Intensive and repetitive training with patient active participation though EMG-controlled robotic hand rehabilitation device: healthy controls and patients validation

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Abstract: - The objective of this work is to describe and test a hand rehabilitation device with particular attention to the key ingredients for a successful neuro-motor rehabilitation training, and in particular: i) adjunctive high duration and intensity therapy sessions; ii) functional orientation of the training; and iii) patient active involvement. The developed system is composed by a PC, the Gloreha hand rehabilitation glove along with its dedicated screen for visual feedback during movements execution, and the MYO armband for EMG signals recording. Two different control approaches have been designed and implemented taking into account the residual muscular activity of the users: EMG trigger controller, and EMG task-selection classifier. Multiple degrees-of-freedom hand functional movements were alternatively triggered (i.e., when the EMG activity overcomes a predefined threshold, the hand robotic rehabilitation device supports the patient-triggered task) or predicted (i.e., two cascaded artificial neural networks were exploited to detect the patient's motion intention from the EMG signal window starting from the electrical activity onset up to the movement onset) depending on the selected approach by means of surface EMG signals. The proposed control approaches were tested on nine healthy control subjects (7 females; age range 16-93 years) and a pilot group of four chronic post-stroke patients. All participants, both from the control group and the patients pilot group successfully calibrated and triggered Gloreha during the testing session using the EMG trigger controller. The EMG task-selection classifier demonstrated an overall mean ± SD testing performance of 80% ± 13% and 67% ± 16%. for correctly predicting healthy users' and pilot post-stroke patient motion respectively. In the control group, the classifier performance was negatively correlated with age, and the pilot patient behaved similarly to elder participants.

Key-Words: Electromyography (EMG), EMG controller, artificial neural networks, hand rehabilitation, movement prediction, electromechanical delay

1 Introduction

Hand functional use plays an important role in everyday life activities, and consequently its loss might be very limiting for patients, once dismissed from the hospital. Indeed, people which experienced a sudden or progressive loss of motor capabilities attribute high value to the maintenance of a direct interaction with daily life objects [1]. Much more effort can be done in dealing with hand rehabilitation after neurological damage (e.g., stroke), with about 65% of patients six months after stroke who cannot incorporate the affected hand into their usual activities [2]. Several studies have demonstrated that motor recovery is associated with reorganization of central nervous system networks [3], even if with a certain intra-subject variability [4]–[6]. Key ingredients for a successful neuro-motor rehabilitation training, beside the onset, where the earlier is the best, include: i) duration and intensity (where the more is the best); ii) functional orientation of the training; and iii) patient active involvement, and effort in contributing with the healing process [7], [8]. In addition and due to economic reasons, the duration of primary rehabilitation is getting shorter and shorter, and therefore home-based rehabilitation is gaining more and more attention [9]. All these constrains makes the design of a hand rehabilitation therapy plan one of the most challenging issues in neurorehabilitation.

The objective of this work is to describe and test a hand rehabilitation robotic device which tackles the aforementioned constrains with the following hypothesis:

i) adjunctive high duration and intensity therapy sessions can be delivered through robotic devices. Indeed, one of the key advantages of neurorehabilitation performed through robotic devices is the possibility to deliver much higher therapy doses with low supervision, and to perform precise and repeatable therapeutic exercises;
ii) functional orientation of the training can be achieved by designing the rehabilitation session with proper functional tasks - in this study we selected grasping, grasp an object, pinching, and wave hand functional tasks;
iii) patient active involvement might be directly, and non-invasively monitored through electromyographic (EMG) activity.

A home-based rehabilitation treatment/device needs to be safe, easy to set-up and to use by non-expert users (i.e., patients themselves or caregivers). In this study these requirements have been considered for the design of the hand rehabilitation robotic device, and the relative controller.

Dealing in particular with surface EMG-based controllers, a lot has been done in literature in terms of prosthetics [10], [11], while EMG-controlled neurorehabilitation devices have had less attention, mainly due to difficulties in effective transition from a research prototype to effective product.

An EMG-based controller architecture might be based on features extraction which are fed into a classifier (or regressor) to identify movement intention toward proportional control (i.e., continuous following of the activation profile) or trigger control. In this study two different approached have been designed and implemented, taking into account the residual muscular activity of the users: EMG trigger controller, and EMG task-selection classifier. It is important to note that the EMG task-selection classifier is designed to provide a prediction before the real task execution, and therefore exploiting the EMG signal temporal window going from muscle activation to kinematic effective movement, i.e. the electromechanical delay phase. In both control solutions therefore the patient is asked to actively engage the movement, and the hand robotic rehabilitation device is activated to support him/her in movement effective execution. We hypothesize that this approach allows to exploit the physiological control loop where the central nervous system programs the consequences of an intended movement which is actually executed instituting a virtuous Hebbian-like motor pathways reinforcement [12], and specific motor strategy adaptation as observed in modified sensorial environments [13].

2 The hand rehabilitation system

The designed system (Fig. 1) is composed by a control PC, a hand rehabilitation robotic glove along with its dedicated screen for visual feedback during movements execution, and an EMG electrodes armband for EMG signals recording. The control PC has different functions: it interacts with the operator (the therapist or the patient himself); it records and processes the EMG signals; and it communicates with the hand rehabilitation robotic glove that controls and actuates the glove.

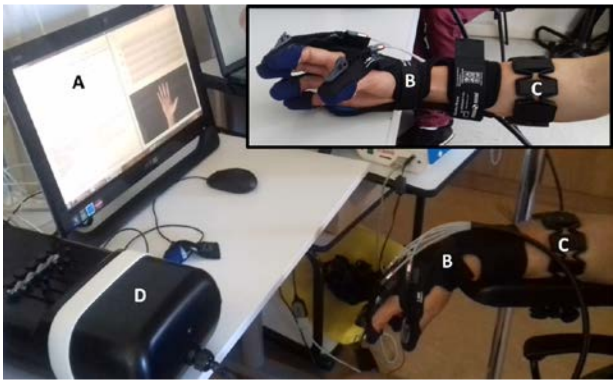

Fig. 1. Experimental set-up. A) control PC with online feedback of the executed movement; B) Gloreha hand robotic rehabilitation device; C) MYO armband; D) Gloreha chassis containing actuation.

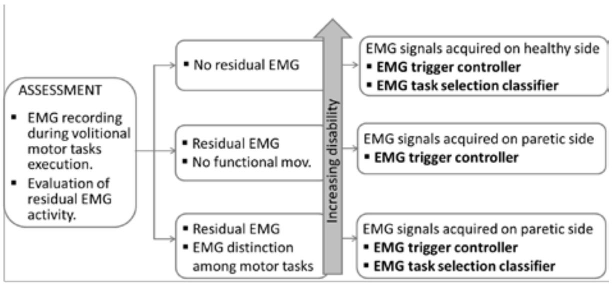

Fig. 2. Three scenarios foreseen in the use of the EMG-controller robotic hand rehabilitation device.

Following a user-centered approach, the system adapts to the actual residual ability of the subject, exploiting any residual control of the end-user. In particular, the interaction of the patient with the system is performed through EMG signals, and two different EMG-based controllers have been identified: EMG trigger controller, and EMG task-selection classifier. Three scenarios have been identified: i) no residual EMG activity on the paretic side; ii) residual EMG activity on the paretic side without functional movement execution; iii) residual EMG activity on the paretic side with partial functional movement execution (i.e. EMG activity is specific with respect to motor task to be executed). In the three scenarios electrodes can be alternatively placed on the paretic or on the healthy side, and the EMG controller can be based on EMG trigger controller or EMG task-selection classifier (Fig. 2).
The two developed control solutions has been designed building up from the results obtained from pilot studies on healthy controls, and pilot stroke patients performed by authors' research team, and previously reported [8], [14]–[16]. However, the present study is performed with different hardware, going toward a low-cost solution easy to wear and to be set-up by non-expert users. The two control solutions have been implemented in Visual C++ environment taking advantage of available MYO SDK and libraries.

2.1 Experimental set-up

Gloreha hand rehabilitation robotic device - Gloreha (GLOve REhabilitation Hand) is a device for neuro-motor rehabilitation of the hand, developed and produced by Idrogenet Srl (Lumezzane, BS, Italy). It is composed by two main elements: a comfortable and light glove, and a chassis containing electromechanic actuators and an electronic board. The device allows the execution of all the combinations of joints flexion-extension. Specifically, fingers movement is performed thanks to 5 electric actuators. Each actuator is linked to a wire. In a compartment of the chassis the operator can adjust the length of the 5 cables which generate the finger movement to set the starting position of the hand, that is also the maximum level of extension the glove will reach during the therapy.
EMG module – Electromyography signals were recorded with the MYO armband (www.myo.com). MYO device is a bracelet composed by eight equi-spaced bipolar dry EMG channels which stream data via Bluetooth to the control PC. MYO was placed on the subject forearm 2–3 cm from the elbow (Fig. 1) after carefully cleaning the skin. In this configuration, the electrodes were not placed specifically on a single muscle [8], [14]–[16], but instead the information recorded from the electrodes was global, and the overall signal was processed to record the patient's motion intention. Since electrodes placement was not dependent on the need to record the signal from particular muscles, the starting point was not fixed. Sampling frequency was set to 200 Hz.

2.2 Connections and communication hardware

MYO armband device streams data via Bluetooth to the control PC which is in turn connected through LAN cable to the local network. Gloreha is controlled by its dedicated PC, which is connected through a LAN cable to the local network as well. The two PCs can be easily integrated in a single one as a future development. The two systems communicate through a TCP/IP protocol where the EMG controller PC is the server and the Gloreha controller PC is the client.

2.3 Participants

This study enrolled healthy volunteers with no neurological or orthopedic impairment from the local population, and from the RSA Maria Immacolata in Varese, Italy. In addition, the EMG-based controllers were tested on a pilot group of chronic post-stroke patients at Villa Beretta Rehabilitation Center, who had inefficient control of the hand, in order to test the effectiveness of the proposed approach. The experiments were conducted with the approval of the local Ethics Committee of Villa Beretta Rehabilitation Centre, and all study participants gave written informed consent after personal illustration of the procedure given by the principal investigator (M.G.).

3 EMG trigger controller

A target hand rehabilitation protocol is defined, composed by proper functional task/s tailored with respect to patient specific needs (i.e., grasping, pinching, etc.). At each movement of the protocol sequence, the patient him/herself is required to start the movement. Only when the EMG activity overcomes a predefined threshold (i.e., the patient is attempting to execute the movement), the Gloreha supports the patient-triggered task.

3.1 Calibration procedure

The patient is asked to perform a sequence of 2/3 movements of the target task/s. So to identify the activation threshold, the EMG signals are processed as previously validated with similar set-up [14], and in particular:

1. The 8 acquired EMG channels are independently pre-processed, by a high-pass filter (3rd order Butterworth filter, cut-off frequency = 10 Hz) to remove the offset; a rectification, and a low-pass filter (3rd order Butterworth filter cut-off frequency = 1 Hz).
2. The 8 pre-processed EMG signals are assessed for the following inclusion criteria (1) and those which meet the inclusion criteria are summed together to obtain an overall EMG signal:

$$\max(EMG_i) - \min(EMG_i) > h * \min(EMG_i) \quad (1)$$

where i indicates the number of samples within the selected channel, and h is a parameter that might be adapted to patient residual ability, i.e., if a patient's contraction is clearly/non-clearly visible on EMG signal. EMG channels selection was motivated by the need to not consider the channels which are not recording any consistent EMG signal. Indeed, the electrodes placement could lead to some electrodes to be placed in non-optimal positions.

3. The EMG signals are windowed to separate open/close movements
4. In each window, the activation threshold is identified as follows (2):

$$threshold = k * (EMG_{max} - EMG_{min}) \quad (2)$$

where k depends on the effort that the clinician wants the patient to perform before Gloreha is activated.

The overall activation threshold was defined as the mean of the activation thresholds obtained for each window. If more than a single target task is selected, the overall activation threshold is fixed to the minimum one.

3.2 Pilot test procedure

Three different tasks were tested: i) grasping; ii) grasp an object, iii) pinching. Tests were performed using a base module composed by 5 repetitions for each task. Movements were auditory guided. The healthy control group executed the protocol with the MYO armband placed on the dominant arm. The pilot group of patients was asked to execute the protocol with the MYO armband placed on the paretic side. The Gloreha was subject-specifically set in order to obtain the selected hand grasp functional tasks.

4 EMG task-selection classifier

The EMG task-selection controller is designed so that the system predicts the intention to perform a certain task from EMG signals measured in a 100 ms window after the EMG onset and thus representing the shortest electrophysiological delay reported in literature [17]. The prediction algorithm is based on a cascade of artificial neural net-works (ANN); it receives as input the 8 EMG signals measured in the 100 ms window and produces the predicted movement as output.

4.1 Tasks definition

Participants were asked to sit comfortably in a chair, with their arm placed on Gloreha armrest, and the hand relaxed with the palm downward, i.e. the resting position (Fig. 1). Four hand functional tasks were selected: (i) grasping: a grasping action with an empty hand that results in a fist; (ii) pinching: a grasping action performed with the thumb and the forefinger to grasp small objects; (iii) grasp an object: a grasping action that depends upon the movement of all of the fingers to grasp an object (e.g. a ball); (iv) wave: sequentially flex the fingers starting from the little finger toward the thumb.

4.2 Control subjects' experimental procedure

Each healthy control participant, after a period of familiarization with the protocol, performed 20 trials of each hand task. Movements were auditory and visually paced with the help of a video every 10 s. Each hand task was acquired in a different run. At least 1 min of rest was provided between each run and it was extended upon the subject's request.

4.3 Neurological patients' experimental procedure

Neurological patients followed the same experimental protocol as healthy control subjects. However, in order to obtain the effective movement execution, they were supported with the Gloreha rehabilitation glove. The EMG-based trigger controller previously described was used to assure that the movement was patient initiated and that the signal related to the electromechanical delay window was effectively produced by the patient him/herself. The MYO armband was placed on the affected side. The Gloreha was subject-specifically set in order to obtain the selected hand grasp functional tasks.

4.4 EMG-based task classifier

The task selection classifier architecture was based on a sequence of ANNs. In particular, each trial to be classified was provided as input in the form of EMG signal portions corresponding to the electromechanical delay – the pattern vector. The pattern vector was provided as the input of successive ANNs with one hidden layer. The first ANN classifies the pattern vector in clusters, defined by a subject specific clustering algorithm in charge of defining subsets of classification groups. Pattern vectors associated with clusters that contain more than one hand grasp task were input to a second ANN in charge of classifying hand grasp tasks within the cluster. For example, let us suppose that the subject-specific algorithm identifies two clusters for subject X, cluster 1 that includes pinching, grasping, and wave tasks, and cluster 2 that includes grasp an object task. Cluster 1 pattern vectors (i.e. pinching, grasping, wave tasks) are input to a second ANN that classifies them as pinching, wave or grasping. Cluster 2 output directly corresponds to the final classification since it only includes one hand grasp task (Fig. 3). The EMG task-classifier specific architecture includes three steps: (1) EMG pre-processing; (2) task-classifier calibration; and (3) task classifier testing. The entire EMG signal (i.e. all 20 trials) underwent EMG preprocessing procedures (i.e. STEP 1), which was then partitioned into calibration trials and testing trials. The calibration of the classifier is subject-specific.

Technical details related to each step have been previously reported [16]. ANN parameters setting (i.e., 25 neurons in the hidden layer, sigmoid as the hidden layer neuron activation function, 0.01 as the learning rate, and six trials for cascade ANN calibration) has been selected as the combination which led to better results among the parameters space investigated in the previous work [16].

4.5 EMG-based task classifier performance

The classifier performance has been evaluated in its ability to discriminate between two, three or four tasks.

The relationship between the developed classifier and age of the end-user has been tested in the healthy control group. In particular, the Spearman correlation coefficient has been calculated between age and the overall mean test performance of the classifier for each subject, as well as for two, three and four tasks discrimination.

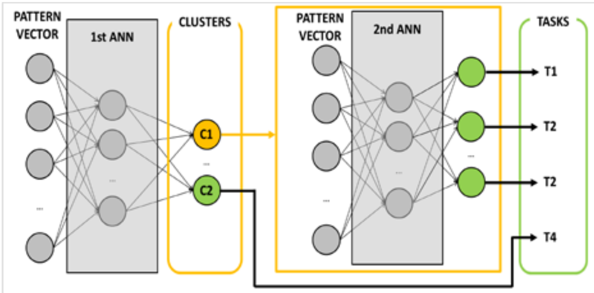

Fig. 3. Graphical outline of the EMG task-classifier architecture. Suppose that the subject-specific algorithm identifies for the depicted subject two clusters, namely cluster 1 (C1), which includes pinching (T1), grasping (T2), and wave (T3) tasks, and cluster 2 (C2), which includes grasp an object task (T4). C1 pattern vectors are input to a second artificial neural network (ANN) that classifies them as pinching, grasping, and wave. C2 output directly corresponds to the final classification since it only includes one hand grasp task.

5 Results

5.1 Participants

Nine healthy subjects (seven females, two males; age range 16-93 years) with no neurological or orthopedic impairment volunteered for this study and all of them succeeded in completing the experimental procedure. A pilot group of four neurological post-stroke patients was also recruited in two separated sessions to test the EMG-trigger controller (PZ01-PZ03), and the task-selection classifier (PZ04). Patients detailed information are provided in Table 1.

	PZ01	PZ02	PZ03	PZ04

Age [years]	41	23	62	50
Sex [M/F]	M	M	M	M
Lesion side [R/L]	L	R	L	L
Lesion location	Pons	Frontal lobe	Capsulo-lenticular region	fronto-parietal lobe
Acute event occurrence	Aug. 1998	Nov. 2011	Mar 2015	Aug 2013
MRC index wrist flexors	4	3	3	1
MRC index elbow flexors	5	3	4	1

Table 1. Patients characteristics. MRC index – Medical Research Council index; M: male; F: female; R: right; L: left

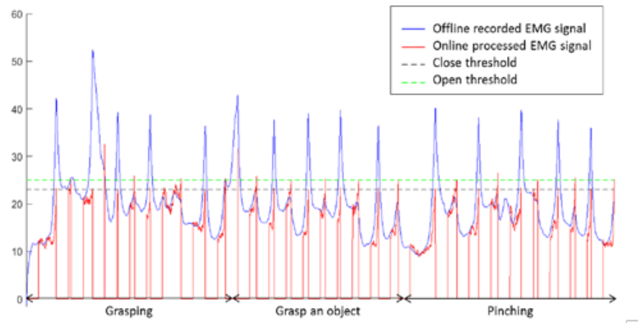

Fig. 4. Protocol execution session exemplificative result (PZ03) during EMG trigger control.

5.2 EMG trigger controller performance

All participants, both the healthy control group, and the patients pilot group, succeeded in the calibration and use of the integrated system. Calibration parameters *h* and *k* were respectively set to 10 and 0.2. Thresholds values obtained by all participants are shown in Table 2. All participants, both from the control group and the patients pilot group successfully triggered Gloreha during the testing session. As exemplificative result, the signals recorded during protocol execution session of PZ03 are shown (Fig. 4).

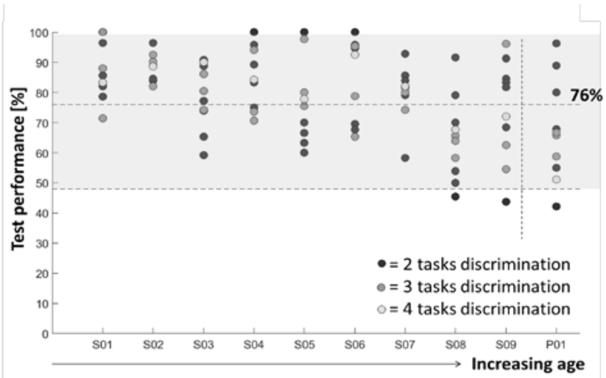

Fig. 5. Success percentage in test performance in discriminating all combinations of two, three and four tasks for the healthy controls group (i.e., S01-S09), and the post-stroke patients (i.e., P04). Grey band represents the results obtained with the research EMG device with self-adhesive electrodes, as described in [16].

	Close threshold	Open threshold
S01	3	3
S02	38	39
S03	8	9
S04	18	19
S05	36	51
S06	17	16
S07	15	15
S08	8	8
S09	14	14
PZ01	10	4
PZ02	26	15
PZ03	3	3

Table 2. Calibration threshold for open and close movement obtained during calibration of the EMG trigger controller. Close and open thresholds values are reported in units of activation (www.thalmic.com/en/myo/).

5.3 EMG-based task classifier performance

ANN parameters set was as follows: 25 neurons in the hidden layer, sigmoid as the hidden layer neuron activation function, 0.01 as the learning rate, and six trials for classifier calibration, which resulted in an overall mean performance of 98% ± 5% during calibration, and 80% ± 13% during testing in healthy control subjects. Healthy controls group mean calibration performances in discriminating all combinations of two, three, and four tasks were 99%, 97%, and 94% respectively, while testing performances were 80%, 79%, and 82% respectively (Fig. 5).

Spearman correlation coefficient resulted to be -0.6167 (p-value = 0.0857), -0.5550 (p-value = 0.1328), -0.8167 (p-value = 0.0108), and -0.5833 (p-value = 0.1080) respectively for overall mean test performance, and two, three and four tasks discrimination in the healthy control group.

Task-selection controller tests on the patient resulted in a mean calibration performance of 94% ± 7% and a mean testing performance of 67% ± 16%, with mean testing performances in discriminating two, three, and four tasks equals to 72%, 64%, and 51% respectively.

6 Discussion and Conclusion

The proposed approach describes and test a hand robotic rehabilitation device which: i) can deliver high therapy doses with low supervision, and can deliver precise and repeatable therapeutic exercises; ii) is able to support movement execution only when the patient has effectively engaged the action hypothesizing a Hebbian-like virtuous circle; iii) has a non-specific EMG electrodes placement which allows safe easy to set-up and use by non-expert users (i.e., patients themselves or caregivers); iv) foresees different use-case options to allow the system to adapt to end-user level of impairment.

Daily life functional tasks, especially those directly involving the hand, always take advantage of the simultaneous involvement of multiple degrees-of-freedom. These considerations lead to the present study choosing to deal with multiple degrees of freedom functional hand movements.

The integrated system was properly working, and the different devices were correctly communicating in order to perform the required protocol. The designed integrated device was tested both on healthy volunteers, and neurological patients for system evaluation. The methodological approach is based on previous studies performed by the same research team as the present study [14]–[16]. However, in this work we used the MYO armband instead of the multi-channel signal amplifier system (PortiTM; Twente Medical System International, Oldenzaal, The Netherlands). This choice has several advantages which include dry electrodes, easy-to-use device from non-expert users (i.e., the MYO armband is worn as a bracelet), wireless data communication, and very low cost. EMG channels are eight with respect to the five acquired from the Porti device for technical reasons, but the EMG signal is sampled at 200 Hz with respect to 2048 Hz of the previous study. However, despite lower temporal resolution, and lower signal to noise ratio, the designed controllers obtained a comparable performance when tested with the MYO armband, both in healthy controls and patients.

As for the EMG trigger controller, all users were able to calibrate and correctly use the system. Patients reported that the system was easy to use and that it effectively followed their intention to move. They reported that the system was more challenging to be used with respect to the standard Gloreha-based rehabilitation session, and required more attention and involvement. It has been shown that the combination between subject volitional contribution and movement assistance provided by the same hand robotic device (i.e., active robot-assisted modality) is able to provide early brain activation associated with stronger proprioceptive feedback [8].

As for the EMG task-selection controller, all participants were able to correctly calibrate the classifier, and the experimental set-up was correctly working. With respect to the classifier performance, the previous study demonstrated an accuracy of 76 ± 14% under testing conditions for the healthy controls group in discriminating three tasks, which are in line with the results obtained with the described approach. Indeed, the healthy controls group obtained 80% ± 13% of corrected classified tasks as the overall mean (i.e., including two, three and four tasks discrimination), and mean calibration performances in discriminating two, three, and four tasks were 99%, 97%, and 94% respectively, while testing performances were 80%, 79%, and 82% respectively. To our knowledge only a single previous work attempted to develop an EMG-based tasks classifier based on the electromechanical delay window [18]. The authors described a support vector machine approach to predict goal-directed movements in the horizontal plane using a 200 ms window, but the classifier failed when tested on neurological patients. Moreover, the authors used muscle activity recorded between -100 ms and 100 ms with respect to the movement onset, which makes the approach not suitable for real-time use. In this study a classifier has been designed with particular attention to possible real time application - ANNs have low computational load, since, once defined, consist of additions and multiplications, and this is important when developing real-time applications; moreover, onsets identification is implemented with a first order low pass filter which allows an on-line onset detection with a two-samples overlapping windows.

With the presented approach, patient’s testing performances were depending on the number of tasks to be classified, and in particular mean calibration performances in discriminating two, three, and four tasks were equal to 72%, 64%, and 51% respectively. The obtained performances are in line with previously described results with the same approach [16] taking into account that PZ04 was severely impaired, and showed an improvement with respect to literature where severely impaired post-stroke patients obtained a mean performance of 37.9%, using a linear discriminant analysis [19].

The EMG task-selection classifier performance shows a trend which depends on age, where the younger the participant the better the performance that is however not statistically significant, probably for the small number of subject recruited. As expected, post-stroke patient performance is similar to aged participants.

In conclusion, the presented results are encouraging toward the development of a hand rehabilitation device which can be used at home for a safe, patient-involving, intensive and functional oriented rehabilitation training. The EMG trigger controller scenario has demonstrated to be ready to be exploited for use. On the other hand, for the effective exploiting of the EMG task-selection controller, higher percentage of correctly classified tasks needs to be achieved in order not to frustrate the patient while using the device for rehabilitation. A possible improvement includes the use of information derived from inertial sensors which are embedded in the MYO armband, and might be exploited so to add information about end-user intention, and forearm prono-supination. Moreover, particular care has to be devoted to electrode-skin coupling by carefully cleaning the skin.

Acknowledgments

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