Slacking in the Context of Agent-based Assessment in Virtual Rehabilitation Systems

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Abstract— **efforts are already underway to develop technology-derived solutions which automate aspects of conventional therapy. Ideally we would like to develop a human-like virtual therapist, in an attempt to enhance automated rehabilitation particularly in the home setting. One interesting skill of the experienced human therapist that we would like to model is the ability to recognize and manage behavior patterns known to decrease the effectiveness of rehabilitation. A particularly compelling example of such behavior is described in the context of robot-assisted therapy, where it has been demonstrated that "assist-as-needed" strategies may impact negatively on rehabilitation outcomes due to an intrinsic property of the human motor systems that encourages "slacking" as a form of energy optimization. In this work we endeavor to explore and extend this concept by giving it context in the standard therapist-patient interaction setting. We developed an apparatus which can measure and quantify grip strength and an agent based virtual therapist that can assess performance and offer simple natural language feedback in real time. We then conducted a series of experiments with healthy subjects in which the mapping between performance and feedback valence is altered. Our results demonstrate that subject performance is dependent on the feedback rules and that in particular, excessively positive feedback yields performance dynamics analogous to those observed in slacking studies. These preliminary results have implications for the design of virtual therapist systems.**

I. Introduction

Traditionally rehabilitation is managed, coordinated and facilitated by professional healthcare specialists. However, due to the increasing number of stroke survivors and the subsequent demand on healthcare systems, researchers are actively creating new technology in the hope of enhancing and scaling conventional forms of therapy. Efforts are already underway to develop solutions beginning with aspects of conventional therapy which may be easiest automated. However, there are particular qualities that the human therapist possesses which are not easily replicated by a silicon therapist. A human therapist has knowledge of their patient's history, understands that a particular patient might perform better at different times of the day and is sensitive to their changing mood. A good therapist can also recognize and distinguish between different causes of performance variation, such as fatigue, frustration and loss of concentration and will subsequently motivate the patient to improve engagement. This ability of the human therapist to comprehend the behavior of their patient's and subsequently adapt their feedback in a way that positively affirm the patient's ability is important as patient compliance and hence outcome in rehabilitation therapy has been shown to have a strong relationship with positive feedback from the therapist [1]. Supporting research suggests that interventions can be enhanced through ensuring the patient believes in the positive effects of the treatment and perceive themselves as having the requisite skills to perform the exercise tasks (self - efficacy) [2]. This is not a surprising result given the role of positive feedback in theories of learning [3,4], it is however a component of automated systems that is worth deeper study.

Replicating these human abilities in a virtual therapist presents an enormous challenge and might not be fully realizable. Yet there are some aspects we might be able to emulate as part of creating a more "human" like assistive agent. In previous work we advocated the use of game theory as a potential tool for observing and analyzing the complex interaction dynamics that exist during standard patient therapist interactions [5]. In this work we begin to highlight patient-agent interactions which can help develop a better understanding of such relationships. One interesting aspect of the human-therapist interaction we wish to capture in a virtual therapist is the ability to recognize and manage known behavior patterns which lead to non-adherence, and other similar adaptations in which the patient may reduce effort and engagement through extracting excessive support from the therapist, either psychologically or physically. An analogous phenomenon has been recognized in the area of a robot-assisted therapy where it has been demonstrated that 'assist-as-needed' strategies may impact negatively on rehabilitation outcomes. A particularly compelling example is described by Reinkensmeyer et al [6] who developed a model of *slacking* in the human motor system in the context of a collaborative motor task and demonstrated that the burden of the task is distributed among the participants as a function of error and system dynamics.

In the work reported in this paper we endeavor to extend this model by giving it context in the standard rehabilitation setting in which the patient performs "active" exercise with no physical assistance from the therapist. Instead, the therapist plays a passive role in which they continually assess the patient's performance and motivate them through affirming feedback. To explorer these dynamics we developed an apparatus which can measure and quantify grip strength and an agent-based virtual therapist that can assess performance and offer feedback. Through a

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series of experiments we show that in the presence of excessively generous affirming feedback from an agent (i.e. feedback is positive over a wide range of efforts) patients will slack in a way that is analogous to that highlighted in Reinkensmeyer's observations.

II. Methods

Grip strength is commonly used as a quantifiable measure of effort/performance and is an accepted indicator used as a measure of recovery [7]. There are many commercially available *dynamometers* for measuring grip strength [8], however a computerized dynamometer which can graphically represent force in real time and store the results can be expensive. In this paper we describe a custom designed, affordable and replicable alternative.

A. Custom hand Dynamometer

This simple yet satisfactory hand dynamometer was made by attaching a strain gauge to an easily available hand exercise device. The strain gauge sensor was positioned and epoxied to a curved section of the apparatus' spring. When force is applied to the devices handle, the spring is slightly deformed causing the strain gauge itself to undergo deformation.

Figure 1. Custom designed hand Dynamometer

The strain gauge consists of an insulating, flexible material on which a metallic foil pattern is etched. When stress is applied the electrical conducting foil becomes narrower and longer causing its electrical resistance to change. The typical change in resistance over the entire operating range may be less than 1% of its nominal unstrained value. An appropriate measurement circuit is to connect the gauge as a variable resistor in a Wheatstone bridge configuration. One side of the bridge consists of two well-balanced identical fixed resistors (R3 & R4, Figure 2), while the other side consists of a sensitive multi-turn potentiometer and a strain gauge (R1 and R2, Figure 2). The potentiometer allows for precise resistance matching to the strain gauge under null conditions (no force applied to strength trainer). At this point, an applied voltage will generate a voltage difference between the two sides of the bridge of 0 V. When force is applied the resistance of the strain gauge changes thus unbalancing the bridge and generating a proportional voltage (difference between V1 V2, Figure 2).

The output of the bridge is typically very small (a few millivolts) and must be amplified greatly before being converted to a digital signal. The amplification is handled using an instrumental amplifier, the AD620AN (Analog Devices Inc, Norwood, USA), with an adjustable gain of (1-10,000) being set by a potentiometer (Rg, Figure 2).

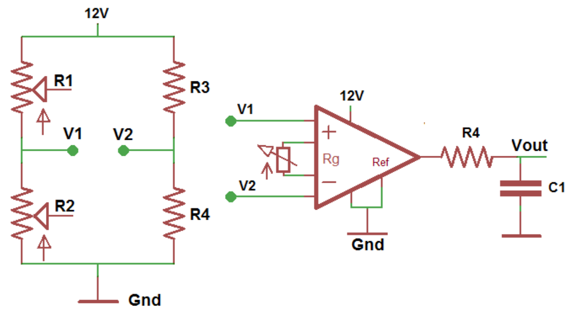

Figure 2. Quarter bridge Weatstone bridge and amplifer circuit

After amplification the signal is filtered using a low pass, anti-alising filter (determined by R4 and C1, see Figure 2) set at less than half the sampling frequency. The filtered signal is then processed by an open-source electronics prototyping platform, the Arduino Uno (Arduino, Smart Projects, Italy), sampled using an internal 10-bit analog to digital converter (ADC) at a rate of 1000 samples/s. The final output signal is then transmitted to a receiving PC over USB through a virtual serial port connection, established through the Arduino's FDTI and UART hardware.

B. Visual representation and recording Software

Custom software written in C# instigates a serial port connection with the Arduino to facilitate the streaming and recording of data from the hand dynamometer. An open source library (ZedGraph [9]) is used to visualize the incoming data and to allow plotting of the sensor data in real time. This feature is primarily used for training, allowing the user to become familiar with the force measuring apparatus and to better understand the relationship between their effort and error, see Figure 3.

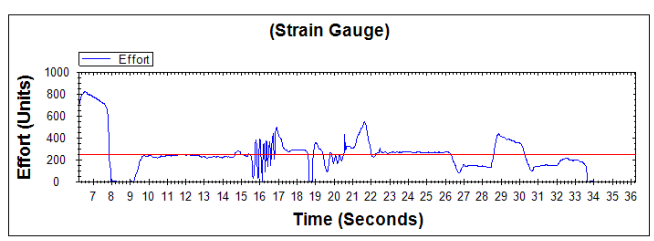

Figure 3. Real time visualisation of applied force (blue) using a moving time window. An example target grip value is shown as a (red) line.

C. Feedback system

Feedback during experiments is not given in the same form as training, with the exception of experiment 1. Instead, feedback is given simply using a text-based rating of performance, ranging from "poor" to "excellent" (see Fig 4).

Mapping between performance and feedback is determined by an internal mapping model (agent) as shown in Table 1.

Figure 4. Verbal feedback system; current feedback is highlight in bold text with an adjacent arrow.

TABLE I. FEEDBACK AND ERROR MAPPING TABLE

Verbal Feedback	**Therapist 1** *"demanding"*	**Therapist 2** **"unconditional"**
Excellent	0	0
V. Good	0.1	-
Good	0.20	-
Fair	0.35	-
Poor	1	1

Agent output in response to quantitative task performance measures (normalized error). The values indicate breakpoints above which the associated row label is produced for each therapist. For example, only a score of 0.1 or below will elicit the response "Excellent" for Therapist 1.

III. EXPERIMENTS

4 subjects, 3 male & 1 female, aging between 23-27 years old, all right handed, willingly participated in the experiments. Each subject was tested to ensure they could achieve momentary grip strength which saturated the upper bounds of our recording device. A preliminary test was then done with each subject to ensure they could easily maintain a constant grip target set at 15% of the maximum recordable value, without discomfort, strain or fatigue (self-reported) for a prolonged contraction longer than the duration of that required in the experiments. Using direct feedback as guidance (Figure 3), all subjects were given adequate time to learn to become familiar with the mechanics of the task and the relationship between error and their effort, before commencing the experiments. Each of the three experiments consists of a sustained grip contraction for 15 seconds, with identical grip target levels, followed by 2 minutes of rest.
Before each experiment the subject is informed that their goal is simply to maintain grip strength equal to the target and that their performance would be assessed by a virtual therapist.

Experiment (1) - Direct Error feedback
In this experiment the subject is given direct (continuous and real time) visualization of their applied force as feedback, see Figure 3.

Experiment (2) – Demanding Therapist
In this experiment the subject is given only verbal feedback as illustrated by Figure 4, by a "demanding" therapist (Therapist 1, Table 1). This therapist can be considered demanding, as very low error is required to achieve the 'EXCELLENT' feedback output.

Experiment (3) - Excessively Affirmative Feedback
In this experiment the subject is again given verbal feedback, initially from a demanding therapist (therapist 1, table 1) however after 5 seconds we switch over to an alternative therapist who gives unconditional feedback, i.e. the 'EXCELLENT' performance label, regardless of error.

IV. RESULTS

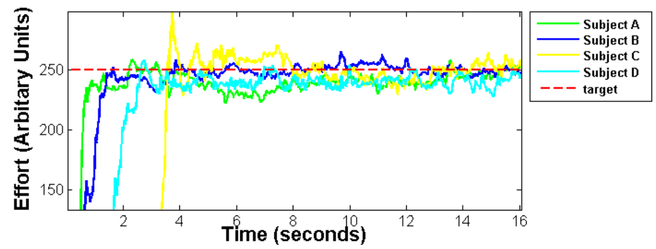

Figure 5. Experiment 1 results - effort over time for each subject while being given direct access to performance.

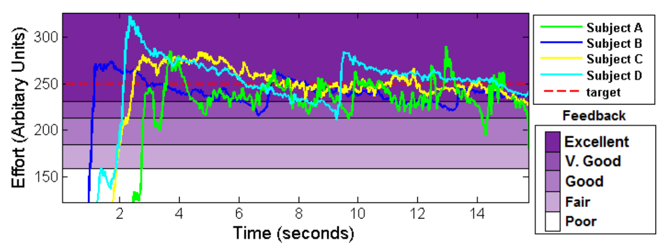

Figure 6. Experiment 2 results - effort over time for each subject while receiving feeback from a 'demanding' therapist (Therapist 1, Table 1).

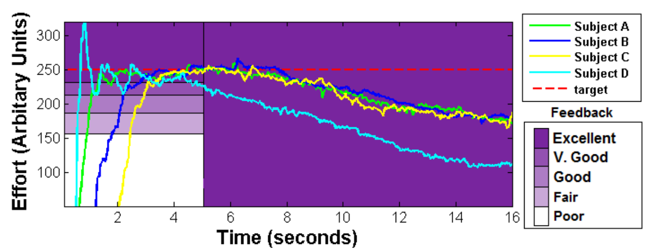

Figure 7. Experiment 3 results – switching after 5 seconds from a '*demanding*' therapist (therapist 1, table 1) to a '*unconditional'* therapist (therapist 2, table 1) who reports 'excellent' feedback regardless of the error.

TABLE II. EXPERIMENT 1 – QUANTIFIED RESULT

	Effort			**Error**
	Min	**max**	**average**	**SSE**
Subject A	222.59	270.48	238.99	1.228*
Subject B	238.50	270.43	250.05	0.241*
Subject C	205.46	270.57	233.28	0.529*
Subject D	229.79	271.43	240.03	0.959*

*. Error is of magnitude 10^5

TABLE III. EXPERIMENT 2 - QUANTIFIED RESULTS

	Effort			Error
	min	**max**	**average**	**SSE**
Subject A	204.32	277.31	239.07	1.643*
Subject B	217.43	280.57	238.03	1.843*
Subject C	204.32	277.31	239.07	1.562*
Subject D	218.04	316.17	255.19	2.837*

*. Error is of magnitude 10^5

TABLE IV. EXPERIMENT 3 - QUANTIFIED RESULTS

	Effort			Error
	min	**max**	**average**	**SSE**
Subject A	179.45	267.95	221.52	13.012*
Subject B	175.08	281.07	224.96	16.962*
Subject C	179.58	267.35	218.79	14.962*
Subject D	108	259.04	173.73	62.680*

*. Error is of magnitude 10^5

V. DISCUSSION

The results of Experiment 1 show that when given direct access to performance all subjects easily maintained their grip strength for the duration of the task, i.e. subjects had relatively low error and average grip strength close to the target, see Table 2.

The results of Experiment 2 show that similar results were obtained when subjects instead received verbal feedback from a 'demanding' virtual therapist. Interestingly, under such a feedback modality all subjects initially overshot the target; however their overall performance during the task had low error and average grip strengths close to the target, see Table 3. The results of the third experiment show that subjects significantly reduced their performance (much greater sum squared error (SSE) and lower average effort, see Table 4) when we switched (after 5 seconds) from a 'demanding' therapist to an 'unconditional' therapist, i.e. one which always reported performance as 'excellent' regardless of the error.

A simple t test demonstrated the changes in SSE, a surrogate for subject effort in this case, was statistically significant when considering each categorized feedback model with respect to the direct error model ($p<0.0001$).

These results might suggest that to maximize performance we simply need to give subjects direct access to error. However, direct error does not capture effort in a comprehensive or forgiving fashion. A patient, particularly one recovering from stroke may produce initially low error but as they progress their error may increase despite the patient's best efforts. Studies of motivation to exercise in adults post stroke suggest that self-efficacy and outcome expectations are key determinants of initiation and adherence to exercise programs [10]. A human therapist is therefore usually sympathetic towards performance errors which are not simply seen as a lack of effort on the patient's behalf but instead arise as a more complex set of parameters both physical and psychological. Consequently measures of performance most be more nuanced than simple error.

VI. DISCUSSION

Enhancing and scaling conventional forms of therapy is important if we are to create effective and accessible therapy, post stroke. Positive feedback from the therapist has been shown to have a strong relationship with patient adherence and subsequently outcomes in rehabilitation therapy. Developing a virtual therapist that can assess patient performance in a manner similar to a human therapist might help towards achieving this goal by improving patient adherence in non-human supervised training.

In this work we describe the first steps towards developing an agent-based therapist capable of administering such feedback. However, with such human-like feedback as that discussed we have revealed the possibility that slacking in the sense as described in robot-assisted systems may manifest (or more likely this is an analogous phenomenon) if an inappropriate agent scoring strategy is used. Subsequently, modelling a virtual therapist that can recognize and manage such behavior will be important.

Further data collection and experimental design is required to better capture the subjects effort dynamics tentatively identified here. In future work we intend to expand our simple agent model to incorporate additional information into its assessment protocol. For example, a measurement of muscle fatigue, concentration, and pass performance characteristics could be included. Such information will allow for a more accurate assessment of the patient's current ability and behavior. The agent could then more appropriately modify feedback to best achieve maximum performance while at the same time maintaining patient adherence.

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