EMG-controlled hand rehabilitation device for clinical and domestic use: intensive and repetitive training with patient active participation

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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 identified in literature, 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. Multiple degrees-of-freedom hand grasp movements (i.e., grasping, grasp an object, pinching, wave) were predicted by means of surface EMG signals. 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. The proposed approach was tested on nine healthy control subjects (7 females; age range 16-93 years) and it demonstrated an overall mean ± SD testing performance of 80% ± 13% for correctly predicting healthy users' motion intention. A pilot post-stroke patient obtained a percentage of correctly classified tasks of 67% ± 16%. The classifier performance was negatively correlated with age, with the pilot patient behaving similarly to more aged 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]–[9]. 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 [10]. 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 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 controller.

Dealing in particular with surface EMG-based controllers, a lot has been done in literature in terms of prosthetics [11], [12], 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. As for the EMG control of the neurorehabilitation device, we decided to use the trigger approach of multiple-degrees-of-freedom functional movements. It is important to note that the classification is designed to provide a prediction before the real execution of the hand grasp task, and therefore exploiting the EMG signal temporal window going from muscle activation to kinematic effective movement, i.e. the electromechanical delay phase. 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 [13], and specific motor strategy adaptation as observed in modified sensorial environment [14].

2 The hand rehabilitation system

The designed system (Fig. 1) is composed by a PC, a hand rehabilitation robotic glove along with its dedicated screen for visual feedback during movements execution, and electrodes armband for EMG signals recording. The 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. The hand rehabilitation robotic glove and the control PC communicates through a TCP/IP dedicated protocol.

The rehabilitation system has been designed from a previous feasibility study performed by authors' research team [15], [16]. 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. Two scenarios have been identified: i) no residual EMG activity on the paretic side; ii) 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 first scenario EMG electrodes are placed on the healthy forearm while in the second scenario on the paretic side.

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 of the skin. In this configuration, the electrodes were not placed specifically on a single muscle [8], [15]–[17], but instead the information recorded from the electrodes was global, and the overall signal was processed to record the patient's motion intention. Since electrode 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 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 controller was tested on a pilot chronic post-stroke patient 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.).

2.3 Tasks definition

Participants were asked to sit comfortably in a seat, with their arm placed on Gloreha armrest, and the hand relaxed with the palm downward (Fig. 1). (i.e. the resting position). 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.

2.4 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.

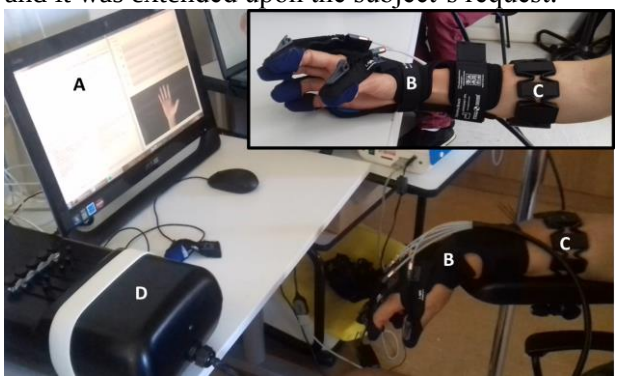

Fig. 1. Experimental set-up. A) control PC with online feedback of the executed movement; B) Gloreha hand robotic rehabilitation device; C) MYO armband; D) Gloreha chassis containing actuation.

2.5 Neurological patient pilot test 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. An EMG-based trigger as described in [17] 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.

2.6 EMG-based task classifier

The EMG task-selection controller design was based on the results obtained from a pilot study on healthy controls, and pilot stroke patients previously reported . However, the present study is performed with different hardware, going toward a low-cost set-up easy to wear and to be set-up by non-expert users. The EMG task-selection classifier has been implemented in Visual C++ environment taking advantage of available MYO SDK and libraries.

In particular, the system predicts the intention to perform a certain hand grasp functional task among a predefined selection from the EMG signals measured in a 100 ms window after the EMG onset. The 100 ms window represents the EMG portion corresponding to the electromechanical delay, i.e. the temporal delay between muscles fiber depolarization and effective kinematic onset of movement. The task 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 input to 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. 2). The EMG task-classifier specific architecture includes three steps: (1) EMG 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].

2.7 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.

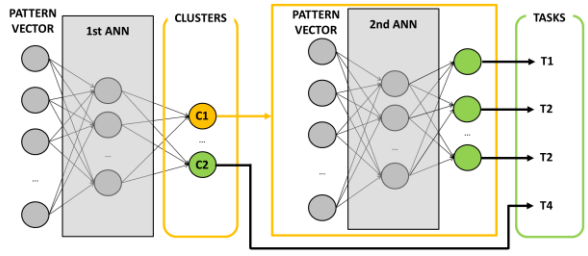

Fig. 2. Graphical outline of the electromyography (EMG) task-classifier architecture. Suppose that the subject-specific algorithm identifies for the depicted subject two clusters, namely cluster 1 (C1), which includes pinching (T1), grasping (T2), and wave (T3) tasks, and cluster 2 (C2), which includes 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.

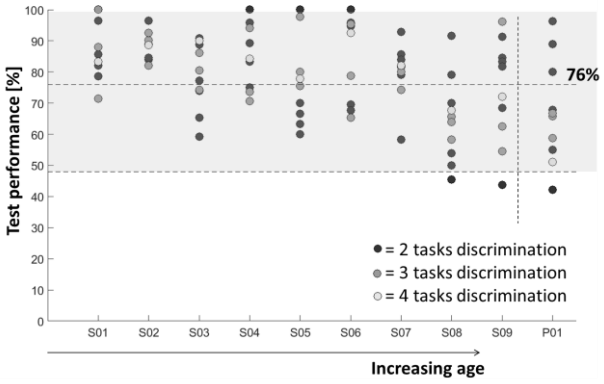

Fig. 3. Success percentage in test performance in discriminating all combinations of two, three and four tasks for the healthy controls group (i.e., S01-S09), and the post-stroke patients (i.e., P01). The grey band represents the results obtained with the research EMG device with self-adhesive electrodes, as described in [16].

3 Results

3.1 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. One neurological post-stroke patients was also recruited. He was a 50-year-old male with a lesion located in the left hemisphere in the fronto-parietal lobe obtained in August 2013. He had impairment to the upper limb contralateral to

the lesion with a Medical Research Council index of 1 for both the wrist and elbow flexors.

3.2 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. 3).

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.

4 Discussion and Conclusion

The proposed approach describes and test a hand rehabilitation device which: i) can deliver high therapy doses with low supervision, and can deliver precise and repeatable therapeutic exercises; ii) is able to predict from the electromechanical window, and therefore before the movement is effectively executed the intended hand task to be performed among a set of four hand functional tasks; iii) has a non-specific EMG markers placement which allows safe easy to set-up and use by non-expert users (i.e., patients themselves or caregivers).

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 use the multiple degrees of freedom functional movements that could be detected though the controller.

All participants were able to correctly calibrate the EMG task-selection controller, and the experimental set-up was correctly working.

The methodological approach is based on a previous study performed by the same research team as the present study [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. As for the 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 allow 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 he was severely impaired, and show 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. However, for the effective exploiting of the proposed approach, 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. Moreover, particular care has to be devoted to electrode-skin coupling by carefully cleaning the skin.

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References:

[1] A. Pedrocchi *et al.*, MUNDUS project: MUltimodal neuroprosthesis for daily upper limb support, *J. Neuroengineering Rehabil.*, vol. 10, 2013, p. 66.
[2] Bruce H. Dobkin, Rehabilitation after Stroke, *N. Engl. J. Med.*, vol. 352, no. 16, 2014, pp. 1677–1684.
[3] C. Calautti and J.-C. Baron, Functional neuroimaging studies of motor recovery after stroke in adults: a review, *Stroke J. Cereb. Circ.*, vol. 34, no. 6, 2003, pp. 1553–1566.
[4] M. Gandolla, F. Molteni, N. S. Ward, E. Guanziroli, G. Ferrigno, and A. Pedrocchi, Validation of a Quantitative Single-Subject Based Evaluation for Rehabilitation-Induced Improvement Assessment, *Ann. Biomed. Eng.*, vol. 43, no. 11, 2015, pp. 2686–2698.
[5] M. Gandolla, N. S. Ward, F. Molteni, E. Guanziroli, G. Ferrigno, and A. Pedrocchi, "The Neural Correlates of Long-Term Carryover following Functional Electrical Stimulation for Stroke, *Neural Plast.*, vol. 2016, 2016, p. 4192718.
[6] C. Casellato *et al.*, Simultaneous measurements of kinematics and fMRI: compatibility assessment and case report on recovery evaluation of one stroke patient, *J. Neuroengineering Rehabil.*, vol. 7, 2010, p. 49.
[7] A. R. Luft *et al.*, Repetitive bilateral arm training and motor cortex activation in chronic stroke: a randomized controlled trial, *JAMA*, vol. 292, no. 15, 2004, pp. 1853–1861.
[8] G. Tacchino, M. Gandolla, S. Coelli, R. Barbieri, A. Pedrocchi, and A. M. Bianchi, EEG Analysis During Active and Assisted Repetitive Movements: Evidence for Differences in Neural Engagement, *IEEE Trans. Neural Syst. Rehabil. Eng.*, Aug. 2016 [Epub ahead of print].
[9] E. Ambrosini, S. Ferrante, T. Schauer, G. Ferrigno, F. Molteni, and A. Pedrocchi, Design of a Symmetry Controller for Cycling Induced by Electrical Stimulation: Preliminary Results on Post-Acute Stroke Patients, *Artif. Organs*, vol. 34, no. 8, 2010, pp. 663-U1.
[10] L. Richards, C. Hanson, M. Wellborn, and A. Sethi, Driving motor recovery after stroke, *Top. Stroke Rehabil.*, vol. 15, no. 5, 2008, pp. 397–411.
[11] A. F. Mak, M. Zhang, and D. A. Boone, State-of-the-art research in lower-limb prosthetic biomechanics-socket interface: a review, *J. Rehabil. Res. Dev.*, vol. 38, no. 2, 2001, pp. 161–174.
[12] D. Borton, S. Micera, J. del R. Millán, and G. Courtine, Personalized neuroprosthetics, *Sci. Transl. Med.*, vol. 5, no. 210, 2013, p. 210rv2.
[13] M. Gandolla *et al.*, Re-thinking the role of motor cortex: context-sensitive motor outputs?, *NeuroImage*, vol. 91, 2014, pp. 366–374.
[14] A. Pedrocchi, G. Baroni, L. Mouchnino, G. Ferrigno, A. Pedotti, and J. Massion, Absence of center of mass control for leg abduction in long-term weightlessness in humans, *Neurosci. Lett.*, vol. 319, no. 3, 2002, pp. 172–176.
[15] M. Gandolla, S. Ferrante, D. Baldassini, M. C. Cottini, C. Seneci, and A. Pedrocchi, Artificial Neural-Network EMG Classifier for Hand Movements Prediction, in *XIV Mediterranean Conference on Medical and Biological Engineering and Computing 2016*, E. Kyriacou, S. Christofides, and C. S. Pattichis, Eds. Springer International Publishing, 2016, pp. 634–637.

[16] M. Gandolla *et al.*, Artificial neural network EMG classifier for functional hand grasp movements prediction, *J. Int. Med. Res.*, Sep. 2016 [Epub ahead of print].

[17] M. Gandolla, S. Ferrante, D. Baldassini, M. C. Cottini, C. Seneci, and A. Pedrocchi, EMG-controlled robotic hand rehabilitation device for domestic training, in *XIV Mediterranean Conference on Medical and Biological Engineering and Computing 2016*, E. Kyriacou, S. Christofides, and C. S. Pattichis, Eds. Springer International Publishing, 2016, pp. 638–642.

[18] B. Cesqui, P. Tropea, S. Micera, and H. I. Krebs, EMG-based pattern recognition approach in post stroke robot-aided rehabilitation: a feasibility study, *J. Neuroengineering Rehabil.*, vol. 10, 2013, p. 75.

[19] S. W. Lee, K. M. Wilson, B. A. Lock, and D. G. Kamper, Subject-Specific Myoelectric Pattern Classification of Functional Hand Movements for Stroke Survivors, *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 19, no. 5, 2011, pp. 558–566.