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Development of a Progressive Task Regulation Algorithm for Robot-aided Rehabilitation

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Abstract— **Patient motivation is an important factor in rehabilitation. The difficulty level of the motor task, the awareness of the performance obtained, and the quantity and quality of feedbacks presented to the patient can influence patient motivation and produce different ways of acting and different performances. This study presents a Progressive Task Regulation algorithm able to evaluate the patient's performance during training and automatically change the features of the reaching movement, so as to adapt automatically the difficulty level of the motor task to the patient's ability. Use of the progressive task regulation algorithm should promote patient motivation throughout the course of treatment.**

I. Introduction

Motivation is an important factor in rehabilitation and is frequently used as a determinant of rehabilitation outcome [1]. In particular, active engagement towards a treatment/ training intervention is usually equated with motivation, and passivity with lack of motivation. The difficulty level of the motor task, the awareness of the performance obtained, and the quantity and quality of feedbacks presented to the patient can influence patient motivation and produce different ways of acting and different performances. The last 10 years of experience with robot-assisted rehabilitation have shown that passive training driven by the robot is not an efficient training strategy [2]. This is due to the fact that passive movements transmit to the central nervous system different feedback from active movements. For this reason it is important to provide the trained subject the correct amount of assistance and an appropriate difficulty level of the motor task. The continuous challenging and assisting can yield substantial advantages in the process of motor learning and improve motor coordination.

Performance-based progressive training schemes have been proposed as a way to gradually reduce the amount of guidance during training. Bell et al. proposed a performance-based progressive guidance scheme for self-learning of a computer-based radar tracking simulation task, which showed significant beneficial effects [3]. A performance-based progressive robot-assisted therapy for stroke patients was first proposed by Krebs et al. [4] in the field of neurorehabilitation. In Krebs' approach, the patients were provided with guidance during a reaching task. In particular a specific algorithm used the mean velocity and the deviation of the patient's motion from a normal movement trajectory to trigger and change the amount of guidance. Similarly, in another robot-assisted rehabilitation study for gait training, human motor adaptation to dynamic environments was modeled as a kinematic error (step height error) corrective learning process and the control gains of the guidance robot were adjusted at each trial based on the error [5]. The results of this study suggest that providing guidance only when needed is more effective than always assisting with a fixed amount. O'Malley et al. demonstrated that a progressive control guidance scheme reduces the dependency of participants on the guidance by adjusting the control gains based on individual participant performance. In particular, a progressive shared control algorithm was applied to expose subjects to an appropriate amount of haptic guidance based on their performance [6]. Basically, progressive control should permit the difficulty of the task to increase while gradually reducing assistance. The ADAPT device [7] provides adaptive and automatic presentation of tasks, but without any limb assistance. Therefore, none of the present robotic devices with assistance or associated control algorithms consider the possibility of changing the type of motor task administered to the patients or changing other features of the task in order to maintain a high level of patient involvement, and hence motivation, throughout the whole course of treatment. For this reason we developed a Progressive Task Regulation (PTR) algorithm able to evaluate patient's performance during training and automatically change the features of the reaching movement, in order to adapt the difficulty level of the motor task to the patient's ability. The aim of this work is to present the algorithm, its design and implementation strategies and its application with simulation and real performance data.

II. Methods

A. System description

The algorithm was preliminarily tested using the performance data obtained in a group of 9 post-stroke patients (4 females and 5 males) who underwent robot-aided rehabilitation. The difficulty level of the task was manually changed by the therapist during the treatment. All patients were in chronic stage, their unilateral cerebrovascular

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accident (CVA) having occurred at least 6 months prior to enrolment (32±27 months from CVA). Inclusion criteria were the presence of a single unilateral CVA and the presence of at least 10° of motion in the treated joints (shoulder and elbow); this latter criterion ensured that only patients who could really be motivated by use of the robot device were enrolled. The two DoF elbow-shoulder manipulator "Braccio di Ferro" was used for the treatment of our patients [8]. The robot apparatus included an end-effector, normally consisting of a sensorized handle which is grasped by the patient and moved through the workspace of the device (i.e. the horizontal plane). Patients had their trunk fastened to the back of the chair by a special jacket to limit compensation phenomena and were placed at the robot desk facing a video screen that provided visual feedback of the assigned motor task. The patient's paretic limb was supported at the elbow by a low friction pad that slid along the surface of the robot workspace. Patients had to make a sequence of point to point reaching movements; a yellow circle displayed on the screen indicated the task's starting position, a red circle the task's target position, and a green circle the current position of the handle. Patients were trained twice a day (40 minutes/ session), 5 days a week for at least three weeks. A practice session preceded the treatment, during which detailed instructions were given to shorten the exercise learning phase. During the exercise, the device stored details of the handle positions, and device status, reporting information about the different robot conditions (patient active, robot active, rest, etc.) acquired at a rate of 100 Hz..

B. Difficulty Level of Motor Task

Usually a motor task is characterized by a set of features determining the so-called "difficulty level of the task"; a change of these features usually produces an increase/decrease of the task's difficulty. In particular, we have identified the following task features:

1) Reaching task sequence

As previously described, the patient is required to make a sequence of point-to-point reaching movements in the horizontal plane; patients are instructed to move the robot handle from the starting point to the end point following the straight line connecting them. In practice the exercise is similar to the tracing of a geometric shape. These shapes have increasing number of edges and complexity (a square represents the easiest reaching task, and a eight directions reaching task the most difficult).

2) Type of assistance

In the present robot version we decided to maintain the force magnitude assisting the patient movements at a predefined value for all the difficulty levels of the task. Therefore, the algorithm can only change the time of its actuation and its direction (assistive or repulsive force moving the arm directly to the target.). Based on these conditions the system we implemented is able to provide three types of assistance:

<u>Time-Triggered Assistance (TTA).</u> This type of assistance is used in more compromised patients. At the beginning of the task the patient is free to move the arm within the workspace, but two seconds after the visualization of the target on the robot display, the assistive force comes into play at a very low magnitude. The assistance is then gradually increased, according to a ramp shape, up to a pre-defined value (soft application of assistance). Then the force is maintained at that magnitude so as to guide the patient's arm to the target. In this way the patient is challenged to independently begin the motor task but at the same time helped in any case to complete the movement, so motivating the patient to perform the exercise.

<u>Activity-Triggered Assistance (ATA).</u> This type of assistance has the objective of enhancing and stimulating the patient's voluntary motor activity. The patient is requested to move the arm from the starting point to the target without any restriction. If during the motor task execution the patient cannot complete the task autonomously, the robot evaluates the current position and, after a period of 3 s in the same place, guides the patient's arm to the target position.

<u>Negative Assistance (NA).</u> In this type of assistance the patient is required to execute the reaching task, working against a resistive force of constant magnitude. This task is designed for less compromised patients or for those who have already made a significant motor recovery and need mainly to improve the quality of their motor control. This type of exercise should allow to increase the number of patients who can benefit from robotic treatment.

3) Target distance

The distance between the starting position and the target can be selected from two options: 150 and 220 mm. An increase of the distance is usually implemented before any change of the shape.

4) Virtual slot

The learning process occurring during the course of rehabilitation refines the selection and coordination of the appropriate muscular contractions, and implies the creation

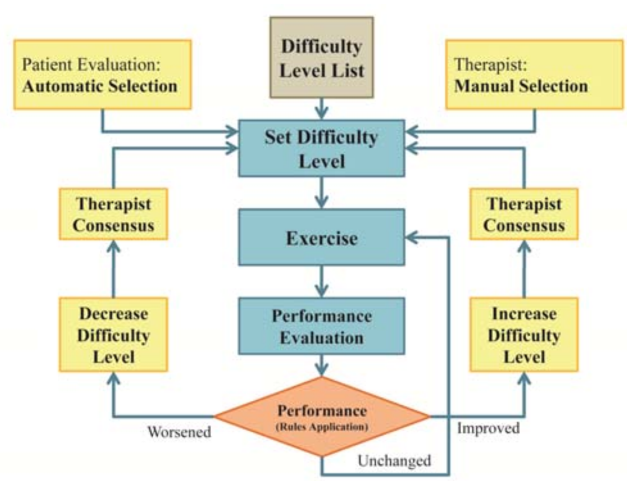

Figure 1. Flow diagram of the Progressive Task Regulation Algorithm

of new motor synergies by combining forces generated across multiple joints in novel kinematic and dynamic patterns. In order to stimulate the patient to recruit the correct muscle synergies during the movement towards the target, we have introduced a virtual slot. Within the virtual slot the patient is free to move anywhere without any resistance; conversely, outside the slot, movements are prevented.

Different patients usually have different motor skills and different rates of motor learning. Therefore, they exhibit different abilities in the execution of specific tasks with different features. We thus took into account the spectrum of variation of the previously defined features, and defined a list of tasks with increasing difficulty levels. This list included for example different reaching sequences like drawing a square or more complex geometrical shapes. The task list was sorted by an expert therapist who assigned the difficulty levels from the easiest to the most difficult.

C. *Measurement of patient's performance*

Before training, the patient undergoes an evaluation session in which, starting from the workspace center, he/she must perform at least two reaching movements in 8 specific movement directions (N, NE, E, SE, S, SW, W, NW). During the evaluation session the device does not generate any assistive force so that only motor behavior due to the patient's voluntary activity is evaluated. During this session the device records the position of the end-effector and computes the percentage of trajectory traveled by means of the patient's voluntary activity (AMI), the mean velocity (MV), the normalized path length (nPL) and the mean distance (MD) from the theoretic trajectory [9]. After the start of training the performance parameters, reported above, are recursively computed at the end of each training session in order to verify if a change in the difficulty level is required (Fig.1). When the TTA assistance is selected the algorithm computes only the AMI parameter during the time window without assistance (2 s window).

D. *Rules for difficulty level transition*

The PTR algorithm adjusts the difficulty level of the exercise on a session by session basis. As in the algorithm presented by O'Malley and coll. [7], for each parameter the process of difficulty level adaptation is controlled by a moving average procedure obtained from three consecutive training sessions. In particular, we defined:

$$P_i = \begin{bmatrix} AMI_i \\ MV_i \\ -nPL_i \end{bmatrix} \tag{1}$$

$$P_{avg1} = \frac{\sum_{i-3}^{i-1} P_i}{3} \tag{2}$$

$$P_{avg2} = \frac{\sum_{i-2}^{i} P_i}{3} \tag{3}$$

where Pi is the performance vector, Pavg2 is the average of the performance obtained in the current and in the two previous training sessions and Pavg1 is the average of the performance in the previous three sessions. If Pavg2 is greater than Pavg1 for at least three consecutive sessions, then the difficulty level of the task is increased. Furthermore, if the average performance is greater than a threshold value the difficulty level is increased. Conversely, if Pavg2 is lower than Pavg1 in the following session or lower than a threshold value, the difficulty level of the task is decreased; this allows to prevent the patient working for a long period at an unsuitable level of difficulty. The threshold values were determined heuristically according to the developed experience of a pool of expert physiotherapists. The nPL value is taken as a negative value so that increases in the parameter equal increases of performance. When the algorithm detects the need for a change of the difficulty level, it requires the therapist's consensus through a specific dialog panel on the computer display. The therapist can decide whether to accept the change or refuse it (leaving the patient working in the same conditions).

III. RESULTS

The algorithm was first tested on some simulation data in which the performance of the patient assumed synthetic improvements and worsening. Fig. 2 (Panel A) shows the results of a typical simulation case. As one can see, the algorithm suggested a difficulty level change at session 8, 25 and 30. Subsequently the algorithm was tested using the performance data obtained in a group of 9 post-stroke patients who underwent robot-aided rehabilitation and where the difficulty level of the task was manually changed by the therapist. Table 1 reports for each subject the number of manual changes, the number of automatic changes and the difference between automatic and manual changes. The results show that in 4 subjects the PTR algorithm and the therapist suggested the same number of changes of difficulty level. In 2 patients the algorithm proposed one additional

TABLE I
PTR ALGORITHM RESULTS

	Number of manual changes	*Manual changes Session #*	*Number of automatic changes*	*Automtic changes Session #*	*Automatic vs.Manual Difference*
P1	1	20	2	8,19	+1
P2	1	18	2	26,31	+1
P3	1	9	1	7	---
P4	1	9	3	7,15,21	+2
P5	1	7	3	7,18,22	+2
P6	1	---	0	---	---
P7	0	---	0	---	---
P8	0	---	0	---	---
P9	0	16	4	9,16,22,26	+3

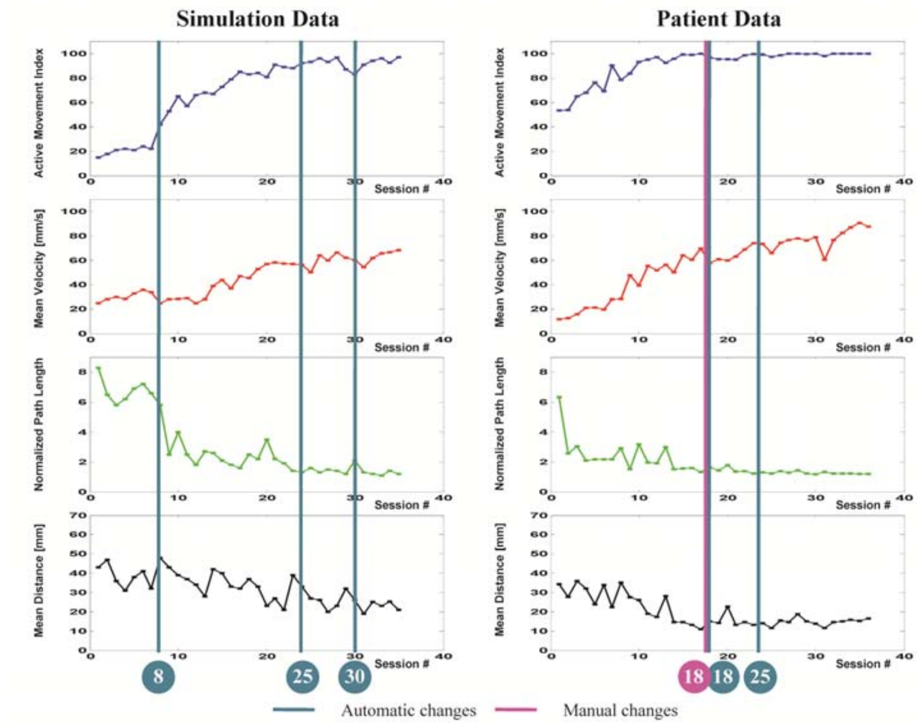

Figure 2. Time course of the robot measured parameters used by the Progressive Task Regulation algorithm and the suggested difficulty level changes (vertical lines). Panel A shows the results obtained using simulation data. Panel B shows the comparison between manual (therapist selection) and automatic changes. The green lines of each panel represent the algorithm-suggested changes and the magenta line on panel B represents the actual change independently selected by the therapist.

change with respect to the therapist. In the last 3 subjects the algorithm proposed two or more changes. This result is not surprising because the automatic regulation algorithm was tested in an open loop condition and hence a greater sensitivity of the algorithm was expected.

IV. Discussion and Conclusions

The PTR algorithm we implemented shows a behavior quite similar to the manual selection implemented by the therapists. This should imply that the difficulty level of the task is adapted automatically to the patient's residual capacity. The availability of this type of architecture should allow to speed-up the learning process of different motor tasks thereby allowing an easier treatment of different pathologic conditions of the neuromuscular system. In addition the automatic changes of difficulty levels, simulating a video-game experience, may be very useful for maintaining the patient's interest high during the whole training, so inducing a better performance and outcome. The results reported here should be interpreted in the light of an open loop testing procedure. Of course a testing protocol to evaluate the algorithm performance in a "closed loop" condition (i.e. a condition in which the automatic regulation will influence the difficulty level selection) is mandatory. Future studies need to address also the assessment of the rate of improvement produced by this algorithm in post-stroke patients in recent and chronic conditions.

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