Therapy Robotics: The Power of the Interface to Motivate

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***Abstract*—Until recently, therapy robotics mainly concentrated on providing the types of exercises that therapists can also give their patients, freeing therapists to perform the difficult tasks of personalizing the exercises to each patient and planning the exercise regimens. In addition, therapists then translated the quantitative diagnoses provided by the machines, in terms of strength and control improvements realized, into quality of life changes through established and validated clinical scales. More recently, the field of therapy robotics has begun to explore new types of exercises through novel interface designs: 1) immersive virtual interfaces provide motivating environments that keep patients engaged in their therapy and increase compliance; 2) distortion-based force and visual feedback interfaces increase the effectiveness of highly repetitive exercises to reestablish cerebral sensorimotor control pathways. These interfaces are turning robots into beneficial, always-on-call, and high-power tools for therapists to speed the delivery of effective treatments. This paper will present progress in the field and discuss the power of the interface to create and enhance engagement.**

I. Introduction

ACCORDINGto the World Health Organization, stroke is the leading cause of disability worldwide, with 80% of first time strokes leading to upper-extremity hemiparesis [1]. Since the majority of daily life activities involve use of one's upper limbs [2], effective rehabilitation for both gross and fine motor movements is crucially needed in order to return stroke survivors back to their independent daily lives.

Over the past two decades, a growing number of studies has been dedicated to the development of upper-limb robotic stroke therapy systems, which have a number of advantages over conventional therapy methods [3], such as the ability to: provide more intense and longer duration therapy, deliver unconventional therapy (e.g., visual error augmentation) via the robots' programmability, increase therapy time provided to each patient and save associated costs by automating a significant part of the therapy. These features thereby allow for workplace multiplication, provide quantitative and more precise measures of a patient's motor function and progression, and finally, make tele-rehabilitation a viable adjunct to less-frequent in-clinic care.

While therapy is based on motor learning principles and the physical, strengthening effect of exercise, motivation of the patient is also a key factor in the success of a therapy regimen. In fact, a qualitative research has shown that patients with low motivation believe they do not have the strength to complete exercise tasks, which in turn will lead to therapy abandonment [4]. Sustaining motivation and engagement becomes even more critical as therapy sessions shift from being therapist-based to robot-based; a therapist can observe a patient's (physical and emotional) condition and shape the exercise task accordingly, while giving positive and motivating verbal feedback. However, programming this into a robot is a difficult challenge.

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To address this issue, robotic therapy research is currently being extended to making it more engaging. For example, virtual reality-based interfaces, video games and immersive experiences increase the patient's engagement in the therapy process. This method, also known as implicit learning, has been proven to be more effective than the conventional paradigm of explicit learning [3], [5].

However, even with improvements in neurorehabilitation strategies implemented in robotic therapy systems (e.g., error augmentation through force fields or visual distortion and bilateral training instead of the massed practice paradigm) and increased task engagement via use of virtual reality, a therapist is still needed to set up appropriate exercise protocols based on each patient's strength, performance and emotional state.

With the well-established literature on the relationship between emotional state and physiological signals, in the recent years it has been suggested that the engagement level of robotic rehabilitation can be increased by monitoring the patient's physiology during therapy. In this paper, we propose a method to incorporate the patient's biofeedback and performance into a robotic rehabilitation system's online decision-making process. We believe that this approach will lead to faster learning and recovery time as well as a reduced risk of abandonment of therapy programs compared to currently existing systems by maximizing patient motivation.

II. Background

During the past two decades, most of the research in the field of robot-assisted rehabilitation has been focused on replicating conventional therapy paradigms (e.g., repetitive movement training or massed practice) with robots [3]. The majority of applications in upper-extremity rehabilitation are dedicated to recovery of gross motor movement, mainly defined as reaching tasks using the shoulder and elbow. A well-known example is MIT-Manus [6] (commercially available as InMotion2; Interactive Motion Technologies, Inc., Boston, MA), which uses an active assistive strategy. This system provides low-impedance force cues to correct the motion of the patient's arm, in planar, straight-line, point-to-point reaching tasks.

Recovery of fine motor movement (e.g., finger movement and grasping) also plays a significant role in restoring daily life quality and independence of stroke survivors. Interactive Motion Technologies introduced InMotion3 as a wrist rehabilitation robot, which uses the same neurorehabilitation principles as InMotion2. Studies have demonstrated improvement of wrist and finger function using the upper-limb subcomponent of the Fugl-Meyer scale [7].

Alongside more conventional rehabilitation paradigms, such as active assistive/resistive strategies, bilateral training of the paretic and non-paretic arms is another strategy. The Mirror Image Movement Enabler (MIME) system was among the first robotic systems that used this approach, guiding the paretic arm to move along the same 3D trajectory, in mirror to the non-paretic arm. A group of subjects training with this system showed larger improvement in the proximal movement portion of the Fugl-Meyer test compared with a control group undergoing conventional therapy [8]. The MIME system has recently been augmented with the hand-function-exercise RiceWrist [9] and is undergoing clinical trials similar to those using the inMotion3 system.

One of the advantages of robotic systems over a human therapist is that robots can be programmed to deliver unconventional therapies. These include use of virtual environments and gaming interfaces, distortion of visual feedback and augmentation of error via force fields. GENTLE/s system uses a HapticMASTER robot (MOOG FCS Robotics Inc., Nieuw-Vennep, The Netherlands) as a means to interact with a virtual environment. Training with this system led to function improvement (measured by upper limb section of Fugl-Meyer scale) in chronic stroke subjects [10]. Driver's SEAT has been used to incorporate a constraint-induced therapy paradigm into a gaming interface (simulation of steering a car) to increase subject motivation and promote coordinated bilateral movement in the upper limbs [11].

Feedback distortion, a growing unconventional therapy paradigm, refers to use of intentionally inaccurate feedback. In recent studies in the labs of Patton [12,13] and O'Malley [14], subjects were asked to use a robotic manipulator to move a round spot to a visual target presented to them on a monitor. Since the robot and the subject's hand were obscured, the only visual feedback was from the moving spot on the monitor. Three target points were placed radially from the starting point and subjects were asked to move to a target when it was highlighted and then go back to the starting point. In this repetitive movement training in a virtual environment, subjects showed faster learning when the position of the point was shown further away from the actual position of it by augmenting the initial trajectory error (measured as deviation from the straight line between starting point and target). Subjects also showed the ability to adapt to a visual distortion (implemented by rotating the subject's actual hand position around the starting point) without a visual error augmentation. This type of training was shown to lead to persistent functional changes with hemispheral post-stroke subjects [12].

As previously mentioned, robotic systems provide objective information about a subject's motor performance, but lack the ability to offer information about a subject's affective state (e.g., motivation, attention and engagement). Real-time analysis of physiological signals, such as electrocardiography, respiration rate, skin conductance and breathing rate, is one way to characterize different aspects of affect. Kulić and Croft developed methods to estimate human affective state in real time using interpretation of psychophysiological signals in a two-dimensional valance-arousal representation [15] using Hidden Markov Models [16] and a Fuzzy Inference Engine [17]. In a recent study, Pan et al. investigated the viability of a physiologically-triggered bookmarking paradigm [18]. In this study, orienting responses (derived through monitoring of the subject's galvanic skin response) to a disruption of attention were used to bookmark electronic media with 84% success, so subjects can resume reading the media after attending to the interruption. Zoghbi et al. developed an explicit method of real time affective state reporting [19]. In this method, the subjects were asked to express their emotions via an in-house developed hand-held joystick called the Affective State Reporting Device (ASRD).

A possible issue with using psychophysiological signals in rehabilitation is that such signals are determined by both a person's psychological state and physical activity. However, investigations by Munih [20,21] suggest that physiological signals can reliably describe a person's psychological state even in the presence of physical activity, and thus they can be useful in designing a bio-cooperative rehabilitation system.

A good example of such a system is demonstrated by the work of Liu et al. in using psychophysiological signals in a closed-loop exercise system [22]. A robot-based basketball task was designed in which the robotic coach can change task difficulty based on anxiety or performance of the human player. This study showed that determining challenge level in a human-robot interaction task based on a human's affective state leads to higher performance improvement compared to setting the challenge based only on the person's performance.

III. Objectives And Approach

In a new line of stroke therapy research at the UBC Collaborative Advanced Robotics and Intelligent Systems (CARIS) Lab, we are integrating the concepts enumerated above, namely physically demanding reaching motions, an engaging interface, distorted feedback, and real-time physiological signal analysis.

Our objective is to design unconventional therapies that will lead to faster improvement of motor function. The final outcome of this research will be a system capable to modulate task challenge (level of distortion or visual error augmentation) in real time using a subject's physiological signals. Thus, the three main components of this system will be: 1) a point-to-point reaching task similar to those used in the works of Patton and O'Malley [12-14], 2) real-time closed-loop use of physiological signals as in the Liu and Sarkar Human-Robot Interaction task [22] and 3) machine learning and control algorithm based on the correlation of these signals with the subject's affective state [16,17], which relates directly to the patient's level of motivation. Our research will be conducted in three stages.

First, we aim to reveal a correlation between task challenge (level of visual distortion and error augmentation) and subject's physiological measures such as skin conductance response, heart rate and respiration rate. Physiological signals will be recorded from subjects while the able-bodied subjects are presented to different levels of task difficulty. Also, an affect grid [15] questionnaire will be used to relate physiological signals with the subject's self-reporting of affective states, which can be used to assess level of motivation. We will investigate correlations between physiological measures, performance and self-reports of attention using statistical tools. A statistically significant correlation from this study will demonstrate the dependency of affect on change of distortion.

In the second stage, we will use physiological signals to modify level of visual distortion and error augmentation with the goal of achieving a stable level of attention and performance. In this stage, we aim to close the control loop and implement use of biofeedback as a decision-making factor in changing the level of challenge, as described in [22]. Again, with able-bodied subjects, we will investigate effectiveness of two different decision-making factors: subject's performance and subject's affective state. Task parameters such as level of trajectory distortion and augmentation of error will be modified with the decision-making factors.

Finally, in stage 3, we will recruit stroke survivors and conduct a pilot study in collaboration with physical therapists to investigate the effects of the system we are developing, especially real-time use of physiological signals on the recovery process.

This research at all three stages will involve iterative design refinement and human subject testing. All studies involving human subjects will be conducted under an approved protocol of the Research Ethics Board of the University of British Columbia.

IV. Preliminary Results

In a preliminary study with one able-bodied subject, we replicated the experiment described in [11]. Using a planar 2-DOF manipulandum, the right-handed subject was asked to reach for six visual targets presented on a flat screen monitor: from the mid-point of the screen to a target point and then back to the starting point. Targets were placed radially from the screen centre, 60 degrees apart from each other. The subject was asked to reach for each target as fast as possible as soon as it became highlighted. A force field as a function of manipulandum end-effector speed perturbed the subject's trajectory laterally from a straight line (i.e., distortion field). Also, the subject's hand and manipulandum were covered so that the only visual feedback was from the monitor.

After 30 reach-and-retract trials without force field to familiarize the subject, the subject was exposed to the force field (distortion) in the subsequent 150 trials (including both first exposure to distortion and trained movement in the distorted environment). This was followed by 30 trials without any distortion to examine after-effects. During the experiment, skin conductance response (SCR) between index and middle fingers of the subject's left hand (non-moving hand) was recorded.

Figure 1 summarizes the data from this experiment. The top half of this figure shows the subject's hand trajectory during each phase of the experiment. In the direction of

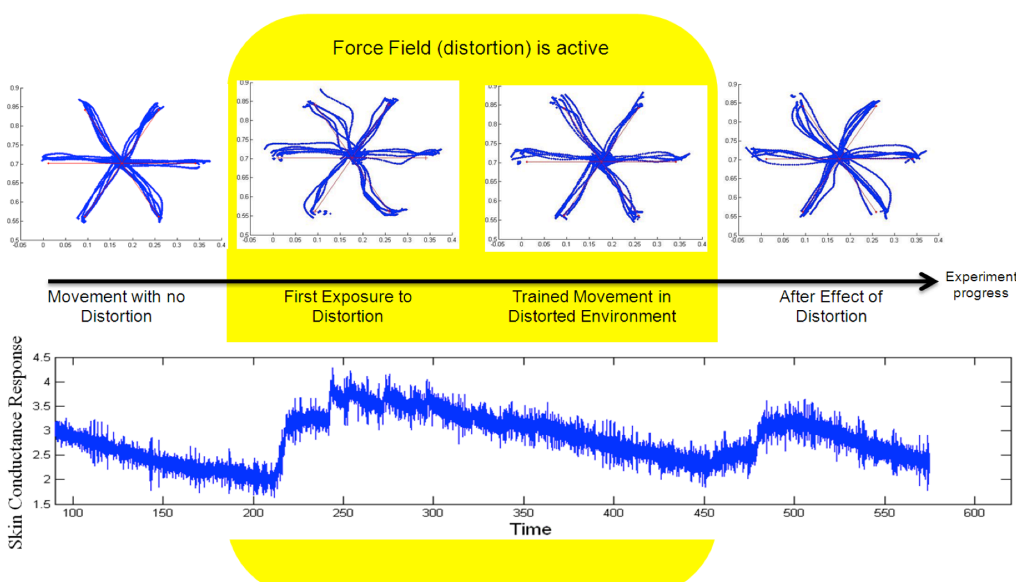

Fig. 1. Summary of data from a preliminary experiment. The top frames show the subject's reaching trajectories in different stages of the experiment, while the bottom graph shows the subject's skin conductance response measured during the experiment.

experiment progress (left to right): (a) the able-bodied subject performed the point-to-point task following almost straight lines; (b) upon the first exposure to distortion, error in movement trajectory grew larger (error is indicated by deviation from the straight line trajectory), but as the experiment progressed and subject trained in the distorted environment, the subject became adapted to the distortion (c) and trajectory error lessened. However, in (d), the last stage when distortion was removed, once again trajectory errors grew larger in the opposite direction, once again indicating adaptation to the force field. Not shown in this figure are the wash-out phase data, which predictably demonstrate a return to baseline, similar to (a).

While these results are not surprising, a more interesting finding is that, upon a change in challenge level of the task (activating and deactivating the force field), there was a sudden change in skin conductance response (SCR) as shown in the lower part of Figure 1. This preliminarily experiment indicates a correlation between SCR and task challenge that we will exploit in our next set of experiments.

V. Conclusion

During the past two decades, neurorehabilitation robotic systems have made significant progress in demonstrating effectiveness. Key features such as programmability and high repeatability make such systems of special interest. Currently, research in this field is focused on finding more effective neurorehabilitation strategies such as unconventional therapy regimens, taking advantage of the power of closed-loop robotic systems that therapists oversee. However, it is vital to address the current disadvantages of robotic systems: how can you replace a therapist's positive verbal reinforcement "good job!" in a robotic therapy system in a convincing manner?

As the physical component of therapy shifts from therapist to robot, the issue of sustaining the patient's motivation and engagement in a therapy regimen grows even more critical. Early research in the closed-loop use of a patient's psychophysiological signals to determine affective state and level of attention (and thus engagement) is highly encouraging. We therefore predict that real-time use of this information as a factor to modify challenge level in novel, unconventional therapy regimens can make robotic therapy systems more engaging.

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