Robots and Play: Evaluation of a Wireless Interface Device for Interaction with a Humanoid Robot Playmate

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***Abstract*— Rehabilitation robots in home environments has the potential to dramatically improve quality of life for individuals who experience disabling circumstances due to injury or chronic health conditions. Unfortunately, although classes of robotic systems for rehabilitation exist, these devices are typically not designed for children. And since over 150 million children in the world live with a disability, this causes a unique challenge for deploying such robotics for this target demographic. To overcome this barrier, we discuss a system that uses a wearable arm glove input device to enable interaction with a robotic playmate during various play scenarios. Results from testing the system with 20 human subjects show that the system has potential, and a user specific device calibration algorithm is proposed to improve the performance of the system.**

I. INTRODUCTION

Many therapeutic interventions for children with physical impairments focus on improving functional movement skills and abilities [1]. Pediatric physical therapy differs from adult therapy in that younger children typically cannot (or may not be willing to) follow direct instructions required of a therapy routine. Thus, clinicians typically incorporate therapy in play to provide an engaging and motivational intervention that may enhance the child's participation in the therapy session. No one will argue about how important play is during childhood. Interactive play is where children learn cognitive, social, and physical skills [2]. As such, in recent years, there has been growing interest in research involving therapeutic play between robots and children, mainly with respect to children with pervasive developmental disorders such as autism. KASPAR [3], a child-sized robot for engaging children with autism, utilizes expressions and gestures to communicate with its human partner. The goal is to provide a mechanism for teaching social interaction skills through the use of joint attention and imitation. Another robot designed to teach social interaction skills is CosmoBot [4], a commercially-available telerehabilitation robot that enables a therapist to record robot movements to enable the performance of repetitive and predictable motions, which adheres to a specified behavioral skill. And [5-7] focus on engaging children with disabilities in imitation-based games. While current research efforts represent the first to make significant progress toward aiding individuals with pervasive developmental disabilities, these robot designs have not been designed to engage children with physical impairments.

On the other hand, tele-operated robots have been shown to enable achievement of play-related tasks that go beyond the child’s own manipulation capabilities. In [8], a tele-operated robot called PlayROB was developed to enable children with physical disabilities to play with LEGO bricks. The robot’s workspace included a LEGO brick surface on which to build structures, with a brick supply system at one edge of the play area. Children with physical disabilities could control the robot using various input methods in order to build structures composed of the LEGO bricks. The ”Handy” robot [9] was used to assist children with cerebral palsy in performing a variety of tasks such as eating and brushing teeth, and in a pilot study showed how the robot could be used to enable drawing. Cook et al. also showed the use of robot arms for assisting children in play related tasks [10]. Although these robots showcased their ability to assist children with severe physical disabilities in achievement of daily living tasks, their design was as a tool to extend the capability of the user, rather than improve the user’s own capability through rehabilitation. These robotic systems therefore were also not autonomous, but rather required a human for remote operation.

To combine the state-of-the-art in this area, we have coupled the concept of robot tele-operation with autonomous robot behavior by developing a system that uses a wireless arm glove input device to enable interaction with a robotic platform during various play scenarios. The robotic agent has the potential to perform as an avatar and can be used as a mediator for social interaction between children. In this paper, we will provide an overview of the wireless arm glove device and components of the robot playmate. We will then discuss the results of a pilot study designed to evaluate performance and satisfaction with the system in order to enable iterative improvements necessary for deployment with children.

II. APPROACH AND METHODOLOGY

A. Wireless Interface Device for Tele-operative Control

In [11], a study was conducted that reviewed a number of different joysticks and switches for use by children with motor impairments. The basic purpose of the study was to develop electronic devices to extend the capability of a child with Cerebral Palsy when all other avenues leading to physical independence had been exhausted. Common considerations found with these devices were 1) most devices had four selection options, typically up, down, left, and right, 2) certain physical requirements had to be met in order for a particular input device to be operational, and 3) in order to be useful, the device had to have reliable behavior and a high degree of accuracy. Motivated by this

*Research partially supported by NSF Grant #EEC-0851643.

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study, we determined that by adapting the slammer switch (a single-switch input device), which was the easiest to use, into a *n*-selection wireless input device, we could provide the most versatility for tele-operation of a robot playmate. The resulting forearm mountable device was designed to slide onto the arm like a sleeve and has four large buttons, which children with upper-arm mobility deficiencies can access given their effective range of motion [13]. The device sensors, consisting of force sensitive resistors coupled with an Arduino microprocessor, were placed on an adjustable brace, with an adjustable Velco strap, to allow one size to fit the majority of a child's forearm (Fig. 1). The raw data from the sensors are fed into the microprocessor and an algorithm designed to recognize "press" and "swipe" gestures was generated from the combination of sensors (Fig. 2). This provides the ability to generate six unique commands using the glove (i.e. by pressing one of the four device sensors or doing a "forward swipe" or "reverse swipe," which occurs when the user slides their hand or fist across multiple sensors in either direction). For our application, a *button* consisted of the union of adjacent sensors, thus expanding the surface contact area associated with a button and increasing accuracy of button selection (which also resulted in a reduction in the number of commands available). Once generated, the readings from the sensors are transmitted wirelessly to the robot playmate via a Wi-Fi connection and converted into a robot-behavior (discussed in the next section).

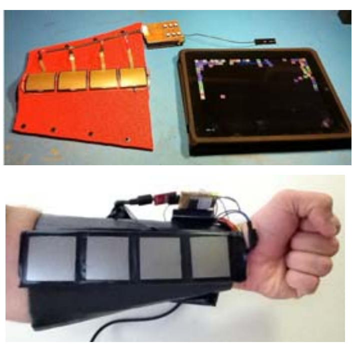

Fig. 1. Two prototypes of the wireless arm glove device

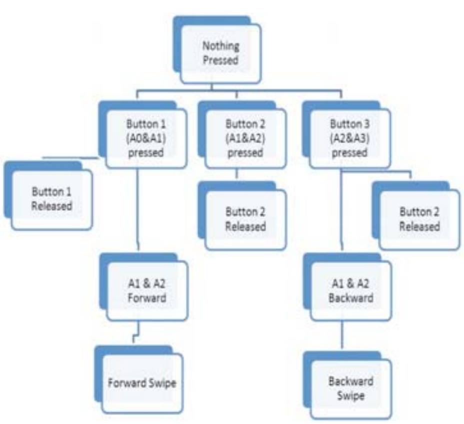

Fig. 2. Algorithm based on Finite State Machine for recognizing button 'swipe' and 'press' gestures

B. Hardware Platform – Humanoid Robot

For our humanoid robot platform, we build a Manoi AT01 humanoid robot, which has 17 DOF and is made up of 17 servos and plastic aesthetics. We also built and attached two hands to the robot (Fig. 3), adding two more DOF. The Robot Operating System (ROS) architecture is used to control the robot through use of groups of code called nodes that subscribe and publish to data topics, and take action based on data published to topics they are subscribed to (http://www.ros.org/). The nodes are written in C++ and Python for use with ROS.

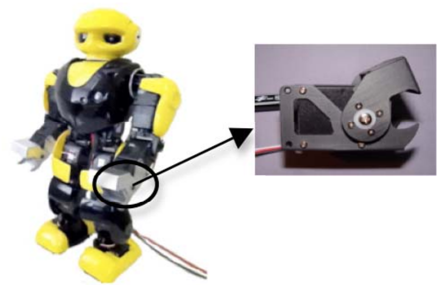

Fig. 3. Our Manoi AT01 humanoid robot and 1-DOF hand

These nodes are programmed so that when the user provides input to the glove device, it triggers one of the robot behaviors. Four behaviors were programmed (1) playing back a user recorded motion [7], (2) performing a "dance" move similar to a shuffle, (3) opening and closing both hands, and (4) sending the robot to a "home" position (Fig. 4). These behaviors are associated with gestures derived from pressing the two sensors located closest to the elbow when mounted (Button 1), the two middle sensors (Button 2), the two sensors closest to the hands (Button 3), and a forward swipe, respectively.

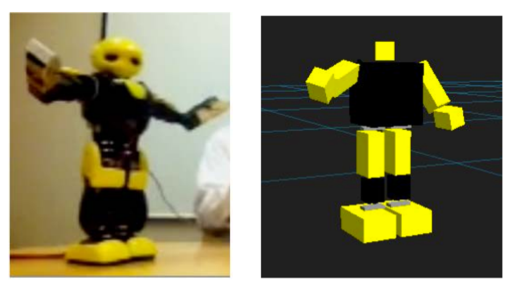

Fig. 4. Robot playmate performing the dance move

III. Experimental Procedure

To evaluate system performance, 20 human subjects tested the system using the arm glove to trigger robot behaviors as directed by the protocol. All subjects signed IRB approved consent forms and were informed of the risks and benefits of being part of the testing. 9 subjects were female and 11 subjects were male. The subjects' ages ranged from 18 to 32 years old with an average age of about 23. Subjects were instructed to use a fist when triggering inputs on the arm glove to simulate limited motor control, and each subject was taught how to trigger each input to the arm glove and given a few attempts at triggering each. When executing forward swipes, each subject was told to apply pressure and sweep across all buttons relatively quickly. After these instructions, each subject attempted to trigger the following behavior sequences in random order:

Sequences:
- Behavior 1
- Behavior 1, Behavior 2, Behavior 4
- Behavior 1, Behavior 2, Behavior 3, Behavior 4
- Behavior 3, Behavior 1(5 times), Behavior 4
- Behavior 2, Behavior 1(5 times), Behavior 4
- Swipe Forward (10 times)

where,
- Behavior 1: Open/close hands
- Behavior 2: Access pre-recorded motion
- Behavior 3: Perform dance move
- Behavior 4: Send robot to home position

In total, each subject was asked to perform 42 distinct actions consisting of a combination of button presses and swipes. During the test sequences, our data collection system recorded the response time of the robot in order to determine how quickly the robot responded to each individual input from the arm glove. Following the testing, each subject was asked to fill out a survey (Table I) and provide suggestions and comments for improvement. The users responded to each question using a 5-point Likert scale.

TABLE I: SURVEY QUESTION LIST

#	Question
1	How easy was it to remember which movements the arm glove inputs corresponded to?
2	How satisfied were you with the robot's response time to the open/close hands command?
3	How satisfied were you with the robot's response time to the dance/shuffle command?
4	How satisfied were you with the robot's response time to the playback recorded motion command?
5	How satisfied were you with the robot's response time to the home command (forward swipe)?
6	How satisfied were you with the robot's response time to input commands overall?
7	How easy was it to trigger the open/close hands command?
8	How easy was it to trigger the "shuffle" command?
9	How easy was it to trigger the playback recorded motion command?
10	How easy did you find triggering the home command (forward swipe)?
11	How easy did you find triggering the robot's movements overall?
12	How much did you enjoy playing with this system overall?
13	How likely do you think this system would hold a child's attention?

IV. RESULTS AND DISCUSSION

Table II displays the average time it took between when a command was triggered by a user and when the robot began to move. The open/close hands command took an average of 0.067 seconds to begin, the playback recorded motion behavior took an average of 0.52 seconds to begin, and the dance command took an average of 0.38 seconds to begin. The forward swipe took 0.031 seconds to begin. We noticed that, in some cases, users interpreted longer delays as the robot failing to respond so they would repeatedly trigger the command before the system had a chance to complete the behavior.

TABLE II. AVERAGE RESPONSE TIME OF INTEGRATED SYSTEM

Arm glove input	Behavior 1	Behavior 2	Behavior 3	Behavior 4
Avg. Response Time (s)	0.067	0.52	0.38	0.031

Fig. 5 shows the distribution of how the subjects responded to the survey. This figure shows that the subjects' responses were generally positive (in the 4-5 range), but enough are in the lower ranges to warrant improvement of the system.

Response	5 (very)	4	3 (somewhat)	2	1 (not at all)
Question #					
Question 1	6	8	6	0	0
Question 2	14	5	1	0	0
Question 3	10	6	2	2	0
Question 4	11	4	3	1	1
Question 5	5	7	4	2	2
Question 6	3	10	6	0	1
Question 7	18	2	0	0	0
Question 8	13	7	0	0	0
Question 9	13	6	1	0	0
Question 10	1	4	7	7	1
Question 11	1	10	8	1	0
Question 12	8	7	4	1	0
Question 13	4	8	6	1	1

Fig. 5. Results from User Survey Response

Of the 20 subjects, 95% responded that they were very satisfied (14) or satisfied (5) with the response time of the open/close hands command. This fits with the hands having the second shortest response time of 0.067 seconds. Users also reported this to be the easiest motion to trigger as 90% of subjects found it very easy and the remaining 10% found it easy. 80% of subjects were either very satisfied (10) or satisfied (6) with the response time to the dance command (question 3), and 75% were either satisfied (4) or very satisfied (11) with the response time of the playback recorded motion command (question 4). These also make sense because their response times were 0.38 and 0.52 seconds, respectively. They are slower than the hands and have a slightly lower satisfaction rating. Users still found these easy to trigger, as 100% of users found it very easy (13) or easy (7) to execute the shuffle command and 95% found it very easy (13) or easy (6) to trigger the playback recorded motion command (questions 8 and 9). However, only 60% responded that they were satisfied (7) or very satisfied (5) with the response of the home command (question 5). This does not fit with the response time data, as the home command had the quickest response time of 0.031 seconds. This is probably related to the difficulty users experienced in successfully executing forward swipes. It also usually took users multiple attempts to successfully execute forward swipes, which explains why only 25% of subjects found forward swipes easy (4) or very easy (1) to trigger (question 10).

These factors likely had a strong influence on the responses to questions 6 and 11, where only 65% of subjects reported being satisfied (10) or very satisfied (3) with the robot's response time to their commands overall (question 6), and only 55% found it easy (10) or very easy (1) to trigger the robot's movements overall (question 11). 75% of the subjects reported enjoying playing the system overall either a great deal (8) or a fair amount (7) (question 12).

These responses indicate that most users enjoyed interacting with the system overall but found some aspects unsatisfactory. Users experienced the most difficulty performing swipes, as indicated by their responses and comments in the survey.

V. Improving Recognition of Swiping

Based on the user dissatisfaction from the swiping behavior, we have improved the system using a pattern recognition technique. The main reason the previous algorithm failed was not taking into account the individual's different intensity and speed using the device (Fig. 6). Some applied force with their large side of the fist, some with their narrower side, some with their hand open, and others using their wrist. In order to recognize meaningful signals from the sensors, we trained six different gestures with hidden Markov models (HMMs) [13]. The biggest advantage of using HMMs is that it can be customized to each individual's needs and ability. For example, if a subject experiences difficulty swiping through all the four sensors, it can be trained to swipe through the last two sensors. Six HMMs were trained and tested: press and release of the four buttons, and forward/reverse swiping.

At the beginning of each subject testing, training data were collected to calibrate and customize the device to fit each individual's habit and motion range. We collected 150 cycles of data for each six gesture per subject. Average sampling rate was 19.62 Hz, and the subjects were asked to repeat the same gesture during the 150 cycles of data collection. Six adult subjects participated in the study, and the total training time ranged from 42 to 60 seconds. Following the training session, testing data were collected in the same manner as the training data. Such collected testing data were used for evaluation. Fig. 7 shows the recognition rate and the confusion matrix. Overall average recognition rate was 96.35\%. The result demonstrates that the gestures generated by different combinations of the sensors can be easily trained and applied to real world applications.

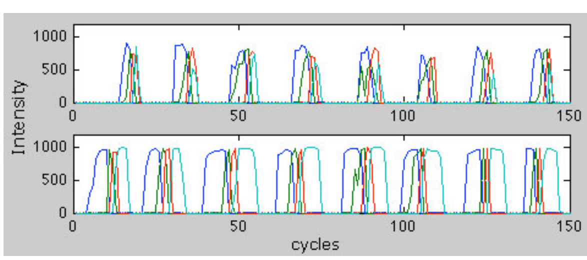

Fig. 6. Two subjects performing *Swiping*. Notice not only the intensity but also the duration on each sensor differs.

VI. Conclusions and Future Work

In conclusion, the data and responses obtained in this project indicate a potential user interface coupled with a robotic agent, which can act as an avatar for children with limited motor capabilities. The users greatly enjoyed being able to control the robot in real-time and trigger different behaviors, but the difficulty of the forward swipe negatively influenced their responses in the survey. Therefore, we have proposed a successful pattern recognition system for the arm glove to calibrate and customize the device for each individual user. We believe the simplicity of this wearable device make it ideal for helping children with limited motor control develop physical and mental dexterity. Currently, the robotic platform is being equipped with KINECT, a 3D motion sensing device, to record motions from a playmate which can then be replayed by our physically challenged subjects. We anticipate this functionality provides a way to engage our subjects in social interactions with their peers.

	Observed						Recognition Rate (%)
Predicted	Button1	Button2	Button3	Button4	Swipe	Reverse-Swipe	
Button1	62				1		98.41%
Button2		65				1	98.48%
Button3			68			2	97.14%
Button4				67			100.00%
Swipe					53	2	96.36%
Reverse-Swipe	4			1	3	55	87.30%
	Average						96.35%

Fig. 7. Confusion Matrix: predicted versus observed number of test sequences are shown. Six subjects participated in the study resulting in an average recognition rate of 96.35%

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