

Hands-Off Therapist Robot Behavior Adaptation to User Personality for Post-Stroke Rehabilitation Therapy

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Abstract— This paper describes a *hands-off therapist robot* that monitors, assists, encourages, and socially interacts with post-stroke users in the process of rehabilitation exercises. We developed a behavior adaptation system that takes advantage of the user’s introversion-extroversion personality trait and the number of exercises performed in order to adjust its social interaction parameters (e.g., interaction distances/proxemics, speed, and vocal content) toward a customized post-stroke rehabilitation therapy. The experimental results demonstrate the robot’s autonomous behavior adaptation to the user’s personality and the resulting improvements of his/her exercise task performance.

Keywords — Rehabilitation Robotics, Socially Assistive Robotics, Social Human-Robot Interaction, Learning and Adaptive Systems.

I. INTRODUCTION

The recent trend toward developing a new generation of robots that are capable of moving and acting in human-centered environments, interacting with people, and participating and helping us in our daily lives has introduced the need for building robotic systems able to learn how to use their bodies to communicate and to react to their users in a social and engaging way. Social robots that interact with humans have thus become an important focus of robotics research.

Nevertheless, Human-Robot Interaction (HRI) for *socially assistive* applications is still in its infancy. Socially assistive robotics, which focuses on the *social interaction*, rather than the *physical interaction* between the robot and the human user has the potential to enhance the quality of life for large populations of users, such as the elderly [32],

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people with physical impairments and in rehabilitation therapy (e.g., post-stroke patients) [8, 29], people with cognitive disabilities and social and developmental disorders (e.g., children with autism, children with attention deficit/hyperactivity disorder (AD/HD)) [24, 25, 26].

In our work, the target user population is post-stroke patients. Stroke is the leading cause of serious, long-term disability among American adults, with over 750,000 people suffering a new stroke each year [18]. Stroke patients are unable to perform movements with the affected limb, even though the limb is not completely paralyzed. This loss of function, termed “learned disuse”, can improve with rehabilitation therapy during the critical post-stroke period. The best strategy of any post-stroke rehabilitation program is the repetitive practice of exercises, which can be passive and active. In the passive exercises (also known as hands-on rehabilitation), the patient is constantly helped by the human (or robot) therapist to move the paretic limb, while in the active exercises, the patient is performing the exercises alone with no physical hands-on assistance. The vast majority of existing work into rehabilitation robotics focuses on hands-on robotic systems (e.g., [4, 5, 23]). However, recent results from physical therapy research show that such therapy may not be the most effective means of recovery from stroke, and are certainly not the only necessary type of much-needed treatment [8].

Our work focuses on *hands-off therapist robots* that assist, encourage, and socially interact with patients during their active exercises. We previously demonstrated [8, 12, 13, 28, 29], through real-world experiments with stroke patients, that the physical embodiment (including shared physical context and physical movement of the robot), the encouragements, and the monitoring play key roles in patient compliance with rehabilitation exercises. Recently, we also investigated the role of the robot’s personality in the hands-off therapy process, by focusing on the relationship between the level of extroversion/introversion (as defined in Eysenck Model of personality [11]) of the robot and the user [29].

Building robotic systems capable of adapting their behavior to user personality, user preferences, and user profile so as to provide an engaging and motivating

customized protocol is a very difficult task, especially when working with vulnerable users. Different learning systems for human-robot interaction have been proposed in the literature [3, 21], but none of them includes the human profile, preferences, and/or personality in their model. To the best of our knowledge, no work has yet tackled the issue of robot behavior adaptation as a function of user personality in the assistive human-robot interaction context. In our work, we address this issue and propose a behavior adaptation system based on reinforcement learning. The robot incrementally adapts its behavior as a function of the user’s introversion-extroversion level and of the amount of exercises he/she has performed, aiming toward a more individualized and appropriately challenging/nurturing therapy style that will help to improve user task performance. Our robot behavior adaptation system monitors the number of exercises performed by the human/patient, which indicates the level of progress, and changes the robot’s behavior in order to maximize this level.

The rest of the paper is structured as follows. Section II presents a brief overview of our interaction design. In Section III the proposed behavior adaptation system is described. Section IV is dedicated to the description of the experimental test-bed and the experimental setup. Experimental results are presented in Section V. Finally, in Section VI, we conclude the paper and discuss future work.

II. INTERACTION DESIGN

To date, none of the existing robotic systems for socially assistive applications integrate the personality dimension in their behavioral model. Inspired by Bandura’s model of reciprocal influences on behavior [2], we believe that it is helpful to incorporate the personality dimension in order to improve human-robot interaction (HRI) and behavior selection. Figure 1 depicts our general behavior control architecture, which integrates the Eysenck model.

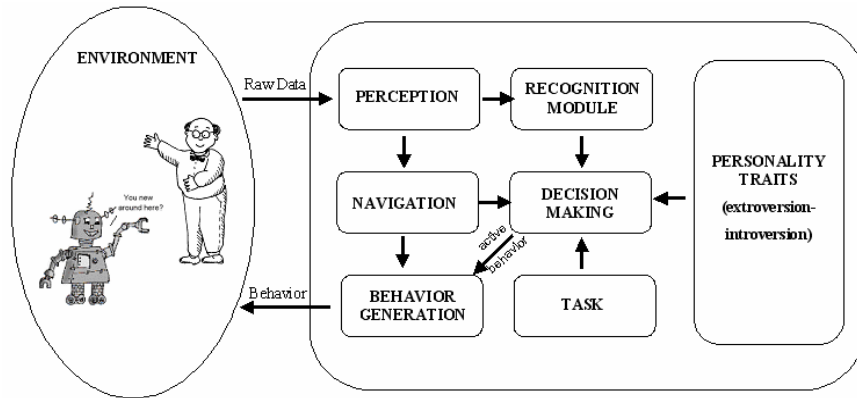


Figure 1: HRI Information Processing using the Personality Model of the User

The extraversion-introversion dimension is based on the observed inter-correlations between traits such as sociability, activity, impulsiveness, liveliness and excitability, all of which strongly influence behavior (see Figure 2).

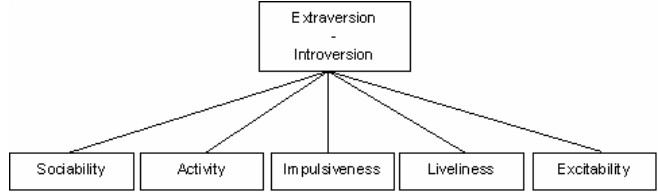


Figure 2: Hierarchical Level of Eysenck’s Extraversion-Introversion Personality

In our interaction design, we chose to use two of those traits: *sociability* and *activity*, which can be most readily emulated in robot behavior. We chose to express these two personality traits through three main parameters that define the therapist robot behavior: interaction design / proxemics, speed, and verbal and para-verbal communication. These are described in more detail below.

A. Sociability

Sociability is the trait that most clearly expresses a person’s level of extroversion-introversion. A large body of research in *social psychology* has shown that individual behavioral differences are most apparent in social situations [7, 9, 17]. In [15], Harkins, Becker and Stonner empirically illustrated that both the presence of others and their social activities are typically more enjoyed by extraverts than by introverts. In [10], Eysenck described the extravert as sociable, friendly, talkative and outgoing. In contrast, the introvert is quiet, introspective, and prefers small groups of intimate friends. We posit that these are directly related to verbal and non-verbal communication patterns. Hence, we identified proxemics and vocal features (i.e., content, volume, and speech rate) as relevant aspects to be embodied in the robot’s behavior. Each is described below.

1) *Proxemics*: The interpersonal space in human interactions has been widely studied in social psychology. Hall [14], pioneer of the field of *proxemics*, identified four general interaction spaces: **Intimate** (up to 0.3m; involves physical contact), **Personal** (between 0.3-1.3m; typically used for family and friend interaction); **Social** (about 1.3-3m; used in business meetings and in public spaces); **Public** (beyond 4m, e.g., the distance between an audience and a speaker) (see Figure 3).

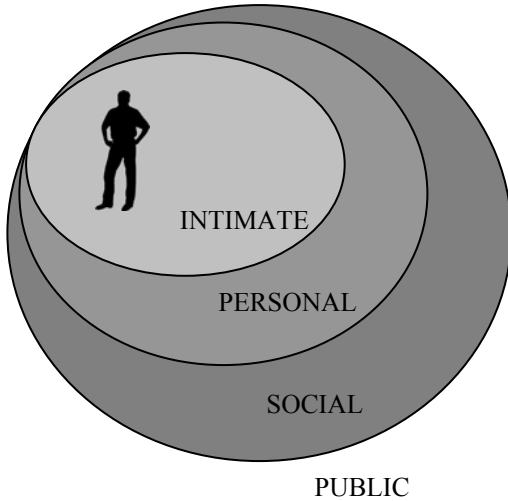


Figure 3: Interaction zones / proxemics: Intimate, Personal, Social, and Public

In this work, we are focusing only on personal and social interaction spaces. Neither the intimate space, nor the public space is appropriate for our application: (a) the intimate implies contact and we are using a non-contact (hands-off) HRI approach; (b) the public space involves no interaction. In [14], Hall analyzed and found a strong link between human sense of space and human behavior and personality type. We posit that extraverted individuals, who like social interactions, may prefer to have the robot physically closer than introverted individuals, who may perceive the robot as invading their space. Therefore, proxemics can be encoded as function of the individual extraversion-introversion level.

2) *Verbal and Para-Verbal Communication*: Both vocal content and paralinguistic cues, such as volume and speech rate, play important roles in human interactions, and express personality and emotion [1, 22, 30]. The similarity-attraction principle, which assumes that individuals are more attracted to other people manifesting the same personality as theirs, has been studied in HCI (e.g., [20]). The interaction scripts that we designed displayed extroverted and introverted personality type through the choice of words and paralinguistic cues. More details

about the different interaction scripts are given in the Experimental Design section (see Section IVA).

B. Activity

In addition to sociability, we also considered the activity trait. Eysenck, in [10, 11], linked the human introversion-extroversion personality trait with the activity level and showed that people with high activity scores are generally energetic and favor physical activity, while individuals with low scores tend to be physically inactive. Therefore, high activity is an extravert characteristic, while low activity tends to characterize introversion. In our system, the activity of the robot is correlated/matched to the user's movement and sociability, and it's represented through robot's movement speed.

III. THE BEHAVIOR ADAPTATION SYSTEM

The main goal of our robot behavior adaptation system consists of optimizing the three main parameters (interaction distance/proxemics, speed and vocal content) that define the therapist robot behavior so as to adapt to the user's personality and improve his/her task performance. The system monitors the user's task performance and the time spent between exercises, and changes robot's behavior in order to maximize the patient's level of progress.

We formulated the problem as *policy gradient reinforcement learning* (PGRL) and developed a learning algorithm. The functioning of PGRL algorithm is the following: (a) parameterization of the behavior; (b) approximation of the gradient of the reward function in the parameter space; and (c) moving towards a local optimum. More details about the algorithm can be found in [16, 27]. Other reinforcement learning techniques, such as Q-Learning, learn an action-value function. Nevertheless, Q-learning, designed for Markov decision processes, cannot directly be applied to our problem since there is no obvious notion of state.

Figure 4 shows the pseudo-code of the *policy gradient reinforcement learning* (PGRL) algorithm. Our n-dimensional policy gradient algorithm implemented for this work starts from an initial set of parameters $\pi = \{\pi_1, \pi_2, \dots, \pi_n\}$ (where $n = 3$ in our case) and generates p random policies in the vicinity of π . The perturbations $\pi^P = \{\pi_1^P, \pi_2^P, \dots, \pi_n^P\}$ are calculated by randomly adding either $+\varepsilon_i$, 0 , or $-\varepsilon_i$ to the initial policy.

Each ε_i is individually chosen for each parameter and is small relative to π_i . The new perturbed parameter set is tested with a user and the reward function is evaluated. Next, the partial derivative in each of the n-dimensions is estimated. This is realized by grouping each π^P into one of three sets for each dimension n , as shown in Figure 2

(steps (12), (13), and (14)). The average rewards (i.e., $Avg_{+\varepsilon,i}$, $Avg_{+0,i}$, and $Avg_{-\varepsilon,i}$) for each parameter for the three cases (i.e., $+\varepsilon_i$, 0 , or $-\varepsilon_i$) are calculated. These three averages give an estimate of the benefit of altering the i parameter by $+\varepsilon_i$, 0 , or $-\varepsilon_i$.

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1   $\pi = \{\pi_1, \pi_2, \dots, \pi_n\} \leftarrow$  Initial policy composed of
   initial set of  $n$  parameters
2   $\pi^P = \{\pi_1^P, \pi_2^P, \dots, \pi_n^P\} \leftarrow$  Perturbed parameter set
   derived from  $\pi$ 
3   $\varepsilon = \{\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n\} \leftarrow$  Parameter step size vector
4   $\eta \leftarrow$  System step size
5  while (not done) do
6    for  $p = 1$  to  $P$ 
7      for  $i = 1$  to  $n$ 
8         $r \in \{-1, 0, 1\} \leftarrow$  Randomly chosen
9         $\pi_i^P = \pi_i + \varepsilon_i * r$ 
10     Evaluate the reward by running the system using
        the parameter set  $\pi$ 
11     for  $i = 1$  to  $n$ 
12        $Avg_{+\varepsilon,i} \leftarrow$  average reward for all  $\pi^P$  with
           positive perturbation in dimension  $i$ 
13        $Avg_{+0,i} \leftarrow$  average reward for all  $\pi^P$  with zero
           perturbation in dimension  $i$ 
14        $Avg_{-\varepsilon,i} \leftarrow$  average reward for all  $\pi^P$  with
           negative perturbation in dimension  $i$ 
15       if  $Avg_{+0,i} > Avg_{+\varepsilon,i}$  and  $Avg_{+0,i} > Avg_{-\varepsilon,i}$ 
16          $A_i \leftarrow 0$ 
17       else
18          $A_i \leftarrow (Avg_{+\varepsilon,i} - Avg_{-\varepsilon,i})$ 
19        $A \leftarrow \frac{A}{|A|} * \eta$ 
20     for  $i = 1$  to  $n$ 
21        $A_i = A_i * \varepsilon_i$ 
22      $\pi = \pi + A$ 

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Figure 4: Pseudo-code for the Policy Gradient Reinforcement Learning (PGRL) Algorithm

The gradient in dimension i , A_i , is considered to be 0 if the average reward for the unperturbed parameter is greater

than the other two average rewards, and is considered to be the difference between the average rewards for the perturbed parameters otherwise. The gradient A is normalized and multiplied by the system step size η , so that the adjustment will remain a fixed size for each iteration. Finally, the parameter set π is adjusted by adding A .

The reward function that we used to evaluate the behavior of the robot was one of the major challenges in implementing the adaptive algorithm. The main issues with computing the reward function and running an adaptive algorithm in our case were the following: (1) the events that mark the interaction between the robot and the participant are discrete, thus computing the reward function can only occur at discrete moments in time; (2) the evaluation of the reward function has to take into consideration both: (a) the fact that as the participant performs the exercises it will incur fatigue, which will slow him/her down, regardless of the personality of the robot or other parameters that we considered, and (b) the fact that the robot is adapting and acting differently can distract the patient, slowing down his/her response.

With these factors in mind, we designed the reward function as follows: (1) we counted the number of exercises performed by the patient during a given period of time, and (2) we normalized the value to reduce the effects of fatigue and the distraction caused by the adaptation procedure.

Similar applications of the adaptive algorithm deal with either more consistent environments, or can evaluate the reward function on a continuous basis, making adaptation seem more real-time. For applications like the one described in [16], the reward function is clearly determined as the speed of the robot. Furthermore, in that case the same robot was used in the same environment for the entire set of tests, reducing thus the number of uncontrolled perturbations that can affect the computation of the reward function.

IV. EXPERIMENTAL SETUP

A. Experimental Design

Two experiments were designed so as to test the adaptability of the robot's behavior to the participant's personality and preferences. Our experimental design attempted to adapt and match robot's behavior and interaction style to different user's personality traits.

In each experiment, the human participant was standing and facing the robot. The experimental task was intended as a functional exercise similar to the exercises used during standard stroke rehabilitation and consisted of moving pencils from one bin on the left side of the participant to another bin on his/her right side. The bin on the right side

of the participant was on a scale in order to measure the user task performance.

The participants were asked to perform the task for 15 minutes, but they could stop the experiments at any time. At the end of each experiment, the experimenter presented a short debriefing.

Before starting the experiments, the participants were asked to fill complete two questionnaires: (1) a general introductory questionnaire in which personal details such as gender, age, occupation, and educational background were determined and (2) a personality questionnaire based on the Eysenck Personality Inventory (EPI) [10] for establishing the user’s personality traits.

Our learning algorithm was initialized with parameter values that were in the vicinity of what was thought to be acceptable for both extroverted and introverted individuals, based on our previous study [29]. These values are described in Table 1.

Table 1: Initial Parameters for the Behavior Adaptation Algorithm

Robot Behavior Parameters		Initial Values	Step Size ϵ
Therapy Style and Robot’s Persona (Vocal content and para-verbal cues)		Id=1	1
Interaction distance/proxemics	Extroverted	0.7m	0.5m
	Introverted	1.2m	
Speed	Extroverted	0.1m/s	0.1m/s
	Introverted		0.05m/s

On the post-experiment survey, the participants were asked to provide their preferences related to the therapy styles, interaction distances, robot’s speed, and robot’s vocal cues (i.e., gender and accent). The participants were also asked to rate their impressions on the robot’s personality on a 7-point Likert scale (i.e., from “strongly agree” to “strongly disagree”).

Experiment 1

The goal of the first experiment was to test the adaptability of the robot behavior to the user personality-based therapy style preference. Four different scenarios were designed for both extroverted and introverted personality types. These therapy styles ranged from coach-like therapy to encouragement-based therapy for extroverted personality types and from supportive therapy to nurturing therapy for introverted personality types (see Table 2). The words and phrases for each of these scenarios were chosen carefully and in concordance with encouragement language used by human therapists. The coach-like therapy script was composed of very strong and aggressive language (e.g., “Move! Move!”, “You can do more than that!”). Higher volume and faster speech rate were used in the pre-recorded transcript voice, based on the evidence that those cues are associated with high extroversion [19]. The aggressiveness of words, the volume, and speech rate diminished along with the robot’s movement towards the nurturing therapy style of the

interaction spectrum. Therefore, the nurturing therapy script contained only empathetic, gentle, and comforting language (e.g., “I’m glad you are working so well.”, “I’m here for you.”, “Please continue just like that”, “I hope it’s not too hard”). The voice used had lower volume and pitch.

Table 2: The Choice of Therapy Styles as a Function of the User- Personality

Parameter	Extroverted			
	Id=1	Id=2	Id=3	Id=4
Therapy Style	Coach-like	Very Challenging	Stimulating	Encourage-based
	Introverted			
	Id=1	Id=2	Id=3	Id=4
	Supportive	Educative	Comforting	Nurturing

A set of 3 interaction distances and speeds were chosen for each introverted and extroverted personality types. These are detailed in Table 3.

Table 3: The Choice of Interaction Distances/Proxemics and Robot’s Speed Parameters as a Function of the User-Personality

Parameter	Extroverted			Introverted		
	Id=1	Id=2	Id=3	Id=1	Id=2	Id=3
Interaction Distance/ Proxemics (m)	0.7	1.2	1.7	1.2	1.7	2.2
Speed (m/s)	0.1	0.2	0.3	0.1	0.15	0.2

Experiment 2

In order to build an engaging and motivating customized protocol, in the second experiment we wanted to ensure the robot was able to adapt to the human preferences. People are more influenced by certain voices and accents than others. Two main scenarios were designed, one for extroverted individuals and one for introverted, respectively. The scenario for the extroverted group was challenge-based while the scenario for the introverted individuals was more nurturing, in conformity with our previous study [29]. We pre-recorded the same scenario with 2 males (one with accent - French native speaker, and one without accent – American native speaker) and 2 females (one with accent - Romanian native speaker, and one without accent – American native speaker) (see Table 4).

Table 4: The Choice of Therapist Robot Persona as a Function of the User- Preferences

Parameter	Id=1	Id=2	Id=3	Id=4
Therapist Persona (gender and English accent)	Female with accent	Male with accent	Male without accent	Female without accent

The choice of interaction distances/proxememics and robot movement speeds was the same as in the first experiment (see Table 3).

B. Robot Test-bed

Our experimental test-bed, shown in Figure 5, consists of an ActivMedia Pioneer 2-DX mobile robot base, equipped with a SICK LMS200 laser rangefinder used to track and identify people in the environment, by detecting reflective fiducials worn by the users. An OHAUS SCOUT Pro Scale, a simple electronic scale measuring weight, connected to a RS232 interface was used to calculate the number of exercises performed by the user.



Figure 5: Robot test-bed

V. EXPERIMENTAL RESULTS

The pilot experimental group consisted of 11 participants (6 male and 5 female). The participants ranged in age between 19 and 35, 27% were coming from a non-technological field, and 73% worked in a robotic or technological related department.

Experiment 1: The results obtained in the first experiment are mainly shown in Figure 6. The Figure 6 shows, for each participant, the percentage of time that it interacted with each of the four therapy styles of the robot. The bars represent the percentages with respect to the total time spent doing the exercises. The crosses represent the preference of the participant, as specified in a post-experiment survey. As illustrated in the Figure 6, the robot adapted to match the preference of the participant in almost every single case. The only exception to the rule was the interaction with participant number 8. Despite the fact that the time spent in the preferred training style of the participant was smaller than the time spent in other training styles, the robot converged to it at the end of the exercise period. The reason for this slight inconsistency was caused by the fact that the initial state of the robot was in a training style that was furthest from the preference of the participant. The fact that we only allowed perturbations to

neighboring training styles corroborated with the relative short duration of the exercise contributed to this result.

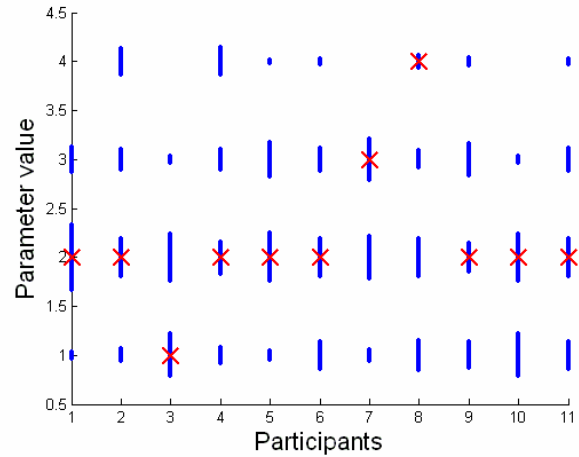


Figure 6: The percentage of time that the 11 participants interacted with each of the four therapy styles of the robot (for extroverted and introverted participants, as described in Table 2). The crosses represent the participants' preferences.

The results show that the robot could adapt its behavior to both introverted and extroverted participants therapy styles preferences.

The adaptability of the robot matched the preferences of the participant even in the case of the preferred distance for interaction, as shown in the Figure 7. Both the extrovert and introvert personalities chose a distance that matched the personal state rather than the social space for their interaction with the robot.

The robot also succeeded to adapt its speed to the user preferences. Introverted users preferred the lower speeds of the robot and extroverted participants preferred the higher speeds of the robot's movement.

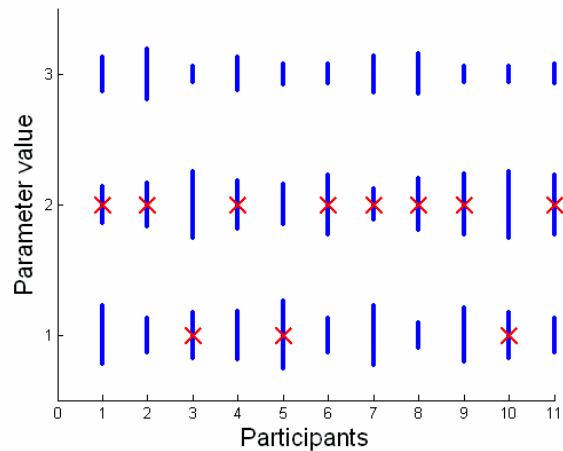


Figure 7: The percentage of time that the 11 participants interacted with the robot at a certain distance (for extroverted and introverted participants, as described in Table 3). The crosses represent the participants' interaction distances preference.

Experiment 2: In the second experiment, the results were again consistent with our assumption that the robot is able to adapt and match to the participant’s preferences. Nevertheless, we encountered two special cases, which we discuss next. First, participant number 5 was not particularly influenced by the variations in voice and accents and, as part of the post-experiment survey mentioned the fact that his second preference was in fact the one in which the robot spent most of the time out of the four choices. Second, participant number 7 had a preference for a male therapist robot but did not care whether it did speak with an accent or not. This is in fact consistent with choices 2 and 3 in which the robot spent 90% of the total time of the exercise.

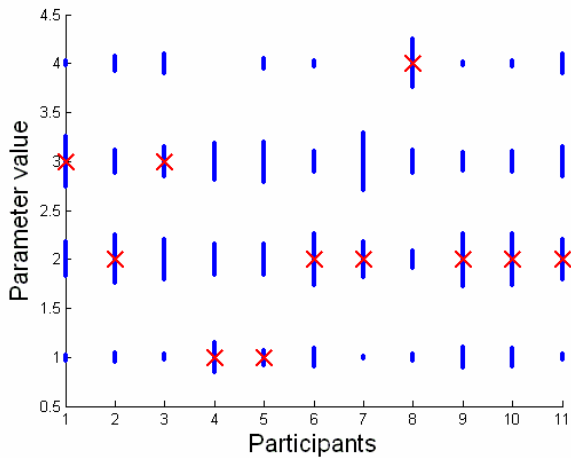


Figure 8: The percentage of time that the 11 participants interacted with each of the four therapist robot persona (gender and English accent, as described in Table 4). The crosses represent the participants’ preferences.

For this case the distance between the robot and the participant (see Figure 9) did not match perfectly the preference of the participant. We believe that this was caused by the fact that the number of adaptation steps was rather small compared to the size of the state space of the parameters and that this parameter had a rather lower impact on the participant reaching his/her goal.

In this second experiment, we obtained similar results for the speeds as the ones resulted in the first experiment.

VI. CONCLUSIONS AND FUTURE WORKS

This paper demonstrated the on-line adaptation of the robot’s behavior (i.e., interaction therapy styles, interaction distance/proxemics, and speed) to the human personality and preferences. Our experiments have shown that with our proposed model the robot can adapt to the human personality and preferences and it can help the participants

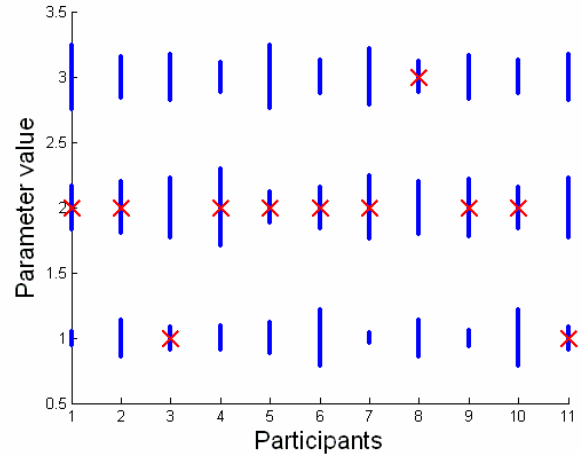


Figure 9: The percentage of time that the 11 participants interacted at a certain distance with the therapist robot (see Table 3). The crosses represent the participants’ preferences.

to improve their task performance, by changing its own behavior. Future work includes exercises over longer periods of time which will allow the robot to better adapt as well as investigating various reward functions that would enable us to understand the impact of each parameter over the success rate of the adaptation process.

Even if socially assistive robotic technology is still in its early stages of development, the next decade promises assistive robotic platforms and systems that will be used in hospitals, schools, and homes in therapeutic programs that monitor, encourage, and assist their users. It is therefore important that potential users, well beyond the technical community, become familiar with this growing technology and help shape its development toward its intended positive impact on numerous lives.

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