Robot therapy for severely impaired stroke survivors: toward a concurrent regulation of task difficulty and degree of assistance

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Abstract—Many exercise protocols for robot therapy are designed to adjust their degree of difficulty in order to maintain a constant challenge level. A simple way to do this is to design exercises that consist of a variable number of sub-movements in different directions - task difficulty is determined by the number of sub-movements. But, how does recovery proceed in these tasks, and how to regulate the magnitude of the assistance provided by the robot in this case? Here we focus on a simple task in which subjects had to complete a square figure. At every trial, an adaptive regulator selects the appropriate degree of robot assistance needed to complete the entire figure. We tested this protocol with four severely impaired stroke survivors during a multisession study. Robotic training succeeded - the controller gradually reduced the degree of assistance while performance remained constant, suggesting that in fact recovery took place. We used a dynamic model of the recovery process to further analyze the effects of the assistive force and the temporal evolution of the subjects’ voluntary control. The model provided an excellent fitting of the subjects’ performance and revealed that magnitude and modalities of recovery are very different in the different sub-movements. These results suggest that in order to maximize the recovery the modulation of assistance should occur at the level of each sub-movement.

I. INTRODUCTION

It has been long recognized that motivation during exercise is a major determinant of neuromotor recovery[10]. For this reason, a major trend in robot therapy for stroke survivors is to design exercise protocols that aim at maintaining a constant challenge level [1]. Computational models of motor learning suggest that large initial errors may prevent learning [14]. The challenge point theory [7] states that optimal learning is achieved when the difficulty of the task is appropriate for the participants level of expertise (i.e. when the challenge point is reached). This would predict that providing a difficult task to a less skilled participant would result in less learning with a similar amount of practice, as compared to training when the task difficulty is adjusted to the skill level.

A way to achieve this is to match task difficulty to the patients’ degree of impairment, and to continuously adjust such difficulty as performance improves. This approach requires the design of tasks whose difficulty can be modulated. A simple technique is to train subjects to perform tasks that consist of a sequence of sub-movements. The number of sub-movements can be taken as a measure of task difficulty and as such it can be adjusted by suitable control algorithms. This technique has been used in rehabilitation scenarios based on virtual reality[1] and also in robot therapy applications in which the robot is used to complete the movement when a timeout threshold is reached[4].

However, stroke survivors are often unable, at least initially, to complete a motor task without external assistance, while still preserving a potential for improvement. With these subjects, robot therapy protocols based on triggered assistance would switch from fully voluntary movement to a purely passive manipulation. In contrast, the robot might be used to actively contribute to the subjects’ effort to reach a target, by continuously providing an assistive force. As subjects improve and therefore their performance increases, the amount of assistance needs to be continuously regulated and adapted to their improvements. Based on this principle, several robot control strategies have been designed, for both the upper limb and gait training; see [11] for a review. In fact, [6], [8] found that a treatment protocol that adapts to the subjects motor ability achieves a better recovery compared to a training protocol in which assistance forces are not adapted.

Overall, these considerations suggest that controllers (i) should maximize the subject’s involvement; (ii) should provide enough assistance so that subjects complete the desired movements, and (iii) should adapt to the subjects’ skill level and to his/her improvements. However, translating these considerations in actual mechanisms of regulation is not simple. The problem of optimally regulating assistance is currently an open research area, and only heuristic, ad-hoc solutions are currently available. A general criterion for regulation of assistance is to decrease assistance as performance improves. This is often achieved through simple linear control models [9], [13]. Control parameters are usually set heuristically. However, stability of the (closed-loop) recovery process is critically dependent on these parameters, which may be a problem as very little prior information is available on the dynamics of the learning/re-learning process. Moreover, the latter may be highly subject-dependent. An alternative approach is to use adaptive controllers that do not rely on such prior information. An example is the adaptive Bayesian regulator proposed by Squeri et al. [16].

However, an issue remains open of how to regulate as-
Table I

**DEMOGRAPHIC DATA**. FMA: FU GL-MEYER AS SES SM ENT, ARM PART

<table>
<thead>
<tr>
<th>Subj.</th>
<th>Sex</th>
<th>Age (yrs)</th>
<th>Hand</th>
<th>Dis. Dur. (mos)</th>
<th>FMA</th>
<th>Sessions (0-66)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>M</td>
<td>54</td>
<td>R</td>
<td>96</td>
<td>14</td>
<td>31</td>
</tr>
<tr>
<td>S2</td>
<td>F</td>
<td>80</td>
<td>R</td>
<td>3</td>
<td>13</td>
<td>33</td>
</tr>
<tr>
<td>S3</td>
<td>M</td>
<td>51</td>
<td>R</td>
<td>96</td>
<td>8</td>
<td>29</td>
</tr>
<tr>
<td>S4</td>
<td>M</td>
<td>54</td>
<td>R</td>
<td>24</td>
<td>6</td>
<td>25</td>
</tr>
</tbody>
</table>

| avg±SD | 60±14 | 55±48 | 10±4 |

assistance when the task consists of multiple sub-movements. To impaired subjects, each sub-movement can exhibit very different challenge levels. Also, the perceived difficulty of the individual sub-movements is likely to differ in different subjects.

Here we address the question of how to regulate assistance to maximize recovery in tasks that involve multiple sub-movements. We use data from a pilot trial in which assistance is regulated globally, at task level through an adaptive Bayesian regulator [16]. We look at the way performance changes over time, both overall and in the individual sub-movements. We use a computational model of recovery [2] to infer the temporal evolution of the ‘voluntary’ component of the observed performance and to assess differences in the recovery modalities of the individual sub-movements.

II. MATERIALS AND METHODS

A. Subjects

Four severely stroke survivors participated to this experiment, three chronic and one sub-acute (S2). Table I reports the subjects’ demographic data.

B. Task

Subjects grasped the handle of a planar manipulandum (Braccio di Ferro, see [3] for details) with their paretic hand (the right for all subjects, see Table I) and were instructed to perform a sequence of four point-to-point reaching movements in the horizontal plane. The points were arranged as the vertexes of a square. The distance between the starting position and the target, i.e. the side of the square, was 150 mm. At each time, only the next (current) target was made visible. The centre of the square was aligned with the shoulder of the patient. The position of the seat was adjusted in such a way that the farthest targets could be reached with an almost fully extended arm. This task is similar to that used in the triggered assistance counterpart of this study; see [4].

After completion of each figure, we calculated and displayed on the screen a performance score, defined as:

\[
\text{SCORE} = \begin{cases} 
0 & \text{if } MT \geq MT_{\max} \\
100 & \text{if } MT_{\min} \leq MT \leq MT_{\max} \\
100 \frac{MT_{\max} - MT}{MT_{\max} - MT_{\min}} & \text{otherwise} 
\end{cases}
\]

where \(MT\) is the movement duration, i.e. the total time needed to complete the whole figure. \(MT_{\min}\) and \(MT_{\max}\) were set, respectively, to 12 s and 68 s that correspond to average durations, for each sub-movement, of 3 s and 17 s.

If a subject stopped and remained in the same position for more than 7 s, the trial was considered as ‘failed’ (SCORE = 0). The robot brought the participant’s hand to the initial position and started a new trial.

C. Scheme of assistance

During movements, the robot generated a position-dependent assistive force, with constant magnitude and directed toward the current target. This form of assistance is uniform throughout the whole movement, irrespective of the distance to the target. The robot also generated an additional small viscous force, intended to damp occasional hand oscillations without significantly affecting the voluntary reaching patterns. Once one target was reached, the force switched to the next target. The assistance controller is summarized as follows:

\[
F(t) = K \cdot \frac{x_T(t) - x(t)}{\|x_T(t) - x(t)\|} \cdot (R(t) - B \dot{x}(t)) \tag{2}
\]

where \(x_T\) is the position of the next (current) target and \(x(t)\) and \(\dot{x}(t)\) are, respectively, hand position and hand velocity. \(K\) and \(B\) are, respectively, the force magnitude and the viscosity coefficients. \(R(t)\) is a ramp and hold function, which is reset at each new target and saturates (to 1) after 0.5 s. In this way, assistance is turned on gradually. The viscosity coefficient was kept constant throughout the task (\(B=5\) Ns/m). The force magnitude coefficient \((K)\) could range from 0 to 30 N. The Bayesian regulator automatically adjusted \(K\) on a trial-by-trial basis. Note that this scheme of assistance specifies neither the timing of the movements nor the trajectory that subjects have to follow in order to reach the target.

Fig. 1. Example of control action in one exercise session (subject S2)

D. Regulation of assistance

At the beginning of each session, the magnitude of assistive force was set to 15 N. At the end of each trial (i.e. completion of the square), the Bayesian regulator calculated
the magnitude of the assistance that the robot would provide on the next trial.

The control action requires that the average SCORE approximately equals a target value, \( \text{SCORE}_{\text{des}} \); for details see [16]. The target score was initially set to 50, but was updated as subjects managed to get a better one. The underlying rationale is [16] that if subjects could complete the figure with a given degree of assistance and could get that score, improved control would allow attainment the same score with less assistance.

In other words, assistance as needed is based on two nested control loops. The inner loop, based on the Bayesian regulator, aims at adjusting assistance so that the SCORE remains close to \( \text{SCORE}_{\text{des}} \). An outer loop ‘clamps’ the target score \( \text{SCORE}_{\text{des}} \) to the best SCORE ever obtained by that subject. In this way, subjects are permanently challenged to perform close their upper limits.

E. Exercise protocol

The exercise protocol involved 25-min sessions, 2 sessions/day, 5 days/week. Depending on their degree of impairment, the number of trials that subjects could complete within one session could vary and, in case of recovery, it could increase across sessions. The total number of sessions was not the same for all subjects, ranging from 25 to 33; see Table I.

F. Model of recovery

We used a linear dynamic model [2] to analyze the effects of the assistive force and the temporal evolution of subjects’ voluntary control. We started with the assumption that these components have an additive effect on performance. In other words, the performance on the \( i \)-th trial, \( y_i \), results from the human generated force, dependent on voluntary control, \( x_i \), and the assistive force provided by the robot \( f_i \). The above assumption can be summarized with the following equation:

\[
y_i = x_i + Df_i
\]  

We took the average speed as the performance measure \( y_i \), and force magnitude \( K \) as the assistive force \( f_i \). Model parameter \( D \) (numerically a fluidity, the inverse of viscosity) accounts for the dependence of performance on the degree of assistance.

At the next trial (\( i+1 \)) voluntary control is determined by two factors: a memory component proportional to the voluntary control \( (x_i) \) on the previous (\( i \)-th) trial and a learning component proportional to an additional input, the driving signal \( u_i \), i.e. the signal which drives the recovery process. The dependence on these two factors is described respectively by another two model parameters, coefficients \( A \) (retention rate) and \( B \) (learning rate):

\[
x_{i+1} = Ax_i + Bu_i
\]

As driving signal, \( u_i \), we took the fraction of target distance after the first sub-movement. We identified the first sub-movement at the first peak of the speed profile. \( u_i \) equals 1 whenever the target is reached with a single motion. This indicator is a measure of performance: greater \( u_i \), better movement performance [2].

Model parameters were identified using a prediction error method. We treated the data from different sessions as separate experiments, but assumed that the model parameters do not change in the course of the whole recovery process. In this way, in addition to model parameters, the identification procedure gives estimates of the internal state (voluntary command) at the beginning of each session. We repeated this procedure for each individual subject’s data. As a comparison, we fitted the performance time series with a static linear regression model based on Eq.3, which implies that no recovery takes place.

III. RESULTS

A. Control action

For a typical subject, Fig. 1 illustrates the control action of the algorithm and the evolution of task difficulty over all the trials of one session. Initially the subject cannot complete the figure and the score is zero. Therefore the magnitude of robot assistance increases. As the square is completed, the target score is set equal to the actual score. From this moment on, the adaptive regulator will modulate assistance so that the average score is close to the target value. Although highly variable, the score tends to settle around its target magnitude. During the exercise, the participant improves his/her performance, and consequently the level of the force decreases to prevent ‘slacking’ [5]. In other words, a sequence of consecutive trials with good performance (\( \text{SCORE} > \text{SCORE}_{\text{des}} \)) triggers a decrease of the assistance (thus the subject needs more voluntary control to complete the task). Conversely, a consistently poor performance would lead to an increase of the level of assistance.

B. Recovery

Fig. 2 summarizes the evolution of the task parameters, over sessions. Subjects are represented in different colors, while the mean over participants is in black. The computed score (Fig. 2.A) gradually increases and at the same time the degree of assistance (Fig. 2.B) modulated by the adaptive regulator decreases from the first to the last session. At the same time, the time needed to complete a figure decreases (Fig. 2.B), and the number of completed figures increases (Fig. 2.D).

C. Performance in sub-movements

The control parameters presented in Fig. 2 are computed for the entire figure, but the sub-movements, each characterized by a different direction, are widely different in terms of performance. The time needed to complete a single sub-movement, as well as the mean speed calculated for each sub-movements exhibit different behaviors - see Fig. 3: sub-movement 3 (D3, in orange) is the fastest movement (smallest duration, greatest speed). In contrast, sub-movement D4 (in blue) is the slowest. The other two sub-movements (D1 and D2, pink and green respectively) place in between.
Fig. 2. Time course of performance over sessions. Average values computed over sessions of the computed SCORE (A), the magnitude, K, of the assistive force (B), movement duration (whole figure) (C) and number of whole figures completed on each session (D). The different colors denote different subjects. The black line denotes the mean±SE over subjects. The plot was truncated at 25 sessions (the minimum number that were completed by all subjects).

### D. Recovery model

Fig. 4 summarizes the model fitting performance for subject S2 for sub-movement D2. The first two panels report the system inputs: with practice, the assistive force decreases and the performance signal that drives the recovery increases. The fitting of the performance output with the dynamical model is excellent (black line), while the simple regression model (green line) completely fails on explaining the performance time series. Moreover, the model succeeded on identifying an increment of the subjects voluntary control. This result was also confirmed by looking at the fitting performance (variance accounted for, VAF) for each subject and all movements directions (see Fig. 5).

Looking at the model parameters, we observed large differences in the individual sub-movements, denoting variability in performance and in the recovery modalities. More specifically, the fluidity parameter $D$ turned out to be smaller in sub-movements D3 (proximal, right to left) and D4 (left, proximal to distal) - this indicates that in these directions the movements are less sensitive to assistance. In contrast, sub-movements D1 (distal, left to right) and D2 (right, distal to proximal) are much more sensitive to assistance; see Fig. 6 (left). As regards the learning rate, B, a much greater magnitude - i.e. a much greater rate of recovery - was observed in sub-movement D3 (proximal, right to left) - see Fig. 6 (right).

Model parameter $A$ determines the time constant of the recovery process. It has been suggested [2] that this parameter reliably predicts the long-term outcome of recovery. We found a time constant of about 80 trials for the horizontal movements (D1 and D3), and > 100 trials for the other directions (D2 and D4). However, these estimates have to be taken with caution because the short duration of each session may result in underestimates of these values.

### IV. Discussion

#### A. An 'assist as needed' method to regulate assistance

In a previous work [16] we demonstrated a general method for the adaptive regulation of assistance (or any task parameter) during robot-assisted learning or re-learning exercises. The controller does not require prior knowledge on the dynamics of the recovery process.

In the present work, for the first time we validate the procedure for the regulation of assistance in a robot therapy protocol aimed at stroke survivors. Session after session, a threshold difficulty value is selected according to the subject’s actual skills. With the proposed procedure, the performance remains close to a pre-determined target level. Both over- and under-performance elicit a change in assistance. Furthermore, for a given target performance an improved voluntary control would lead to a decrease in the degree of assistance. Our results (see Fig.1) are consistent with these
predictions. In particular, while performance remains stationary and near the desired score, the degree of guidance (K) is automatically decreased. This is an indirect indication that subjects are learning to complete the task under increasingly challenging conditions.

In conclusion, the proposed methodology may be seen as a basic building block for ‘assist as needed’ control schemes, in which assistance (i) decreases as subjects’ performance improves; (ii) is adjusted to patient skills to prevent errors that may affect motivation and even safety, and (iii) is robust to performance variability (i.e. noise).

B. Effect of assistance at sub-movement level

Overall, the adaptive regulation of assistance works as expected. However, the individual sub-movements exhibit very different behaviors. At the level of the individual sub-movements, the evolution of performance exhibits large differences - see 3, which suggests that some sub-movements tend to be more challenging. Correspondingly, a recent work [12] shows that motor recovery followed different mechanisms to recover movements towards (and from) different target locations.

The estimated parameters of the recovery model provide a novel understanding of these differences. Some sub-movements (namely, D3 and D4) are less sensitive to assistance - thus suggesting that they would need more to achieve a given performance. These movements correspond to complete elbow extension (D4) and shoulder adduction (D3), which are known to be particularly challenging to rehabilitation[15]. The sub-movements also differ in the rate of recovery (learning rate, B).

A limitation of our modeling approach is that we treated the time series of movement speed along the different
directions as independent processes. This may not be the case (improvement in some direction is likely to affect performance in other directions). Future versions of the model will address this form of generalization [18], [17].

In conclusion, we found that the individual sub-movements differed in performance, sensitivity to assistance and rate of recovery. These findings point to the need of regulating assistance at the sub-movement level. Models of the recovery process may help to identify the desired goals and features of such regulation.

REFERENCES
