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Robots and Therapeutic Play: Evaluation of a Wireless Interface Device for Interaction with a 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 wireless arm glove input device to enable interaction with a robotic playmate during various play scenarios. Results from testing the system with 20 human subjects shows that the system has potential, but certain aspects need to be improved before deployment with children.**

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 children 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 teleoperated 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 achieving various tasks, their design was as a tool to extend the capability of the user, rather than improve the user's own capability through therapy. These robotic systems 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 humanoid robot during various play scenarios. The motivation for such a system is two-fold: 1) to extend the concept of play for children with disabilities by enabling control of a robot avatar, i.e. an embodied personification of the child that can move around and act in the child's stead and 2) to improve upper extremity function, similar to constraint-induced movement therapy for children with Cerebral Palsy, by providing a motivating reason to use the affected limb. 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

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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 study, we determined that by adapting the slammer switch (a single-switch input device), which was the easiest to use, into an *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 pressure sensors, which children with upper-arm mobility deficiencies can access given their effective range of motion [12]. 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.

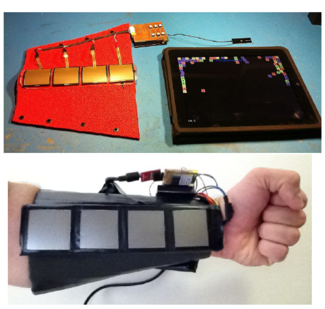

Fig. 1. Two prototypes of the wireless arm glove device

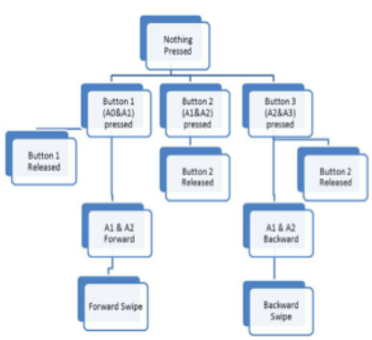

Fig. 2. Algorithm based on Finite State Machine for recognizing button 'swipe' and 'press' gestures

B. Hardware Platform – Humanoid Robot

For our humanoid robot platform, we built a Manoi AT01 humanoid robot, with 17 DOF, and fabricated two hands that were then attached to the robot (Fig. 3). 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.

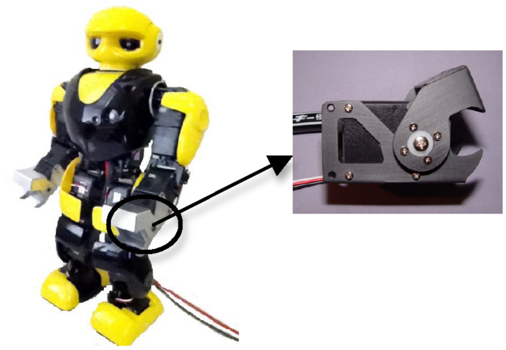

Fig. 3. Our Manoi AT01 humanoid robot and one 1-DOF hand

The nodes were programmed so that when the user provided input to the glove device, it triggered an autonomous robot behavior. 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 were 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.

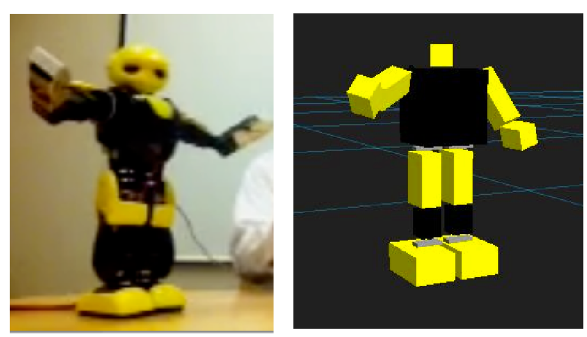

Fig. 4. Robot playmate performing the dance move

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. 9 subjects were female and 11 subjects were male. The subjects' ages ranged from 18 to 32 years old with an average age of 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 on 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

where
Behavior 1: Open/close hands (Button 2)
Behavior 2: Access pre-recorded motion (Button 0)
Behavior 3: Perform dance move (Button 1)
Behavior 4: Send robot to home position (Forward Swipe)

In total, each subject was asked to perform 22 distinct actions consisting of a combination of button presses and swipes. During the test sequences, our data collection system recorded 1) the response time of the robot and 2) the number of times the user had to repeat a button press or swipe command before being recognized. 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?
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 dance/shuffle command?
9	How easy was it to trigger the playback recorded motion command?
10	How easy did you find triggering the home command?
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 1) the average time it took between when a command was triggered by the user and when the robot began to move and 2) the number of times the user had to repeat the command (i.e. interact with the glove) before the robot responded. Overall, the average response time ranged from 0.031 to 0.52 seconds, with an overall average response time under 0.25 seconds. For command-repeats, the button presses were successfully recognized 100% of the time. Unfortunately, for the home position behavior, users had to trigger the forward swipe command repeatedly at least 50% of the time. This is an issue, which we will further discuss in Section V.

TABLE II. RESPONSE TIME AND RECOGNITION RATE OF SYSTEM

Arm glove input	Button 0 (Behavior 2)	Button 1 (Behavior 3)	Button 2 (Behavior 1)	Forward Swipe
Avg. Response Time (s)	0.52	0.38	0.067	0.031
Rate of Recognition (%)	100	100	100	50

Fig. 5 shows the distribution of how the subjects responded to the survey. Of the 20 subjects, the majority (95%) were very satisfied or satisfied with the response time of the open/close hands behavior. This fits with the hands having the second shortest response time of 0.067 seconds. All subjects reported this to be the easiest motion to trigger. A smaller majority (75-80%) of subjects were either very satisfied or satisfied with the response time to the dance command and the playback recorded motion command. These also make sense because the response times of these behaviors were 0.38 and 0.52 seconds, respectively. They are slower than the hands and have a slightly lower satisfaction rating. The majority of users also found these behaviors easy to trigger (95-100%). However, only 60% of the users responded that they were satisfied (7) or very satisfied (5) with the response of the home command (i.e. forward swipe). 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 since it usually took users multiple attempts to successfully execute forward swipes, which can also explain why only 25% of subjects found forward swipes easy (4) or very easy (1) to trigger.

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

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, and only 55% found it easy (10) or very easy (1) to trigger the robot's movements overall. The majority of the subjects (75%) though reported enjoying playing with the system overall.

These responses indicate that most users enjoyed interacting with the system overall but found some aspects unsatisfactory. Based on these responses, we felt that a key element for improving the interaction process was to increase the gesture recognition rate of the system. We accomplished this by individualizing the gesture recognition process.

V. Individualizing the Gesture Recognition Process

Based on analysis of the corresponding sensor data derived from subject interaction, we noticed that each individual varied in the amount of force they applied to the device and the location on each sensor at which they applied their initial force. This was especially true when subjects performed a forward swipe command. As such, we decided to incorporate a device calibration routine that would enable recognition of commands that were customized to each individual's needs and ability. For example, if an individual experienced difficulty swiping through all four sensors (i.e. the current definition of a forward swipe), the device can be calibrated such that a swipe involves only the last two sensors. Our calibration process was implemented by training the system using Hidden Markov Models (HMMs) [13] (Fig. 6), which is a well-known speech recognition algorithm that has also been applied to research in gesture recognition [14].

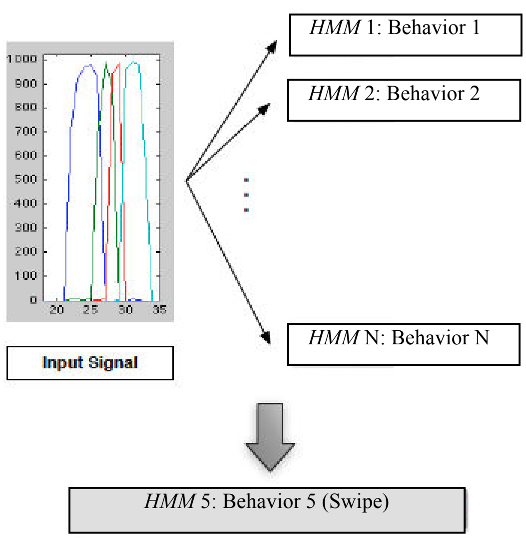

Fig. 6. Device sensor values are evaluated and uniquely associated with the likeliest HMM-trained gesture

To define the calibration parameters, the system was trained by having a user perform a sequence of six gestures that include as many sensor presses, forward swipes, and backward swipes possible, each within a 15 second window. This data is then used to associate a model (HMM) to each gesture (and, by default, a corresponding robot behavior). To evaluate the performance of this new calibration routine, we had six adult subjects perform the training sequence. This data was then used to train an individual HMM-based library of gestures. Following this, the subject was asked to randomly perform sensor presses, forward swipes, and backward swipes, in any order of their choosing. As data arrived, the system computed the maximum likelihood of a command belonging to one of the six gesture models and labeled the gesture as such. Results from this evaluation showed the device was able to achieve an overall recognition rate of 96.4%. Of importance, the forward swipe recognition rate (originally at 50%) increased to 96.4%, which we believe now addresses the issues highlighted in the user survey results.

VI. Conclusions and Future Work

In this paper, we have presented a promising wireless arm glove input device that enables interaction with a robotic platform during various play scenarios. The data and responses obtained from initial evaluation led to inclusion of a calibration routine that individualizes device usage. We believe the simplicity of this device makes it ideal as a tool for engaging children with limited motor control in pediatric physical therapy. Next steps involve working on integrating a new behavior that enables the robot to bend over and pick up a toy object as well as a mechanism for allowing therapists to easily program other robot behaviors. Further studies are also on schedule with child subjects for evaluation of system performance and usefulness of the device in pediatric settings.

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