Socially Assistive Robots: The Link between Personality, Empathy, Physiological Signals, and Task Performance

Adriana Tapus and Maja J Mataric'

Robotics Research Lab/Interaction Lab,
Department of Computer Science, University of Southern California
Los Angeles, USA
adriana.tapus@ieee.org; mataric@usc.edu

Abstract

This paper describes a hands-off socially assistive therapist robot designed for monitoring, assisting, encouraging, and socially interacting with users engaged in rehabilitation exercises. We investigate the role of the robot's personality, empathy, and physiological signals in the hands-off therapy process, focusing mainly 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 toward customized rehabilitation therapy based on the user's personality traits and task performance. The experiments validate our hypotheses of mapping the user's extroversion-introversion personality dimension to a spectrum of robot therapy styles that range from challenging to nurturing and of adapting the robot's therapy styles based on user personality and performance.

Introduction

The start of the 21st century, with its confluence of scientific and technological sophistication, presents a unique opportunity for robotics to positively impact human quality of life. Therefore, the trend toward developing a new generation of robots capable of operating in human-centered environments, interacting with people, and participating in and assisting 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. Significant and growing societal needs include the lack of personalized one-on-one care for the growing populations of elderly individuals, children with developmental disorders, and those with special life-long cognitive and social needs. Developing systems capable of contributing to such application domains in human everyday life require great strides in the domains of assistive robotics and human-robot interaction (HRI). Thus, social robots that interact with humans have thus become an important focus of robotics research.

Our main research focus is on assistive human-machine interaction methods aimed at facilitating research toward robot systems capable of aiding people in daily life. The potential benefit of using robotics in providing physical assistance is well-recognized, spanning mobility and manipulation aides for the elderly and people with physical disabilities and physical rehabilitation, training, and prosthetics. In contrast, the consideration of robots as social tools is a newer area of scientific pursuit. Based on the premise that intelligent, personalized robots can provide individualized care through monitoring, coaching, encouragement, and motivation toward specific educational and therapeutic goals in a broad range of contexts, including convalescence, rehabilitation, special major issues in assistive human-robot interaction (HRI) must be addressed.

Socially Assistive Robotics

Socially Assistive Robotics (SAR) focuses on assisting through social, not physical, interaction (Feil-Seifer and Mataric' 2005). The fundamental principle of SAR is that the robot's physical presence and shared physical context create an engagement between the robot and the user, a relationship that is inherently different from other types of human-machine interactions that do not involve physical embodiment. Eliminating physical contact between the user and the robot, results in the reduction of safety concerns. The concerns naturally cannot be entirely eliminated since even unintended physical interaction is possible even in the absence of robot-initiated contact and application of force (Mataric' et al. 2007). While increased safety is a benefit of SAR, it is not its goal, and the hands-off nature of SAR naturally begs the question of why a physical robot is needed.

Socially assistive robotics presents multi-faceted research challenges. Our work focuses on personality, empathy, physiological signals, and adaptation. Each is addressed in turn:

Personality

Personality has strong impact on human social interactions. While there is no generic definition of personality, we use one consistent with the literature (Woods et al. 2005; Morris 1979), referring to personality as *the pattern of collective character, behavioral, temperamental, emotional and mental traits of an individual that have consistency over time and situations.* Evidence from psychology has shown a direct relationship between personality and behavior. Morris (Morris 1979) indicated that 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, we posit that personality is also a fundamental factor in human-robot interactions. Little research to date has addressed personality in human-robot social interactions and no work has yet addressed the issue of personality in the assistive human-robot interaction context. Our work highlights the importance of embodying personality in a robot as an inherent component of the assistive context. The importance of personality has long been recognized, yet this area has not yet been addressed in a consistent fashion by the HRI community. We propose to develop a rich model of robot personality that will enable the expression of appropriate personality traits in robot behavior in order to match the user and adapt to the user's needs in the hands-off socially assistive robotics.

Empathy

Empathy plays a key role in patient-centered therapy, because it implies the comprehension of another's inner world and a joint understanding of emotions. Empathy is an interesting and provoking construct, evoking debate over its measurement, and its potential applications in robotics. One reason for our interest in empathy in socially assistive robotics is the findings of many psychologists showing that empathy plays a key role for therapeutic improvement (e.g., (Rogers 1975)) and their assumption that empathy mediates pro-social behavior (e.g., (Eisenberg 1986), (Hoffman 1981)). Rogers (Rogers 1975) showed that patients who have received empathy, genuineness, and unconditional positive regard from their therapist recovered faster. Therefore, we posit that empathy can ameliorate patient satisfaction and motivation to get better, and enhance adherence to therapy programs in the context of patient-therapist interaction.

There are very few research projects (e.g., (Bickmore 2003), (Paiva *et al.* 2004)) in human-computer interaction (HCI) that attempt to emulate empathy in virtual agents. We are not aware of any studies that have examined the role of empathy in assistive embodied human-robot interaction. While machines cannot feel empathy, they can express it. One of the most complete definitions on empathy was given by (Davis 1983) and defines it as *the capacity to take the role of the other, to adopt alternative perspectives vis a vis oneself and to understand the other's emotional reactions in consort with the context to the point of executing bodily movements resembling the other's.* This definition implies that empathy is expressed through perspective taking, that it is an internal state similar to emotion, and that this emotional state can sometimes be recognized through imitative bodily movements.

According to Davis (Davis 1983), there are two main ways defining the empathy: as process and as outcome. The process of empathy refers to something that happens when someone is exposed to another person (e.g., taking the other's perspective or unconsciously imitating the other's facial expression). The outcome of empathy is something that results from the processes of empathy, and can be affective or cognitive. The affective outcome of empathy is considered an important motivator of pro-social behavior. The feelings or condition of a person can generate strong vicarious emotion in others. The emotion is vicarious in that neither the conditions that affect the person who is the object of empathy nor his/her emotions have any direct effect on the empathizing person. The cognitive outcome of empathy relates to awareness, understanding, knowing of another's state or condition or consciousness, or how another might be affected by something that is happening to him/her. This is also referred to as role taking or perspective taking. By taking inspiration from the existing literature on empathy in social psychology, we propose a new methodology for emulating and embodying empathy on robotic systems for rehabilitation therapy.

Physiological Signals

Understanding user's physiological internal state represents a key issue in socially assistive robotics so as to be able to create a customized one-on-one therapy style. Some of the physiological signals proposed for use in human-machine interfaces (human-robot interaction and/or human-computer interaction) include skin conductance, heart rate, pupil dilation, and brain and muscle activity. Even if physiological signals have the potential to provide objective measures of the human’s internal state, they are difficult to interpret. This is due in part to their variability from one person to another, and to multiple emotional states activation for one physiological signal. Hence, it can be difficult to understand the internal user’s emotional state. The psychophysiology literature recommends using a multi-modal physiological system capable of detecting simultaneously an array of physiological signals corresponding to a certain state (e.g., heart rate and galvanic skin response for measuring the user’s arousal). Some of the human-robot interfaces discussed in the literature are using only one physiological signal due to the difficulty of measuring them (Takahashi et al. 2001; Yamada et al. 1999). Our system is designed to be applied in the assistive context. The system that we propose, aim providing the user with constructive coaching feedback as well as encouragement to continue with proscribed rehabilitation activities. Based on Yerkes-Dodson law

(Yerkes and Dodson 1908), through the use of physiological signals (galvanic skin response and body temperature), the robotic system will be capable of improving and optimizing user performance through coaching behavior modification strategies.

Behavior Adaptation

Behavior adaptation is a recognized challenge in robotics. 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 challenging target, especially when working with vulnerable user populations. In the socially assistive robotics context, behavior adaptation must address both short-term changes that represent individual differences and long-term changes that allow the interaction to continue to be engaging over a period of months and even years. Various learning approaches for human-robot interaction have been proposed in the literature (Berlin et al. 2006; Breeazeal and Scassellati 2003), but none include the user's profile, preferences, and/or personality. The proposed work aims to create socially assistive robots capable of monitoring and enhancing physical therapy in such a way as to have a lasting impact on the patient's ability and willingness to engage in physical therapy even without the robot's prompting. Toward that end, we propose a methodology for evaluating a reinforcement-learning-based approach to robot behavior adaptation. The learning approach will incrementally adapt the robot's behavior to better model the user's personality and needs, therefore attempting to improve user task performance.

HRI Model

Our developed HRI model is shown in Figure 1. This is created to allow us to study the research issues discussed above. Our inspiration comes from Bandura's model of reciprocal influences on behavior (Bandura 1969). Consequently, we posit that it is necessary to incorporate personality and empathy in order to facilitate human-robot interaction (HRI) and robot behavior selection. We use a multi-modal behavioral approach that allows the robot to be responsive both in terms of temporal and social appropriateness. We express the robot's personality and empathy through multi-modal cues that include: interpersonal distances/proxemics, verbal and non-verbal communication, and activity. Our previous work (Tapus and Mataric' 2006) has already begun the development of a behavior control architecture capable of expressing personality traits along the extroverted-introverted spectrum, which we are currently expanding.

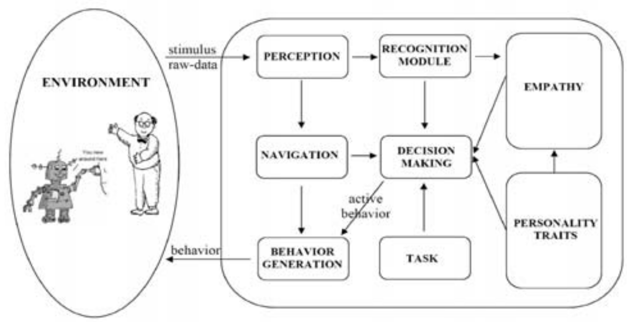

Figure 1: HRI Information Processing using the Personality Model of the User and the Empathy level

The use of social space in human interactions has been widely studied in social psychology, since the seminal paper by Hall (Hall 1966) who coined the term *proxemics*. Hall identified four general interaction spaces: (1) Intimate: Up to 0.25m from the body; usually involves contact (e.g., embracing, comforting), can be uncomfortable and intrusive; (2) Personal: Between 0.3-1m; typically used for family and friend interactions; (3) Social: About 1-3m; used in business meetings and public spaces; and (4) Public: Beyond 3m; e.g., the distance between an audience and speaker (see Figure 2).

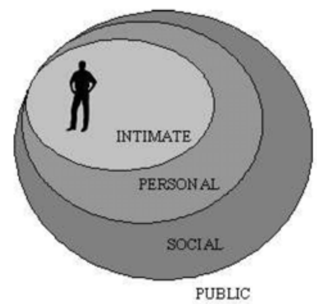

Figure 2: Interaction zones / proxemics: intimate, personal, social, and public

A social embodied robot must make appropriate use of social space so that a human user can feel safe, comfortable, and in concordance with his/her personality preferences. Hall in (Hall 1966) found a strong link between the human sense of space and behavior and personality type. Analogously, people have stronger empathic emotions and reactions when the interaction episodes are associated with others with whom they have a social relationship (e.g., friends, family) or a common background (e.g., a person who lived through a similar experience). Therefore, proxemics can be encoded, adapted, and controlled as a function of the individual personality type and empathetic level. Communication is a rich multi-modal process. Our approach is accordingly multi-modal, involving both verbal (e.g., vocal content and paralinguistic cues, such as volume and speech rate) and non-verbal (e.g., body movement) interaction to express personality and empathy (Apple et al. 1979; Tusing and Dillard 2000; Pittman 1994). 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., (Nass and Lee 2001)). Also, many psychological studies (Brown et al. 1975) have found that prosodic characteristics are linked with features of personality, e.g., excitement or arousal (e.g., extroversion-introversion) are strongly correlated to prosodic features such as pitch level (Trouvain and Berry 2000), pitch range, and tempo (Apple et al. 1979). By having these findings as our source of inspiration, we propose to design different interaction scripts that will display personality type through the choice of words and paralinguistic cues. The robot's non-verbal communication is another powerful means of expressing personality and manifesting empathy. As with any area of HRI research, a careful consideration and management of the user's expectations is taken into account. The robot's empathy and personality is made sufficiently believable, but not so realistic as to provoke expectations that cannot be met (Masahiro 2005). Importantly, the robotic system is built to always subordinate itself to the patient's desires and preferences, thereby promoting patient-centered practice and avoiding the complex issues of taking control away from patients and dehumanizing health care. Social psychologists have observed a strong relationship and synchrony between verbalization and movement in everyday human social interactions (Condon 1986). Therefore, we posit that the robot's empathic state can be reinforced by appropriate verbal communication; the robot can express its understanding through empathetic tone of voice and phrases that are appropriately matched to the emotional state of the user. Recent research work in linguistics (Cordella 2004) showed that a doctor's empathetic voice encourages the patient to adhere to the treatment regime and helps to building doctor-patient trust. Hence, we use both language and "body language" as HRI tools to express empathy. The robot's activity will also serve as an interaction parameter, since physical activity levels are correlated with personality as well as rates of recovery. The robot's speed and the amount and complexity of body movement (regardless of the form of embodiment) are all controllable parameters. Some studies (Sterling and Gaertner 1984) have shown a positive correlation between empathy, personality, and physiological indices (e.g., heart rate acceleration, palm sweating). These physiological responses can also be used by the robot as a significant source of sensory information for real time interaction and emphatic response.

By separating the individual control parameters of the HRI model as per above, we are able to conduct fine-tuned experiments that focus on sub-components of the HRI process. We applied statistical learning to the full interaction space of the robot in order to adapt to the user over time. Our method allows us to dynamically optimize the interaction parameters: interaction distance/proxemics, speed, and vocal content (what the robot says and how it says it), and the other controllable personality and empathy parameters described above. These define the behavior, and thus personality, of the therapist robot, which are adaptable to the user's personality in order to improve the user's task performance. Task performance is measured as the number of exercises performed and/or time-on-task, depending on the nature of the trial.

We formulate the problem as *policy gradient reinforcement learning (PGRL)* and propose a learning algorithm that consists of the following steps: (a) parametrization of the robot's overall behavior (including all parametric components, listed above); (b) approximation of the gradient of the reward function in the parameter space; and (c) movement towards a local optimum. Our policy gradient algorithm starts from an initial policy, composed of 3 parameters in our case. For each parameter we also define a perturbation step 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 an initial policy, and its learning process can be summarized as the following steps: (1) The robot acts given the current set of parameters; (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.

We have already performed a pilot study of a smaller version of this system, using only three adaptive parameters: proxemics, activity, and vocal content. Proxemics involved three zones (all beyond the minimal safety area), activity was expressed through the amount of robot movement, and vocal content varied from nurturing ("You are doing great, please keep up the good work.") to challenging ("Come on, you can do better than that.") and extroverted (higher-pitched tone and louder volume) to introverted (lower-pitched tone and lower volume), in accordance with well-established personality theories referred to earlier.

Experimental Scenarios and Results

Our experiments try to address mainly two issues. First, we investigate the user-robot personality matching. Secondly, 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.

A. User-Robot Personality Matching

In order to test the user-robot personality matching, and based on the principle of similarity attraction (Nass and Lee 2001), we formulated the following two hypotheses:

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.

As explained earlier, the personality of the robot is expressed through the extroversion-introversion trait. The introverted vocal content was nurturing and the script contained gentle and supportive language (e.g., ”I know it's hard, but remember it's for your own good.”, ”Very well, continue just like that.”). The typical para-verbal cues used for introversion are low pitch and volume. For the extroverted personality a challenging language (e.g., ”You can do it!”, ”Concentrate on your exercise!”) and high pitch and volume are used.

The robot's behavior had a range from non-social to social and from low activity to high activity so as to express the extroversion (challenging) or introversion (nurturing) therapy styles.

Before participating in the experiment, each subject was asked to complete two questionnaires. The first one was a general questionnaire for determining personal details such as gender, age, occupation, and educational background, and the second questionnaire was for establishing the subject's personality traits based on the Eysenck Personality Inventory (EPI) (Eysenck 1953).

Our target population is post-stroke patients. The 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 books from a desktop to a raised shelf;
- Moving pencils from one bin to another;
- Turning pages of a newspaper.

At the end of each experiment, the experimenter presented a short debriefing. 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. 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”.

The subject pool for this experiment consisted of 19 participants (13 male, 6 female; 7 introverted and 12 extroverted). 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). 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 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). 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 3 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.

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.

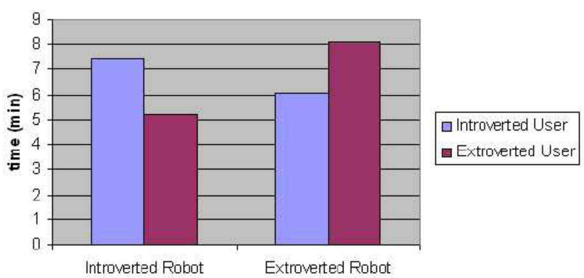

Figure 3. The average interaction time (minutes) spent by introverted/extroverted users with introverted/extroverted robots, respectively

B. 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 human participant stood and faced the robot. The experimental task was a common object transfer task used in 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) for establishing the user's personality traits. The robot adapted 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.

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

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: 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. 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. 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.

The subject pool consisted of 12 participants (7 male and 5 female). The results support our hypothesis that the robot could adapt its behavior to both introverted and extroverted participants. The pilot experimental results provided first evidence for the effectiveness of robot behavior adaptation to user personality and performance: users (who were not stroke patients) both tended to prefer personality matched robot therapists, and performed more or longer trials under the personality matched and therapy style matched conditions. The latter refers to nurturing styles being correlated with the introversion side of the personality spectrum, and challenging styles correlated with the extroversion side of the spectrum. It is important to note that in all cases parameters are on a continuous spectrum, not arbitrarily binary-valued.

2) In this second 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 for extroverted and one for introverted individuals, respectively. 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 first study. We pre-recorded the same scenario with 2 males (one with a French accent and one with an American native accent) and 2 females (one with a Romanian accent and one with an American native accent). The experimental group for this experiment consisted of 12 participants (7 male and 5 female). 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 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.

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.

Also, 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.

Conclusions

In this paper, 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 research is aimed at facilitating socially assistive robot systems capable of aiding people with special needs in daily life. Therefore, the work conducted in this paper involves novel multidisciplinary collaboration including robotics, medicine, social and cognitive psychology. The consideration of robots as social tools is a new area of scientific pursuit, based on the premise that intelligent, personalized robots can provide individualized care through monitoring, coaching, encouragement, and motivation toward specific therapeutic goals.

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