Lag-lead based assessment and adaptation of exercise speed for stroke survivors

Angelo Basteris*[1], Sharon M. Nijenhuis[2], Jaap H. Buurke[2,3] , Gerdienke B. Prange[2,4] , Farshid Amirabdollahian[1]

Abstract

The SCRIPT project aims at delivering robot-mediated hand and wrist exercise for people with stroke in their homes. In this context, adapting the exercise to the individual needs potentially enhances recovery.

We designed a system composed of an orthosis, a personal computer and an arm support. The system enables users to exercise their hand and wrist movements by playing videogames. Movements and their required speed are tailored on the individual's capabilities. During the exercise the system assesses whether the subject is in advance (leading) or in delay (lagging) with respect to a reference trajectory. This information provides input to an adaptive mechanism aimed at making the exercise not too easy nor too challenging by adapting the required movement speed accordingly.

In this paper, we show results of the adaptation process in a study involving seven persons with chronic stroke who completed a six weeks training in their homes. We defined session types as *challenging, challenging-then supporting, supporting, under-supporting* and *under-challenging*, based on the patterns observed in difficulty and lag-lead score. We show that the mechanism of adaptation has been effective in 195 of 248 (78.6 %) sessions.

Based on our results, we propose the lag-lead based assessment and adaptation as an auto-tuning tool for rehabilitation robotics.

[1] Adaptive Systems Research Group, University of Hertfordshire, College Lane, AL95HX Hatfield, United Kingdom;
[2] Roessingh Research and Development, Roessinghsbleekweg 33b, 7522 AH Enschede, the Netherlands;
[3] Department of Biomedical Signals and Systems, University of Twente, Drienerlolaan 5, 7522 NB Enschede, the Netherlands
[4] Department of Biomechanical Engineering, University of Twente, Drienerlolaan 5, 7522 NB Enschede, the Netherlands

Email: Corresponding author: Angelo Basteris* – angelobasteris@gmail.com; Sharon M. Nijenhuis – s.nijenhuis@rrd.nl; Jaap H. Buurke – j.buurke@rrd.nl; Gerdienke B. Prange – g.prange@rrd.nl; Farshid Amirabdollahian – f.amirabdollahian2@herts.ac.uk

1 Introduction

Due to an aging society, the number of people suffering a stroke will increase, leading to increased demands for healthcare, while the availability of healthcare professionals is decreasing [1]. Overall, this will have a strong impact on healthcare services and related costs. Therefore, new ways of providing healthcare services, such as remotely supervised intensive treatment and self-administered exercises, e.g., in the patient's home, address a major issue for future healthcare organisation [2].

1.1 Robotic rehabilitation for stroke

Functional recovery from stroke demands a long period of physical rehabilitation. Research into motor relearning and cortical reorganization after stroke has provided a neurophysiological basis for restoration of arm function: high training intensity, active initiation and execution of movements, feedback and application of functional exercises are key aspects [3, 4]. Technological innovations provided an opportunity to design interventions that combine many of such aspects, of which rehabilitation robotics is a well-known example. With such a robotic device, the required amount of movement support can be provided, thereby allowing active practice when this is not possible otherwise. This facilitates intensive training with a high dosage, while the patient is actively contributing to the movement. Robotic systems have an additional advantage in that they potentially allow unsupervised training. This enables the patient to train frequently without a therapist present, even in his/her own home environment.

The application of rehabilitation robotics has been shown to be effective for the hemiparetic arm, although transfer of robotic training effects to activities of daily living is less pronounced [5]. Contemporary robot-aided therapy focused mainly on the proximal arm, resulting in improvements in the proximal arm, but with limited generalization to the wrist and hand [6-8]. Without additional involvement of the hand in exercises, the functional nature of the training is not optimally employed. Moreover, the wrist and hand play a major role in a person's functional independence. In order to maximize independent use of the upper extremity in daily life, it is important to involve functional practice of the wrist and hand in an intensive way in treatment [9]. Therefore, involving the wrist and hand in robotic training is important, but this is currently not applied to a large extent.

1.2 The SCRIPT project

To accommodate treatment incorporating the abovementioned key aspects for motor relearning, the SCRIPT (Supervised Care and Rehabilitation Involving Personal Telerobotics) project aims to apply robot-aided therapy at home as it would enable self-administration of more intense and more frequent exercise, focusing on hand and wrist exercise. These aspects are combined in the SCRIPT1 system, consisting of a passive-actuated orthosis (which provides an off-set force towards extension of fingers and wrist using elastic cords and leaf springs [10]), interactive games that require hand opening/closing and/or wrist movements to control the games, and a personal computer, installed at a patient's home for independent training with off-line remote supervision by a healthcare professional [11].

1.3 The need for adaptive exercises

Besides optimization of the dosage of treatment, active contribution of a person to such treatment should be emphasized as well. Self-initiated and self-generated activity stimulates brain plasticity underlying functional reorganisation of the cortex after a stroke [12]. The importance of self-generated activity over being guided passively was emphasized in a study by Lotze and colleagues in healthy subjects, where training of voluntary induced wrist movements resulted in larger increases in performance and cortical reorganisation compared to passively induced movements. Along the same lines, repeatedly completing reaching movements of stroke patients by a robotic device when they couldn't reach the target (with the patient being passive) was inferior to making active reaching movements without robotic assistance [13].

To optimally encourage active contribution of the patients themselves, more specific control and adaptation of training environments to persons´ abilities and needs is required. It is increasingly recognized that patients respond differently to a certain treatment for the upper extremity, e.g. in the field of robot-aided therapy [14]. The current challenge is to understand how to customize arm training programmes to each patient's needs and abilities. This is especially important as the time course of recovery and treatment responses vary considerably across patients [14].

With a robotic device, haptic guidance can be used to stimulate motor relearning. Different types of haptic guidance have been implemented in robotic devices, ranging from passive guidance (no active contribution of the patient needed) to soft or hard guidance, guiding a patient along a pre-defined trajectory where deviations are resisted to a larger or smaller extent [14, 15]. A comparison of four specific types of haptic guidance (passive guidance, hard guidance, soft guidance and error-augmentation) with no guidance (active movements without interference from the robot) during reaching movements in healthy persons indicated that motor adaptation (as a basis for motor learning) was largest and fastest in the two guidance conditions that didn't restrict movement errors and required the largest effort: active movement and error-augmentation [16].

Stimulating improvement of arm/hand function via optimal engagement and active contribution requires that the exercises are challenging; meaningful not being too difficult nor too easy, at all times. According to the Challenge Point framework, this is expected to improve motor learning and neuromotor recovery [17]. This implies that, ideally, the training environment adapts to the performance of the patient. This must also take into account that the stroke population is highly heterogeneous in terms of limitations caused by the stroke and the time course of functional improvement. There is also an element of relearning involved in rehabilitation which allows us to use taxonomies from learning theory, shown in Figure 1. In this domain, balancing between supporting and challenging the student allows achieving optimal learning [18].

When applying support from technology to the upper extremity in order to improve arm/hand function, according to abovementioned considerations it is important to promote active movement, allow errors and variability, and continuously adapt the amount of support to the varying performance of movements. In robotic gait training, these issues have been incorporated into an 'assist-as-needed' guidance algorithm that optimizes movement error and robotic support, including a forgetting factor to reduce the robotic support when error is small, while at the same time allowing the variability of movements that are natural to human movement [19].

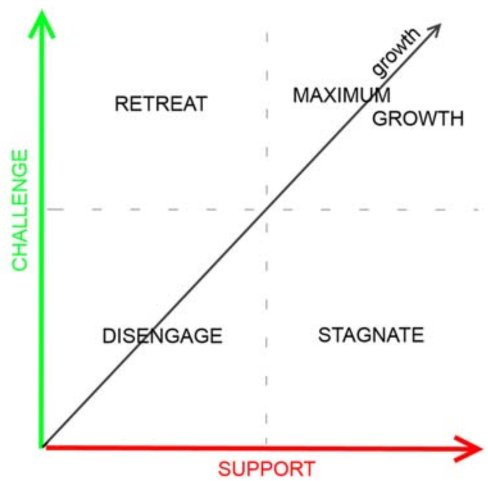


Figure 1 Sanford hypothesised that for growth and personal development to occur, a student needs to have a challenge/support balance. Too much support, and the student will never really learn …too much challenge, and the student will become frustrated and possibly quit trying.

1.4 Adaptive exercises

Besides providing assist-as-needed support by a device, tailoring exercise to the individual's performance can be done by considering a wide variety of inputs and outputs. The simplest step in this sense is to evaluate subject's active range of motion (ROM) prior to each session and scale the training environment accordingly. Typically such scaling is maintained constant during the session, also for safety reasons.

Another possibility, is to evaluate subject's motor improvement for a session, based on a statistical model, and increase the exercise difficulty if the subject has overcome a predefined target [20]. Again, this mechanism operates at a session level, and in this case it also requires the final decision of a healthcare professional prior to changes to the exercise difficulty.

When considering an online adaptation instead, a possibility is to adapt the robot dynamics based on subjects' performance [21]. An alternative output for the online adaptation process is the exercise difficulty. A computation mechanism based on Fitts' Law has been validated on reaching movements in a single study session [22]. In this case, the system switched among three levels of difficulty. The task difficulty – and the related cognitive workload – can also be adjusted by combining performance data with psychophysiological measurements [23].

Regarding wrist movements, an adaptive procedure based on the number of successful (i.e. those with limited contribution by the robot) movements was used to introduce an offset in terms of joint angle by shifting from pathologic towards natural posture [24].

1.5 Lag-lead based mechanism of adaptation

The SCRIPT1 system assesses the active ROM and movement duration during the calibration phase prior to each session, and then adapts the task difficulty by altering the exercise speed online within the training session [25]. The system can assess whether the subject is anticipating (leading) or in delay (lagging) with respect to a desired trajectory for each articulation, i.e. hand flexion or wrist extension. Using the lagging or leading status, a score is calculated that provides input to an adaptive mechanism aimed at making the exercise not too easy nor too challenging. We previously tested this approach on healthy subjects by regulating the movement time, based on a lag-lead indicator, in a reaching task [26]. Our study provided support for the online adaptation with healthy subjects. In this study, we hypothesize that if such an approach is able to adapt a training environment to varying performance across subjects with stroke and within subjects with stroke over time, this would present a way to provide independent training for stroke subjects at a proper challenge level within each training session, motivating the subjects to practice more. In the present study, the feasibility and effect of the lag-lead approach for adaptation of the exercise environment to personal performance is examined during home-based training of the hand and wrist by subjects with chronic stroke. We considered that by observing the progression of task difficulty within a training session it is possible to determine whether the subject was challenged or supported by the system. Hence, we defined types of sessions based on patterns in the adaptation behaviour, and verified whether our approach effectively challenged and motivated subjects without making the exercise nor too easy nor too difficult.

2. Methods

2.1 Experimental setup

The SCRIPT system, shown in Figure 2, consists of several components. A passive-actuated hand and wrist orthosis is used to assist the wrist and hand during training [10]. The orthosis is an exoskeleton on the forearm and hand, which interacts physically with the user by providing forces to the wrist and hand through elastic cords and leaf springs. The orthosis is equipped with resistive sensors to measure joint excursions of the wrist and fingers. A Windows based personal computer contains all custom-

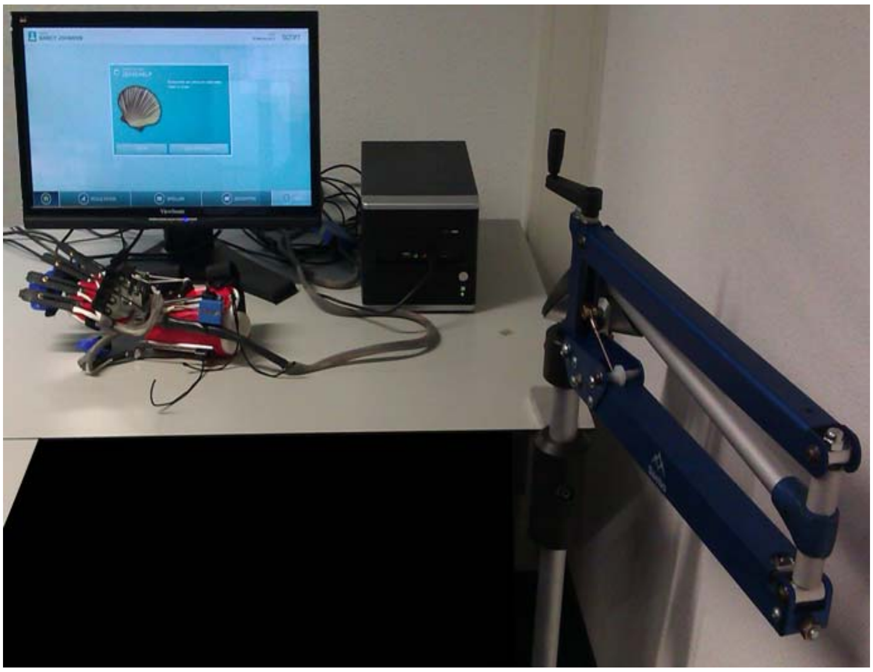


Figure 2 The SCRIPT1 system - composed by passive orthosis, touchscreen display, personal computer and arm support.

developed software components needed to complete a training session, including data acquisition and processing, patient user interface and games.

Five finger sensors are used to measure hand opening. This happens considering hand opening as the standard deviation of positions of the five finger tips, estimated by applying the finger sensors readings as input to a kinematic model of the hand. The wrist angle is measured in a range of approx. 45 degrees of extension to 90 degrees of flexion by a potentiometer. For each session, these signals are normalized with respect to the maximum and minimum measured value during a preliminary calibration phase.

At the time of this study, the system included two video games (*seashell* and *supercrocco*) aiming at enhancing subject's motivation by having their speed tailored to the individual's performance. In the first game, the subject operates a seashell (*cursor*) by opening and closing the hand. The shell has to catch fishes (*targets*) which appear on the screen (i.e. the subject has to close the hand on time to close the shell and catch a fish). In the second game, *supercrocco,* the subject controls a crocodile (*cursor*) by flexing and extending the wrist to avoid obstacles (*targets*). The speed of both games is set according to the corresponding movement duration measured before each session during the calibration.

An arm support (SaeboMAS, Saebo Inc, Charlotte NC, USA) provided gravity compensation of the proximal arm. A telesupervision platform enables the healthcare professional to remotely monitor the progress of the therapy by accessing a secure dedicated web user interface.

2.2 Lag-lead based assessment of performance

In order to achieve the adaptive behaviour of the game, it was needed to assess subject's movement on the fly (i.e. as practice progressed). During the exercise, the target onset triggers the acquisition of the movement excursion signal, either hand opening or wrist angle. The acquisition finishes when the current target passes the cursor. Then, the movement profile is considered only within the interval corresponding to a minimum and maximum value, respectively m and M. The time interval between these two points is considered as movement duration, T, and N_Q is the number of samples within this time frame. If the movement lasts less than 0.5 seconds (thus not reflecting any volitional control of the subject), then it is withdrawn and no score is computed. Otherwise, the system generates a reference trajectory x_R, of the same size matching N_Q. For finger movement (hand opening), we use a model validated for healthy subjects and stroke survivors [27]:

$$x_R(t) = m + M - \left[c_1 + c_2 \cdot \tanh\frac{t - c_3 \cdot T}{c_4 \cdot T}\right] \qquad (1)$$

where $c_1 = (m+M)/2$, $c_2 = (M-m)/2$, $c_3 = T/2$ and $c_4 = T/6$, while for the wrist angle excursion we use a minimum jerk profile [28] :

$$x_R(t) = m + (M - m) \cdot \left[6 \cdot \left(\frac{t}{T}\right)^5 - 15 \cdot \left(\frac{t}{T}\right)^4 + 10 \cdot \left(\frac{t}{T}\right)^3\right] \qquad (2).$$

The sampled signal x is then compared with the reference trajectory, and the lag-lead score LL is defined as the fraction of samples in which the signal was higher (for an increasing signal) or lower (for a decreasing one) than the reference trajectory:

$$LL = \frac{\sum_{N=1}^{N_Q} (x_N \geq x_{RN})}{N_Q} \qquad (3),$$

thus varying in range [0,1]. Hence, the worst case, 0 means that the subject is constantly in delay with respect to the reference (lagging), whilst the best case 1 represents systematic advance (leading). Note that, given the greater or equal than sign in (3), the case where a subject is exactly in sync with the reference trajectory also results in a score 1.

2.3 Adaptive behaviour of the system

The lag-lead score is used to adapt the exercise, in order to make it easier for subjects who were often in delay with respect to the reference trajectory (failure), and harder for those able to anticipate it (success).

This was achieved by multiplying the speed of the game by a factor λ which was the outcome of an adaptive process. Let th_+ and th_- be the thresholds for the lag-lead score which determine success and failure, respectively. If among the last N trials there is a number of successes (or failures) higher than $N+$ (or $N-$) , the current value of the multiplier factor λ is divided (or multiplied) by 0.9.

In our case, λ started at 1 and we used $N=20$, $N+=N-=10$, $th_+=0.8$ and $th_-=0.4$. This implied that a subject was considered failing when lagging for the 40% of the time within one movement repetition (LL<0.4), and successful when leading for at least the 80% of the time (LL>0.8). If a subject was failing for at least 10 of the last 20 movement repetitions (more than 10 of the 20 trials), the game speed was multiplied by 0.9, while it was divided by 0.9 if one was leading on 10 or more of the last 20 trials.

2.4 Classification of session type based on pattern of adaptation

Based on the observed patterns in exercise difficulty and score, we defined five types of sessions, namely *challenging, challenging - then supporting, supporting, under-challenging* and *under-supporting* (summarized in Table 1). The former three are those in which the adaptation mechanism was effective in holding the score within the target region. Ideally, this happened with a progressive increase in speed (*challenging* session). If such increase was followed by a decrease in speed prior to session's end, the session was classified as *challenging – then supporting*. In a *supporting* session, the success was achieved by progressively decreasing the speed of the exercise. Finally, the adaptation mechanism could eventually fail and lead to sessions with scores respectively higher (*under-challenging*) or lower (*under-supporting*) than the target region.

Table 1 Definition and conditions specifying five adaptation types – categories shaded in green represent effective adaptation

Adaptation type	Rationale	Conditions
Challenging	The score is held within the target range, but there is a progressive increase in the difficulty of the exercise during the session, possibly due to warming and motor learning. This constantly new challenging is supposed to engage the subjects	$th_- < \overline{LL} < th_+$ max(λ)>1 λ_N=max(λ)
Challenging- then supporting	After such constant increase in speed (challenging phase), subject's performance might decrease (e.g. because of loss of attention, fatigue). In such a case, we would observe a decrease in difficulty (supporting phase) towards the end of the session.	$th_- < \overline{LL} < th_+$ max(λ)>1 λ_N<max(λ)
Supporting	The lag-lead score results in the target range, but this is achieved by progressively reducing the difficulty. This means that the game somehow supports the subject.	$th_- < \overline{LL} < th_+$ max(λ)=1
Under-supporting	This is a failure of the adaptation mechanism, for which the score is lower than the target range. This possibly results in a frustrating experience for the subject, who is not able to accomplish his/her task.	$\overline{LL} < th_-$
Under-challenging	This is a failure of the adaptation mechanism, for which the score is higher than the target range. This possibly limits the outcome of the exercise, since the subject performs well below his/her capabilities.	$\overline{LL} > th_+$

Consider each training session as including N_R movement repetitions. This results in having two arrays of size N_M, which contain respectively the difficulty scaling factor λ and the lag-lead score LL for each movement repetition. The abovementioned classification relies on imposing the conditions specified in Table 1 over these two vectors.

2.5 Experimental protocol

Data from a sub-set of seven chronic stroke patients participating in an ongoing clinical evaluation [29] was used for the present study. The study protocol was approved by local medical ethics committees (Enschede, the Netherlands and Rome, Italy) and all participants provided informed consent. For participation in the study, subjects had to meet the following inclusion criteria: 1) between 6 months and 5 years after stroke; 2) age between 18 and 80 years; 3) clinically diagnosed with partial central paresis of the arm and hand because of a stroke, but with 15° active elbow flexion and a quarter range of active finger flexion; 4) living at home and having internet access; 5) having a carer who is co-resident or closely involved in their care; 6) able to understand and follow instructions; 7) no additional orthopaedic, neurological, or rheumatologic disease of the upper extremity; and 8) no severe neglect or uncorrected visual impairments.

Subjects received six weeks of arm and hand training at home using the SCRIPT system. Trained healthcare professionals (HCP) installed the system in the first training week in the subjects' homes, and instructed them how to operate it towards performing daily exercises mediated via interactive games. All subjects trained independently, and were remotely supervised, off-line, by a HCP. Subjects were recommended to train 180 minutes per week (equalling a schedule of 6 days per week, 30 minutes per day), but they were free to choose their own preferred training time, and were allowed to practice whenever desired.

During the first training week, the HCP contacted each subject three times, in order to ensure competence with the SCRIPT system. During the other training weeks, the HCP visited each subject once per week to check on the subject's performance.

2.6 Data analysis

In order to evaluate the performance of the lag-lead based assessment and adaptation, we considered for each session the array of lag-lead scores and the corresponding array of game difficulty (scaling factors λ). These values were computed on-the-fly during subjects' exercise. For each session, we considered as indicators of the amount of usage, the time spent playing and the number of movements repetitions.

Primary indicator of the performance of the adaptation mechanism was the percentage of sessions in which this was effective (types *challenging*, *challenging – then supporting* and *supporting*). We considered its overall efficacy, differences among movements and subjects.

We also hypothesized that the success of the adaptation effectively motivated subjects to train more. Hence, we tested whether the duration of a session (measured either by number of repetitions or session duration) was higher in sessions where the adaptation was effective.

3. Results

3.1 Amount of exercise

Data from seven subjects were included in the study. Their demographic characteristics and results about training duration are shown in Table 2. Overall, subjects performed a total of 248 training sessions (35±11 sessions per subject). This led to a gross total of 63 hours of practice (9±4 hours per subject). Table 2 shows the overall exercise duration, the number of game instances for which the adaptation process has been analysed and the partitioning among hand and wrist movements for each subject.

Table 2 Characteristics of the subjects in this study and amount of exercise, sessions and partitioning among wrist and hand movements

Subject	Sex	Age (years)	Time post stroke (months)	FM score at inclusion	ARAT score at inclusion	Total Exercise duration[h]	Sessions [#]	Average session duration [m]	Hand movements [#]	Wrist movements [#]	
nl01	M	34	11	56	47	4.14	40	6.2	2525	574	
nl02	M	52	10.5	17	5	13.03	30	26.1	1871	1130	
nl03	M	43	26	11	4	9.91	58	10.3	1975	5621	
nl04	M	58	10.5	44	31	9.36	25	22.5	1003	783	
nl05	F	61	10	9	3	2.87	39	4.4	350	4177	
it02	M	62	8	16	3	10.65	30	21.3	7645	99	
it04	F	66	11	46	54	12.88	26	29.7	1028	1137	

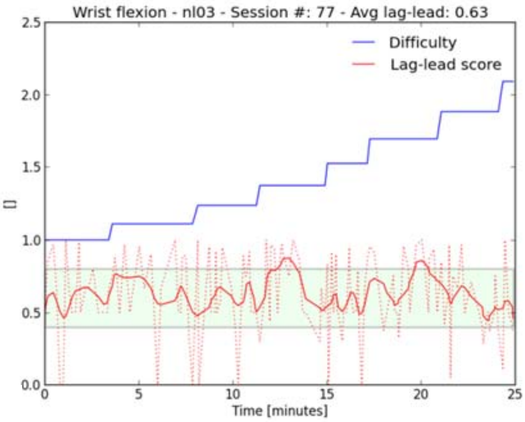
Abbreviations: FM score = Fugl-Meyer test score; ARAT score = Action Research Arm Test score

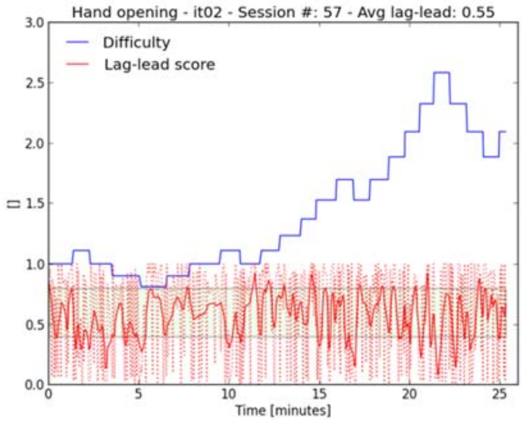
3.2 Game difficulty and evolution of score in different types of sessions

Figure 3 shows examples of the five types of sessions for several subjects, including both hand and wrist movements. Each of these figures shows time progression of score and game speed.
Figure 3a shows a *challenging* session in which *patnl02* performed 165 movements of wrist flexion, and the game speed progressively increased to about twice (2.05) the initial value. This happened in about 25 minutes.

Figure 3b shows a *challenging – then supporting* session performed by subject *patit02*. In this case, the difficulty did not exclusively increase (since after about 2, 10 and 17 minutes this was decreased by the adaptation rules). However, there was an overall increase up to 2.6 times the initial speed, after 22 minutes. After that, the speed was then decreased until 2.05 times the initial value. Then the subject decided to stop, after 25 minutes of exercise.

b)





d)

Figure 3 Time progression of score and difficulty (game speed) for sessions of different categories: (a) challenging ,(b) challenging – then supporting ,(c) supporting ,(d) under-challenging ,(e) under-supporting . Solid line for score represents filtered signal (moving average, N=5), dashed line represents raw values. The green area represents the interval defined as successful by setting the regulator parameters th+=0.8 and th-=0.4.

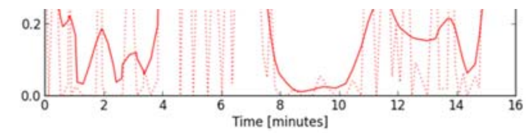


Figure 3c shows a *supporting* session performed by *patnl02*. In this case, during the 5 minutes of practice the difficulty was reduced to 0.81 times the initial value and the observed average lag-lead score was 0.46, thus within the target region.
Figure 3d shows an *under-challenging* session performed by *patnl04*. In this case, the difficulty progressively increased to 1.37 times the initial value. This value was still too low, provided that the average score for the 5 minutes of the session (0.89) remained above the target value.
Finally, Figure 3e shows an *under-supporting* session performed by *patnl01*. In this case, despite the fact that the difficulty decreased to 0.65 times the initial value within the 15 minutes of duration, the average score (0.2) was below the target value.

3.3 Performance of the adaptation algorithm

The adaptation process ran for 123 sessions for wrist exercise and in 125 hand exercise sessions. Out of these 248 sessions, there have been 195 cases of effective adaptation. The frequency of each of the session types is shown in Figure 4.

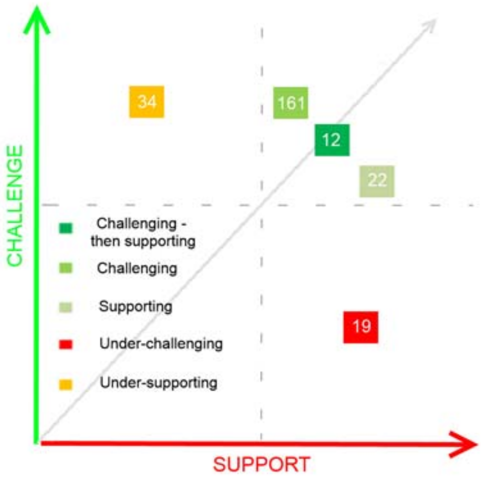


Figure 4 Partitioning among the different session types with respect to the challenge and support theory. The numbers represent the frequency of each type.

Table 3 Number of observations of different session types for hand and wrist exercises.

	Effective			Ineffective		
	Challenging - then supporting	Challenging	Supporting	Under-challenging	Under-supporting	
Wrist	1	94	10	18	0	123
Hand	11	67	12	1	34	125
Total	12	161	22	19	34	248

Table 3 shows how the number of observations differs between wrist and hand exercise. Regarding the wrist the adaptation has been effective in 105 episodes (85%). This includes challenging (94), supporting (10) and challenging – then supporting (1) sessions. Failures resulted exclusively in a under-challenging (18 sessions). Also, no episodes of under-supporting adaptation (i.e., subjects scoring consistently below the target score) have occurred.

The number of sessions including exercise of hand movements was similar (125). In this case, the adaptation was effective in 90 sessions. These include challenging (67), supporting (12) and challenging- then supporting (11) sessions. Overall, the success rate resulted lower than for wrist movements (72%). In this case, failures consisted mainly in under-supportive sessions (34), while we observed only one under-challenging session.

Figure 5 shows the number of sessions for each of the five categories, for each subject. It is noteworthy that under-challenging sessions happened for three out of seven subjects (*patnl01*, *patnl04* and *patit04*).

Error! Reference source not found.5b shows the session types for hand movement. In this case, the under-supporting sessions involved five subjects, including the same subjects who produced under-challenging sessions for the wrist (*patnl01*, *patnl04* and *patit04)*.

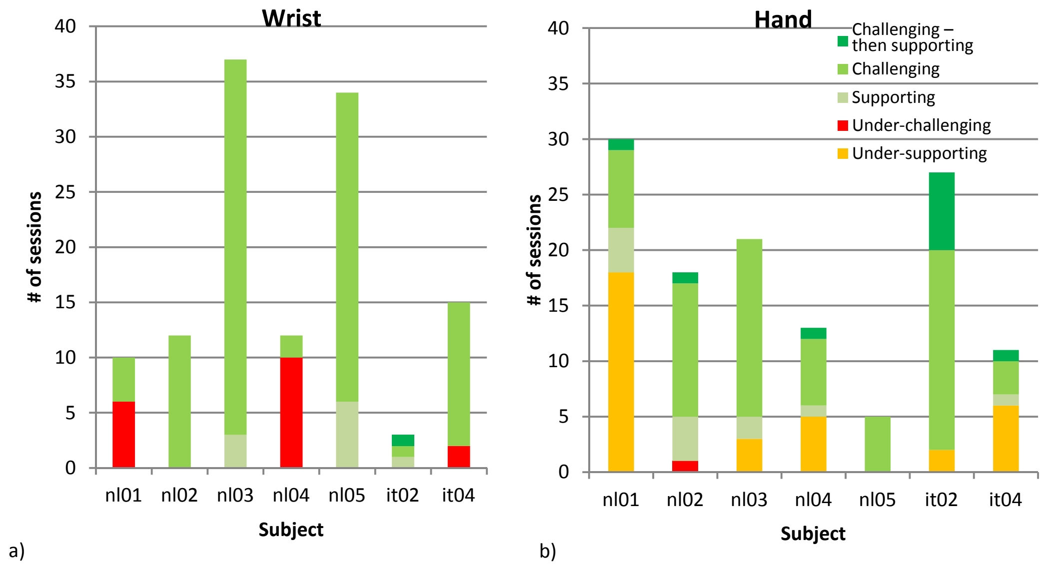


Figure 5 Number of training sessions for each of the five types, for each subject, for wrist (a) and hand exercises(b)

3.4 Effect of adaptation on training duration

We had hypothesized that the successful adaptation resulted in higher subject motivation and consequently in longer – more intense sessions. An ANOVA test confirmed significantly larger number of movement repetitions performed by subjects when the adaptation was effective (p=0.001). Subjects performed a larger number of repetitions in session with effective adaptation also when considering separately wrist (p=0.025) and the hand (p=0.01), as shown in Figure 6. Although Pearson correlations test show that number of movements and session duration are significantly correlated (R=.377, p<0.001), efficacy of the adaptation does not have a significant effect on training duration (p=0.066).

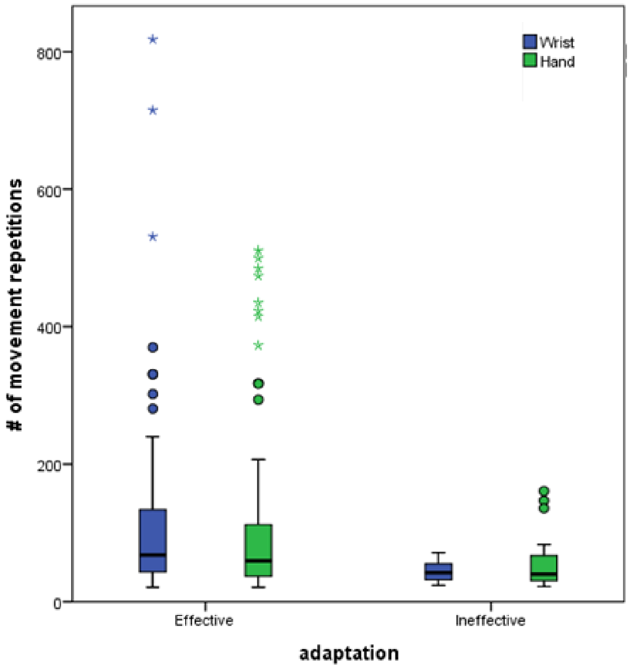


Figure 6 Efficacy of adaptation in making subjects perform higher number of movement repetitions per session

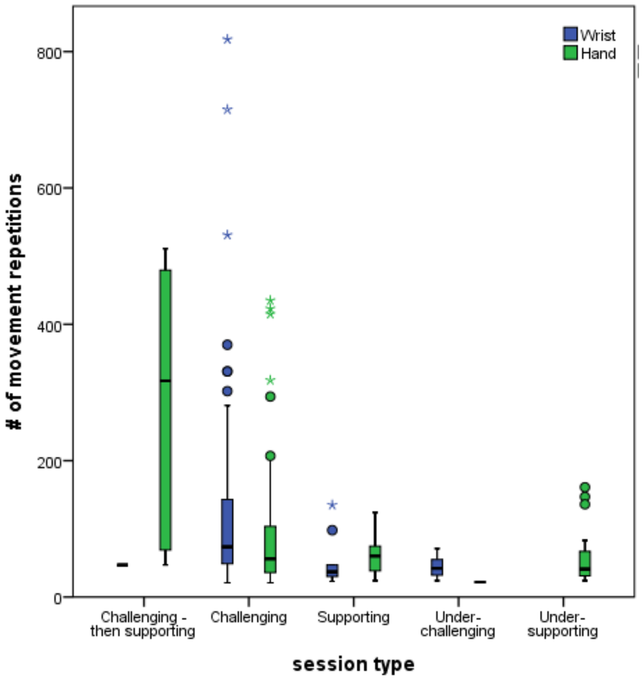


Figure 7 Role of challenge in increasing the number of movement repetitions per session. Note the higher number of repetitions for challenging and challenging – then supporting categories in comparison to all others.

Also, as reflected by ANOVA results, when considering each session type separately there are significant differences in number of movement repetitions between categories ($p<0.001$). Again, this effect is observed also when considering wrist ($p=0.04$) and hand only ($p<0.001$), as shown in Figure 7. Contrast analysis reveals that challenging – then supporting and challenging sessions led to higher number of movements repetitions with respect to other types of session ($p<0.05$ in all cases). Moreover, no significant difference in session duration was found among categories.

4. Discussion

4.1 Amount of exercise

In this study, we considered data from subjects who participated in an ongoing evaluation. The participants (seven subjects with chronic stroke) covered a wide range of impairment (Fugl-Meyer [30] score ranging from 9 to 56, Action Research Arm Test [31] ranging from 3 to 54). They were allowed to choose when and for how long to exercise. Overall, they did not practice as much as advised (6 sessions of 30 minutes each per week). However, the amount of exercise was solely their choice. Session durations varied on average from 4.4 to 29.7 minutes across subjects.

It is also noteworthy that, even in this small sample, there were strong differences in training – arising again from individual choices. By observing the number of hand and wrist movements, one can notice that some subjects trained primarily on either hand (*nl01*, *it02*) or wrist movements (*nl03*, *nl05*) while the remainders (*nl02*, *nl04*, *it04*) tended to practice both hand and wrist movements.

4.2 Game difficulty and change of score in different types of sessions

Based on existing literature in learning theory and the challenge point framework, we proposed a framework for the classification of the session types based on the pattern of the task difficulty obtained by an adaptive mechanism. This categorization can be applied to any context in which there is an automatic adaptation of the task difficulty. We showed that regardless of duration, number and type of movements, each session can be classified as one of these types. Although there is a strong variation among movement repetitions in the lag-lead score, its average value across one session can be used as an indicator for the performance of the subject. In particular, by considering its value and the pattern visible in game difficulty changes, one can assess whether the assigned task has been of the adequate difficulty for a subject.

4.3 Performance of the adaptation algorithm

We proposed a mechanism of adaptation based on a spatio-temporal kinematic parameter, a lag-lead index, in order to adapt the task speed in a robot-assisted exercise. In this domain, one typical approach is that of using speed, time or the EMG signal to modulate the impedance of a robot [21]. This differs from our case, in which given the passive nature of our device changing system impedance during interaction was not possible.. Instead, our proposed approach used the visual channel and speed of stimuli presentation to provide a varying level of challenge during the interaction based on performance.

Overall, our algorithm was effective in 79% of the sessions. Considering only the wrist movement, its effectiveness was higher (85%). In this case, ineffective cases consisted only in under-challenging sessions. Such case has only the minor disadvantage of a too easy exercise, thus possibly boring the subject. It is also remarkable that such condition occurred only for those patients mildly impaired (*nl01 ,nl04, it04*). Instead, those patients who practiced mostly the wrist movements (*nl03, nl05*) experienced mostly challenging sessions, and eventually supporting exercises.

Regarding hand movements, the adaptive system was less effective (72%) when compared to the wrist, yet still presenting a substantial number of cases where our algorithm was effective. In particular, opposite to the case of the wrist, failures consisted nearly exclusively of under-supporting sessions. This occurred for five subjects out of seven. These included those mildly impaired for whom the wrist exercise was too easy. Another aspect which suggests the higher difficulty of the hand exercise is the larger number of challenging – then supporting sessions for the hand, compared to wrist movements.

4.4 Relation between categories and number of repetitions

The adaptation mechanism enhanced subjects' engagement, as proven by the increased number of repetitions in case of effective adaptation. Although the average number of repetitions resulted higher for challenging – then supporting sessions, there is a large number of outliers for the challenging type. In many cases, subjects performed within a challenging session more repetitions than in a challenging – then supporting one – i.e. they performed better for a longer time. This confirms the effect of challenge on subjects' motivation, i.e. by challenging the subject it is possible to extend the training intensity without affecting his/her performance. The role of challenge in motivation is also confirmed by the lower number of repetitions in under-challenging sessions compared to the under-supporting ones (read over-challenging in this case).

5. Conclusions and future work

In this feasibility study, we used a lag-lead score to evaluate the performance of stroke survivors during robot-assisted wrist and hand movements. This was calculated as the fraction of movement in which one is moving in advance of a reference trajectory. An adaptive controller based on the history of such score, assigning faster tasks if one was performing above the desired level and slower if below this level, successfully maintained the average score within a target range. We proposed a framework for the classification of session types based on patterns in the process of adaptation. These types were *challenging, fatiguing, supporting, under-supporting* and *under-challenging*. Overall, the adaptation was successful in maintaining the score within the target range in 79% of cases.

We observed different behaviours amongst hand and wrist movements, representing a relative easiness in wrist movement compared to hand movements. These observations can be used towards further tuning of the lag-lead reference trajectory models as well as defining interactive games where difficulty in individual movement components, i.e. wrist flexion and extensions or hand opening and closing, can be separately tuned. In this study, wrist actions occurred mostly during the supercrocco game where subjects' wrist flexion and extension resulted in diving under or jumping over approaching obstacles. We used the minimum jerk trajectory model for wrist flexion and extension. Based on our observations, it appears that our chosen model provided a challenging interaction, while having only one occurrence of challenging-then-supporting. This was different for the hand, as more occurrence of challenging-then-supporting was observed. In our future studies, we intend to identify whether this observation was due to the use of different reference trajectory model used, or if it occurred due to the way games reacted to these gestures differently, or whether this was linked to the state of wrist and hand in individual's recovering from stroke.

One of the limitations of this study is the small sample size. In current study, it is not possible to draw inference from patient's level of impairment in conjunction with the observed categories in their sessions. The same adaptation mechanism is hence currently being tested on a larger number of subjects thus to see if patient's impairment is likely contributor to the type of challenge mostly overcome. Also, a further limitation arises from small number of games available. In a planned future study, we increased the number of available games, thus to provide chances to provide a more appealing context for practice, hoping to retain patients in an exercise session for a longer duration. Presence of cases where under-challenging or under-supporting categories are observed can be indicative of apparent ease or over-whelming task difficulty as possible by one game. Having a larger subset of games would allow us to compare and contrast between presence of these categories and patient's choice of preferred games.

In summary, the findings from the present study indicate that the lag-lead model is promising to use as an adaptation regulator to adapt exercise difficulty within a game to the current performance of a subject.

Acknowledgement

This work has been partly funded by the European Community Seventh Framework Programme under Grant agreement no.FP7-ICT-288698 (SCRIPT).

References

1. Vugts, C.J., et al., *Behoefteraming fysiotherapeuten 2002-2015.* Rapport NIVEL, 2003: p. www.nivel.nl.
2. Hjelm, N.M., *Benefits and drawbacks of telemedicine.* Journal of Telemedicine and Telecare, 2005. **11**: p. 60-70.
3. Krakauer, J.W., *Arm function after stroke: from physiology to recovery.* Semin Neurol, 2005. **25**(4): p. 384-95.
4. Schaechter, J.D., *Motor rehabilitation and brain plasticity after hemiparetic stroke.* Prog Neurobiol, 2004. **73**(1): p. 61-72.
5. Mehrholz, J., et al., *Electromechanical and robot-assisted arm training for improving generic activities of daily living, arm function, and arm muscle strength after stroke.* Cochrane Database Syst Rev, 2012(6): p. CD006876.
6. Prange, G.B., et al., *Systematic review of the effect of robot-aided therapy on recovery of the hemiparetic arm after stroke.* J Rehabil Res Dev, 2006. **43**(2): p. 171-184.
7. Kwakkel, G., B.J. Kollen, and H.I. Krebs, *Effects of robot-assisted therapy on upper limb recovery after stroke: a systematic review.* Neurorehabil Neural Repair, 2008. **22**(2): p. 111-21.

8. Mehrholz, J., et al., *Electromechanical and robot-assisted arm training for improving generic activities of daily living, arm function, and arm muscle strength after stroke.* Cochrane Database Syst Rev, 2012. **6**.
9. Oujamaa, L., et al., *Rehabilitation of arm function after stroke. Literature review.* Ann Phys Rehabil Med, 2009. **52**: p. 269-293.
10. Ates, S.L., P. ; van der Kooij, H.;Stienen, A.H., *SCRIPT Passive Orthosis: Design and Technical Evaluation of the Wrist and Hand Orthosis for Rehabilitation Training at Home*, in *International Conference on Rehabilitation Robotics (ICORR)*2013: Seattle, USA.
11. Prange, G.B., et al. *SCRIPT: Tele-robotics at home - Functional architecture and clinical application*. in *Proceedings of the 6th International Symposium on E-Health Services and Technologies (EHST) and the 3rd International Conference on Green IT Solutions*. 2012. Geneva, Switzerland: SciTePress.
12. Fisher, B.E. and K.J. Sullivan, *Activity-dependent factors affecting poststroke functional outcomes.* Top Stroke Rehabil, 2001. **8**(3): p. 31-44.
13. Kahn, L.E., et al. *Comparison of robot-assisted reaching to free reaching in promoting recovery from chronic stroke*. 2001. Amsterdam, the Netherlands: IOS Press.
14. Huang, V.S. and J.W. Krakauer, *Robotic neurorehabilitation: a computational motor learning perspective.* J Neuroeng Rehabil, 2009. **6**: p. 5.
15. Reinkensmeyer, D.J., J.L. Emken, and S.C. Cramer, *Robotics, motor learning, and neurologic recovery.* Annu Rev Biomed Eng, 2004. **6**: p. 497-525.
16. Van Asseldonk, E.H.F., et al., *Influence of haptic guidance in learning a novel visuomotor task.* J Physiol, 2009. **(in press)**.
17. Guadagnoli, M.A. and T.D. Lee, *Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning.* J Mot Behav, 2004. **36**(2): p. 212-24.
18. Sanford, N., *Self and society: Social change and individual development*2006: Transaction Books.
19. Emken, J.L., R. Benitez, and D.J. Reinkensmeyer, *Human-robot cooperative movement training: learning a novel sensory motor transformation during walking with robotic assistance-as-needed.* J Neuroeng Rehabil, 2007. **4**: p. 8.
20. Panarese, A., et al., *Tracking motor improvement at the subtask level during robot-aided neurorehabilitation of stroke patients.* Neurorehabil Neural Repair, 2012. **26**(7): p. 822-33.
21. Krebs, H.I., et al., *Rehabilitation robotics: Performance-based progressive robot-assisted therapy.* Autonomous Robots, 2003. **15**(1): p. 7-20.
22. Zimmerli, L., et al., *Validation of a mechanism to balance exercise difficulty in robot-assisted upper-extremity rehabilitation after stroke.* J Neuroeng Rehabil, 2012. **9**: p. 6.
23. Koenig, A., et al., *Real-time closed-loop control of cognitive load in neurological patients during robot-assisted gait training.* IEEE Trans Neural Syst Rehabil Eng, 2011. **19**(4): p. 453-64.
24. Squeri, V., et al., *Wrist Rehabilitation in Chronic Stroke Patients by Means of Adaptive, Progressive Robot Aided Therapy.* IEEE Trans Neural Syst Rehabil Eng, 2013.
25. Basteris, A. and F. Amirabdollahian, *Adaptive human-robot interaction based on lag-lead modelling for home-based stroke rehabilitation*, in *IEEE Systems, Man and Cybernetics*2013: Manchester (UK).
26. Chemuturi, R., F. Amirabdollahian, and K. Dautenhahn, *Adaptive training algorithm for robot-assisted upper-arm rehabilitation, applicable to individualised and therapeutic human-robot interaction.* J Neuroeng Rehabil, 2013. **10**: p. 102.
27. Carpinella, I., J. Jonsdottir, and M. Ferrarin, *Multi-finger coordination in healthy subjects and stroke patients: a mathematical modelling approach.* J Neuroeng Rehabil, 2011. **8**: p. 19.
28. Flash, T. and N. Hogan, *The coordination of arm movements: an experimentally confirmed mathematical model.* J Neurosci, 1985. **5**(7): p. 1688-703.

29. Nijenhuis, S.M., et al., *Feasibility of a personalized arm/hand training system for use at home after stroke: results so far*, in *International NeuroRehabilitation Symposium (INRS)*2013: Zürich, Switzerland.
30. Fugl-Meyer, A., et al., *The post-stroke hemiplegic patient. 1. a method for evaluation of physical performance.* Scandinavian journal of rehabilitation medicine, 1974. **7**(1): p. 13-31.
31. Lyle, R.C., *A performance test for assessment of upper limb function in physical rehabilitation treatment and research.* International Journal of Rehabilitation Research, 1981. **4**(4): p. 483-492.