User-Robot Personality Matching and Robot Behavior Adaptation for Post-Stroke Rehabilitation Therapy

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Intelligent Service Robotics manuscript No.
(will be inserted by the editor)

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Received: date / Accepted: date

Abstract This paper describes a hands-off socially assistive therapist robot that monitors, assists, encourages, and socially interacts with post-stroke users engaged in rehabilitation exercises. We investigate the role of the robot's personality in the hands-off therapy process, focusing on the relationship between the level of extroversion-introversion of the robot and the user. We also demonstrate a behavior adaptation system capable of adjusting its social interaction parameters (e.g., interaction distances/proxemics, speed, and vocal content) toward customized post-stroke rehabilitation therapy based on the user's personality traits and task performance. Three validation experiment sets are described. The first maps the user's extroversion-introversion personality dimension to a spectrum of robot therapy styles that range from challenging to nurturing. The second and the third experiments adjust the personality matching dynamically to adapt the robot's therapy styles based on user personality and performance. The reported results provide first evidence for user preference for personality matching in the assistive domain and

This work was supported by USC Women in Science and Engineering (WiSE) Program and the Okawa Foundation.

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demonstrate how the socially assistive robot's autonomous behavior adaptation to the user's personality can result in improved human task performance.

Keywords Rehabilitation Robotics · Socially Assistive Robotics · Social Human-Robot Interaction · Learning and Adaptive Systems

1 Introduction

The recent trend toward developing a new generation of robots capable of operating in human-centered environments, interacting with people, and participating and helping us in our daily lives, has introduced the need for robotic systems capable of learning to use their embodiment 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 assistive applications is still in its infancy. *Socially assistive robotics* [15], which focuses on aiding through social rather than physical interaction between the robot and the human user has the potential to enhance the quality of life for large user populations, including the elderly [50], people with physical impairments and those involved in rehabilitation therapy (e.g., post-stroke patients) [10], and people with cognitive disabilities and social and developmental disorders (e.g., children with autism, children with attention deficit/hyperactivity disorder (AD/HD)) [39,41,42]. Hence, one of the main goals of socially assistive robotics is to create stimulating and engaging interactions in which a user actively participates for an extended period of time in order to achieve the goals of the task (therapy, rehabilitation, training, etc.).

In this work, the target user population is post-stroke patients. Stroke is the leading cause of serious, long-term disability among adults, with over 750,000 people suffering a new stroke each year in the US alone [35]. Rehabilitation helps stroke survivors re-learn skills that are lost when part of the brain is damaged. Paralysis affecting the face, an arm, a leg, or an entire side of the body is one of the most common disabilities resulting from stroke. Stroke patients with one-sided paralysis have difficulty with everyday activities such as walking and grasping objects. This loss of function, termed "learned disuse", can be diminished with intensive rehabilitation therapy during the critical months of the post-stroke period. One of the most important elements of any rehabilitation program is the practice of carefully directed, well-focused and repetitive exercises, which can be passive or active. In passive exercises (also known as hands-on rehabilitation), the patient is helped by a human (or robotic) therapist to appropriately exercise the affected limb(s). In contrast, in active exercises, the patient performs the exercises with no physical assistance.

The majority of existing work in rehabilitation robotics focuses on hands-on robotic systems for passive exercise, focusing on attempting to recover upper-limb function primarily through robotic manipulation of the affected-limb. Burgar, Shor et al. [7] developed a robot-assisted arm therapy workstation, in which patients can exercise their upper limbs and evaluate their

performance. A similar device, which also depends on hands-on robotic technology, was developed by [23]. Other related systems have been investigated in [5] and [38].

Recent results from physical therapy research show that hands-on therapy may not be the most effective means of recovery from stroke, and is certainly not the only necessary type of needed treatment [10]. Consequently, our work focuses on hands-off therapist robots that assist, encourage, and socially interact with patients during their active exercises. Our previous work [10] demonstrated that that the physical embodiment, including shared physical context and physical movement of the robot, encouragement, and continuous monitoring play key roles in stroke patient compliance with rehabilitation exercises. We also studied the role of physically embodied interaction in such assistive contexts [15,17,47]; those results form the foundation for the work described here.

Achieving a psychological "common ground" between the human user and the robot is necessary for a natural, nuanced, and engaging interaction. Therefore, in this work we investigated the role of the robot's personality in the assistive therapy process. We focus on the relationship between the level of extroversion-introversion (as defined in the Eysenck Model of Personality [13]) of the robot and the user, addressing the following research questions:

- Is there a relationship between the extroversion-introversion personality spectrum (assessed with the Eysenck model [11]) and the challenging vs. nurturing style of patient encouragement?
- How should the behavior and encouragement of the therapist robot adapt as a function of the user's personality and task performance?

Examining and answering these questions will begin to address the role of assistive robot personality in enhancing patient task performance in rehabilitation exercises as well as other task domains.

Creating robotic systems capable of adapting their behavior to user personality, user preferences, and user profile in order to provide an engaging and motivating customized protocol is a very difficult task, especially when working with vulnerable user populations. Various learning approaches for human-robot interaction have been proposed in the literature [4], but none include the user's profile, preferences, and/or personality. To the best of our knowledge, no work has yet tackled the issue of robot personality and behavior adaptation as a function of user personality in the assistive human-robot interaction context. In the work described here, we address those issues and propose a methodology for evaluating the user-robot personality match and a reinforcement-learning-based approach to robot behavior adaptation. In the learning approach, the robot incrementally adapts its behavior and thus its expressed personality as a function of the user's extroversion-introversion level and the amount of performed exercises, attempting to maximize that amount. The result is a novel stroke rehabilitation tool that provides individualized and appropriately challenging/nurturing therapy style that measurably improves user task performance.

The rest of the paper is structured as follows. In Section 2, our research is placed in the context of the relevant work in assistive robotics. Section 3

presents the Eyseck Model of Personality. Section 4 overviews our human-robot interaction design. Section 5 describes the proposed behavior adaptation system. Section 6 provides a description of the experimental test-bed, the experimental setup, and the experimental results. Section 7 discusses future work and concludes the paper.

2 Related Work and Open Challenges

In this section we briefly review related work in assistive robotics to which our research most directly contributes.

An active component of assistive robotics research is focused on designing robotic systems for eventual in-home use, mainly involving contact-based interaction. A common theme of the work is a high degree of task specialization toward capabilities that would enable elderly and/or disabled people to accomplish tasks they could not do otherwise and to be commanded in some form by a user with one or more communication disabilities. Movement aides that have been developed include the GuideCane [1], a robotic guide cane for the blind, the PAMM intelligent walker [44], Wheelesey [54], and the NavChair [24], which involved speech control of the wheelchair [43]. Some work has addressed the safety aspects of such systems [43],[54] and suggested common metrics for their testing and evaluation.

Another target domain of assistive robotics consists of hospitals, nursing homes, and managed care homes. The research in that domain has ranged from robotic companions [50], to story telling robots [37], to robots that serve as guides and schedule reminders [40], to aides in rehabilitation therapy [10].

Animal-assisted activities (AAA) and animal-assisted therapies (AAT) have served as inspiration for past work in socially assistive robotics. First efforts focused on robotic pets, companions that attempt to reduce stress and depression [50]. Companion robots are designed to fulfill some of the roles of animal pets, but without the associated pet care. Researchers have used robotic animal toys, such as a seal(i.e., PARO [50, 52]), a cat [50], a dog (i.e., SONY AIBO), and a teddy bear (i.e., the Huggable [45]) to attempt to improve psychological health in elderly patients. These studies have shown that elderly users smiled and laughed more, and became less hostile to their caretakers and more socially communicative as a result of interacting with the robots. However, the novelty factor of the impact of such systems has not yet been studied [21].

Flo, and later Pearl, were mobile nurse's assistant robots for use in telepresence, data collection in a hospital or nursing home, as a cognitive prosthetic for patients, and as a vehicle for social interaction [40]. The robots were controlled through a remote tele-operation GUI, speech recognition, or a touch screen. The possible demeanor for such robots was studied [18]; it was found that while a playful robot generated a positive response from patients, a serious robot received more cooperation. Pearl was a more complex such system [25] that allowed for the study of the intricacies of temporal planning in an assistive setting, determining an effective plan based on user inputs by creating a personalized cognitive orthotic. The resulting systems

combined the guide functions of previous systems to create a nurses' assistant and cognitive orthotic for patients, and was evaluated in a nursing home setting [29].

We propose a fundamentally different approach to robot-assisted convalescence and rehabilitation, one that involves no physical contact between the patient and the robot. Our approach fits within a new research area termed Socially Assistive Robotics [15], which has a broad focus on gaining new insights about human-robot social interactions in the assistive context and using those to develop and deploy robotic systems that assist people. Making those systems safe and affordable predominantly implies hands-off, non-contact interaction between the robot and its user(s). The Nursebot project [40,18,29,25] is one of the most mature efforts in this new field, involving a mobile robot that roams the hospital, makes deliveries, and verbally interacts with patients. Another active area of socially assistive robotics is studying robots as tools toward automated diagnosis and socialization therapy for children with autism, where robots have been shown to have great potential [27,28,41].

Our research program defines a new niche of assistive robotics, one that involves an autonomous robot providing contact-free rehabilitation monitoring, assistance, and encouragement to stroke patients, while also being capable of providing detailed reports of patient progress to physicians and therapists. The robot's physical embodiment, its physical presence and appearance, its shared context with the user, its personality, and its empathetic traits are all fundamental in time-extended, sustained, personalized exercise supervision, motivation, and encouragement in rehabilitation therapy. In the work described here, we focus on user-robot personality matching and robot behavior adaptation to user's personality and preferences, aiming toward a customized therapy protocol for stroke and other rehabilitation and exercise application domains. We start by describing the model of personality we use.

3 Eysenck Model of Personality

Personality is a key determinant in human social interactions. A direct relationship between personality and behavior has long been recognized [8,10, 34]. In [30], Morris indicated that, to a personality psychologist, the behaviors of greatest importance are those that are:

1. relatively pervasive in the person's life-style in that they show some consistency across situations;
2. relatively stable in the person's life-style across time;
3. indicative of the uniqueness of the person.

Consequently, personality is also a key factor in human-robot interactions (HRI) [32,33]. It has been argued that robot personality should match that of the human user [33]. While there is no generic definition of personality, our working definition, based on the literature [53,9,30], defines *personality as the pattern of collective character, behavioral, temperamental, emotional and mental traits of an individual that have consistency over time and situations.*

To date, little research into human-robot personality matching has been performed. In [53], Woods et al. explored the topic, showing that subjects perceived themselves as having stronger personality traits than robots. A similar study [18] found that people enjoyed interacting with humorous robots but complied with the more serious ones. No work has yet addressed the issue of personality in the assistive human-robot interaction context. That topic is the focus of the work presented here.

Quantification of personality is controversial since there is no universally accepted number of personality dimensions. The Eysenck model of personality (3 model factor - PEN) [12], the Five-factor model of personality (Big5) [26] (extroversion-introversion, neuroticism, agreeableness, conscientiousness, and openness) and the Myers-Briggs model [31] (extroversion-introversion, sensation-intuition, thinking-feeling, and judging-perceiving) are the dominant models in the literature. In this work, we use the biologically-based Eysenck [13] Model of Personality (PEN) that advocates three major dimensions or super-factors in the description of personality: (**P**) **P**sychoticism, (**E**) **E**xtroversion, and (**N**) **N**euroticism. The extroversion vs. introversion dimension is related to the social interest and positive affect. Eysenck showed that extroversion-introversion is a matter of the balance of neural "inhibition" and "excitation", since extroversion is based on cortical arousal, measurable through skin conductance. Neuroticism or emotional stability vs. instability corresponds to the stability of behavior over time and the person's adaptation to the environment. Neuroticism is based on activation thresholds in the sympathetic nervous system, measurable through heart rate, blood pressure, hand temperature, perspiration, and muscular tension. Finally, psychoticism is associated with rebelliousness, aggressiveness, and impulsiveness, and is related to testosterone levels.

We chose the PEN model of personality because of its biologically inspired nature and its explicit treatment of introversion and extroversion, factors that are specifically relevant to the assistive context. Our previous work with stroke patients [10] demonstrated significant personality differences in patient response to the robot therapist. This work aims to address those differences directly, by focusing on the extroversion-introversion personality dimension. Another inspirations for this work is the observed influence of the pre-stroke personality on post-stroke recovery. It has been noted that subjects classified as extroverted before the stroke mobilize their strength easier to recover than do introverted subjects [16]. Since the extroversion dimension (see Figure 1) is comprised of many different factors, habits, and behaviors, in this study we give higher importance to extroversion-introversion traits, in order to map them to the spectrum of therapy styles that range from nurturing to challenging.

4 Interaction Design

To date, none of the existing robotic systems for socially assistive applications integrate personality in their behavioral model. Inspired by Bandura's model of reciprocal influences on behavior [3], we believe that it is helpful to incorporate personality in order to facilitate human-robot interaction (HRI)

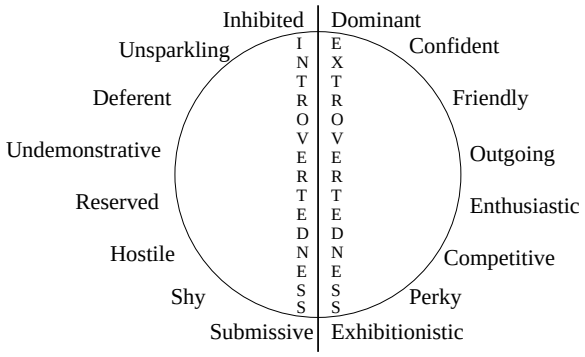

Fig. 1 The Eysenck [13] Introvert and Extrovert Adjectives of Human Personality

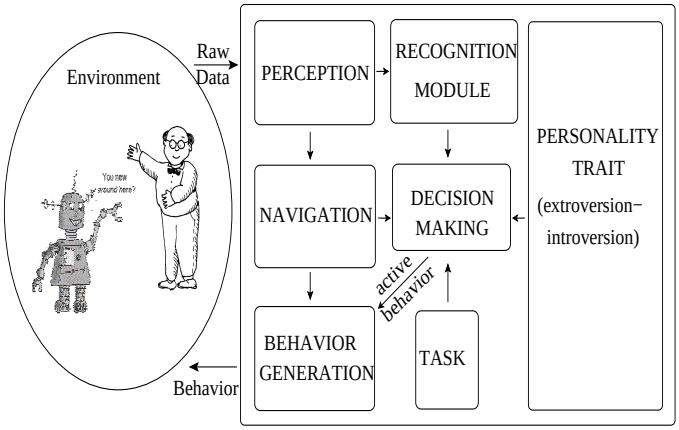

Fig. 2 HRI Information Processing using the Personality Model of the User

and robot behavior selection. Figure 2 depicts our general robot behavior control architecture, which integrates the Eysenck model.

The extroversion-introversion dimension is based on the observed intercorrelations between traits such as sociability, activity, impulsiveness, liveliness and excitability, all of which strongly influence behavior. In our interaction design, we chose to use two of those traits: 1) sociability and 2) activity. These traits can be most readily emulated in robot behavior. We expressed those traits through three main parameters that define the therapist robot behavior: 1) interaction distance / proxemics, 2) speed, and 3) verbal and para-verbal communication. These are described in more detail below.

4.1 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 [9,11,

30]. In [20], Harkins, Becker and Stonner empirically illustrated that both the presence of others and their social activities are typically more enjoyed by extroverts than by introverts. In [10], Eysenck described the extrovert 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.

4.1.1 Proxemics

The interpersonal space in human interactions has been widely studied in social psychology, since the seminal paper by Hall [19] who coined the term proxemics. Recently, roboticists have begun to use proxemics in social spatial interactions [8,17,51]. Hall identified four general interaction spaces (see Figure 3):

- Intimate: Up to 0.25m from the body; usually involves contact (e.g., embracing, comforting), can be uncomfortable and intrusive.
- Personal: Between 0.3-1m; typically used for family and friend interactions;.
- Social: About 1-3m; used in business meetings and public spaces.
- Public: Beyond 3m; e.g., the distance between an audience and speaker.

The robot must ensure its own appropriate use of and respect for interaction space so that a human user can feel safe, comfortable, and in concordance with his/her personality preferences. In this work, we focus only on personal and social interaction spaces. Neither intimate space nor public space is appropriate for our application; the former intimate implies contact and we are using a non-contact (hands-off) HRI approach and the latter involves no interaction. Hall [19] found a strong link between human sense of space and human behavior and personality type. We posit that extroverted 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 extroversion-introversion level.

4.1.2 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 [2,36,49]. The similarity-attraction principle, which assumes that individuals are more attracted to others who manifest the same personality has been studied in HCI (e.g., [34]). Also, many psychological studies [6] have found that prosodic characteristics are linked with features of personality, e.g., excitement or arousal (extroversion-introversion) are strongly correlated to prosodic features such as pitch level [48], pitch range, and tempo [2]. The interaction scripts that we designed in this work display extroverted and

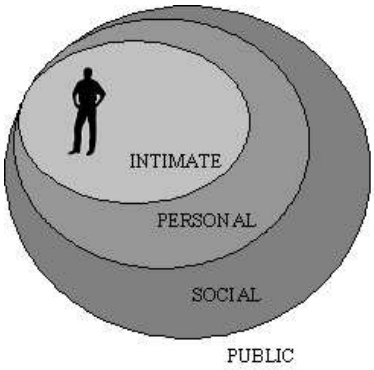

Fig. 3 Interaction zones / proxemics: intimate, personal, social, and public

introverted personality type through the choice of words and paralinguistic cues. More details about the different interaction scripts are given in the Experimental Validation part (see Section 6).

4.2 Activity

In addition to sociability, we also considered the activity trait. Eysenck [12, 13], linked the human extroversion-introversion 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. He suggested that high activity is an extrovert 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 is expressed through the robot's speed of movement.

5 Behavior Adaptation System

The main goal of our robot behavior adaptation system is to enable us to optimize on the fly the three main parameters (interaction distance/proxemics, speed, and vocal content) that define the behavior (and thus personality) of the therapist robot, so as to adapt it to the user's personality and thus improve the user's task performance. Task performance is measured as the number of exercises performed in a given period of time; the learning system changes the robot's personality, expressed through the robot's behavior, in an attempt to maximize the task performance metric.

We formulated the problem as *policy gradient reinforcement learning (PGRL)* and developed a learning algorithm that consists of the following steps: (a) parametrization of the behavior; (b) approximation of the gradient of the reward function in the parameter space; and (c) movement towards a local optimum. More details about the PGRL classical algorithm can be found in [22] and [46]. Other reinforcement learning techniques, such as Q-Learning, learn an action-value function. However, 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 our PGRL algorithm. The n-dimensional policy gradient algorithm implemented for this work starts from an initial policy $\pi = \{\theta_1, \theta_2, \ldots, \theta_n\}$ (where $n = 3$ in our case). For each parameter θ_i we also define a perturbation step ϵ_i to be used in the adaptation process. The perturbation step defines the amount by which the parameter may vary to provide a gradual migration towards the local optimum policy. The use of PGRL requires the creation of a reward function to evaluate the behavior of the robot as parameters change to guide it towards the optimum policy. The robot is started given the initial policy π, and its learning process can be summarized as the following steps:

1. The robot acts given the current set of parameters (π_{run}).
2. The reward function is evaluated to measure the performance of the robot.
3. The loop returns to step 1, possibly with an updated policy due to the adaptation process, until the time limit for the exercise is reached.

The reward function is monitored to prevent it from falling under a given threshold, which would indicate that the robot's current behavior does not provide the patient with an ideal recovery scenario. This triggers the activation of the PGRL adaptive algorithm phase to adapt the behavior of the robot to the continually-changing factors that determine the efficiency of the recovery process. The adaptation algorithm has the following main steps:

1. Generate k random policies in the vicinity of the current parameter set π_{run} (lines 15-20). Each of the perturbed arrays in the set $\mathcal{P} = \{\pi^1, \pi^2, \ldots, \pi^k\}$ is calculated by randomly adding either $+\epsilon_i$, 0, or $-\epsilon_i$ to each of the parameters in the current policy π_{run}.
2. Record the performance of the robot (the reward function) for each perturbed array.
3. When all the k perturbed arrays have been evaluated proceed to compute the new "stable" parameter set that will presumably increase the performance of the robot (lines 22-40).

Computing the direction in which to change each parameter to maximize the user's task performance is done over the recorded reward functions for the k perturbed arrays. This has itself three steps, as follows:

1. For each parameter p_i compute the average reward over the k perturbed runs for each of the types of perturbations (i.e. $+\epsilon$, 0, $-\epsilon$) of the parameter. The average rewards are recorded in the array avg, as described between lines 25 and 27 in the algorithm presented in Figure 4. These three averages give an estimate of the benefit of altering parameter i by $+\epsilon_i$, 0, or $-\epsilon_i$.
2. The direction in which each parameter slides is computed between line 28 and line 32 in the algorithm. If the most performance was obtained with the parameter un-altered then the parameter should remained un-altered (thus $a_i = 0$). Otherwise, compute which direction $+\epsilon$ or $-\epsilon$ produced better results (line 31).
3. Use the contents of a to compute the new set of parameters for use in the steady (non-adaptive) state.

```
    Initial policy composed of the initial set of n parameters
1:  π = {θ_1, θ_2, ..., θ_n}
    Parameter step size vector
2:  ε = {ε_1, ε_2, ..., ε_n}
    The reward for each perturbed parameter array
3:  reward = {reward_1, reward_2, ..., reward_k}
4:  mode = NON_ADAPTIVE
5:  while (not done) do
6:      if (mode == NON_ADAPTIVE) then
7:          π_run = π
8:      else // choose a policy from the perturbed array
9:          π_run = π^idx
10:     end if
11:     robot_behavior(π_run)
12:     reward_run = evaluate_set(π_run)
13:     if (low_performance(reward_run) and
            mode == NON_ADAPTIVE) then
14:         mode = ADAPTIVE
            Generate the set of k perturbed policies from π
            P = {π^1, π^2, ..., π^k}
15:         for p=1 to k do // generate policy π^p
16:             for i=1 to n do
17:                 r = random choice from {-1, 0, 1}
18:                 θ_i^p = θ_i + ε_i * r
19:             end for
20:         end for
21:         idx=0 // start iterating through random policies
22:     else if (mode==ADAPTIVE) then
23:         if (idx==k) then //finish adaptation stage
24:             for i = 1 to n
25:                 avg_i^+ε ← average reward for all π^p with
                        positive perturbation (for which
                        r was 1) in dimension i
26:                 avg_i^0 ← average reward for all π^p with
                        no perturbation (for which r was
                        0) in dimension i
27:                 avg_i^-ε ← average reward for all π^p with
                        negative perturbation (for which
                        r was -1) in dimension i
28:                 if (avg_i^0 > avg_i^+ε and avg_i^0 > avg_i^-ε)
29:                     a_i = 0
30:                 else
31:                     a_i = (avg_i^+ε − avg_i^-ε)
32:                 end if
33:             end for
34:             π =adjust_policy (π, a⃗)
35:             mode=NON_ADAPTIVE
36:         else
                Store the reward for the final adjustment
37:             reward_idx = reward_run
38:             idx++
39:         end if
40:     end if
41: end while
```

Fig. 4 Pseudo-code for the Policy Gradient Reinforcement Learning (PGRL) Algorithm

The decision of reward function to use 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 the adaptive algorithm in our case were the following: (1) the events that mark the interaction between the robot and the participant are discrete, so computing the reward function can only occur at discrete moments in time; (2) the evaluation of the reward function must take into consideration both: (i) the fact that as the user performs the exercises s/he will become fatigued which results in slowing down of performance regardless of the personality of the robot and the other parameters that we considered, and (ii) the fact that the robot adapts and acts 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 user during a given period of time, and (2) we adjusted the threshold value to reduce the effects of fatigue and distraction caused by the adaptation procedure.

Other research that uses the same mechanism for adaptation has been been conducted either in more consistent environments than ours, or with the ability to continuously evaluate the reward function, which makes adaptation take place in real-time. For applications like the one described in [22], where the authors try to maximize the speed of a robot the reward function is clearly determined; it is the speed of the robot. In our application we have to measure the efficiency of the robot in encouraging and directing the patient through the recovery process, which is a highly subjective and hard to measure metric. Furthermore, in that project the same robot was used in the same environment for each variation of the parameters. This allowed for a more accurate account of improvements for each variations of the parameters by reducing the number of uncontrolled factors that can affect the computation of the reward function. In our application the reward function depends not only on the robot's parameters, but also on the user, who can be unpredictable and inconsistent in its action, which makes the evaluation of the reward function more difficult, and possibly inaccurate.

6 Experimental Validation

In this section we present a series of hypothesis about the matching between the personality of the user and that of the robot it interacts with and we validate them using a set of experiments. Our experiments try to address two issues. First, we investigate the user-robot personality matching. Second, using the results of the first experiment we refine the matching process between the user and the robot using our adaptation algorithm to increase the user's efficiency in performing the task at hand. We analyze how varying minor characteristics of the robot's personality impacts the efficiency of the user and whether the robot is able to converge to a set of characteristics that are in consensus with the user's preferences.

To date, our system has been validated only with healthy participants. In order to be able to obtain more relevant results, the healthy volunteers used their non-dominant limb (their weaker side) while doing the specified tasks.

Fig. 5 Robot Test-bed; an ActiveMedia Pioneer 2-DX mobile robot equipped with a SICK laser range scanner, a camera, and speakers.

They were also encouraged to establish a social relationship with the robot based on its personality and act as they would normally do when interacting with a person with similar personality characteristics.

We begin this section by introducing the robot system that was used in our experiments and continue with the overview of the experiments we conducted.

6.1 Robot Test-bed

Our experimental test-bed, shown in Figure 5, consisted of an ActiveMedia 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 users. On the stroke-affected limb, the users wore a light-weight motion-capture system based on inertial measurement units (IMU) that allowed the robot to detect and track the user's limb movement.

Physical form and appearance of the robot was not a focus of the presented research. Based on the results of our previous study [10], in which we evaluated a new stroke rehabilitation approach that used a non-anthropomorphic socially assistive robot that interacted with post-stroke patients, we chose to use the same platform in the current study. The robot's physical appearance is an important issue in human-robot interaction. Our future work will make use of a new biomimetic humanoid torso mounted on the mobile platform illustrated above, in order to test the role of physical embodiment and the effectiveness of an anthropomorphic vs. a non-anthropomorphic robot in a rehabilitation program.

6.2 User-Robot Personality Matching

6.2.1 Hypotheses

Based on the principle of similarity attraction [34], the following hypotheses were formulated in order to test the user-robot personality matching.

Table 1 Choice of Vocal Content and Para-verbal Cues for Testing the User-Robot Personality Matching

Personality Trait	Vocal Content and Para-verbal Cues
Introversion	– nurturing, script containing gentle and supportive language (e.g., "I know it's hard, but remember it's for your own good.", "Very nice, keep up the good work.") – low pitch and volume
Extroversion	– challenging language (e.g., "You can do it!", "Concentrate on your exercise!") – high pitch and volume

Hypothesis 1: A robot that challenges the user during rehabilitation therapy rather than praising her/him will be preferred by users with extroverted personalities and will be less appealing to users with introverted personalities.

Hypothesis 2: A robot that focuses on nurturing praise rather than on challenge-based motivation during the training program will be preferred by users with introverted personalities and will be less appealing to users with extroverted personalities.

6.2.2 Experimental Design

The study had a 2(sociability) x 2(activity) design. Hence, the robot could manifest (non)social and (low)high activity traits through its behavior to express the extroversion (challenging) or introversion (nurturing) therapy styles. The vocal content and para-verbal cues used in this experiment are described in Table 1.

Before participating in the experiment, each subject was asked to complete two questionnaires: one for determining personal details such as gender, age, occupation, and educational background, and another for establishing the subject's personality traits based on the Eysenck Personality Inventory (EPI) [14]. The four experimental tasks were intended as functional exercises similar to those used during standard stroke rehabilitation:

– Drawing up and down, or left and right on an easel;
– Lifting and moving books from a desktop to a raised shelf;
– Moving pencils from one bin to another;
– Turning pages of a newspaper.

The participants were asked to perform the four tasks in a sequence as part of a predefined scenario, but they could stop the experiments at any time by saying "stop". Each task lasted for 4 minutes, after which the robot verbally advised the user to change the task. At the end of each experiment, the experimenter presented a short debriefing.

Fig. 6 The first experimental setup: the participant is performing Task 4 (turning pages of a newspaper) with the robot at a social distance. The laser fiducial is on the participant's right leg, the motion sensor on the right arm, and a microphone is worn on standard headphones.

Vocal data was collected from the user using a microphone and it was interpreted using automatic voice analysis software. The robot was capable of understanding the following utterances: "yes", "agree", "no", and "stop". The participant wore a motion sensor on the (weaker, if post-stroke) upper arm to monitor movement and a reflective laser fiducial was strapped around the lower leg to allow the robot to locate him/her, as shown in Figure 6.

Each participant was exposed to two different assistive personalities of the robot: one that matched his/her personality according to the Eysenck Personality Inventory (EPI) and one that was randomly chosen from the remaining options. The system evaluation was performed based on user introspection (questionnaires). After each experiment, the participant completed two questionnaires designed to evaluate impression of the robot's personality (e.g., "Did you find the robot's character unsociable?") and about the interaction with the robot (e.g., "The robot's personality is a lot like mine."). All questions were presented on a 7-point Likert scale ranging from "strongly agree" to "strongly disagree".

Table 2 Average of results obtained for testing the matching between the user's and robot's personality (disagreement = 1, agreement = 7)

	Extroverted Users Mean	Introverted Users Mean	Overall Mean
Extroverted Robot	4.91	3.57	3.68
Introverted Robot	3.16	4.57	4.42

6.2.3 Experimental Results

The subject pool for this experiment consisted of 19 participants (13 male, 6 female; 7 introverted and 12 extroverted). A small portion (16%) was under 20 years old, but none younger than 18. Approximately, 22% were 21-25 years old and 63% were 26-30. Most of the participants (except three) were students; 79% worked in a technology-related area.

To test the match between the user's and robot's personality, we asked the participants to rate whether they felt that the "'robot's personality was a lot like yours", on a Likert scale from 1 (strongly disagree) to 7 (strongly agree). Table 2 shows averaged results

While the overall mean of the responses was very close to the midpoint, "neither agree, nor disagree", for both the interaction with the introverted and the extroverted robot, the participants tended to match their personality to the robot's as described below. Extroverted users rated the extroverted robot as significantly closer to their personality than the introverted robot (extroverted robot $M = 4.91$, introverted robot $M = 3.16$). Introverted users thought that the introverted robot matched their personality better ($M = 4.57$) than the extroverted one ($M = 3.57$). To validate our hypotheses and to make sure that the variation in the means between extroverted and introverted users for interaction with each type of robot personality is significant and that it is due to the variation between the treatment levels (the user's personality) and not due to random error we did an analysis of variance (ANOVA).

The first set of data consisted of the answers provided by all participants during their interaction with the extroverted robot. The results obtained in this case for a significance level $\alpha = 0.05$ were: $M_{extro-user} = 4.91$, $M_{intro-user} = 3.57$, $F_{0.05}[1, 17] = 10.7680$, $p = 0.0044$. Thus, our hypothesis was validated by the results in this case. The probability ($p = 0.0044$) that the null hypothesis, which affirms that the variation is only due to random error, is valid is extremely low. The results obtained from data collected during the interaction with the introverted robot validated our hypothesis as well: $M_{intro-user} = 4.57$, $M_{extro-user} = 3.16$, $F_{0.05}[1, 17] = 15.810$, $p = 0.0010$. In this case the validity of the null hypothesis is even lower ($p = 0.001$).

By design, the extroverted robot had a challenge-based style of user encouragement, while the introverted robot used a nurturing therapy style. We also analyzed the correlation between the extroversion-introversion personality of the robot and the user's perception of challenge-based vs. nurturing style of encouragement that it used. The users were asked to rate the robot encouragement style on a Likert scale from 1 (Nurturing) to 7 (Challenging).

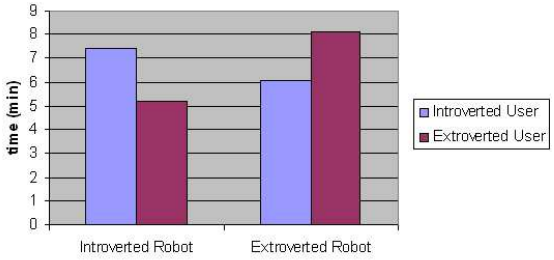

Fig. 7 The average interaction time (minutes) spent by introverted/extroverted users with introverted/extroverted robots, respectively.

On average, the participants classified the introverted robot as more nurturing ($M = 3.21$) and the extroverted robot as more challenging ($M = 5.10$).

None of the 38 trials was terminated by the experimenter. The end of a trial was either a sequence of "stop" utterances said by the user or the end of the four exercises. Because of the high sensitivity of the speech recognition system, participant breathing and ambient noise were on occasion incorrectly detected as a "stop" or "no", ending the interaction prematurely. Figure 7 shows the average interaction time (in minutes) spent by the extroverted/introverted users with extroverted/introverted robots, respectively. To validate our hypothesis that the interaction time with each type of robot personality was significant we did an analysis of the variance (ANOVA). The results strongly supported our hypothesis, as follows. For the interaction with the introverted robot the means and probability of the null hypothesis being true were: $M_{intro-user} = 7.41$, $M_{extro-user} = 5.21$, $F_{0.05}[1, 17] = 10.4337$, $p = 0.0049$. For the interaction with the extroverted robot the results were: $M_{intro-user} = 6.1$, $M_{extro-user} = 8.11$, $F_{0.05}[1, 17] = 9.8092$, $p = 0.0061$.

Another interesting finding gathered from the exit debriefings was that a large percentage of participants (77%) would have preferred to speak more with the robot and to have a more complex dialog with it. Our future work will enrich the verbal communication between the participants and the robot.

In summary, the experimental studies validated our two hypotheses. The participants with extroverted personalities had a preference for a robot that challenged them during exercises over the one that focused the interaction on praise. Analogously, users with introverted personalities preferred the robot that focuses on nurturing praise rather than on challenge-based motivation during the training program. Thus, the results show user preference for human-robot personality matching in the socially assistive context. Further experiments with larger and more representative participant pools (i.e., stroke patients) are being addressed in our continuing work.

6.3 Robot Behavior Adaptation

Two experiments were designed to test the adaptability of the robot's behavior to the participant's personality and preferences. In each experiment, the

Table 3 Initial Parameters for the Behavior Adaptation Algorithm

Robot Behavior Parameters		Initial Values	Step Size ϵ
Therapy Style and Robot's Personality as expressed through vocal content and para-verbal cues		Id=1	1
Interaction distance / proxemics	Extroverted	0.7m	0.5m
	Introverted	1.2m	0.5m
Speed	Extroverted	0.1m/s	0.1m/s
	Introverted	0.1m/s	0.05m/s

human participant stood and faced the robot. The experimental task was a common object transfer task used in post-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 was on a scale in order to measure the user's task performance. The system monitored the number of exercises performed by the user.

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 complete the same two questionnaires as in the previous experiment: (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) [14] for establishing the user's personality traits.

The robot used the algorithm described in Section 5 to adapt its behavior to match each participant's preferences in terms of therapy style, interaction distance and movement speed. The 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 the user-robot personality matching study described above. The values are shown in Table 3.

The PGRL algorithm used in our experiments evaluated the performance of each policy over a period of 60 seconds. The reward function, which counted the number of exercises performed by the user in the last 15 seconds was computed every second and the results over the 60 seconds "steady" period were averaged to provide the final evaluation for each policy.

The threshold for the reward function that triggered the adaptation phase of the algorithm was set to 7 exercises at each evaluation for the first 10 minutes of the exercise and it was lowered to 6 exercises from 10 minutes to 25 minutes into the exercise. The threshold was adjusted to account for the fatigue incurred by the participant. The threshold and the time ranges are all customizable parameters in our algorithm. The values for these parameters were chosen based on empirical data collected during trial runs before the actual experiment was conducted.

In the post-experiment survey, the participants were asked to provide their preferences related to the therapy styles or robot's vocal cues, interac-

Table 4 The Choice of Therapy Styles as a Function of the User-Personality

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

Table 5 The Choice of Interaction Distances/Proxemics and Robot's Speed Parameters as a Function of the User-Personality

Parameter	Extroverted			Introverted		
Interaction Distance/ Proxemics (m)	Id=1	Id=2	Id=3	Id=1	Id=2	Id=3
	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

tion distances, and robot's speed from the values used in the experiments, as described below.

6.3.1 Robot Behavior Adaptation to User Personality-Based Therapy Styles

Experimental Design The goal of this 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: the 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 4). The words and phrases for each of these scenarios were selected in concordance with encouragement language used by professional rehabilitation therapists. The coach-like therapy script was composed of 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 [34]. The aggressiveness of words, the volume, and the speech rate diminished along with the robot's movement towards the nurturing therapy style of the interaction spectrum. 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.

A set of 3 interaction distances and speeds were chosen for each introverted and extroverted personality type, as shown in Table 5.

Experimental Results The subject pool consisted of 12 participants (7 male and 5 female). The participants ranged in age between 19 and 35,

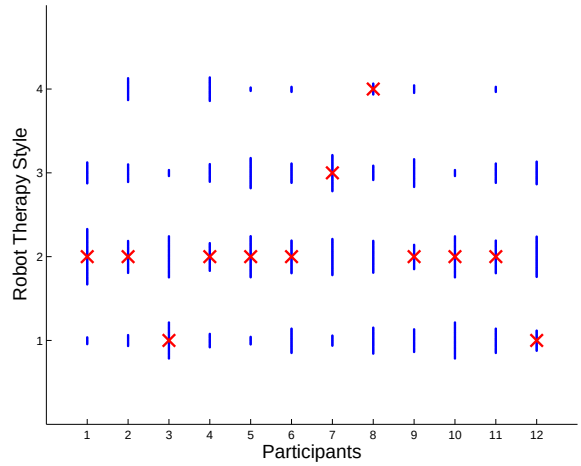

Fig. 8 The percentage of time that the 12 participants interacted with each of the four therapy styles of the robot (for extroverted and introverted participants, as described in Table 4). The crosses represent the participants' preferences.

27% were coming from a non-technological field, while 73% worked in a technology-related area.

Figure 8 summarizes the collected data as a graph of the participants and the therapy style choices. For each participant and possible therapy style, we display a bar representing the percentage of time spent by the robot in the given therapy style while interacting with the participant. The relative size of the bars for the same participant illustrates the percentage of time spent in each of the four therapy styles of the robot. The crosses represent the top preference of the participant as reported in the post-experiment survey. As shown in Figure 8, the robot adapted to match the preference of the participant in almost every single case.

The only exception was the interaction with participant 8. Despite the fact that the time spent in the preferred training style of that participant was smaller than the time spent in other training styles, the robot converged to it at the end of the exercise period. The cause for this slight inconsistency was 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, combined with the relative short duration of the exercise contributed to this result.

Figure 9 shows the adaptability of the robot to the interaction distance preferred by the participant. Results are shown on the same type of graph, but here there were only three options for the parameter. The results support our hypothesis that the robot could adapt its behavior to both introverted and extroverted participants. The graph shows small inconsistencies (3 cases) between the preferred interaction distance and the distance that was used most by the robot during the exercise. It is worth noting however that in all three cases the time spent in each of the two options (the robot's choice and the user's preference) were almost equal. After a more detailed analysis of the

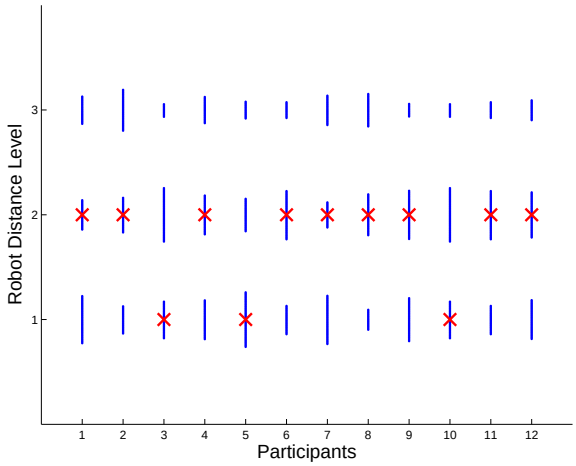

Fig. 9 The percentage of time that the 12 participants interacted with the robot at a certain distance (for extroverted and introverted participants, as described in Table 5). The crosses represent the participants' interaction distances preference.

data we realized that the mitigating factors for this effect were: (1) the user performed almost indistinguishable when the robot found itself in any of the two options, which prevented the robot from having any basis for discerning between the two; and (2) both options were in the social space, making it harder to distinguish between them. We believe that increasing the length of the exercises and using a different reward function for this parameter might improve the adaptation process.

On a general note, both the extroverted and the introverted personalities chose the interaction distance within the personal space rather than in the social space.

The results obtained for the third parameter in our system, the speed of the robot when moving around the user, were subject to more misses than those for the first two parameters. While the robot used higher speeds for interacting with extroverted participants and lower speeds for interacting with introverted participants, it overshot the preference of the user in many cases. We believe the reason was that the parameter had a lower impact on user's performance. Also, as resulted from our discussion with the participants after the experiment was completed, many participants were taken somewhat by surprise by the questions regarding the preference in speed, as they were not able to clearly identify the three speed steps used by the robot during the experiment.

6.3.2 Robot Behavior Adaptation to User Preferences

Experimental Design In the third experiment we wanted to ensure the robot was able to adapt to the human preferences, in order to build an engaging and motivating customized protocol. People are more influenced by certain voices and accents than others. Two main scenarios were designed, one

Table 6 The Choice of Therapist Robot's Personality as Expressed through English Accent and Voice Gender as a Function of the User-Preferences

Parameter	Id=1	Id=2	Id=3	Id=4
Therapist Robot's Personality as Expressed through English Accent and Voice Gender	Female with accent	Male with accent	Male without accent	Female without accent

for extroverted and one for introverted individuals, respectively (see Table 1). The scenario for the extroverted group was challenge-based while the scenario for the introverted individuals was more nurturing, in accordance with the results of our previous study. We pre-recorded the same scenario with 2 males (one with an accent of a French native speaker, and one without an accent as an American native English speaker) and 2 females (one with an accent of a Romanian native speaker, and one without an accent as an American native English speaker), as shown in Table 6).

The choice of interaction distances/proxemics and robot movement speeds was the same as in the previous experiment (see Table 5).

Experimental Results The experimental group for the third experiment consisted of 12 participants (7 male and 5 female). The participants ranged in age between 19 and 35, 27% were coming from a non-technological field, while 73% worked in a robotic or technology-related department.

The results of the third experiment, which tested the ability of the robot to adapt to the user's preference of a certain robot's personality as expressed through accent and voice gender are presented next. The results were again consistent with our assumption that the algorithm we employed would allow the robot to adapt and match the participant's preferences in most cases.

Figure 10 shows the results on the same axes as those used in our previous experiment. The results show three special cases. In all three cases a detailed analysis shows that the performance of the participant (number 4, 5 and 7) was almost indistinguishable when the robot acted under the participant's first choice of robot's personality as expressed through accent and voice gender and the state in which the robot spent most of the time in. In fact, the second top choice of the user, as rated in the post-experiment survey, was in fact the one in which the robot spent most of the time.

For this experiment the distance between the robot and the user (see Figure 11) did not perfectly match the preference of the user. We believe that this was caused by several factors:

- The number of adaptation steps was rather small compared to the size of the state space of the parameters (we used 5 variations of the parameters with each adaptation sequence out of the 36 possible variations).
- Furthermore, the changes in the robot's personality expressed through accent and voice gender parameter were too distracting (male-to-female or female-to-male changes in robot's voice), which diminished the importance of other parameters involved in the adaptation process.

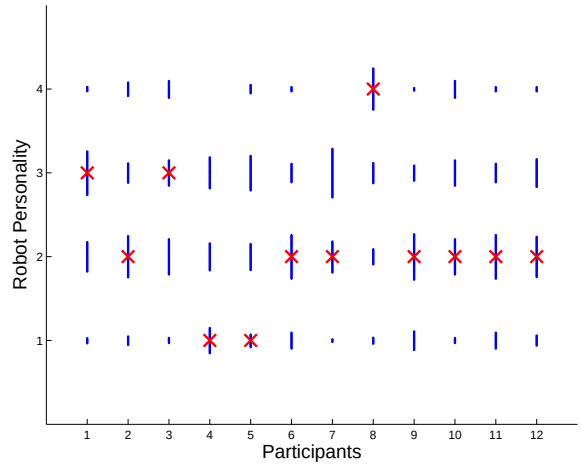

Fig. 10 The percentage of time that the 12 participants interacted with each of the four therapist robot's personality as expressed through accent and voice gender (gender and English accent, as described in Table 6). The crosses represent the participant's preferences.

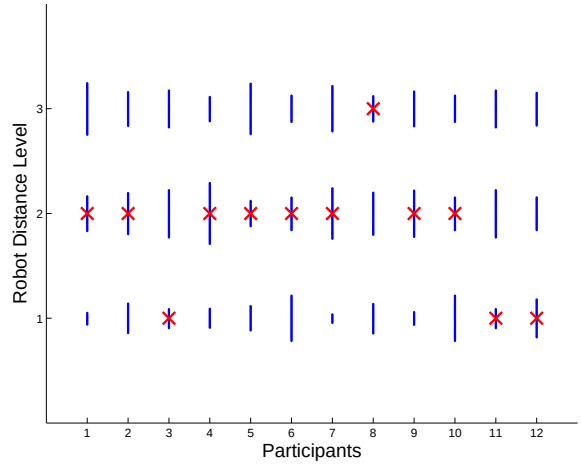

Fig. 11 The percentage of time that the 12 participants interacted with the robot at a certain distance (for extroverted and introverted participants, as described in Table 5). The crosses represent the participants' interaction distances preference.

– This parameter had a rather lower impact on the user performance compared to the other parameters.

To improve the adaptation process we plan on varying only one of the parameters at a time. This will allow for more accurately measuring the impact of each variation on user performance and for adapting more efficiently to each dimension of the parameters space.

Finally, the results obtained for the third parameter (the speed of the robot) were similar to those for the distance. This supports our idea that in

certain cases where changes in one parameter are more distracting and have a stronger impact on the participant the analysis should be separated by varying one parameter at a time. We also consider implementing this option as another component of the adaptation process.

The result obtained in the adaptation experiments pointed out one possible limitation of our approach. Due to the large number of combinations of parameter values that have to be investigated during the adaptation phase the optimal policy might be obtained only after a period of time that exceeds our session of exercise (i.e., 15 minutes). However, we feel that this does not reduce the efficiency of our approach or the relevance of our results, as our research targets interaction with patients for an extended period of time and where many therapy sessions are required for complete rehabilitation. Thus, if the optimal policy is not reached during one therapy session the adaptation process can be extended over several sessions, with most of the interaction occurring with the optimal policy in place. In fact, this is very similar to real-life situations where therapists get to know patients over several therapy sessions and respond to their clues to provide a more efficient recovery environment.

7 Discussion and Conclusion

We presented a non-contact therapist robot intended for monitoring, assisting, encouraging, and socially interacting with post-stroke users during rehabilitation exercises. The role of the robot's personality in the hands-off therapy process was investigated, with a focus on the relationship between the level of extroversion-introversion of the robot and the user and the ability of the robot to adapt its behavior to user personality and preferences expressed through task performance. The experimental results provide first evidence for the preference of personality matching in the assistive domain and the effectiveness of robot behavior adaptation to user personality and performance.

Our future work is aimed at evaluating the approach in a time-extended user study with post-stroke patients. The longitudinal study will allow us to eliminate the effects of novelty, and will also provide the robot to adapt better to the user given vastly more learning trials. Further, it will allow us to investigate various reward functions toward understanding the impact of each parameter over the success rate of the adaptation process. Further research will also focus on including empathy in the robot's behavior control architecture and using physiological data as a way of measuring and interpreting the user's internal state.

Our work to date demonstrates the promises of socially assistive robotics, a new research area with large horizons of fascinating and much needed societally-relevant research. Our ongoing efforts are aimed at developing effective embodied assistive systems, and expanding our understanding of human social behavior. Socially assistive robotic technology is still in its infancy, but near future 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.

Acknowledgment

The authors thank Yann Petiot, Emily Mower, and Nate Koenig for lending their voices to the therapist robot.

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