Assistive Technologies for Children with Autism Spectrum Disorders

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ABSTRACT

With a growing proportion of the population being diagnosed with different Autism Spectrum Disorders (ASDs), it is important to find ways to improve both the diagnostic process and available therapies. Research has shown that children with Autism Spectrum Disorders respond positively to robots, and pervasive technology is becoming more common in our daily lives. These two areas have a lot to offer when it comes to assisting ASD diagnosis and therapy. In this paper, I will give a brief explanation of ASDs, explain some current diagnostic procedures and how they can be improved by technology, and show some current ASD therapies and how technology can assist them.

Categories and Subject Descriptors

H.1.2 [**User/Machine Systems**]: Human information processing; J.4 [**Social and Behavioral Sciences**]: Psychology

General Terms

Human Factors

Keywords

autism, robotics, pervasive technology, assistive technology, diagnosis, therapy

1. INTRODUCTION

Current research suggests that Autism Spectrum Disorders (ASDs) are being diagnosed in a larger portion of the population than ever before, with about 1 in 300 people being diagnosed with an ASD [13]. With such a large percentage of the population diagnosed with a social disability, it is important to determine what can be done to assist those with ASDs.

The term Autism Spectrum Disorder covers a range of social disorders including Autism, Asperger's, and Pervasive Developmental Disorder Not Otherwise Specified (PDD-NOS) [16]. Each of these conditions have unique characteristics, but they have many similarities as well. All of these conditions are characterized by an inability to relate to other people [13], a difficulty with self-initiation of social behaviors [5], as well as impairments in the development of social interaction, communication, and imagination [11]. ASDs are thought to be genetic, but the actual cause is unknown. This makes the diagnostic process challenging. There are no definitive tests that can prove if someone has an ASD or not; diagnosis depends on a clinician observing behaviors and determining if they meet the criteria for an ASD. There are currently many therapies for people with ASDs, with varying levels of effectiveness for different people in different situations. The sheer number of therapies means that parents of children with ASDs have a great deal of information to sort through and possibly many different therapies to try. The therapies can be both time consuming and expensive. Modern technology can improve the diagnostic process and make some therapies cheaper and less time consuming. In Section 2, I will discuss the ASD diagnostic process and how robots and pervasive technologies can improve it. In Section 3, I will talk about current ASD therapies as well as how robots and pervasive technologies can be used to assist or improve current ASD therapies.

2. AUTISM DIAGNOSIS

Autism Spectrum Disorders are diagnosed either by observing a child's behavior, an interview with the child's parent, or both [16]. Since the cause of ASDs is unknown, there is no test that can be administered to definitively diagnose a child. The pediatrician or psychologist examining the child has to use their best judgment to determine if the child has an ASD. Technology can be used to increase the accuracy and specificity of diagnosis by assisting the pediatrician or psychologist in the diagnostic process and therefore reducing the number of people diagnosed with PDDNOS instead of more specific ASDs. In the next few sections, I will discuss the current diagnostic procedures for ASDs, how robots could be beneficial to the diagnostic process, and how pervasive technology can assist in the diagnostic process.

2.1 Current Diagnostic Procedures

ASD diagnosis is based on behavior, not physical causes, because the cause of ASD is unknown. Therefore, to diagnose a child with an ASD, the child's behavior is compared to a set of behavioral norms. Some clinicians choose to diagnose directly from the Diagnostic and Statistical Manual for Mental Disorders (DSM) which is the primary text on the classification of different mental disorders [16]. The DSM states that the diagnostic criteria for Autistic Disorder is "exhibiting at least six symptoms total, including at least two symptoms of qualitative impairment in social interaction, at least one symptom of qualitative impairment in communication, and at least one symptom of restricted and repetitive behavior" [16]. This is many behaviors for a clinician to keep track of, so some diagnostic tools were created to assist in the diagnostic process. The Childhood Autism Rating Scale (CARS) rates children on a scale from 1 to 4 for various behaviors such as relationship to people, emotional response, and so on. CARS then yields a composite score that translates into non-autistic, mildly autistic, moderately autistic, and severely autistic [16]. While the DSM and CARS help define what behaviors should be examined, it is still the role of the clinician to observe the child and collect data on many different behavior patterns. Recent research suggests that technological supports for diagnosis can assist in this process.

2.2 Robots and Diagnosis

Children can display different behavior patterns when they are around new people than they do when they are in a place that is more comfortable to them. To accurately observe a child's behavior, the child should optimally be in a place that does not frighten them. Children with ASDs struggle with interacting with people that are new to them, and some are quite anxious around new people. If the child could be in a situation that promotes social behavior, a clinician could more easily examine those behaviors and more accurately determine if the child has an ASD.

Previous work has shown that children with ASDs respond positively to robots, and that those robots can focus the attention of the children and could hypothetically be used to encourage social behaviors [7]. Feil-Seifer and Matarić hypothesized that a child interacting with a robot that responds to their behavior will exhibit more social behavior than interacting with a robot that responds randomly [7]. If a child will be more social with a robot that responds to their actions, observing a child interacting with a robot that responds to their actions will provide a clinician more opportunities to observe the social behavior of the child and more accurately form a diagnosis. Feil-Seifer and Matarić had 3 children interact with a bubble-blowing robot that would either blow bubbles when one of its buttons was pushed or would blow bubbles randomly. Each child spent time with both robot configurations. Each interaction with the robot was video recorded. Human observers annotated the video, looking for speech/vocalizations, gestures, movement, ASD-typical behavior (such as hand flapping), joint attention/ eye contact, and actions to control the robot.

Figure 2.2 shows the results from the bubble blowing robot study. The lighter colored bars in the graph represent interactions with the randomly responding robot and the darker colored bars represent interactions with the robot responding to button pushes. The amount of total child speech, speech to the robot, speech to the parent, total amount of interaction with the robot, button presses, responses to the robot, and directed interactions (a parent-child play-therapy based form of communication [14]) all increased when the robot responded to the actions of the child instead of acting randomly. This suggests that robots could assist the ASD diagnostic process because interacting with a robot increases social behaviors, making them easier for a clinician to observe.

2.3 Pervasive Technology and Diagnosis

The issue with ASDs being diagnosed primarily by observation is that people are not perfect; they make mistakes and they do not have the ability to process all the information they are observing at once. Pervasive technology can assist the clinician by helping to recognize different behaviors. This technology can be used during the observation process to help the clinician recognize particular gaze directions of the child all while examining other behaviors.

In [13], Scassellati hypothesizes that passive sensors could be used to record social information without directly engaging in interactions. To test this hypothesis, he outfitted some clinical evaluation rooms with cameras, microphones, and software that records and interprets data while subjects are engaged in standard evaluations. Previous studies have shown that people with ASDs will focus more on the mouth region of the face while typically developing people will focus on the eyes [13] so Scassellati decided to use his passive sensing evaluation rooms to attempt to record gaze patterns of individuals. He used both a commercial eye-tracking system that requires the user to wear a baseball cap with a camera to monitor the eyes and computational systems that use the built-in cameras in the room [13].He then trained a classifier to replicate the gaze patterns of that individual with 90-92% accuracy. By applying a classifier trained on one individual to another individual, he can evaluate the similarities in the gaze patterns of the two individuals. When trained by a typically developing person, his classifier could accurately identify the gaze patterns of typically developing people 86% of the time and people with ASDs 72% of the time. When trained on someone with an ASD, his classifier could accurately identify the gaze patterns of another person with an ASD 73% of the time. This shows that typically developing people have similar gaze patterns to each other while people with ASDs have much less similarities in gaze patterns both to typically developing people and others with ASDs. A clinician could compare the gaze patterns of the child they are observing to the gaze patterns of a typically developing child to see if the child under observation has atypical gaze patterns which can be sign of an ASD.

3. AUTISM THERAPY

We know that ASDs encompass a spectrum ranging from the non-vocal to those with above average intelligence and language skills, and therefore the therapies for these different ranges in the spectrum vary extensively. Regardless of where a child is in the ASD spectrum, some things remain the same. Parents will go through many different therapies, sometimes 10 or more, but eventually settle on a handful of therapies they use simultaneously [8]. Researching and trying multiple therapies can be stressful for the parents of children with ASD. Once successful therapies are found, parents then dedicate hours a day to working with their child and attempting to increase their social understanding. If a child has low-function autism, they may never be able to live on their own, causing parents to worry about long-term care for their child. Having a child with ASD is also very expensive. Medical bills for children with ASD are ten times higher than those of typically developing children [1].

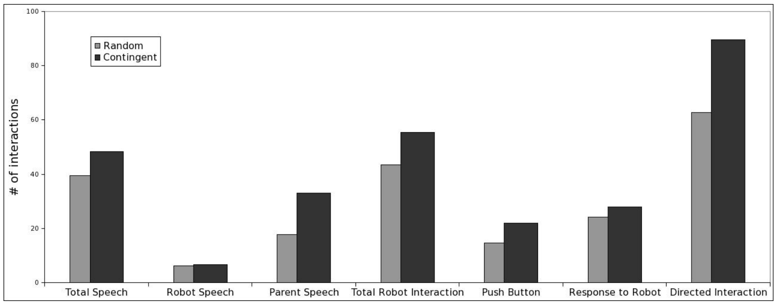

Figure 1: Results from the Feil-Seifer and Matarić bubble robot socialization experiment [7].

If there are ways to make effective ASD therapy less expensive or time consuming, it would have a huge impact on the families of children with ASD. Cheaper therapy would be accessible to more people, and less time consuming therapy would make it easier to incorporate into the average family's life. In the next few sections, I will be explaining some current ASD therapy, research on incorporating robots into ASD therapy, and research on using pervasive technology as tools for ASD therapy.

3.1 Current Autism Therapy

There are many different therapies for ASD; every child is different and every ASD case is different. The three major subcategories of ASD therapies are behavior therapy, drug therapy, and communication assistance for non-vocal children with ASD [16]. I will focus on behavior therapy and communication assistance because these are areas where robotics or pervasive technology could be used to assist in the therapy.

Applied Behavioral Analysis (ABA) is the most popular behavior therapy used today. It has been studied for decades and its results are easily measurable [16]. ABA deals with the manipulation of stimuli in the environment to help people emit responses that are socially important [3]. Children with ASD do not automatically react to situations in the same way that typically developing children do. This can cause improper social behavior. ABA works to teach children with ASD the proper social protocols and to make those behaviors more second nature. ABA essentially requests a particular behavior from a child and then rewards them if they display that behavior. The success of the child is closely monitored over time so that their true performance can be evaluated [3]. ABA has been used by therapists, parents in their own homes, as well as special education departments of schools. If a child's behavior could be more closely monitored, then their performance could be more accurately determined. Technology could be used to manipulate stimuli in the environment, provide a resource for practicing newly-learned social behaviors, or help obtain observation data.

The Picture Exchange Communication System (PECS) is a picture-based system of communication for children with social and communication problems. The PECS system is a notebook that uses Velcro to hold pictures representing words or phrases. Children use the pictures to form sentences [2]. This system helps non-vocal children to become more social because it enables them to communicate with people without requiring others to know a secondary language, like sign language. PECS is limited by the number of cards a child is able to carry at one time. If augmented with modern technology, the entire system becomes more portable and customizable. Words and phrases could be added or removed so that the child is not overwhelmed with word choices but can increase their vocabulary over time, allowing the formation of more accurate or complex communication.

3.2 Robotics and Therapy

Children with ASDs are not motivated by traditional social feedback, so to encourage learning social behaviors different rewards need to be used. In the research of Lehmann, *et al.*, they discovered that interacting with robots had a positive influence on children with ASD's social development [11]. This work showed that social behaviors are encouraged by the presence of a robot, but it did not determine if specific actions of the robot would increase social behaviors as well. If robots reacting to specific behaviors of children with ASDs could be proven to encourage vocalizations and other social behaviors, then robots could be incorporated into behavior therapies as a motivational tool.

In section 2.2, Feil-Seifer and Matarić were able to show that robots could be used as a catalyst in social situations for children with ASD and therefore could play a useful role in ASD therapy. Including robots in behavior therapy could help speed up the learning of new social behaviors, but it is important to make sure robots will not have a negative effect on the learning of social behaviors. Even though research has shown that in general children with ASD are motivated by robots, this will not always be the case. If the robot frustrates or frightens a child during behavior therapy, it could be detrimental to the child's success. In [6], Feil-Seifer and Matarić studied the correlation between robot behavior and positive or negative reactions by the child. They also wondered if a child's reactions could be automatically detected and classified by a robot so that the robot would not frighten or frustrate the child further. They hypothesized that the robot could move farther away from the child and avoid interaction until the child's behavior becomes more positive.

Feil-Seifer and Matarić's study involved a child with an ASD, the child's parent, and a humanoid robot (see Figure 2). The robot could move its head and arms as well as move about the room. The robot used a camera mounted to the ceiling of the room and infrared sensors on the robot to show position and orientation, allowing the robot to move autonomously throughout the room. The robot used a background subtraction algorithm (an algorithm to detect moving objects; for more information see [12]) to identify the

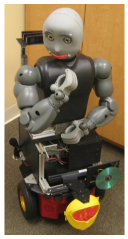

Figure 2: The robot used in Feil-Seifer and Matarić's behavior classifier study [6].

parent and child in the room. The researchers told the parent to wear a brightly colored shirt so that the algorithm could distinguish between the parent and the child.

Eight children participated in the study and each child had three, five-minute sessions in the experiment room. In one session, the child interacted with the robot that responded to the actions of the child. For example, if the child moved toward the robot or vocalized, the robot would nod its head or vocalize encouragingly. When the child moved away from the robot, it would lower its head and make a sad vocalization. If the child touched a button on the robot or vocalized to the robot, the robot would respond by blowing bubbles. The robot would also move about the room while interacting with the child [6]. Each child then had a session with the robot where the robot would act randomly. The robot would perform the same actions, but at random intervals. The behavior of the robot was not influenced by any of the child's actions. The children also had one session playing with a non-robotic toy as a control.

Feil-Seifer and Matarić then had an anthropologist specializing in ASDs study footage of the sessions and they observed common behaviors of the children when interacting with the robot. They classified the behaviors as avoiding the robot (the child is moving farther away from the robot), interacting with the robot or the bubbles, staying still (not moving and not near a wall or the parent), near parent (touching the parent or next to the parent while not moving), against the wall (touching the wall while not moving, usually facing the robot), and none of the above [6]. The authors went through each frame of the tape from the sessions with the robot and classified each frame into one of the behavior categories. They found that children that had negative reactions with the robot would avoid the robot, be against the wall, or interact with their parent far more than children with positive reactions. They also spent less than 20% of the session time interacting with the robot or bubbles, see Figure 3. On the other hand, children that had positive reactions to the robot spent more than 80% of their session time interacting with the robot or bubbles. This data suggests that the behavior classifications are correlated to whether the child was having a positive or negative reaction to the robot. The authors wanted to figure out if such behaviors could be automatically detected and classified so that the robot could autonomously adapt its behavior to that of the child.

Feil-Seifer and Matarić created an 8-dimensional feature vector to track important distances in each video frame. Previous research has shown that image coordinates can be used as part of a feature vector. In social interaction, the current location of objects are not as important as the distances between them. Feil-Seifer and Matarić's vector is represented as

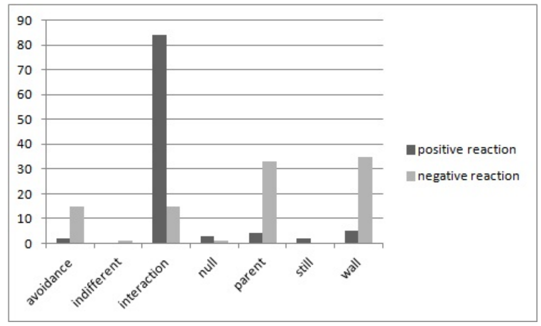

Figure 3: Percentage of session time spent in each interaction state [6].

$$v =< d_r^c, d_p^c, d_w^c, \psi_r^c, v_c, v_r^c, v_w^c, v\psi_r^c >$$

where d_r^c is the distance between the child and the robot, d_p^c is the distance between the child and the parent, d_w^c is the distance between the child and the closest wall, ψ_r^c is the orientation (angle) of the child to the robot, v_c is the absolute velocity of the child, v_r^c is the velocity of the child to the robot (a positive v_r^c means that the child is moving towards the robot and a negative v_r^c means that the child is moving away from the robot), v_w^c is the velocity of the child relative to the nearest wall (a positive v_w^c means that the child is moving towards the robot and a negative v_w^c means that the child is moving away from the robot), and $v\psi_r^c$ is the change in orientation (angle) of the child to the robot.

To create the behavior classifier, Feil-Seifer and Matarić grouped the data (all of the recorded frames) into 3216 "tiles" where each tile contained 30 consecutive observations (2 consecutive seconds of video). 10% of the tiles were used for training the classifier and the other 90% were used for testing. The researchers then fit the training data using a Gaussian Mixture Model [6]. A Gaussian Mixture Model is a plane containing data points (in this case, the feature vectors for each "tile") and these data points are grouped into clusters [9]. First, the feature vectors for each tile in the training set are added to the plane. Then, the optimal number of clusters is calculated using Bayes Information Criterion. How Bayes Information Criterion specifically works is beyond the scope of this paper, but it helps reduce the number of clusters in the model by adding a penalty for having too many clusters. This prevents the Gaussian Mixture Model from being over-fit to the data [9]. Depending on which data was used for training, Feil-Seifer and Matarić got between 23 and 25 clusters for their Gaussian Mixture Model [6]. The center point for each cluster is randomly selected on the plane. For each data point in the plane, the closest cluster center is identified. That data point is then considered to be a part of that cluster. After all data points have been assigned a cluster, the center point of the cluster is assigned to the average of all the points in that cluster. The process of assigning each data point to a cluster and updating the cluster center is repeated until the cluster assignments cease to change [9]. This final plane of clustered data points is the Gaussian Mixture Model that will be used to classify observed behaviors (the remaining 90% of tiles).

Once the clusters in the Gaussian Mixture Model have

Table 1: Confusion between behaviors, after doubling fitted model order (data from [6]).

	avoidance	interaction	parent	wall
avoidance	**52.7619**	0.7993	1.4000	2.5850
interaction	34.8571	**97.5295**	7.6000	11.5646
parent	9.9048	1.5077	**90.8000**	3.6735
wall	2.4762	0.1635	0.2000	**82.1769**

Table 2: Confusion between behaviors (data from [6]).

	avoidance	interaction	parent	wall
avoidance	**34.7648**	1.1052	3.8680	1.2587
interaction	55.8282	**97.7024**	25.5973	16.3636
parent	8.2822	1.0276	**70.5347**	3.2169
wall	1.247	0.1648	0	**79.1608**

been created, they need to be classified with the behavior they represent. To do this, the researchers add human-labeled behaviors to the model and the closest cluster to that behavior is labeled with the appropriate observation. This classification process can be summarized with the formula

$$p(o|c)$$

where p is the probability that the closest cluster of observations (o) is the human-labeled behavior (c). New observations are classified similarly. The feature vector of the new observation is added to the model and the closest cluster to the observation is classified behavior. This can be shown with the formula

$$argmax_c p(c|o)$$

where p is the probability that the behavior to be classified (c) is in the clustered observation o. *Argmax* means that the cluster with the highest probability of including c is the classified behavior of c.

Feil-Seifer and Matarić then classified the test data. The following results will only discuss the avoidance, interaction, parent, and wall behaviors since they covered 90% of the session time [6]. Table 2 shows the confusion of the classifier between the different behaviors. Each column represents the correct behavior classification and each row within that column is what the classifier classified those behaviors as. For example, the first column represents all of the avoidance behaviors from the test data. 35% of the time those behaviors were correctly classified as avoidance while they were incorrectly classified as interaction 56% of the time. As you can see from Table 2, the classifier was very accurate in classifying interaction behavior, but was hardly better than chance at guessing avoidance. Thinking that number of clusters in the model might be causing the poor accuracy, the authors doubled the number of clusters in the model. Their new results are in Table 1. This brought the overall accuracy of the classifier up to 91.4%.

Feil-Seifer and Matarić were able to show that a classifier can be created that can accurately identify positive and negative reactions. By comparing Figure 3(human-classified observations) and Figure 4(computer classified observations), one can see that both graphs depict that in each interaction state, there are observable differences in the amount of time children with positive reactions to the robot spent in that

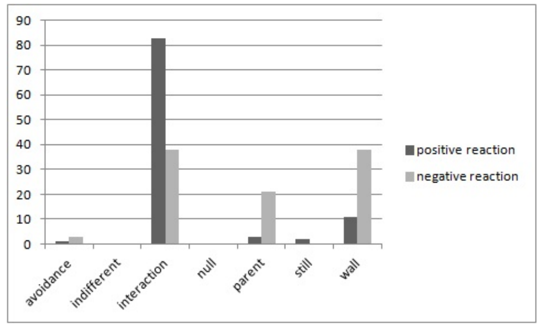

Figure 4: Classified percentage of session time spent in each interaction state [6].

state compared to children with negative reactions to the robot. This means that a classifier could accurately determine if a child is having a positive or negative reaction to a robot and that robot could alter its behavior to prevent hurting a child's success in therapy by causing more stress or frustration to the child.

3.3 Pervasive Technology and Therapy

Smart phones and Tablets are becoming more and more integrated into our daily lives. They provide a powerful computing device that many people already carry around with them. These devices are more affordable than a robot and can provide children with ASDs support in their daily lives without being intrusive. Both the MOSOCO smart phone application [4] and the tablet applications developed by Hourcade, *et al.*, [10] can provide this support to children with ASDs.

3.3.1 MOSOCO Phone Application

MOSOCO is a mobile application that follows the Social Compass curriculum that uses stories and visual supports to teach children with ASDs social skills. They address proper eye contact, space and proximity, starting interaction, asking questions, sharing interests, and finishing interaction [4]. The purpose of the MOSOCO phone application is to allow students to practice the Social Compass curriculum outside of their regular behavior therapy or special education classes.

The MOSOCO system runs on an Android smartphone and is wirelessly connected to a server. MOSOCO uses the smartphone's camera to augment a real life social situation while providing visual supports during the interaction [4]. MOSOCO was designed to be used both individually and in a group setting. To assist an individual, MOSOCO has an identifier for each student using the system, student progress reports (gold stars that can be earned), a self-report to be filled out after each interaction, and social cues to assist in a social situation (what a user should and shouldn't do when interacting with others). To assist in a group setting, MOSOCO has a 6-step schedule that walks the user through an interaction called an Interaction Visual Schedule, a potential interaction partner (the person they should interact with), and a roster of students using the MOSOCO system [4]. When used in a group setting, students are instructed to find their first potential interaction partner. When the system has detected that the potential interaction partners are near each other, it synchronizes their Interaction Visual Schedules. The students then work through the social steps in the Interaction Visual Schedule. MOSOCO monitors the completion of the skills in the Interaction Visual Schedule and warns the student if a social misstep occurred [4]. These social missteps are recorded and used to track the progress of the student. MOSOCO monitors tone of voice, personal space, interrupting or breaking an interaction, and eye contact [4]. The specifics of how MOSOCO is able to detect social missteps was not covered in the paper, but more information can be found here [15]. Escobedo, *et al.*, created the MOSOCO system and created a user study to test its effectiveness. They had a group of children with and without ASDs practice having conversations using the MOSOCO system. They found that their system showed the children with ASDs improving in social interactions (gaining more gold stars) and the typically developing children had a greater understanding of ASDs [4]. The MOSOCO system would be a useful addition to behavior therapy for children with ASDs because it allows them to continue practicing social skills on their own as well as with other people.

3.3.2 Mutlitouch Tablet Applications

Hourcade et al. created 4 different tablet applications to help children with ASDs [10]. Three of the applications were meant to create situations where children with ASDs would be forced to work with others to reach a certain goal. The other application allows children to modify pictures of faces to express different emotions. The goal of this paper was to show that there is not one application that will cover every area where children with ASDs need practice [10]. Through their work and case studies, they showed that all of the applications were helpful in different ways to different children. As a part of ASD therapy, a child could have many different applications at their disposal for practice as well as assistance in live social situations. This would provide children with ASDs a mobile toolkit of assistive applications.

4. CONCLUSION

ASDs are becoming more prevalent in society and because of this, researchers are trying to find ways to incorporate technology. Technology can be used to assist in the ASD diagnostic process by monitoring some of the behaviors clinicians usually have to monitor by hand, allowing the clinician to focus on fewer behaviors at one time and therefore increasing the accuracy of ASD diagnosis. Technology can also be inserted into different ASD therapies, making some more portable and usable by children and allowing ASD therapy to occur outside of school or an office-based therapy session. With research in this field increasing, hopefully ASDs can become more manageable.

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