Personalization of Assistance and Knowledge of Performance Feedback on a Hybrid Mobile and Myo-electric Robotic System for Motor Rehabilitation After Stroke

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Abstract. Upper limb motor deficits caused by stroke have a large impact on a person's daily activities and independence. The personalization of the rehabilitation tasks to the needs of the patient as well as the enhancement of the feedback provided to the patient are strategies for promoting motor relearning. In this paper we describe the development and pilot evaluation of a portable system that uses a robotic orthosis to deliver assistance and meaningful feedback during rehabilitative training. Two software modules are implemented, one that investigates an optimal calibration method for the personalization of the level of assistance, and another one that combines the orthosis with a mobile application running on a tablet that provides graphical knowledge of performance feedback to stroke patients while performing therapy. Here we present two preliminary studies and discuss the potential of this technology.

Keywords: Myo-electric orthosis · Personalization · Stroke · Motor rehabilitation · Knowledge of performance · Mobile devices

1 Introduction

Motor impairment of the upper limb, cognitive and emotional sequels are commonly observed in stroke survivors [1, 2]. These deficits have a huge impact on a person's activities of daily living (ADL), creating dependence on others in order to perform simple daily tasks. Rehabilitation is essential for motor learning and helping in the acquisition of skills that can improve independence in everyday tasks. Here, several elements can contribute to a more successful rehabilitation process for enhancing motor performance, from different occupational therapy approaches to the use of novel technology to stimulate the reorganization of the brain motor areas [2–4].

The benefits of the advances in technologies in the rehabilitation area are well known, and the applications range from brain computer interfaces [5] to robotic systems [6]. Technology provides novel ways to adapt the rehabilitation process to the patient's needs, which is essential to provide more personalized therapy training. In this area, several approaches have combined intelligent training personalization with

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Virtual Reality (VR) or Games [7] and shown to have a positive effect on the rehabilitation [8]. Currently, it is known that training through passive movement exercising is able to engage motor networks by means of proprioceptive feedback [9]. However, it has been shown to be an ineffective way of engaging overt execution motor areas [10]. One way of restoring active movement is to use of an actuated upper extremity orthosis that utilizes electromyography to support successful arm movements. For this reason, novel approaches using robotic assistive devices have been developed to restore active movement capabilities in order to engage patients in a physical training with meaningful goal oriented actions [11,12]. Thus, personalization and adaptation to each patient can be achieved by adjusting the degree of assistance being provided by the robotic orthosis according to the patient's muscular activity patterns [13]. Unfortunately, in most cases, the assistance settings of those devices are configured manually through an interface or menu based on expert knowledge, making it difficult for patients to be autonomous in their training. Ideally, these devices should be able to personalize the assistance levels by self-adjusting the settings, thus minimizing the need of expert knowledge.

As important as providing personalization through the use of novel assistive technologies is to be able to provide meaningful and valuable feedback that supports patients in their motor relearning tasks. Nowadays it is widely accepted that there are two types of extrinsic feedback that play a crucial role in providing information about motor task execution: *Knowledge of Results* (KR) and *Knowledge of Performance* (KP) [14,15]. KR feedback is given after completing the desired task and relates to how well the task has been performed, while KP provides information about what is being done during the execution of the training task in order to aid the patient in achieving the best outcome [15]. Current computer based approaches for motor rehabilitation are very well suited to provide KR by embedding training in the form of games that provide quantitative measurements of results [16,17]. However, KP has not been so widely addressed, this type of feedback being generally provided verbally by trained therapists during task execution. To be able to incorporate KP features in rehabilitation systems requires specific sensing technology, such as wearable or remote sensing devices, capable of measuring and assisting the rehabilitation process in a safe and unobtrusive way. In this sense, the combination assistive technologies that can partially restore active movement capabilities in patients with motor deficits - while allowing the capture of important physiological and kinematic information such as electro-myographic signals or arm position - with software applications that provide appropriate KP have a large potential.

The goal of this project is to develop a fully portable system that uses an upper limb myo-electric robotic orthosis to enable and enhance active movement therapy by means of: an intelligent calibration module for personalizing the level of assistance to each user; and a training module that provides KP based on multimodal information captured from the user in real-time during the execution of the task. Both, calibration module and KP module, are implemented as an Android application that connects wirelessly with the robotic orthosis. These modules allow the user to modify in real-time the settings of the device by searching for the parameters that are more suitable for his/her muscular performance, and are designed to provide real-time feedback on KP during training from both physiological and kinematic data. In this paper we present the development and results of two pilot evaluations to (1) identify the optimal calibration parameters concerning the assistance level of the myo-electric orthosis, and (2) assess the impact of KP feedback when physiologically based feedback or when kinematic based feedback are used.

2 Methods

We developed a portable system relying on a mobile device and a myo-electric limb orthosis that enables active movement training and provides KP. First, in order to identify the optimal settings for the robotic orthosis, we developed and evaluated a calibration module. Then, we created a feedback module to investigate which type of KP feedback (physiologically or kinematic based feedback) would provide the patient with more useful information during motor training. The software modules developed in this project were designed for mobile devices that run Android OS (Google Inc., Mountain View, California, U.S.), and were implemented using the Android SDK and Unity 3D (Unity Technologies, San Francisco, USA).

2.1 Myo-electric Limb Orthosis

We used the mPower 1000 (mPower 1000, Myomo Inc., Boston, USA), a robotic limb orthosis that is portable and has one actuated degree of freedom (elbow join). The orthosis uses two electrode sensors placed on the biceps and triceps of a user, thus reading his/her electromyography (EMG) plus the orthosis motor position (i.e. elbow flexion). By activating the biceps or triceps during the arm movement, the EMG readings enable the device to assist users with motor impairments of the upper limb in completing the desired movements. The mPower 1000 has several configurable parameters to determine the amount of assistance. Independent assistance levels can be set for extension and flexion movements. Each level of assistance can be set with values that range from 0 to 20 (where 20 provide the highest level of assistance) through a virtual serial port over Bluetooth communication channel. In addition, the device offers three control modes, allowing the user to control the orthosis using only biceps or triceps muscles individually or both of them simultaneously.

2.2 Data Collection

For further analysis, all software modules collect synchronously all kinematic and physiological data available from the mPower 1000. Recorded data include pre-processed normalized amplitude values of the envelope of EMG signals from biceps and triceps (0–14), position of the arm (degrees), time (ms), average speed (degrees/s), values of the assistance levels for both extension and flexion (0–20) and the number of arm flexions and extensions. Due the fact that the EMG signal is noisy, a finite impulse response filter was applied to smooth the EMG data. Data are logged directly on the mobile device, sampled every 100 ms and stored as a CSV text file.

2.3 Calibration Module

For the calibration module, we developed a native Android application implemented using Android SDK tools. It uses the built-in Bluetooth capability of a mobile device to connect to the mPower. This application allows the user to adjust the extension and flexion assistance levels, increasing or decreasing the assistance using the plus and minus buttons in the touch screen (see Fig. 1). Two additional functions were implemented for conducting experiments: 'Reset EMG' resets the baseline values of the EMG readings; and 'Reset' initializes the assistance levels with random values (0 to 20). Because the experimental task requires the participant to search for the optimal assistance settings, the calibration module does not provide information about the current assistance values. This way we prevent the participants from memorizing the settings and avoid biases in the search.

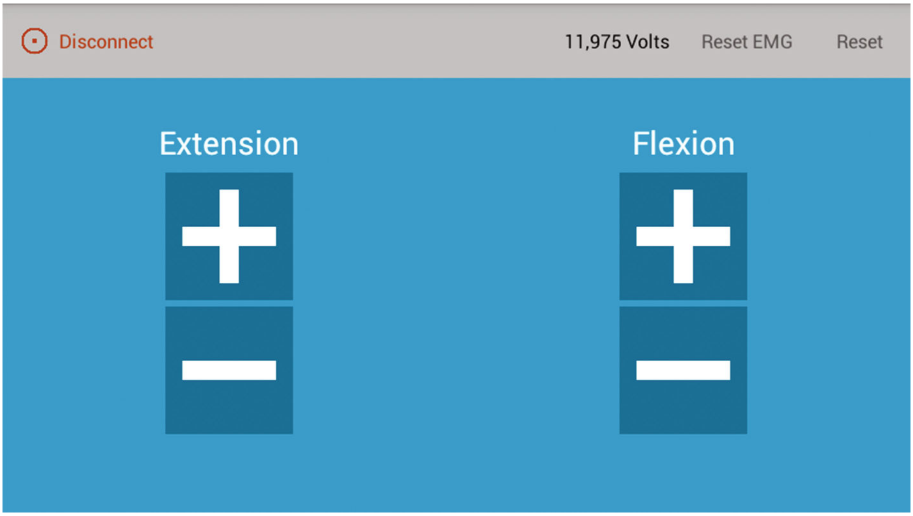

Fig. 1. Calibration module that controls the assistance levels of the mPower 1000. The module does not display the actual calibration values; it only has buttons to increase and decrease the assistance for extension and flexion movements.

2.4 Maximizing Movement Control Through Intelligent Adaptation

In order to identify the mPower 1000 settings that maximize performance for each user, we run a pilot study with 15 healthy volunteers with an average of 26.5 ± 4.3 years (see Table 1.). All participants were informed about the purpose of the study and gave their signed consent.

Before the experiment, participants had a training period to get familiarized with the robotic device and the mobile application. The experiment had duration of 20 min during which the participants wore the mPower 1000 and had to perform multiple elbow flexion/extension sequences. During that time they used the calibration module to change the levels of the assistance in flexion and extension movements with the goal

Table 1. Participant demographics

Participant	Age	Gender	Dominant arm
P1	28	Male	Right
P2	27	Male	Right
P3	22	Male	Right
P4	21	Male	Right
P5	28	Female	Right
P6	28	Male	Right
P7	39	Female	Right
P8	28	Female	Right
P9	23	Female	Right
P10	24	Female	Right
P11	24	Female	Right
P12	26	Male	Right
P13	24	Female	Right
P14	29	Male	Right
P15	27	Male	Right

of identifying the configuration that would give them more control over the orthosis device. After the user considered that he/she had found the best settings, the current assistance values were stored and replaced by random values, and the user had to repeat the process until new optimal settings were found. Each participant repeated the process several times during the 20 min experimental session. After the session, the user filled a questionnaire that consisted on 6 questions concerning the use of the mPower 1000, the level of control, comfort, fatigue, and also the perception of the participant about the "best calibration". To reduce the complexity of the task, in this study the assistance was determined using the biceps EMG information only. This means that users had to activate the bicep muscle to 'close' the device (flexion) and relax the biceps to 'open' de device (extension).

2.5 Feedback Module

This module leverages the information gathered from the myo-electric limb orthosis to provide stroke survivors with KP to assist and improve their rehabilitation exercises. This module has two main interfaces that are intended to deliver either physiologically or kinematic based KP feedback.

Physiologically Based Knowledge of Performance. In this KP mode, the mobile application presents feedback based on the physiological readings of the mPower 1000. Biceps and triceps EMG activation levels are represented in real-time as vertical bars accompanied by a numerical value (Fig. 2, top panel) under the label "flexion" and "extension". The bar values correspond to normalized EMG activation values, with 0 and 10 corresponding to the minimum and maximum muscular activation levels, respectively. This view enables the user to see their muscular activation patterns easily

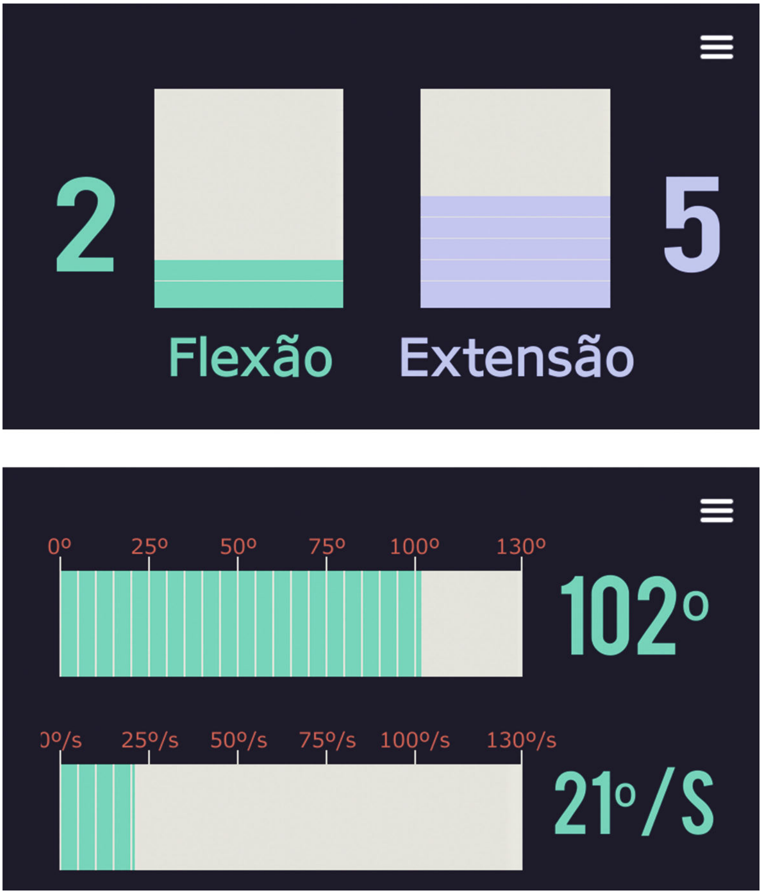

Fig. 2. Mobile assistance for knowledge of performance. The mobile application can provide a physiologically based feedback (top panel), and a kinematic based feedback (bottom panel) based on muscular activation or movement kinematic data respectively. 'Flexão' and 'Extensão' are Portuguese for 'Flexion' and 'Extension' respectively.

represented as bars, thus allowing the user to better understand how successful movement results from muscle activation.

Kinematic Based Knowledge of Performance. In this KP mode, the mobile application represents the real-time position and velocity of the arm movements in degrees/s (Fig. 2, bottom panel). Thus, this configuration relies on arm movement kinematic data and presents it, consistent with the physiologically based representation, as bars and their corresponding numerical value. Both kinematic and physiological data were chosen to be represented with the same amount of information channels (two bars) in a visually consistent manner. However, given the similarity of the two feedback representations and to avoid confusions, the kinematic based feedback is presented using horizontal bars.

2.6 Physiological vs. Kinematic Knowledge of Performance

In order to understand which feedback mode provides patients with a more useful and understandable information about their performance during the training, we ran a pilot study with stroke survivors. In this experiment we assessed how patients reacted to the two different types of feedback, i.e. physiological and kinematic (see Subsect. 2.5).

Three stroke survivors participated in this pilot evaluation (Table 2). The pilot took place at Hospital Dr. Nélio Mendonça and Hospital Dr. João de Almada, in Funchal. All the participants gave their informed consent and the study was approved by the ethics committee of the Madeira Health System (SESARAM).

Table 2. Patient demographics

Patient	Age	Stroke type	Side	Time post-stroke
1	74	Ischemic	Right	40 weeks
2	54	Ischemic	Left	5 weeks
3	78	–	Right	30 weeks

In this experiment, patients sat and wore the mPower 1000 robotic orthosis on their paretic arm (Fig. 3). Placed in front of them, a tablet ran the feedback training module (Fig. 2). Prior to the evaluation session, all patients had a training period to get familiarized with the mPower and the mobile application. After this period, the patients were presented with both KP feedback forms, that is, based on EMG activation and based on movement kinematics. The session consisted on the repetition of a simple arm movement (arm flexion and extension) during blocks of 4 min. Between blocks, patients had a few minutes to rest. After they completed the training, patients were asked about their opinion about each type of KP feedback.

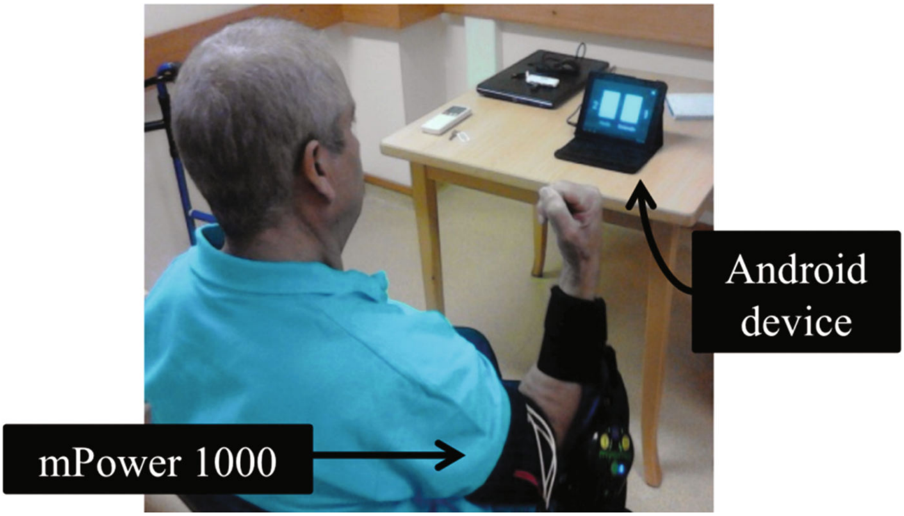

Fig. 3. Experimental setup. Stroke patient using the mobile knowledge of performance system for upper limb rehabilitation.

3 Results

3.1 Calibration Module: Maximizing Movement Control Through Intelligent Adaptation

This experiment involved healthy participants that had to find the optimal settings of the myo-electric robotic orthosis. For analyzing the data collected, all data collected were divided into two datasets: the first one containing all data related to flexion/extension exercising in which the optimal calibration settings were not found (*worst*), and the second one containing the data for the optimal calibration settings (*best*).

Figure 4a shows a best calibration data sample (EMG and elbow flexion) of a participant's session block. This particular data sample has a significant although very low Pearson correlation coefficient (r = -0.15, $p < 0.001$) between muscle activation (EMG) and actual movement (motor position). We computed the correlation coefficient for both datasets (Fig. 4b) and compared them with the non-parametric matched pairs Wilcoxon test. Although the correlation coefficient for the best configurations is statistically higher ($p < 0.05$), correlation values are low with a median below 0.4.

It can be observed that there is a large time lag between the muscle activation and the performance of the movement itself (Fig. 4a). Thus, in order to time correct the two time series (EMG and elbow flexion) a cross-correlation measure (Fig. 5a) was used. For the previous example in Fig. 4a we can observe that the maximum coefficient for the correlation (r = 0.81, $p < 0.001$) is found with a time lag of 10 time steps. Since each data point is collected at a rate of 100 ms, the 10 unit lag represents a second of delay between the muscle activation and the actual movement.

The analysis of all experimental sessions shows a higher time corrected correlation for the *best* settings dataset (r = 0.61) (see Fig. 5b), with an average time lag of

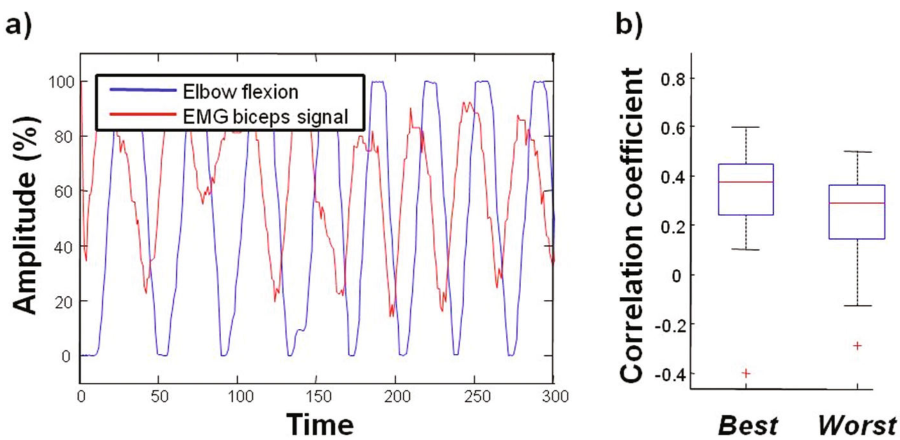

Fig. 4. Correlation analysis. (a) Normalized EMG vs. arm flexion (motor position) example data of one session of the *best* calibration dataset. The x axis represents time (100 ms per data point) and y axis normalized signal amplitude. (b) EMG vs. elbow position correlation analysis for all sessions of both datasets.

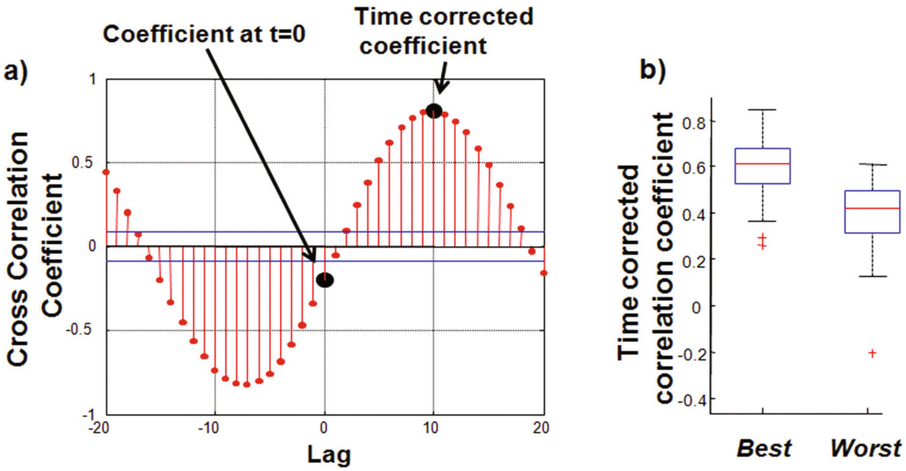

Fig. 5. Cross-correlation analysis. (a) Cross-correlation of the EMG vs. elbow flexion (motor position) of the example data in Fig. 4a. (b) EMG vs. elbow position time corrected correlation analysis for all sessions of both datasets.

12 × 100 ms. In this case, we find that the time corrected correlation is approximately 50 % better for the *best* dataset that when we consider all other settings in the *worst* dataset (r = 0.4147). A non-parametric matched pairs Wilcoxon test confirmed the differences to be significant ($p < 0.05$). Consequently, these data supports the idea that the best settings according to the user subjective reports are those that maximize the time corrected correlation between EMG activity and the movement performed by the myo-electric robotic orthosis. Further, an analysis of the parameter values used for the best calibrations for all sessions indicates that the median assistance levels for extension and flexion are Mdn = 9, SD = 4.5 and Mdn = 16, SD = 4.6 respectively, being the assistance in flexion about 40 % higher than in extension. These findings will lead to the implementation of an unsupervised algorithm that determines the mPower 1000 settings to maximize the time corrected correlation during motor movements (flexions and extensions).

Through the questionnaire (Table 3), participants reported a high level of control and comfort using Myomo (M = 7.8 and M = 6.8 respectively). In addition, users felt that the system was easy to use (M = 8.1) and understood well the calibration (M = 7.9).

Table 3. Responses to the user questionnaire (0-10).

Question	Responses
What was the level of control over Myomo?	7,8
What was the level of comfort when using Myomo?	6,8
What was the level of resistance that Myomo has provoked?	6,7
Level o fatigue after each block?	4,4
Do you think you managed to do calibration well?	7,9
Use of the myo-electric orthosis was easy?	8,1

Although users reported some resistance (M = 6.7), they did not report high levels of fatigue (M = *4.4)*. Most concerns from the users where related to the heavy weight of the robotic orthosis.

3.2 Feedback Module: Physiological vs. Kinematic Knowledge of Performance

We performed a pilot experiment with 3 stroke survivors where all participants were exposed to the mPower and with an Android tablet that displayed both KP feedback forms, that is, based on EMG activation and based on movement kinematics. The first observation is that the EMG signals of patients were weak and irregular (Fig. 6), as opposed to what was observed in the previous experiment with healthy subjects (Fig. 4a). Triceps signals were more unreliable than biceps; and the dual control mode, based on both biceps and triceps EMG activation, was reported very challenging. All participants reported difficulties in understanding the physiologically based feedback. We believe that the large oscillations on the EMG signals combined with the need of

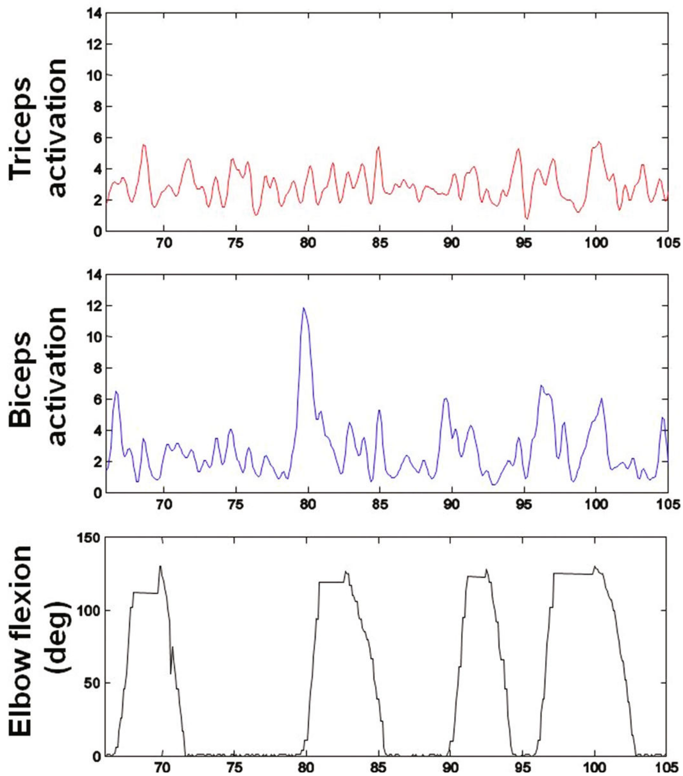

Fig. 6. Data sample for biceps and triceps EMG activation, and arm flexion for one patient performing repetitive arm flexion and extension training using the mPower 1000 myo-electric orthosis.

understanding the antagonistic nature of biceps and triceps EMG for the generation of the correct movement, made the physiologically based feedback less intuitive. When asked about which mode they preferred, all participants favored the more direct relation between kinematic feedback and movement execution, claiming that the kinematic feedback was easier to understand.

4 Discussion and Conclusions

In this project, we proposed a novel hybrid mobile rehabilitation approach by means of a myo-eletric driven orthosis in order to restore and enhance active movement training. To that end we developed a mobile system consisting of two software modules, a calibration and a feedback module, and evaluated them on healthy users and stroke patients. From the findings of the evaluation of calibration module, it is possible to conclude that a time corrected correlation on the muscular activation patterns (EMG) and actual movement can be used to assess the level of control by the user, and therefore to determine the best assistance settings. Hence, there is potential to build an intelligent system that is capable to self-calibrate only using actual user movements, without expert knowledge, and making myo-electric robotic assisted training more patient friendly. In addition, users reported high levels of acceptance of the technological solution.

On the feedback study, patients reported that the kinematic type of feedback was easier to understand. Unfortunately, we observed that also cognitive deficits derived from stroke interfered with the feedback comprehension, which resulted in a small sample of patients having criteria for participating in this evaluation. Despite these limitations, we believe that this tool has potential for supporting specific stroke survivors during their rehabilitation process. This mobile system does not only assist in action execution by virtue of the displayed feedback, contributing to generating knowledge of performance, it also serves to quantitatively assess and monitor changes in the muscular activation patterns of the biceps and triceps, making it also possible to quantify long term changes and improvements.

Overall, such a system can be valuable for supporting the execution of rehabilitation tasks in users with motor deficits of the upper extremities, offering personalized exercise assistance with enhanced feedback on performance. In the future we want to integrate both modules into a single application, providing both a self calibration method and enhanced feedback for the execution of motor tasks. We aim at conducting further experiments with a larger sample of stroke survivors to better understand both the effect of the nature of the feedback provided for knowledge of performance as well as its long term implications in the recovery of normal arm kinematics and muscle activation patterns.

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