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

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Abstract

The SCRIPT (Supervised Care and Rehabilitation Involving Personal Telerobotics) project aims at delivering robot-mediated hand and wrist exercise for chronic stroke survivors in their homes. The consortium has produced a passive-actuated orthosis which assists extension of the fingers and the wrist. Through the device, subjects are enabled to exercise via interactive games which require opening of the hand, grasping, extending and/or flexing the wrist. The system, composed by an orthosis, a personal computer, and a touchscreen display is deployed at subjects' homes for six weeks. Trained healthcare professionals install the system at subjects' homes and instruct them on how to operate it towards performing daily exercises. Visits by the healthcare professionals occur three times during the first week and once a week during the following weeks, but subjects are allowed to perform at any time – for as long as they would like to practice.

The exercises are highly tailored on the individual's performance. A quick preliminary assessment of a subject's motor skills happens prior to each session, and during the exercises the system assesses whether the subject is anticipating (leading) or in delay (lagging) with respect to a reference trajectory for each articulation, i.e. hand flexion or wrist extension. This lag-lead score provides input to an adaptive mechanism aimed at making the exercise not too easy nor too challenging by varying the speed of the exergames in order to maintain the score itself within a target. This is expected to improve motor learning and neuromotor recovery, according to the Challenge Point framework.

In this paper, we show results of the adaptation process gathered from seven chronic stroke survivors who completed the six weeks training protocol. Based on the patterns in exercise difficulty and score, we defined five types of sessions, namely a) *challenging, b) fatiguing, c) supportive, d)under-supportive* and e) *under-challenging.* Ideally, the adaptation resulted in a progressive increase in speed (*challenging* session). This increase might be followed by a decrease prior to session's end (*fatiguing*). In a *supporting* session, the successful regulation of the score has been achieved by progressively making the exercise slower. C*hallenging,*

fatiguing and *supporting* sessions represent a successful performance of the control loop, having all of them maintained the score within the target range. The adaptation mechanism could eventually fail and lead to scores respectively higher (*under-challenging*) or lower (*under-supporting*) than the target. We collected 248 sessions with high within- and between-subject variability in number of sessions, exercise duration and movement performance. The mechanism of adaptation has been successful in 195 of these (78.6 %), with main reason for failure being the short duration of the exercise.

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

1 Introduction

Because of the 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 patients' 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 has 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. 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 [18].

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 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 [19]. Again, this mechanism operates at a session level, and in this case it also requires the final decision of a healthcare professional.

When considering an online adaptation instead, a possibility is to adapt the robot dynamics based on subjects' performance [20]. 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 [21]. 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 [22].

As regards 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 [23].

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 online adapts the task difficulty (intended as exercise speed) within the training session [24]. The system can assess whether the subject is anticipating (leading) or in delay (lagging) with respect to a reference trajectory for each articulation, i.e. hand flexion or wrist extension. This lag-lead score provides input to an adaptive mechanism aimed at making the exercise not too easy nor too challenging by maintaining the score itself within a target. We previously tested this approach on healthy subjects by regulating the movement time, based on a lag-lead indicator, in a reaching task [25]. 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 patients at a proper challenging level within each training session. 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 chronic stroke patients. We kconsidered 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 subjects without making the exercise nor too easy nor too difficult.

2. Methods

2.1 Experimental setup

The SCRIPT system, shown in Figure 1~~Figure 1~~, 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-developed software components needed to complete a training session, including data acquisition and processing, patient user interface and games.

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The 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 sessions, these signals are normalized with respect to the maximum and minimum measured during a preliminary calibration phase.

At the time of this study the system included two video games (*shell* and *crocco*) aiming at enhancing subject motivation by being tailored to the individual's performance. In the first, 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 at the due time). In the second game, *crocco*, the subject controls a crocodile (*cursor*) by flexing and extending the wrist to avoid obstacles (*targets*). In both games, the speed of the targets is set accordingly to the measured duration for the corresponding movements during calibration before each session, as well as the individual active maximal movement range.

An arm support (SaeboMAS, Saebo Inc, Charlotte NC, USA) provides gravity compensation of the proximal arm.

A telesupervision platform enables the healthcare professional to remotely monitor the progress of the therapy by accessing the restricted area of a 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 triggered the acquisition of the movement excursion signal, either hand opening or wrist angle. The acquisition finished until the current passed the cursor. Then, the movement profile was considered only within the interval corresponding to minimum and maximum value, respectively *m* and *M*. The time interval between these two points was considered as movement duration, *T*, and N_Q is the number of samples within this time frame. If the movement lasted less than 0.5 seconds (thus not reflecting any volitional control of the subject), then it was withdrawn and no score was computed. Otherwise, the system generated a reference trajectory x_R, of the same size N_Q. For finger movement (hand opening), we used a model validated for healthy subjects and stroke survivors [26]:

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

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 used a minimum jerk profile [27] :

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

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:

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

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 anticipation (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 was used to adapt the exercise, in order to make it easier for subjects who were often in delay with respect to the reference trajectory (fail), 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 fail, respectively. If among the last N trials there is a number of successes or fails higher than $N+$ or $N-$, the current value of the multiplier factor λ is multiplied (divided) 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 implicated that a subject was considered lagging when 40% of samples within one movement repetition was in delay of the reference trajectory, and leading when 80% of samples was in advance of the reference trajectory. If a patient was lagging (so LL score of less than 0.4) 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, and 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 patterns in difficulty exercise and score, we defined five types of sessions, namely *challenging*, *fatiguing*, *supportive*, *under-challenging* and *under-supportive* (summarized in Table 2~~Table 2~~). The former three are those in which the adaptation mechanism successfully held 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*fatiguing*. In a *supporting* session, the performance score was maintained within the target region by progressively reducing the difficulty 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.

Consider each training session as including N_M movements. 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 repetition. The abovementioned patterns of adaptation are classified by imposing the conditions specified in Table 2~~Table 2~~ over these two vectors.

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2.5 Experimental protocol

Data of a sub-set of seven chronic stroke patients participating in an ongoing clinical trial [28] was used for the present study. The clinical trial 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. 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) per movement repetition. These values were computed on-the-fly during subjects' exercise and stored. The percentage of sessions in each adaptation type was considered as primary indicator of the efficacy of the adaptation algorithm.

We also investigated whether such results relate to the duration of a session.Considered that there was no fixed duration of the therapy for each subject, we considered as first indicators of amount of usage the overall time spent playing and the number of movements performed (separately for hand and wrist movement). Such measurements were used to relate whether the performance of the proposed methods of assessment and adaptation were affected by the amount of practice. The same indicators (exercise duration and number of movements) were also computed for each single training session.

3. Results and discussion

3.1 Amount of exercise

Data of seven subjects were included in the study. Their demographic characteristics and results about training duration are shown in Table 1~~Table 1~~. The seven subjects performed in total 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 1~~Table 1~~ 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.

In general, subjects did not exercise as much as advised (6 sessions of 30 minutes each per week, which would have led to 18 hours). This is reflected by short session durations (ranging from 4.4 to 29.7 minutes across subjects). This is partly related to exercise duration being recorded as actual minutes spent performing movements within a game. However, it did not include set up and termination of the session and calibration procedures before each game (order of minutes). Anecdotal feedback by health care professionals visiting the subjects suggested that subjects tended to consider such phases as part of the exercise.

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

3.2 Game difficulty and score evolution different types of sessions

Figure 2~~Figure 2~~ shows examples of each of the five adaptation types of sessions, for several subjects, including both hand and for wrist movements. Each of these figures shows time progression of score and game difficulty. Figure 2~~Figure 2~~a 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 3~~Figure 1~~b shows an example of fatiguing 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 regulator). However, there was an overall increase up to 2.6 times the initial speed, after 22 minutes. After that, the difficulty was then decreased until 2.05 times the initial value, when the subject decided to stop, after 25 minutes of exercise. **Error! Reference source not found.**

~~Figure 2~~c 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. **Error! Reference source not found.**

~~Figure 2~~d 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 2~~Figure 2~~ 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.

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3.3 Performance of the adaptation algorithm

The adaptation process ran 123 times for wrist movements. Figure 3 shows the number of sessions for each of the five session types for wrist movements, for each subject. Out of these sessions, the adaptation process has been effectively maintaining the average lag-lead score within the desired range in 105 episodes (85%). This includes challenging (94), supporting (10) and fatiguing (1) sessions. The failure of the adaptation process resulted exclusively in an under-challenging adaptation (i.e., subjects achieving higher scores than the target, due to excessively easy/slow task) behaviour (18 sessions), which happened for three out of seven subjects (*patnl01*, *patnl04* and *patit04*) during an average of x% of the time spent exercising. 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 sessions). In this case, the adaptation process resulted successful in 90 sessions. These include challenging (67), supporting (12) and fatiguing (11) sessions. Overall, the success rate of the adaptation mechanism resulted lower (72%) than for wrist movements. While failures for the wrist movements consisted only of under-challenging adaptation, for hand movements we observed only one of such episodes and rather a high number of under-supportive adaptation episodes (34). These involved five subjects, including the same subjects *patnl01*, *patnl04* and *patit04* who produced under-challenging sessions for the wrist. This suggests a difference in the behaviour of the adaptation process between wrist and hand movements.

4. Conclusions and future work

In this feasibility study, we evaluated the performance of stroke survivors during robot-assisted wrist and hand movements by using a lag-lead score. This was calculated as the fraction of movement in which one is anticipating a reference trajectory. An adaptive controller based on the online 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. Based on patterns in the process of adaptation, we classified sessions as *challenging*, *fatiguing*, *supporting*, *under-supporting* and *under-challenging*. Overall, the adaptation was successful to provide challenging practice within the target range in at least 72% of cases (for hand opening, while this was 85% for wrist movements). The difference in outcome of the adaptation process for wrist and hand movements suggests that different mechanisms are implied in the two tasks. Limitations of this study reside in the small sample size and in the high inter-individual variability. The same adaptation mechanism is hence currently being tested on a higher number of subjects.

Nevertheless, 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. By adaptation of the training environment to each persons´ abilities and needs in this way, optimal encouragement of active contribution of patients to their exercise is enabled [14]. This enables customization of a person's training programme, which is thought to ultimately benefit training outcome via enhanced motor relearning (Guadagnoli 2004?).

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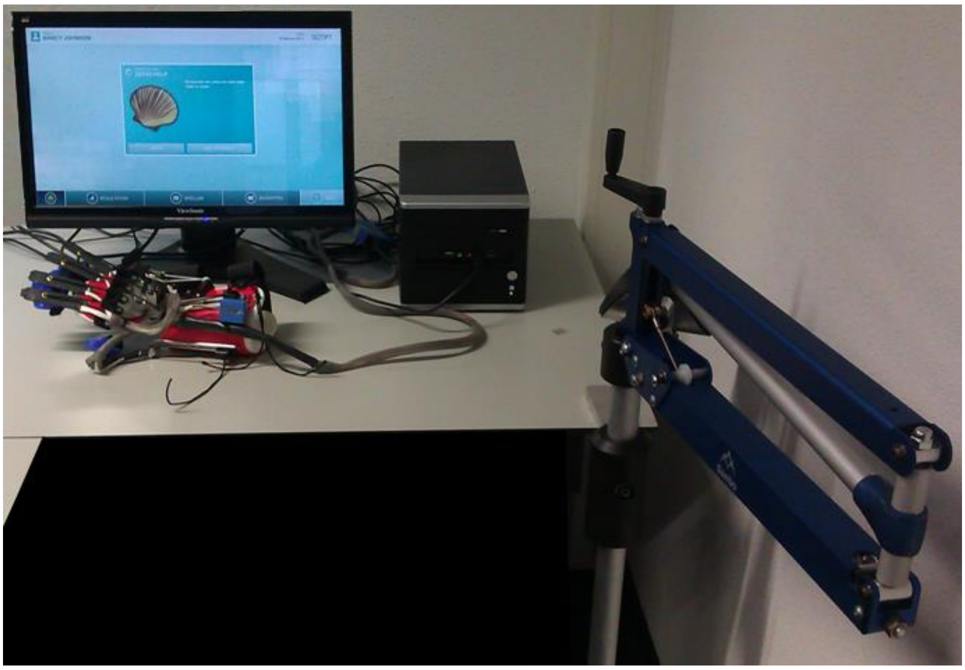

Figure 1 The SCRIPT1 system - composed by passive orthosis, touchscreen display, personal computer and arm support.

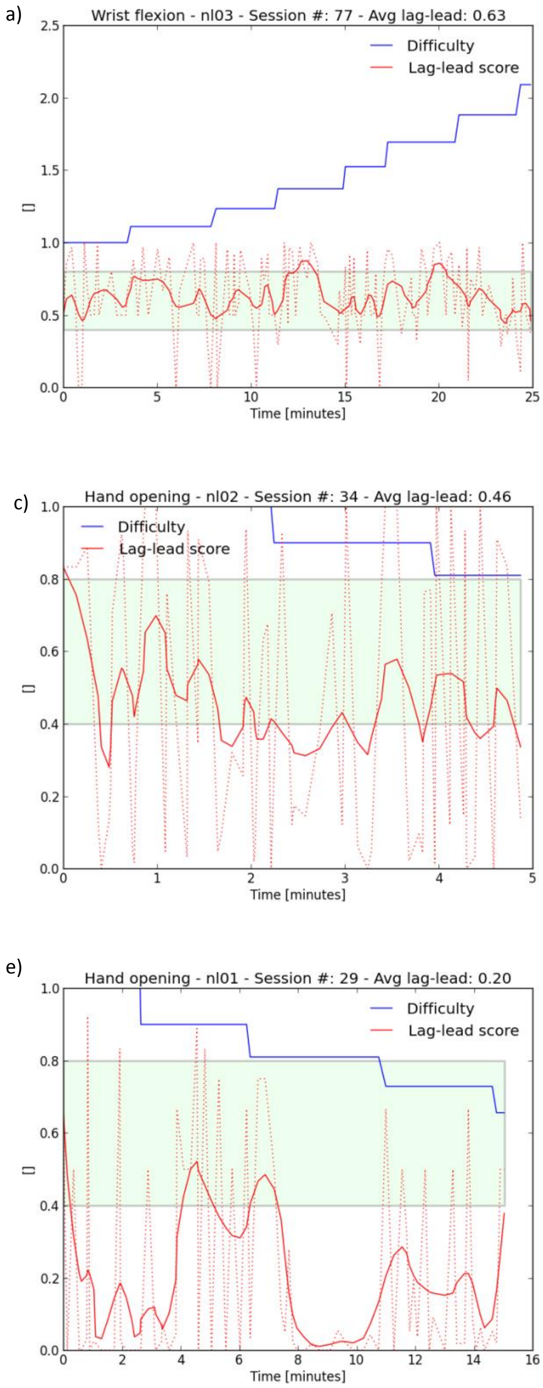

Figure 2 Time progression of score and difficulty (game speed) for sessions of different categories: challenging (a), fatiguing (b), supporting (c), under-challenging (d), under-supporting (e). Solid line for score represents filtered signal (moving average, N=5), dashed line represents raw values. The green area represents the interval defined as successful by setting the regulator parameters th+=0.8 and th-=0.4.

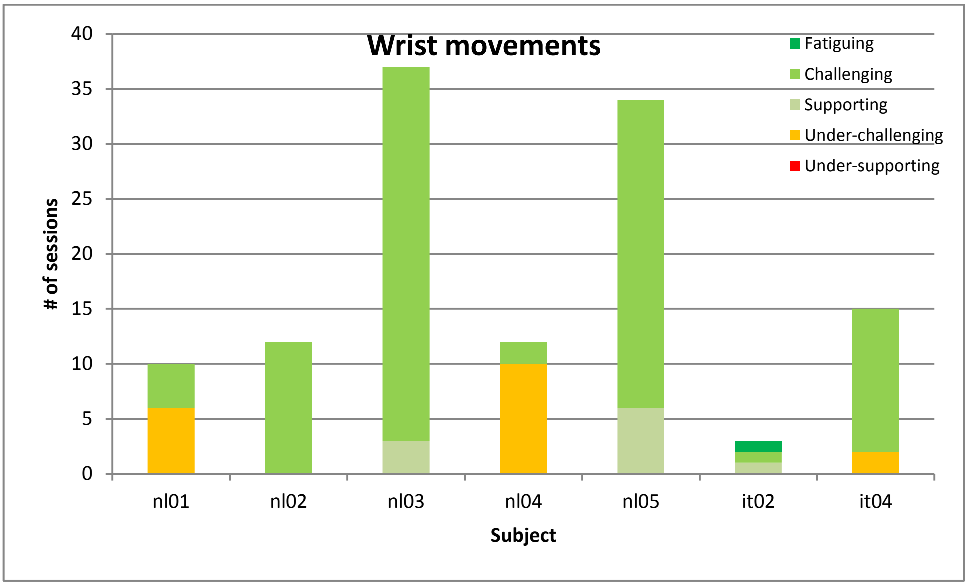

Figure 3 Number of training sessions for each of the five categories, for each subject, for wrist flexion/extension

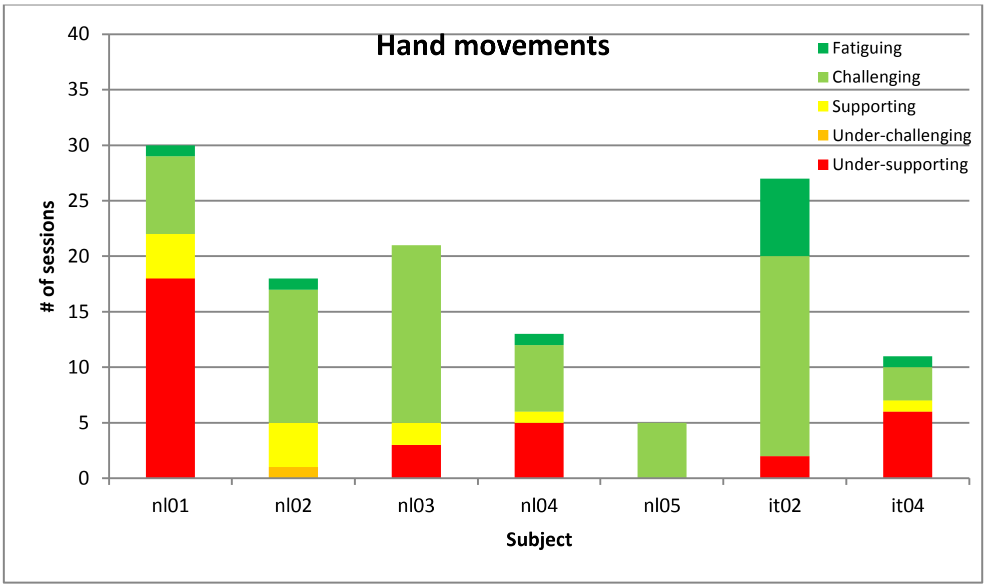

Figure 4 Number of sessions for each of the five categories, for each subject, for finger flexion/extension

Table 1 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	Exercise duration[h]	Games [#]	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

Table 2 Definition and conditions specifying five adaptation types

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)
Fatiguing	After such constant increase, considered that subjects were allowed to stop playing whenever they desired, this might have happened after the onset of fatigue. In such a case, we would observe a decrease in difficulty towards the end of the session.	$th_- < \overline{LL} < th_+$ max(λ)>1 λ_N<max(λ)
Supportive	The lag-lead score results in the target range, but this is achieved by progressively reducing the difficulty.	$th_- < \overline{LL} < th_+$ max(λ)=1
Under-supportive	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.	$\overline{LL} > th_+$

Table 3 Amount of exercise, sessions and partitioning among wrist and hand movements

Subject id	Exercise duration[h]	Games [#]	Average session duration [m]	Hand movements [#]	Wrist movements [#]
nl01	4.14	40	6.2	2525	574
nl02	13.03	30	26.1	1871	1130
nl03	9.91	58	10.3	1975	5621
nl04	9.36	25	22.5	1003	783
nl05	2.87	39	4.4	350	4177
it02	10.65	30	21.3	7645	99
it04	12.88	26	29.7	1028	1137