calculate the value function. The model does not necessarily need to be predetermined but can also be learned from data. Such methods are called *model-based*. Monte-Carlo methods use sampling to estimate the value function. The Monte-Carlo methods are *model-free.* These methods are episodic and during each episode a certain policy is running. The frequencies of transitions and rewards are kept track of and are used to estimate the value function. Unlike the Monte-Carlo methods, Temporal Difference methods do not have to wait until an estimate of the return is available to update the value function. Rather, they use temporal errors and only have to wait until the next time step. The temporal error is the difference between the old estimate and the new estimate of the value function, integrated with the reward received in the current sample. In contrast to dynamic-programming methods, they do not need a model and only take into account the sampled successor state. In this setting, the value function can be only estimated from sampled transitions (states and actions).

The value state-value function is updated using the formula below:

$$V(s) = V(s) + \alpha\,[\,r + \gamma\,V(s') - V(s)] \qquad (5.1.4)$$

This is the simplest method, known as TD (0), where s is the current state, r is the observed reward for the current state, α is the step-size or learning-rate and *s'* is the next state. The equivalent temporal difference learning algorithm for state-action value function is SARSA which stands for State, Action, Reward, State, Action, represents the elements of quintuple of events, $(s_t, a_t, r_{t+1}, s_{t+1}, a_{t+1})$ that make up transition from one state-action pair to the next. The corresponding formula is defined as below:

$$Q(s,a) = Q(s,a) + \alpha\,[\,r + \gamma\,Q(s',a') - Q(s,a)] \qquad (5.1.5)$$

SARSA is an *on-policy* method, which means it collects sample information from the environment using the current policy. As a result, exploration should be embedded into policy and determines the speed of policy improvement. In this method we continually estimate $Q^{л}$ for the policy л, and at the same time change л toward greediness with respect to $Q^{л}$. SARSA converges with probability of 1 to an optimal policy and action-value function as long as all the state-action pairs are visited an infinite number of times and the policy converges to the greedy policy.

One of the *off-policy* TD algorithm, is Q-Learning, within which, the learned action-value function, Q, directly approximates the optimal action-value function, Q^*, independent of the policy being followed. The policy still has an effect in that it determines which state-action pairs are visited and updated.

The formula for Q-learning algorithm is as below:

$$Q(s,a) = Q(s,a) + \alpha \left[r + \gamma \, max_{a'} Q(s',a') - Q(s,a) \right] \qquad (5.1.6)$$

Briefly, Q-learning directly learns an optimal policy, whilst SARSA learns a near-optimal policy while exploring. To be able to learn an optimal policy using SARSA there need to be an algorithm to decay exploration (i.e. decay ϵ in ϵ-greedy action choice). Additionally, SARSA allows for possible penalties from exploratory moves, while Q-learning ignores it. This result to SARSA acting as a more conservative algorithm avoiding dangerous (i.e. high negative reward optimal paths).

5.2 Methods and Parameters

To design an adaptive human robot interaction session and examine our hypotheses we used RL. in this section we explain about the algorithm design, choice of parameters and facial expression imitation materials.

5.2.1 Facial Expression Imitation Materials

One of the goals of this study was to expose children with ASD to different presentations of facial expressions to observe if there is any differences in terms of facial expression imitation performance and preference that results from different methods. To realize this goal, we tested four facial expressions that were disgust, fear, happiness, and sadness. Additionally, we used three different methods of presenting the facial expressions to children. The methods we used were images of facial expressions demonstrated by a human, videos of facial expression demonstrated by a human and facial expressions demonstrated on the humanoid social robot's face, Ryan.

The videos of facial expressions were obtained from the MMI database [6]. The videos were then cropped and scaled to remove the extra part of images. All the expressions in the videos were demonstrated with 100% intensity, starting from neutral expression, and progressing to 100% intensity level. All the videos ended with the last frame staying on the screen. Since the second study did not show any effect of background in 100% intensity and in this study all the imitation materials are presented with 100% intensity, we did not use any of the thematic backgrounds in this study, so the videos were the same videos used in the second study without thematic backgrounds integrated with them. We used the last frame of each video as the image of that expression. Additionally, we used the humanoid social robot, Ryan, to demonstrate the expressions on its face. Figure 5-1 shows the images and the last frame of videos for facial expressions. Figure 5-2 shows the facial expression demonstrated by Ryan.

Fig 5-1. Four basic facial expression. Left to right) disgust, fear, happiness, sadness, [61]

Fig 5-2. Expression demonstrated by Ryan. Left to right) disgust, fear, happiness, sadness

5.2.2 Reinforcement Learning Algorithm Parameters

The goal of our RL is using the human robot interaction to find the effective method in terms of performance and preference of each individual for each expression and adjust the session based on the gained information from the interacting with the participant. For this application we choose temporal difference method because first, there is not any available model of the interaction between the participant and the robot prior to the study, second, the session needs to be updated online based on the gained information and reward during the interaction.

During the interaction the algorithm should update the policy based on the gained reward. We define the reward function as the integration of imitation performance and the participant's preference with given priority to the imitation performance score. It says, we defined two scores. The first score is the imitation score (r_i) given by a human supervisor based on how well the expression is imitated. The score range for the imitation score is defined as follow: -1 for not imitation, 0 for poor imitation, 1 for average imitation and 2 for good imitation. The second score is the preference score (r_p) which is given by the participants which is defined as follow: 0 if they do not like the expression presentation and 1 if they like the expression presentation. The formulated reward (T based on these two scores is defined as below:

$$r = \left[r_i + r_p * \frac{(r_i+1)}{3}\right] * 10 \tag{5.2.1}$$

this formulation sums the imitation reward and the scaled preference reward based on the imitation score. It says, if the imitation score is higher the effect of preference is taken more into account, otherwise, if there is poor imitation the effect of preference is decreased.

For this application, we prefer SARSA over Q-learning because we expect the agent to follow exact policy and take into account all the gained rewards (including negative rewards) and adjust the session and the policy accordingly based on the gained rewards. In order to avoid over-exploration and to converge to steady choices at the end of the session we manually tune the ϵ parameter for ϵ-greedy algorithm. Therefore, we used the SARSA equation 5.1.5 to update the state-action value function in this application we define the expressions as the states and the methods as the actions taken in each of the states (i.e. in total 4 states and 3 actions). During the experiments, we choose the states randomly with uniform distribution so that participants will be equally expose to all the expressions. The algorithm chooses the actions for each state, based on exploration or exploitation, it either can discover new actions or can continue with the action that has the highest reward based on its current information.

The stop criterion is the number of iterations (72) that is set based on some simulation results. This number of iteration seems to be enough for the algorithm to explore and decide for the most optimal policy, as well as, not over-tiring the participants during the session. The iterations were divided to four sections. The first section is the initialization part (including 13 iterations) which displays all the stats and the actions in a sequence to the participants to make them familiar with the experiment and to make sure all the state-action pairs have been visited and gained a reward at least once. This approach needs to be taken due to low number of iterations otherwise some of the state-action pairs might remain unseen through the interaction. the second section includes 12 iterations with 0.5-greedy algorithm allowing for high exploration. Each of the remaining two sections include 24 iterations and are 0.25-greedy and 0.1-greedy respectively.

We set the α parameter to one. Although in most studies it is preferred to decay the learning rate (α) toward the end of the experiment, in this setup due to nature of the study we prefer to keep α constant to be able to detect any changes in the reward function at any point of the study. In this design, each of the states are generated randomly and they are independent. So, each of the expressions updates their own state-action function, and the only connection they have is the impact of the participants. Due to independence of the expressions we are interested in immediate reward rather than future rewards, therefore, we set the discount factor to a low number, 0.2, to discount the future rewards and only allow the compensation for the impact of expression of each other and on the dynamic of the session.

Before running the real application, we tested all the parameters using simulation. We set the rewards to different values and observed the results of simulation to tune the parameters finely and decide about the best reward formulation. Observing the simulation results it was the most important for us that with set of parameters the algorithm can make the different actions distinguishable.

For the pilot study, we recruited two ASD participants. A 13-year-old female and a 13-year-old male participant both with formal diagnosis of ASD. An IRB approval was obtained for this study and all the participants and their parents signed a consent form. The study was conducted in the social robotics laboratory at the University of Denver.

The session started with Ryan greeting the participants and explaining about the study. A researcher was present in the room to score the facial expression imitations demonstrated by participants. Then the facial expression materials were displayed with different methods based on the different phase of the RL algorithm. The expressions were displayed either on the robot's face or in the form of video or image on the tablet on Ryan's chest. Before each expression displayed the researcher told the participants where to look. After each expression the researcher asked the participant to imitate that and state if he/she liked the method or not. The session finished when the algorithm reached the 72th iteration and Ryan appreciated the participant's effort and time.

5.3 Results and Discussion

As discussed before, a SARSA algorithm considers all the gained rewards (including the negative reward) to update the policy. In the exploration phase the algorithm faces state-action pairs that result to negative rewards (e.g. in our case "no imitation" results to large negative reward). Considering this fact, one of the methods to examine a successful SARSA is to investigate the value function. Figure 5-3 shows the average accumulative state-action value function for the all states and the actions. Despite the low number of iterations and the exploratory moves, the algorithm successfully increased accumulative rewards for each of the participants, which explains the success of the algorithm in finding the effective methods and adapt the session based on those. Figure 5-3 demonstrates the accumulative average state-action value function over the iterations for each of the participants. Figure 5-4 demonstrate the accumulative average state-action value function over the iteration for each of the expressions.

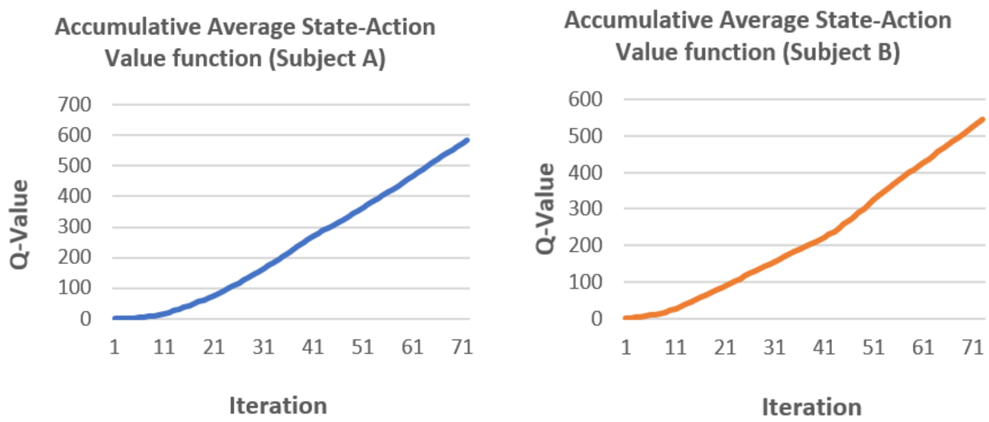


Fig 5-3. The accumulative average state-action value function (Q-function) subject A (left) subject B (right)

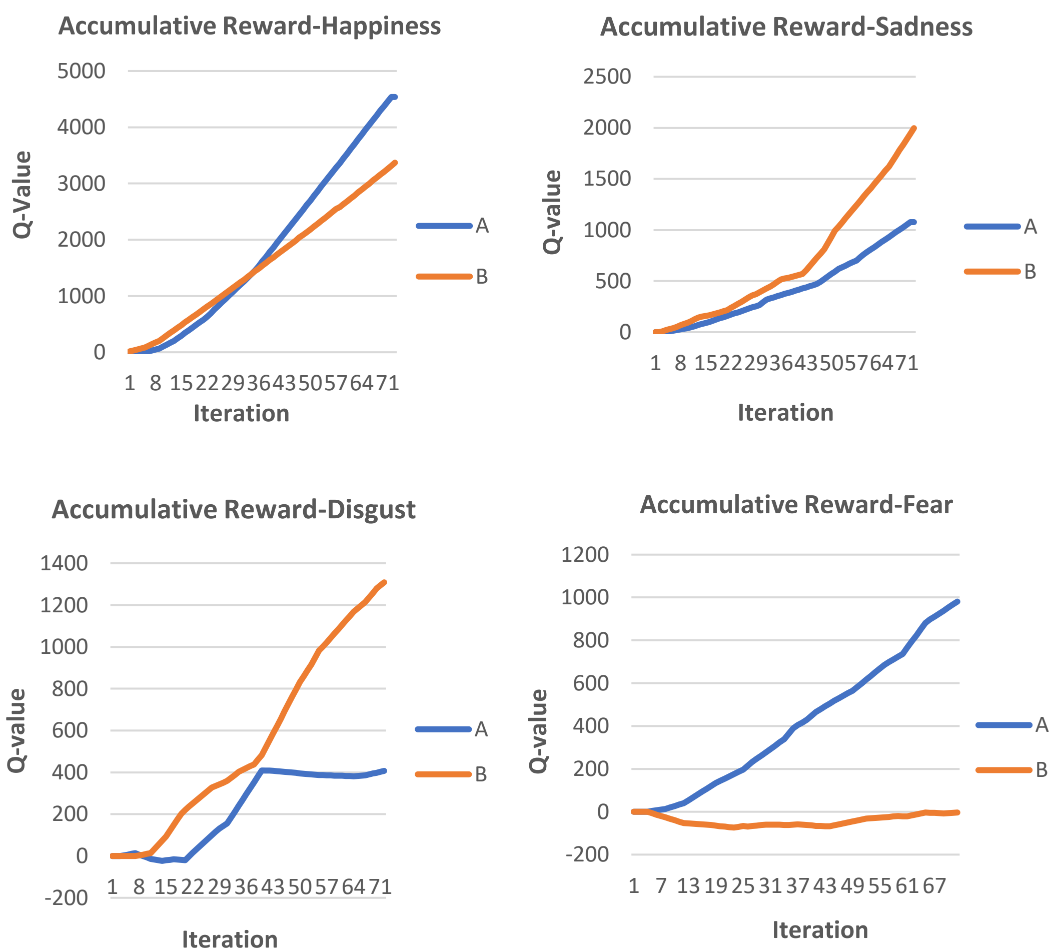
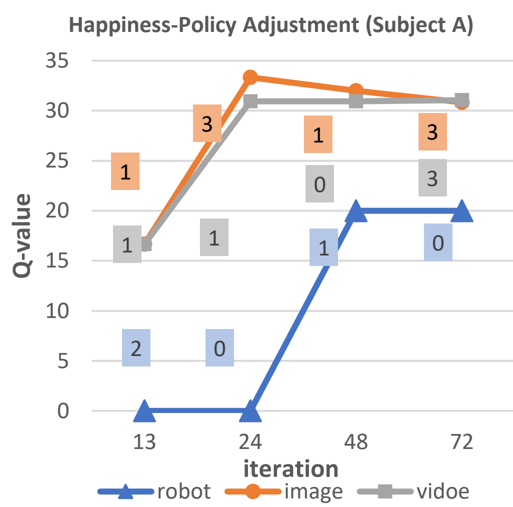


Fig 5-4. The accumulative average state-action value function (Q-function) for each expression

As mentioned earlier the goal of this study was to design and use an adaptive human robot interaction in a facial expression imitation session to study the effect of different method and to see if the RL algorithm is able to detect and address these differences based on rewards and feedbacks received from each individual. To answer these questions, we examine the state-action value function for each expression-method combination.

Figure 5-5 shows the exact value of state-action value function at the end of each quadruple section (i.e. initialization, 0.5-greedy, 0.25-greedy and 0.1-greedy) for each of the methods. And the number above each line shows that how many times that method was used during the next section.



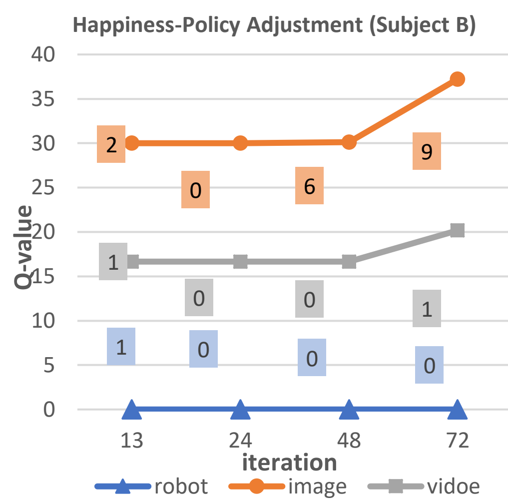


Fig 5-5. Policy adjustment for each expression based on the gained reward, Subject A (left) subject B (right)

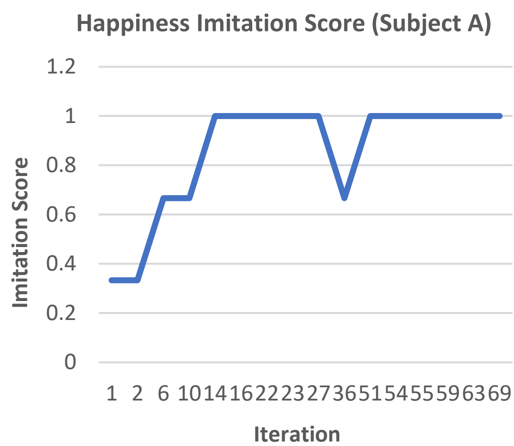
Figure 5-5 demonstrates how the algorithm reacts to positive and negative rewards given by the participants and the researcher. The first section (i.e. up to 13th iteration) is the initialization phase and common between all the expressions, after this phase, the next two phases spend respectively, half of the time and one-fourth of the time exploring and the rest of the time following the optimal policy based on the Q-function values available up to that point. In the last phase which is less exploratory we expect the algorithm behaves more accordingly based on the Q-function values, which is exactly what the graphs are demonstrating.

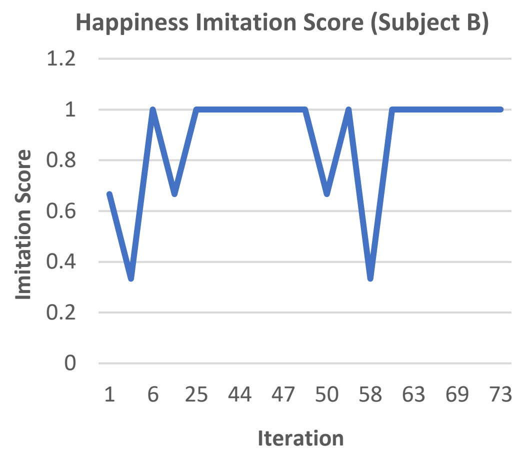
An interesting phenomenon happens in Figure 5-5 for Subject B in sadness expression. Right before the last phase (48th iteration), the video Q-value is much higher than the robot Q-value; however, the algorithm repeats the robot action twice while it repeats the video action just once. We explored the reason for this phenomenon by looking the closer look at the data. In the 49th iteration the combination of sadness-video happens and due to receiving a lower reward, the new update of Q-function drops the Q-value of this combination to one, then a combination of sadness-robot happens in the 52nd iteration which seems to be an exploratory move. This combination receives a high reward resulting the algorithm to choose this combination for the next turn of sadness expression. Another phenomenon is observed in the last phase for Subject B in disgust expression. The performance drops no matter which method is used. The algorithm seems to choose the most optimal action, which is the image with less drop compared to video. One of the reasons that all the actions receive negative rewards for the disgust expression might be due to exhaustion of the subject.

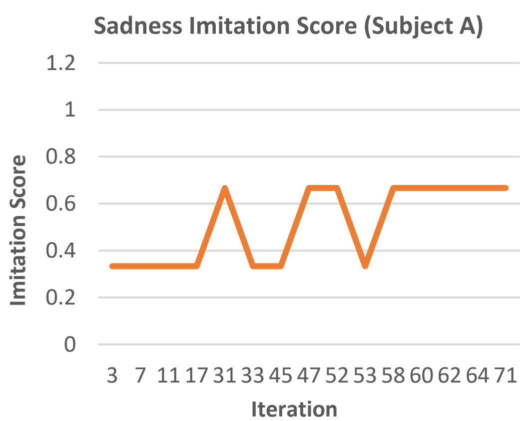
We ware were able to observe these effects because the learning rate was set to one so we can detect any changes even toward the end of the session where the algorithm is less exploratory. In contrast to many RL studies, the state-action value function (i.e. Q-function) for this application does not reach to a steady number and sudden changes are detected at any point of the session. For our purpose it is not a drawback because we want to adapt the session based on the participants' performance and preferences at any time of the session and recognize the meaningful behavioral patterns of participants. For example, we can explain that the sudden drop of the Q-values for Subject B in all the expressions except happiness is due to exhaustion or losing the motivation toward the end of the study which matches to the Subject's mood and comments observed by the researcher. Additionally, the sudden increase of the value function for the sadness-robot combination can be an indicator that the subject started feeling more comfortable with the robot toward the end of the session, which could not be detectable using a usual setting.

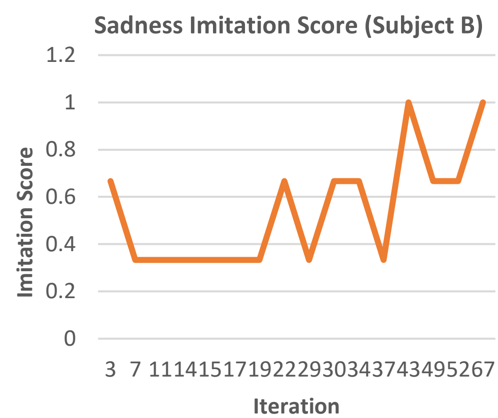
Looking at Figure 5-5, we can observe each participant had different performance and preference in imitating facial expressions in response to different methods. These differences are not only obvious between the participants, but also obvious among the expressions for each participant. All of the differences and changes were successfully discovered by the algorithm and the session was accordingly adjusted and customized for each of the participants based on their performance.

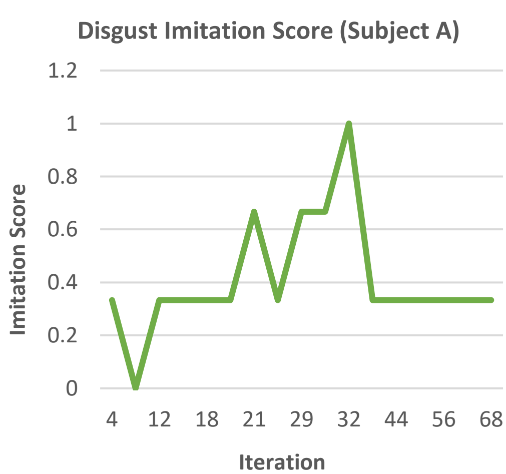
Figure 5-6 demonstrates the raw imitation score for each participant and each expression, given by a researcher.

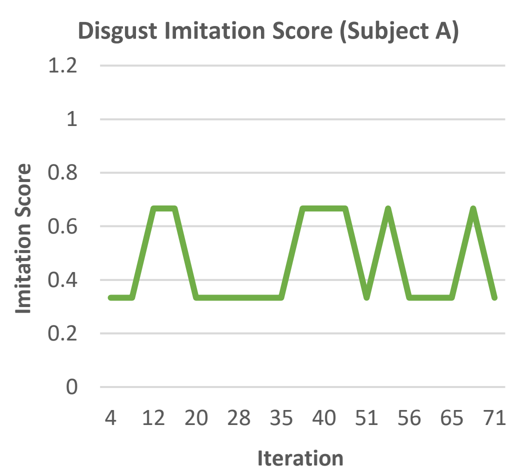

Happiness Imitation Score (Subject A)
1.2
1
0.8
0.6
0.4
0.2
0
Imitation Score
1 2 6 10 14 16 22 23 27 36 51 54 55 59 63 69
Iteration


Happiness Imitation Score (Subject B)
1.2
1
0.8
0.6
0.4
0.2
0
Imitation Score
1 6 25 44 47 50 58 63 69 73
Iteration


Sadness Imitation Score (Subject A)
1.2
1
0.8
0.6
0.4
0.2
0
Imitation Score
3 7 11 17 31 33 45 47 52 53 58 60 62 64 71
Iteration


Sadness Imitation Score (Subject B)
1.2
1
0.8
0.6
0.4
0.2
0
Imitation Score
3 7 11 14 15 17 19 22 29 30 34 37 43 49 52 67
Iteration


Disgust Imitation Score (Subject A)
1.2
1
0.8
0.6
0.4
0.2
0
Imitation Score
4 12 18 21 29 32 44 56 68
Iteration


Disgust Imitation Score (Subject A)
1.2
1
0.8
0.6
0.4
0.2
0
Imitation Score
4 12 20 28 35 40 51 56 65 71
Iteration

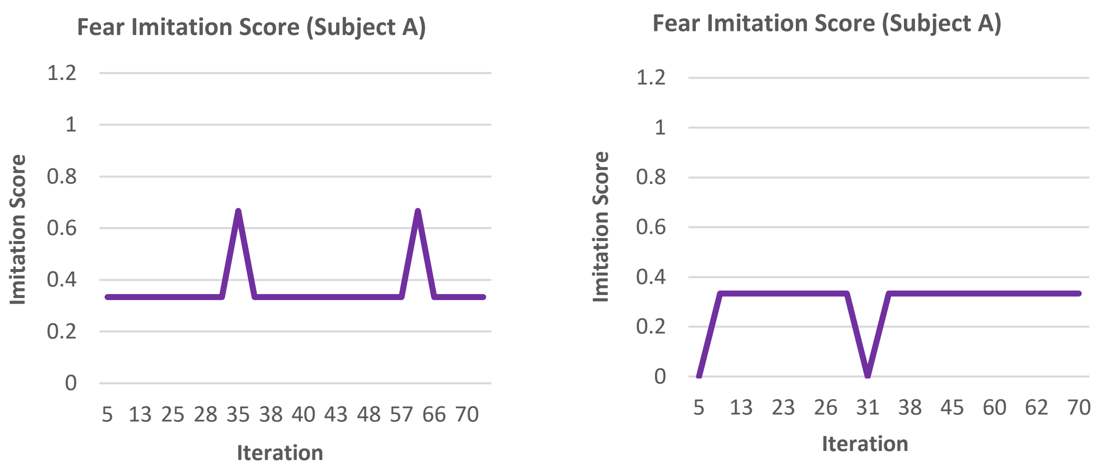


Fig 5-6. Imitation scores for each expression, Subject A (left) subject B (right)

Chapter 6 Conclusion and Future Work Direction

6.1 Conclusion

This thesis consists of three studies on facial expression recognition and imitation by children with ASD. The pilot study on facial expression recognition using Ryan, presented a comparative pilot study on how children diagnosed with ASD compared to their TD peers can recognize expressions demonstrated by a rear-projected humanoid robot. It also presented the effect of using different intensities on the expression recognition accuracy. It showed in a group of 12 participants, there was no significant impairment in the ASD group compared to the TD group in recognizing the basic facial expressions on average. Moreover, a strong impairment for both groups was found in recognizing fear and disgust. Additional analysis of the results showed that increasing the intensity from 25% to 50% and to 75%, significantly affected the expression recognition accuracy in both groups.

One lesson learned from this research is that a general assumption of impairment in expression recognition for children with ASD should not be assumed when designing SAR-based therapies for them. It says the robots used for Autism therapy can be the same as the robots for TD children, in terms of facial expressions complexities. The robots for children need to have more clarity on fear and disgust expressions because both groups seem to confuse these two expressions with other expressions especially in lower intensities. The findings of this study therefore support the results of other studies such as [23] that have shown individuals with ASD are overall successful in matching expressions in still images. Also, the capability of Ryan to successfully convey all the six basic facial expressions and its potential to be used in future studies of SAR was investigated. Furthermore, this study did not observe any significant expression misrecognition due to defective or confusing expression demonstration by Ryan. A study [69] that used the same setup for TD adults showed that the recognition accuracy of disgust and fear is not significantly different from other expressions. Therefore, in this study we can conclude that fear and disgust expressions are less recognized due to difficult nature of the expressions. Moreover, Ryan provides flexibility to redesign and customize facial expressions, from simplistic non-sophisticated expressions to nearly realistic human-like expressions, which make it a great choice for further SAR studies. The result of this study is similar to another facial expression recognition study [42] using humanoid robot, Zeno.

The study on facial expression recognition using thematic backgrounds focused on how children diagnosed with ASD compared to their TD peers recognize facial expressions integrated with thematic backgrounds. A set of facial expression videos with six basic expressions, five intensity levels and nine different background images in three categories was presented to 12 participants. As expected in the first hypothesis, we found that the ASD group showed lower performance than the TD children on average. In the ASD group, sadness had the lowest recognition accuracy, whereas in the TD group fear was the least recognized expression. Additional analyses showed that increasing the intensity from 20% to 40% significantly affected expression recognition accuracy in both groups, which supports the second hypothesis. Moreover, in partial support of the third hypothesis the study found the different effect of negative and positive backgrounds in both groups in fear and sadness expressions with the intensity of 20%. However, the effect was not significantly different between groups and was not visible for all the expressions, which does not fully support the third hypothesis. Finally, the effect of background happened at 20% intensity, which was anticipated as the fourth hypothesis.

This study was able to find differences in overall performance between the groups and the effect of intensity; therefore, the lack of significance between an effect of context on each group cannot seem meaningful. It shows that children with ASD used the background to inform their expression judgments in the same manner as TD kids. Additionally, the effectiveness of negative backgrounds was more visible because there are more negative expressions that are consistent with the negative backgrounds. Whereas, it is hard to find the effect of positive backgrounds on the consistent positive expression (i.e. happiness) because the recognition is perfect. Briefly, it is not the negative nature of the negative backgrounds that is important; it is the congruency between the background and the expression that matters.

The effectiveness of background is visible only when the intensity is low (i.e. 20%) and the expressions is less recognizable; it shows the importance of the effect of intensity. In this study, all of the children could easily understand the instructions provided by Ryan and could conveniently follow the robot. The children occasionally had questions for Ryan (i.e. the robot's age or favorite activity) that is, an indicator of showing interest towards the robot.

Finally, the last study explored the effect of using a RL-based active learning in human robot interaction to identify and adapt based on the individual differences in expression imitation in response to different facial expression presentation methods. Four facial expressions (i.e. disgust, fear, happiness and sadness) were presented with three different methods (i.e. image, video and robot) to be imitated. One female (Age = 13) with ASD and one male (Age = 13) with ASD participated in this study. The result of this pilot study showed individuals with ASD have different performance and preference in response to different methods of presenting the facial expressions. It showed each individual perform differently and for one individual, the effective method(s) are different for each of the expressions.

In this study we observed that a flexible RL method is able to learn the individual differences and adjust the session based on the findings through interaction with the environment. The algorithm in this study was specially designed to detect any changes even in the last phase of the session. It allows for more knowledge on every aspect of individual's preferences. One important lesson from this study is that different setups and materials result to different outcome for individuals, therefore, in designing human robot interaction session it is important to consider individual's differences and preferences to gain the best result. The result of this research is three papers listed as below:

1. Askari, Farzaneh, Huanghao Feng, Timothy D. Sweeny, and Mohammad H. Mahoor. "A Pilot Study on Facial Expression Recognition Ability of Autistic Children Using Ryan, A Rear-Projected Humanoid Robot." (RoMan 2018).
2. Askari, Farzaneh, Abdollahi, Hojjat, Timothy D. Sweeny, and Mohammad H. Mahoor. “A Study on the Effect of Thematic Background on Facial Expression Recognition in Children with Autism Spectrum Disorder.” (FG 2019) -submitted
3. Askari, Farzaneh, Abdollahi, Hojjat, Timothy D. Sweeny, and Mohammad H. Mahoor. “Adaptive Socially Assistive Robotic for Children with Autism Using Reinforcement Learning.” (IROS 2019) -under preparation

6.2 Future Work Direction

Finally, the feature work direction would be recruiting more participants to run a more precise and extensive facial expression recognition study using different methods of presenting facial expressions (i.e. images, video, robot) to address facial expression recognition deficiency in children with ASD and to compare the results of different methods. Additionally, more ASD participants can be recruited for the adaptive human-robot interaction study as well as TD participants to compare both groups. Also, other methods of scoring the facial expression imitations can be used to improve the results and look more deeply into the facial expression imitation baselines too. Finally, we can improve the RL study by adding another state that takes care of participants’ motivation. This state happens when the average total reward drops drastically in numerous consecutive iterations which are a sing of low motivation or exhaustion.

This state will be dedicated to increase the subjects’ motivation by using methods such as a conversation between the subject and Ryan.

Bibliography

[1] S. J. Rogers, “Developmental regression in autism spectrum disorders,” *Mental Retardation and Developmental Disabilities Research Reviews*. 2004.

[2] American Psychiatric Association, “Diagnostic and Statistical Manual of Mental Disorders, 5th Edition (DSM-5),” *Diagnostic Stat. Man. Ment. Disord. 4th Ed. TR.*, 2013.

[3] S. Ozonoff, K. Heung, R. Byrd, R. Hansen, and I. Hertz-Picciotto, “The onset of autism: Patterns of symptom emergence in the first years of life,” *Autism Research*. 2008.

[4] S. E. Bryson *et al.*, “A prospective case series of high-risk infants who developed autism,” *J. Autism Dev. Disord.*, 2007.

[5] S. Baron-Cohen, *Mindblindness: An essay on autism and theory of mind*. 1995.

[6] S. Baron-Cohen, H. A. Ring, E. T. Bullmore, S. Wheelwright, C. Ashwin, and S. C. R. Williams, “The amygdala theory of autism,” *Neuroscience and Biobehavioral Reviews*. 2000.

[7] S. Ozonoff, B. F. Pennington, and S. J. Rogers, “Are there Emotion Perception Deficits in Young Autistic Children?,” *J. Child Psychol. Psychiatry*, 1990.

[8] F. Castelli, “Understanding emotions from standardized facial expressions in autism and normal development,” *Autism*, 2005.

[9] S. J. Rogers, S. L. Hepburn, T. Stackhouse, and E. Wehner, “Imitation performance in toddlers with autism and those with other developmental disorders,” *J. Child Psychol. Psychiatry Allied Discip.*, 2003.

[10] J. H. G. Williams, A. Whiten, and T. Singh, “A systematic review of action imitation in autistic spectrum disorder,” *Journal of Autism and Developmental Disorders*. 2004.

[11] S. J. Rogers, G. S. Young, I. Cook, A. Giolzetti, and S. Ozonoff, “Imitating actions on objects in early-onset and regressive autism: Effects and implications of task characteristics on performance,” *Dev. Psychopathol.*, 2010.

[12] B. Ingersoll, “The social role of imitation in autism: Implications for the treatment of imitation deficits,” *Infants Young Child.*, 2008.

[13] D. Feil-Seifer and M. J. Matarić, “Defining socially assistive robotics,” in *Proceedings of the 2005 IEEE 9th International Conference on Rehabilitation Robotics*, 2005.

[14] T. Fong, I. Nourbakhsh, and K. Dautenhahn, “A survey of socially interactive robots,” in *Robotics and Autonomous Systems*, 2003.

[15] F. Michaud *et al.*, “Mobile robotic toys for autistic children,” *Proc. Int. Symp. Robot. Montral*, 2000.

[16] M. J. Matari??, J. Eriksson, D. J. Feil-Seifer, and C. J. Winstein, “Socially assistive robotics for post-stroke rehabilitation,” *J. Neuroeng. Rehabil.*, 2007.

[17] C. Plaisant *et al.*, “A storytelling robot for pediatric rehabilitation,” in *Proceedings of the fourth international ACM conference on Assistive technologies - Assets ’00,* 2000.
[18] H. Feng, A. Gutierrez, J. Zhang, and M. H. Mahoor, “Can NAO robot improve eye-gaze attention of children with high functioning autism?,” in *Proceedings - 2013 IEEE International Conference on Healthcare Informatics, ICHI 2013*, 2013.
[19] I. Werry, K. Dautenhahn, B. Ogden, and W. Harwin, “Can social interaction skills be taught by a social agent? The role of a robotic mediator in autism therapy,” *Cogn. Technol. Instruments Mind*, 2001.
[20] A. Klin, W. Jones, R. Schultz, F. Volkmar, and D. Cohen, “Visual fixation patterns during viewing of naturalistic social situations as predictors of social competence in individuals with autism,” *Arch. Gen. Psychiatry*, 2002.
[21] O. Golan, S. Baron-Cohen, and Y. Golan, “The ‘reading the mind in films’ task [child version]: Complex emotion and mental state recognition in children with and without autism spectrum conditions,” *J. Autism Dev. Disord.*, 2008.
[22] S. Baron-Cohen, “The hyper-systemizing, assortative mating theory of autism,” *Progress in Neuro-Psychopharmacology and Biological Psychiatry*. 2006.
[23] D. J. Ricks and M. B. Colton, “Trends and considerations in robot-assisted autism therapy,” in *Proceedings - IEEE International Conference on Robotics and Automation*, 2010.
[24] E. Kim, R. Paul, F. Shic, and B. Scassellati, “Bridging the Research Gap: Making HRI Useful to Individuals with Autism,” *J. Human-Robot Interact.*, 2012.
[25] E. Horvitz, J. Breese, D. Heckerman, D. Hovel, K. Rommelset, and K. Rommelse, “The Lumiere Project: Bayesian User Modeling for Inferring the Goals and Needs of Software Users,” *Fourteenth Conf. Uncertain. Artif. Intell.*, 1998.
[26] Y. Kuniyoshi, M. Inaba, and H. Inoue, “Learning by Watching: Extracting Reusable Task Knowledge from Visual Observation of Human Performance,” *IEEE Trans. Robot. Autom.*, 1994.
[27] P. Abbeel and A. Y. Ng, “Apprenticeship learning via inverse reinforcement learning,” in *Twenty-first international conference on Machine learning - ICML ’04*, 2004.
[28] M. N. Nicolescu and M. J. Mataric, “Natural Methods for Robot Task Learning: Instructive Demonstrations, Generalization and Practice,” *Proc. Second Int. Jt. Conf. Auton. Agents Multiagent Syst.*, 2003.
[29] C. BREAZEAL *et al.*, “TUTELAGE AND COLLABORATION FOR HUMANOID ROBOTS,” *Int. J. Humanoid Robot.*, 2004.
[30] W. D. Smart and L. P. Kaelbling, “Effective Reinforcement Learning for Mobile Robots,” *IEEE Int’l Conf. Robot. Autom.*, 2002.
[31] M. Cakmak, C. Chao, and A. L. Thomaz, “Designing Interactions for Robot Active Learners,” *IEEE Trans. Auton. Ment. Dev.*, 2010.

[32] D. Feil-Seifer and M. J. Matarić, “B3IA: A control architecture for autonomous robot-assisted behavior intervention for children with Autism Spectrum Disorders,” in *RO-MAN 2008 - The 17th IEEE International Symposium on Robot and Human Interactive Communication*, 2008.
[33] P. Ekman, “Are There Basic Emotions?,” *Psychol. Rev.*, 1992.
[34] D. Mazzei *et al.*, “The FACE of autism,” in *Proceedings - IEEE International Workshop on Robot and Human Interactive Communication*, 2010.
[35] D. Hanson *et al.*, “Realistic humanlike robots for treatment of ASD, social training, and research; shown to appeal to youths with ASD, cause physiological arousal, and Increase Human- to-Human Social Engagement,” *5th Int. Conf. PErvasive Technol. Relat. to Assist. Environ.*, 2012.
[36] J. Wainer, B. Robins, F. Amirabdollahian, and K. Dautenhahn, “Using the humanoid robot KASPAR to autonomously play triadic games and facilitate collaborative play among children with autism,” *IEEE Trans. Auton. Ment. Dev.*, 2014.
[37] A. Duquette, F. Michaud, and H. Mercier, “Exploring the use of a mobile robot as an imitation agent with children with low-functioning autism,” *Auton. Robots*, 2008.
[38] H. Kozima, M. P. Michalowski, and C. Nakagawa, “Keepon,” *Int. J. Soc. Robot.*, 2008.
[39] H. Kozima, C. Nakagawa, and Y. Yasuda, “Children-robot interaction: a pilot study in autism therapy,” *Progress in Brain Research*. 2007.
[40] G. Pioggia *et al.*, “Human-robot interaction in autism: FACE, an android-based social therapy,” in *Proceedings - IEEE International Workshop on Robot and Human Interactive Communication*, 2007.
[41] B. Robins, K. Dautenhahn, and P. Dickerson, “From isolation to communication: A case study evaluation of robot assisted play for children with autism with a minimally expressive humanoid robot,” in *Proceedings of the 2nd International Conferences on Advances in Computer-Human Interactions, ACHI 2009*, 2009.
[42] M. J. Salvador, S. Silver, and M. H. Mahoor, “An emotion recognition comparative study of autistic and typically-developing children using the zeno robot,” in *Proceedings - IEEE International Conference on Robotics and Automation*, 2015.
[43] M. Salvador, A. S. Marsh, A. Gutierrez, and M. H. Mahoor, “Development of an ABA autism intervention delivered by a humanoid robot,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2016.
[44] S. AL MOUBAYED, G. SKANTZE, and J. BESKOW, “THE FURHAT BACK-PROJECTED HUMANOID HEAD–LIP READING, GAZE AND MULTI-PARTY INTERACTION,” *Int. J. Humanoid Robot.*, 2013.

[45] A. Mollahosseini *et al.*, “ExpressionBot: An emotive lifelike robotic face for face-to-face communication,” in *IEEE-RAS International Conference on Humanoid Robots*, 2015.
[46] D. Morooka and M. Hashimoto, “Robot facial expression using a curved surface display,” *IEEE Conf. Robot. Autom. 2004. TExCRA Tech. Exhib. Based.*, 2004.
[47] J. De Greeff, F. Delaunay, and T. Belpaeme, “Towards retro-projected robot faces: An alternative to mechatronic and android faces,” in *Proceedings - IEEE International Workshop on Robot and Human Interactive Communication*, 2009.
[48] P. Ekman and E. L. Rosenberg, *What the Face Reveals: Basic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System (FACS)*. 2012.
[49] F. Askari, H. Feng, T. D. Sweeny, and M. H. Mahoor, “A Pilot Study on Facial Expression Recognition Ability of Autistic Children Using Ryan , A Rear - Projected Humanoid Robot,” pp. 790–795, 2018.
[50] A. Mollahosseini, H. Abdollahi, and M. H. Mahoor, “Studying Effects of Incorporating Automated Affect Perception with Spoken Dialog in Social Robots,” pp. 783–789, 2018.
[51] H. Abdollahi, A. Mollahosseini, J. T. Lane, and M. H. Mahoor, “A pilot study on using an intelligent life-like robot as a companion for elderly individuals with dementia and depression,” in *2017 IEEE-RAS 17th International Conference on Humanoid Robotics (Humanoids), 15-17 Nov. 2017*, 2017.
[52] C. Tardif, F. Lainé, M. Rodriguez, and B. Gepner, “Slowing down presentation of facial movements and vocal sounds enhances facial expression recognition and induces facial-vocal imitation in children with autism,” *J. Autism Dev. Disord.*, 2007.
[53] F. Shic, J. Bradshaw, A. Klin, B. Scassellati, and K. Chawarska, “Limited activity monitoring in toddlers with autism spectrum disorder,” *Brain Res.*, 2011.
[54] I. J. Lee, C. H. Chen, and L. Y. Lin, “Applied Cliplets-based half-dynamic videos as intervention learning materials to attract the attention of adolescents with autism spectrum disorder to improve their perceptions and judgments of the facial expressions and emotions of others,” *Springerplus*, 2016.
[55] H. Over and M. Carpenter, “The Social Side of Imitation,” *Child Dev. Perspect.*, 2013.
[56] N. Mitsunaga, C. Smith, T. Kanda, H. Ishiguro, and N. Hagita, “Robot behavior adaptation for human-robot interaction based on policy gradient reinforcement learning,” in *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2005.
[57] J. Hemminghaus and S. Kopp, “Towards Adaptive Social Behavior Generation for Assistive Robots Using Reinforcement Learning,” in *International Conference on Human-Robot Interaction (HRI)*, 2017.
[58] C. Ashwin, E. Chapman, L. Colle, and S. Baron-Cohen, “Impaired recognition of

negative basic emotions in autism: a test of the amygdala theory.," *Soc. Neurosci.*, 2006.
[59] C. Lord *et al.*, "Autism Diagnostic Observation Schedule (ADOS)," *Journal of Autism and Developmental Disorders*. 2000.
[60] "(SRS™) Social Responsiveness Scale™ | WPS." [Online]. Available: https://www.wpspublish.com/store/p/2993/social-responsivenessscale-srs-by-john-n-constantino-md. [Accessed: 30-Sep-2018].
[61] M. Pantic, M. Valstar, R. Rademaker, and L. Maat, "Web-based database for facial expression analysis," in *IEEE International Conference on Multimedia and Expo, ICME 2005*, 2005.
[62] Q. You, J. Luo, H. Jin, and J. Yang, "Building a Large Scale Dataset for Image Emotion Recognition: The Fine Print and The Benchmark," 2016.
[63] D. Leyzberg, S. Spaulding, M. Toneva, and B. Scassellati, "The Physical Presence of a Robot Tutor Increases Cognitive Learning Gains," *34th Annu. Conf. Cogn. Sci. Soc.*, 2012.
[64] C. W. Chang, J. H. Lee, P. Y. Chao, C. Y. Wang, and G. D. Chen, "Exploring the possibility of using humanoid robots as instructional tools for teaching a second language in primary school," *Educ. Technol. Soc.*, 2010.

[65] M. Fridin, "Storytelling by a kindergarten social assistive robot: A tool for constructive learning in preschool education," *Comput. Educ.*, 2014.
[66] S. M. Mavadati, H. Feng, M. Salvador, S. Silver, A. Gutierrez, and M. H. Mahoor, "Robot-based therapeutic protocol for training children with Autism," in *25th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN 2016*, 2016.
[67] J. Kober, J. A. Bagnell, and J. Peters, "Reinforcement learning in robotics :Asurvey," *Int. J. Rob. Res.*, 2015.
[68] R. S. Sutton and A. G. Barto, *Reinforcement Learning : An Introduction*. 2016.
[69] A. Mollahosseini, H. Abdollahi, T. D. Sweeny, R. Cole, and M. H. Mahoor, "Role of embodiment and presence in human perception of robots' facial cues," *Int. J. Hum. Comput. Stud.*, 2018.