2017 SCHOOL & SYMPOSIUM ON ADVANCED NEUROREHABILITATION

SCHOOL AND SYMPOSIUM ON ADVANCED NEUROREHABILITATION (SSNR2017)

Proceedings

September 17-22, 2017
Baiona (Spain)

NRG INSTITUTO CAJAL CSIC Imperial College London

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Modeling human behavior through functional analysis: applications in assistive robotics and HRI

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***Abstract*— Hands are our preeminent organ to interact with and explore the external environment. This interaction is guided by our brain using upper limb degrees of freedom. Despite the enormous complexity of hand bio-mechanics, many studies in literature showed that brain uses few principal movements patterns, called synergies, to control such a complexity. This synergistic behavior can be also observed in other human related phenomena, such as muscular activity in performing tasks and lower limbs kinematics during walking movements. In our work, our goal is to describe the complexity of the upper limb movements in a synergistic way by modeling them under a functional point of view. In fact, such a role is essentially dynamic, since different temporal evolutions of upper limb joints would result in different final hand poses. Our approach allows to describe these behaviors taking into account temporal informations and defining functional synergies for upper limb movements during Daily Living Activities. Applications for the design and control of assistive robotics and HRI will be discussed.**

I. Introduction

Human hands represent an extraordinary tool to explore and interact with the external environment. Not surprisingly, a lot of studies have been devoted to model how the nervous system can cope with the complexity of hand sensory-motor architecture [10].

However, to correctly understand human manipulation, in addition to hand analysis the role of whole upper limb movements should be also taken into account. Indeed, the whole upper limb motions are devoted to guide and optimize position and orientation of the hand w.r.t. external targets.

For these reasons, in addition to many works devoted to analyze hand behavior, it is also possible to find studies modeling human upper limb motor workspace, either from a kinematic point of view, or from a muscular or neural point of view [4], [7]. However, none of the previous studies considered the dynamic aspects of human upper limb motion. For this reason, we propose to use for the first time Functional Principal Component Analysis (fPCA) to describe upper limb principal movements [9].

To achieve this goal, we designed an experimental setup for studying upper limb movements, based on a Motion Capture (MoCap) system (*Phase Space*®). Using this tool, we carried out a series of experiments with humans considering a comprehensive dataset of daily living activities (ADLs) and grasping/manipulation actions [3], and considerations on human upper limb movement workspace [1], [8].

Our analysis has led to the reduction of complexity of upper limb trajectories by describing these as linear combinations of few principal functions (or modes). Implications for robotics are also discussed.

II. Experimental Protocol and Setup

In order to develop a comprehensive study of human upper limb movements, one of the key features for the generation of a valid dataset is the definition of a set of meaningful actions. For this reason, we selected a set of 30 movements, driven by the study of grasping taxonomies [3], and the analysis of human upper limb movement workspace [1], [8]. Tasks are meant to be executed three times with dominant hand, the subject seating on a chair, with the objects placed on a frontal table at a fixed distance. At the end of the task the subject returned to the starting point. We focused on kinematic recordings, which was achieved using a commercial system for 3D motion tracking with active markers (*Phase Space*®). Ten stereo-cameras working at 480Hz tracked 3D position of markers, which were fastened to supports rigidly attached to upper limb links. Seven adult right-handed subjects (5 male and 2 female, aged between 20 and 30), performed the experiment. The object order was randomized for every subject. No subject knew the purpose of the study, and had history of neuromuscular disorders. Each participant signed an informed consent to participate in the experiment, and the experimental protocol was approved

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by the Institutional Review Board of University of Pisa, in accordance to the declaration of Helsinki. In this work, we used a trade-off between complexity and accuracy by adopting a model with 7 degrees of freedom (DoFs), and 3 invariable shape links. The parameters of the kinematic model must be adapted for the specific subject that performs the experiments. The optimal parameters were obtained by solving a constrained least-squares minimization problem: $(x^*, p_G^*) = arg\min_{x_k \in D_x, p_G \in D_p} \frac{1}{2} \sum_{k=1}^{N_p} r_k^T r_k$ The residual function r_k is calculated as $r_k(x_k, p_G) := y_k - f(x_k, p_G)$, where: y_k is the marker position vector measured with PhaseSpace; x_k is the vector of estimated joint angles; p_G is the vector of model kinematic parameters; D_x is the upper limb joints range of motion; D_p is the variation around a preliminary estimation of parameters performed with manual measurements; $f(x_k, p_G)$ is the estimated positions vector of markers using the forward kinematics. Taking inspiration from [6], the calibrated model was then used to identify the joints angles using an Extended Kalman Filter (EKF).

III. Data Analysis

The analysis of kinematic data was composed by: segmentation, to divide the repetition of each task; time warping, to synchronize in time all the elements of the dataset; fPCA to extract principal functions. 15 5th order spline basis elements were used to implement fPCA, taking inspiration for the polynomial description in [5]. Our analysis shows that the first fPC by itself account for 60-70% of the variation w.r.t. the mean function, with a mean value between the DoFs of 65.2%, a minimum value of 54.4% and a maximum of 76.9%. What is noticeable is that reconstruction with the first fPCs provides good results, in fact the explained variance of the first three fPCs is higher than 84% for all DoFs. The reconstruction using one fPC has a mean reconstruction error lower than $0.2\ rad$, adding other fPCs, the reconstruction error is reduced, i.e. using three fPCs the mean reconstruction error is around $0.1\ rad$.

IV. Conclusion

In this work we have shown that the complexity of upper limb movements in activities of daily living can be described using a reduced number of functional principal components. The findings of this work can be used to pave the path towards a more accurate characterization of human upper limb principal modes, opening fascinating scenarios in rehabilitation, e.g. for automatic recognition of physiological and pathological movements. At the same time, the here reported results and future investigations could also offer a valuable inspiration for the design and control of robotic manipulators. First, recognizing that few principal modes describe most of kinematic variability could provide insights for a more effective planning and control of robotic manipulators. Second, using human-like primitives for controlling robotic systems could improve the effectiveness and safety of Human - Robot Interaction (HRI). Furthermore, the here reported experimental and analytical framework could be used to identify principal actuation schemes for under-actuated robotic devices [2]. Finally, the integration of other sensing modalities, such as Electro-encephalographic recordings, could be used to study neural correlates of human upper limb motions, thus possibly inspiring the development of effective Brain-Machine Interfaces for assistive robotics.

References

[1] Karim Abdel-Malek, Jingzhou Yang, Richard Brand, and Emad Tanbour. Towards understanding the workspace of human limbs. *Ergonomics*, 47(13):1386–1405, 2004.

[2] S. Casini, V. Tincani, G. Averta, M. Poggiani, C. Della Santina, E. Battaglia, M. G. Catalano, M. Bianchi, G. Grioli, and A. Bicchi. Design of an under-actuated wrist based on adaptive synergies. In *IEEE International Conference of Robotics and Automation, ICRA2017*, In Press.

[3] Mark R Cutkosky. On grasp choice, grasp models, and the design of hands for manufacturing tasks. *IEEE Transactions on robotics and automation*, 5(3):269–279, 1989.

[4] Andrea d'Avella, Alessandro Portone, Laure Fernandez, and Francesco Lacquaniti. Control of fast-reaching movements by muscle synergy combinations. *The Journal of neuroscience*, 26(30):7791–7810, 2006.

[5] Tamar Flash and Neville Hogan. The coordination of arm movements: an experimentally confirmed mathematical model. *The journal of Neuroscience*, 5(7):1688–1703, 1985.

[6] Marco Gabiccini, Georg Stillfried, Hamal Marino, and Matteo Bianchi. A data-driven kinematic model of the human hand with soft-tissue artifact compensation mechanism for grasp synergy analysis. In *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3738–3745. IEEE, 2013.

[7] Omid Heidari, John O Roylance, Alba Perez-Gracia, and Eydie Kendall. Quantification of upper-body synergies: A case comparison for stroke and non-stroke victims. In *ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, pages V05AT07A032–V05AT07A032. American Society of Mechanical Engineers, 2016.

[8] Jadran Lenarcic and Andreja Umek. Simple model of human arm reachable workspace. *IEEE transactions on systems, man, and cybernetics*, 24(8):1239–1246, 1994.

[9] James O Ramsay, Giles Hooker, and Spencer Graves. *Functional data analysis with R and MATLAB*. Springer Science & Business Media, 2009.

[10] Marco Santello, Martha Flanders, and John F Soechting. Postural hand synergies for tool use. *The Journal of Neuroscience*, 18(23):10105–10115, 1998.

Neurophysiological constraints of control parameters for a brain computer interface system to support post-stroke motor rehabilitation

Emma Colamarino, Floriana Pichiorri, Donatella Mattia and Febo Cincotti

Abstract— **The Promotœr is an all-in-one Brain Computer Interface (BCI)-system developed at Fondazione Santa Lucia (Rome, Italy) to support hand motor imagery practice after stroke. In this paper we focus on the optimization of control parameters for the BCI training. We compared two procedures for the feature selection: in the first, features were selected by means of a manual procedure (requiring "skilled users"), in the second a semiautomatic method, developed by us combining physiological and machine learning approaches, guided the feature selection. EEG-based BCI data set collected from 13 stroke patients were analyzed to the aim. No differences were found between the two procedures (paired-samples t-test, p=0.13). Results suggest that the semiautomatic procedure could be applied to support the manual feature selection, allowing *no-skilled users* to approach BCI technology for motor rehabilitation of stroke patients.**

I. Introduction

BRAIN-computer interfaces (BCI) are devices that directly measure and process in real time the brain activity (e.g. electrical activity) with the aim of enabling the interactions between the user and his environment [1] and/or providing him with feedback of specific processes occurring in his brain. A growing field of application of BCI technology regards motor rehabilitation after stroke. In this context two main approaches have been identified: the first employs brain activity to control devices to assist movement, the second aims at modifying brain activity to improve motor behavior [2].

At IRCCS Fondazione Santa Lucia (Rome, Italy) the multidisciplinary team (neuroscientists, bioengineers and clinical rehabilitation experts) of the Neuroelectrical Imaging and BCI Lab conceptualized and developed a BCI prototype to support hand motor imagery (MI) training in stroke patients [3]. The rationale behind such BCI approach was based on the assumption that the practice of mental imagery with motor content could influence brain plasticity and, thus, enhance post-stroke functional motor recovery [4]. The combination of MI practice by means of BCI technology allows the access of MI content under controlled condition [5] thus revealing the rehabilitative potential of MI. The core of the device is a non-invasive electroencephalogram (EEG)- based BCI which allows quantitative and controlled monitoring and reinforcement of EEG patterns generated by MI and provides patients with an ecologically enriched feedback: a realistic virtual representation of their own hands.

To prove the clinical efficacy in improving hand functional motor recovery of this approach as add-on intervention, a randomized controlled clinical trial was performed with twenty-eight subacute stroke patients [6]. It was demonstrated that an EEG-based BCI-support MI training can improve motor rehabilitation of the upper limb with clinically relevant benefits (e.g. significant increase of Fugl-Meyer score) as well as greater involvement (i.e. significant increase of EEG motor-related oscillatory activity after training) of the affected hemisphere in the target groups (14 patients) with respect to a matched control group performing MI training without BCI (14 patients).

The device, presented as an all-in-one BCI-supported MI training station and called *Promotœr*, is currently employed as add-on to standard therapy in one of the rehabilitation wards of Fondazione Santa Lucia.

Further efforts target the improvement of system's usability in a twofold sense by defining

- physiologically-driven algorithms for spatial filtering and EEG feature extraction/selection,
- multimodal approaches (i.e. monitoring also the residual muscular activity of the affected limb) to let the patients re-learn their motor scheme by having voluntary (covert and/or overt) access to the affected limb.

In this study we focus on the EEG feature selection issue. Identifying the optimal control features taking into account neurophysiological principles is a milestone in rehabilitation protocols supported by BCI technology. Consequently, this task requires expert professional users. Supporting this procedure with a semiautomatic method, that combines physiological and machine learning approaches, has a twofold aim: reduce the operator variability and facilitate users without experience with BCIs, increasing, therefore, the *usability* of BCI technology in post-stroke motor rehabilitation. In this study we propose a preliminary comparison between classification performances obtained using features selected by both skilled user (manual procedure) and semiautomatic method (guided procedure).

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II. Material and Methods

A. Data Collection

EEG dataset previously acquired from 13 subacute stroke patients (the BCI group involved in the randomized controlled trial [6]) were analyzed to compare manual versus guided procedure in terms of classification performance.

All patients were trained to perform motor imagination of the affected hand movements (grasping and finger extension).

EEG data from the initial screening session [6], collected from 61 electrodes according to an extension of the 10–20 International System, were analyzed to identify the control features. For the performance evaluation step, scalp EEG potentials during the first training session, [7] for details, from a subset of 31 electrodes distributed over the scalp centroparietal regions were considered. All data were sampled at 200 Hz.

B. Data Analysis

EEG data were re-referenced to the common average reference and divided into epochs of 1 second. Spectral features (spectral amplitude at each bin for each EEG channel) were extracted using the Maximum Entropy Method (16th order model, 2 Hz resolution, no overlap).

Two types of features selection were considered: the manual selection in which skilled users (neurologists and/or therapists) identified the control features and assigned them weights just basing on the EEG pattern visualization; the guided selection in which users defined some (e.g., topographical) constraints and the semiautomatic method, implemented as a stepwise regression algorithm, ran the feature selection and the weight evaluation.

The linear combination of the selected features and weights (for both manual and guided procedures) was the score value used for the performance assessment evaluated with the Area Under Curve (AUC) of Receiver Operating Characteristic (ROC) curve. AUC values (manual vs guided procedure) were compared with the paired-samples t-test (statistical significance threshold set to $p < 0.05$).

To support even no-expert users in the EEG feature selection a (user-friendly) tool, called GUIDER, was developed. It allows to import and analyze BCI data using several modules in cascade, for signal conditioning, feature extraction, statistical analysis and visualization.

III. Results

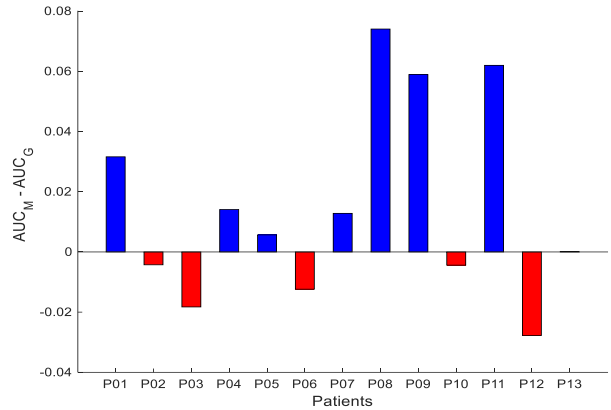

Fig. 1. For each data set (13 stroke patients, P) the difference between AUC values obtained with features selected by manual (M) and guided (G) procedures. For positive (negative) differences AUC values in manual procedure are higher (lower) than in guided procedure. No statistical differences were found between the two procedures (paired-samples t-test, p=0.13).

IV. Discussion

The improvement of the BCI system's usability goes through the optimization of its control parameters (EEG features). The feature selection requires specific knowledge and expertise and, so, skilled users. The physiologically-driven algorithm developed for EEG feature selection aims at facilitating this procedure for no-expert BCI users, combining both neurophysiological and machine learning approaches. The tool designed to support the selection allows users without any programming skills to import and analyze BCI data.

Providing BCI control parameter selection with a physiologically-driven semi-automatic procedure could boost the transferability of BCI technology to support motor rehabilitation after stroke, guiding plasticity phenomena underlying functional recovery.

V. Conclusions

No statistical differences were found between manual and guided procedure; the second would allow even users without experience with BCIs to approach this technology for motor rehabilitation of stroke patients.

References

[1] J.R. Wolpaw and E.W. Wolpaw, *Brain-computer interfaces: principles and practice.* Oxford University Press, 2012, ch.1.

[2] J. J. Daly and J. R. Wolpaw, "Brain-computer interfaces in neurological rehabilitation," *The Lancet Neurology*, vol. 7, no. 11, pp. 1032–1043, 2008.

[3] F. Cincotti, F. Pichiorri, P. Aricò, F. Aloise, F. Leotta, F. de Vico Fallani, J. del R. Millán, M. Molinari and D. Mattia, "EEG-based brain-computer interface to support post-stroke motor rehabilitation of the upper limb," *Proceedings of IEEE, EMBS*, 2012, pp. 4112–4115.

[4] N. Sharma, J.-C. Baron, and J. B. Rowe, "Motor imagery after stroke: relating outcome to motor network connectivity," *Ann. Neurol*., vol. 66, no. 5, pp. 604–616, Nov. 2009.

[5] F. Pichiorri, F. De Vico Fallani, F. Cincotti, F. Babiloni, M. Molinari, S.C. Kleih, C. Neuper, A. Kübler and D. Mattia, "Sensorimotor rhythm-based brain-computer interface training: the impact on motor cortical responsiveness," *J Neural Eng*, vol. 8, no. 2, Apr. 2011.

[6] F. Pichiorri, G. Morone, M. Petti, J. Toppi, I. Pisotta, M. Molinari, S. Paolucci, M. Inghilleri, L. Astolfi, F. Cincotti and D. Mattia, "Brain-computer interface boosts motor imagery practice during stroke recovery," *Annals of Neurology*, vol. 77, no. 5, pp. 851–865, 2015.

[7] G. Morone, I. Pisotta, F. Pichiorri, S. Kleih, S. Paolucci, M. Molinari, F. Cincotti, A. Kübler and D. Mattia, "Proof of principle of a brain-computer interface approach to support poststroke arm rehabilitation in hospitalized patients: design, acceptability, and usability," *Arch Phys Med Rehabil*, vol. 96, no. 3 Suppl, pp. S71-78, Mar. 2015.

Factors Influencing Premotor Potentials and how their Combination Can Increase this Potentials

O. Herrero Giménez

Abstract— **Electroencephalographic signals allow us to record and monitor brain electrical activity. The execution and planning of voluntary motor tasks generate cortical patterns (BP -Bereitschaftspotential; CNV-Contingent Negative Variation) defined in specific frequency bands and areas of the brain.**

Through the implementation of different paradigms, I propose the evaluation of a series of approaches that help to promote the generation of these premotor potentials. These paradigms provide different instructions for the subject to perform the task focusing on a particular aspect, either speed, force or reach a target (complexity of the task), or focusing on the combination of two or more of these factors.

If there is a better characterization of the premotor potentials in any of these conditions (expected in the combined paradigms), this discovery could be applied to the field of rehabilitation since the identification of these mechanisms would help to optimize the performance of BMI (Brain Machine Interface) interventions and, therefore, to apply care therapies under an associative approach effectively.

I. Introduction

A few seconds before we perform a voluntary movement, changes in the electroencephalographic (EEG) activity are observable over certain areas of the scalp. The movement-related cortical patterns (MRCPs) observed before voluntary movements start and reflected as a slow negative drifts of the EEG amplitudes have been typically divided into a subset of subcomponents by many studies published in the last three decades, although their interpretation and possible uses for neural rehabilitation purposes are still far from been mastered [1]. A simplified classification of the pre-movement MRCPs divides them into two parts: early and late bereitschaftpotential (BP). However, there is some controversy in the classification of this cortical patterns because almost every author has used a different terminology to refer to them [2].

Similar to the BP, the Contingent Negative Variation (CNV) is a negative shift of the EEG before voluntary movements, but this refers only to changes taking place in externally paced paradigms. The CNV was discovered in 1964 [3] and to achieve this particular cortical pattern, the first experiments associated a ready stimulus (S_1) and an imperative stimulus (S_2), after which the subject had to make a motor response. Nowadays, other kind of paradigms are used to elicit this premotor potential [4].

Several studies have shown that there are factors that influence the generation of BP and CNV. Some of these factors are the force exerted in the task [6], the speed of the movement, the complexity of the task [7] or the precision required among others.

Currently, many of the Brain-Machine-Interface (BMI) are based on motor-related EEG signals. The modulation of the movement planning patterns through the optimal configuration of the motor tasks the subject has to perform can allow to reinforce the BCI interventions and improve their results [4], [8]. An increase of these premotor potentials could help the BMI to characterize with greater precision the moment in which the subject is going to make a movement.

II. Methods

A. Experimental protocol

Each participant is measured during one single session. The study is performed in a sound and light-attenuated room. Participants sit in a comfortable chair with their arms supported on a table. During the measurement phase (countdown and execution of the task), subjects are instructed to remain relaxed, to maintain their eyes on the circle and not to blink.

The task consists of an abduction movement of the index finger, through which the activity of the First Dorsal Interosseous (FDI) muscle is recorded by electromyography (EMG). In the first place, the subject is told the factor(s) on which he/she should focus (this message appears only once in each condition). In the CNV condition there is a countdown consisting of a circle that becomes smaller and fades, after which the subject has to perform the movement. In the CNV-like condition, the circle disappears before becoming smallest, trying to guess the subject when it would completely vanish and perform the task at that time. In the BP condition, the participant performs the movement at will. After each movement has been performed, a feedback which consists of a score between 1 and 100 is given to the subject.

There are eight different conditions. The first is the control condition, in which the subject has to perform 40 consecutive movements without specific instructions. The feedback is randomly given. The following three conditions are randomized for the simple factors: **speed**, **strength** and **complexity**. The last four conditions correspond to the

I thank the Ministerio de Educación Cultura y Deporte (MECD) of Spain`s government for the FPU scholarship which is allowing me to carry out my PhD.

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combination of these factors: **speed/force**, **velocity/complexity**, **force/complexity** and **velocity/force/complexity**. For these last seven conditions, the subject performs two series of 20 movements, so in the end each subject has performed 40 trials for each condition.

B. Data Acquisition

EEG signals are recorded by 28 positions (AFz, F3-F4, FC3-FC4, C5-C6, CP3-CP4, P3-P4 and Oz according to the international 10-20 system) using active Ag/AgCl electrodes (Acticap, Brain Products GmbH, Germany). The reference is set to the voltage of the earlobe contralateral to the finger moved and Oz is used as ground. Besides, EMG signals are obtained by two bipolar electrodes placed at FDI muscle. EEG and EMG signals are amplified using the gUSBamp (g. Tecgmbh, Austria) and are sampled at 256 Hz.

To measure the subject index finger`s angle when performing the task, a custom-made platform is used (figure 1). The participant inserts the finger into the movable arm, whose angle in the rest position is 0.

The method by which the EEG classifies the movement is explained in [8].

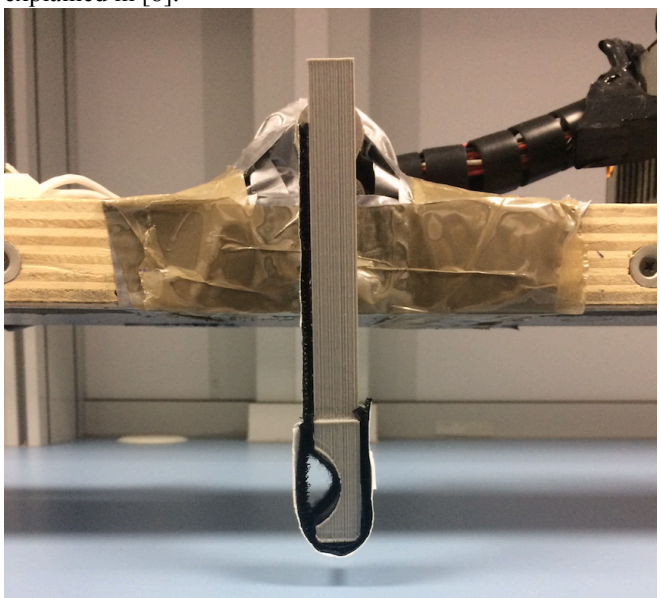

Fig. 1. The platform for upper-limb. The movable arm is in the rest position, so the angle is 0.

C. Performance

In the **velocity condition**, the feedback is higher the closer the participant generates the movement with respect the circle has completely vanished. In order to obtain that instant, we measured with the EMG the moment at which the subject activates the FDI muscle above a threshold that has been delimited by means of the EMG activity during the countdown.

For the **force condition**, the maximum voluntary contraction (MVC) of FDI muscle is used to obtain a normalized score. A maximum score in this case corresponds to EMG activations over 70% of the MVC.

Finally, in the **complexity condition**, the subject is asked to reach a particular point (obtained with a specific FDI extension). The participant gets more score the closer he/she is to the point.

For the conditions in which the factors are combined, the score is the average of the scores for each factor involved.

III. RESULTS

The expected results are a greater generation of the premotor potentials under the conditions in which several factors are combined.

IV. DISCUSSION AND CONCLUSION

If the generation of premotor potentials is enhanced under the conditions in which the subject must focus on more than one aspect of the task, this could mean that motor planning with greater cognitive activity leads to the enhancement of this type of potentials. These paradigms can be used for BMIs based on EEG signals to characterize with more precision the exact instant at which the subject plans to move.

The BMI offline averaged, in the training phase, the instant at which there is a greater drop in BP/CNV [4]. Using the BMI online allows us to consider each movement by itself, having a greater temporal precision of the intention of movement.

REFERENCES

[1] H. Shibasaki, G. Barret, E. Halliday & A.M. Halliday, *Components of the Movement-Related Cortical Ptential and Their Scalp Topography* in *Plastics*. Electroencephalography and Clinical Neurophysiology, (1980), 49, pp. 213–226.

[2] H. Shibasaki & M. Hallett. *What is the Bereitschaftpotential?* Clinical Neurophysiology, (2006), 117, pp. 2341-2356.

[3] W.G. Walter, R. Cooper, V. J. Aldridge, W. X. McCallum & A. L. Winter, *Contingent Negative Variation: An Electric Sing of Sensori-motor Association and Expectancy in the Human Brain.* Nature, (1964), 203 pp. 380–384.

[4] N. Mrachacz-Kersting et al. *Efficient Neuroplasticity Induction in Chronic Stroke Patients by an Associative Brain-Computer Interface.* Journal of Neurophysiology, (2016), 115 pp, 1410-1421.

[5] G. Pfurtscheller & F.H. Lopes da Silva. *Event-Related EEG/EMG Synchronization and Desynchronization : Basic Principles.* Clinical Neurophysiology, (1999), 110 pp, 1842-1857.

[6] S. Slobounov, M. Hallet & K. M. Newell. *Perceived Effort in Force Production as Reflected in Motor-Related Cortical Potentials.* Clinical Neurophysiology, (2004), 115 pp, 2391-2402.

[7] R. Benecke, J. P. R Dick, J. C. Rothwell, B. L. Day & C. D. Marsden. *Increase of the Bereitschaftspotential in Simultaneous and Sequencial Movement.* Neuroscience Letters, (1985), 62 pp, 347-352.

[8] J. Ibañez, J. I. Serrano, M. D. del Castillo, E. Monge-Pereira, F. Molina-Rueda, I. Alguacil-Diego & J. L. Pons. *Detection of the Onset of Upper-Limb Movements Based on the Combined Analysis of Changes in the Sensoriomotor Rhythms and Slow Cortical Potentials.* Journal of Neural Engineering, (2014), 11, 056009.

INPUT – H2020 EU project to advance hand prosthetic control

Sebastian Amsüss, Markus Schachinger, and Michael F. Russold

***Abstract*— INPUT is a European H2020 project (02/2016-02/2020) that focuses on advancing upper limb prosthetics by tackling the most significant aspects of successfully fitting such a device to a user: Improved socket for more comfortable fit and wearing; Improved training to maximize the outcome with the patient; Improved recognition algorithms for better and more robust control; Improved evaluations to make sure that the devices are tested in clinically relevant scenarios.**

We will achieve this by increasing our theoretical knowledge on the control generating mechanisms, by ample end user testing (2 of the 4 project years are dedicated to user testing) and by implementing the project as an Innovation Action, meaning an increased focus on high market readiness.

I. Introduction

WOLF Schweitzer, transradial amputee since August 2008, writes on his Technical Right Below Elbow Amputee Issues blog: "Academic research is interesting, but for the most part has failed to deliver any improvements to upper arm prosthetics in the last 50 years. By and large people tend to be a bit shocked when I show them real stuff, when I tell them what really is going on. Reality of academic prosthetic research has it that they never end up actually helping amputees".
(http://www.swisswuff.ch/tech/?page_id=2, 2014)

» Prosthetic users are frustrated with the technology available on the market today [1]. The main objective of INPUT is to translate clinically relevant research results on advanced upper limb prosthetic control made in the past from the laboratory to an everyday usable solution for end-users – straight after donning of the prosthesis, under the motto "don and play".

To reach this objective, INPUT will build upon long experience in this field by the involved institutions and results achieved within two preceding EU projects working on advanced arm prosthetics – the EU FP7 IAPP projects AMYO (Grant No. 251555, 2011-2014) and MYOSENS (Grant No. 286208, 2012-2015).

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 687795, project Acronym INPUT. The content of this article does not reflect the official opinion of the European Union. Responsibility for the information and views expressed therein lies entirely with the authors.

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II. Project Overview

A. Motivation

As also noted in the introductory quote by an end-user, despite many decades of research on improvement of upper limb prosthetic control, the most advanced commercially available technologies are still disappointing. Compared to natural arms, they significantly lack functionality required by amputees. Daily use of complex, highly dexterous wearable robotic arms is still not clinical reality. The vast majority of high-end myoelectric arm prostheses rely on a very simple, almost half a century old, electromyographic (EMG) interface with two electrodes. The acquired EMG signals are commonly used to drive "hand open" and "hand close" functions of the robotic device. More functions (shoulder, elbow, wrist, individual fingers) are not directly controllable, so that (if at all available) unintuitive switch- and sequential menu based schemes have to be applied. The movements lack naturalness, dexterity and somehow do not fit in today's picture of modern technology – with self-driving cars, intelligent robots and smart phones, which fit in our pockets and whose processors and memory capacities are ~1000 times more powerful than that of the computer used for the moon landing of Apollo 11 in 1969. Compared to these advancements in electronics of the last 40-50 years, the advancements of upper limb prosthetics have virtually stalled. No wonder that this reflects in user dissatisfaction: The acceptance of myoelectric prosthesis was reported to be only 61% in amputation levels of elbow or above and 33% of myoelectric users reported unsatisfying function [2], which was the most prominent problem found in that study, ranking above issues with cosmesis, fit and maintenance. Several other studies show similar results on arm prosthesis rejection.

B. Main project goals

In INPUT, a multi-functional arm prosthesis is being developed that enables users to control their devices in a natural, easy and – most importantly [3]-[6] – reliable way. INPUT channels research efforts of the past decades into one, finally clinically viable system: ready for market introduction by the project coordinator and prosthetics world market leader, Ottobock.

The efforts of INPUT do not just focus on new technology, but INPUT also aims to develop new tools to help the end-user achieve a higher level of functional use of the prosthesis. Therefore, a substantial part of the project is devoted to develop a proper rehabilitation training that can be used with the new device. Training is important because

even with a prosthetic device, which has natural and intuitive control, patients need guidance to restore consistent muscle signals. The developed rehabilitation exercises will use a serious game, because in a fun training environment patients can be motivated to exercise longer due to the aspect of play involved, while being educational. Furthermore, such a training environment allows individualizing feedback that enlarges the chances of optimal performance improvement. The level of improvement with the new device and of the training developed is tested in functional tasks and daily life situations, to assess improvement in the behavioural domains most important for the end-users.

INPUT aims to significantly advance the state of the art in machine learning based upper limb prosthesis control. The particular focus lies on natural control, robustness, user training and frequent end-user tests. INPUT will advance the involved technologies from a technology readiness level (TRL) of 4/5 to one which will allow testing a qualified and complete prototype in its operational environment (TRL 8). The main focus of the project will thus be to provide natural, dexterous control of complex arm prostheses, while minimizing the efforts users have to make for mastering and maintaining this high functionality.

In particular, the following goals will be reached in INPUT:

- Simultaneous control of at least 4 DOF of a modern arm prosthesis (hand, wrist, elbow functions)
- Proportional control of each DOF
- Intuitive, natural control as exemplified by increased functional use of the prosthesis
- High robustness as assessed by experiments with end-users in real life situations
- Self-calibration and automatic parameter tuning for ease of use, especially after donning of the prosthesis (“don and play”)
- A wearable prototype with high TRL of 8 (“system complete and qualified”)
- A motivating and effective user training environment employing specific guided training
- Extensive tests and validations with end-users in real life settings and during activities of the daily living, including suitable biomechanical analysis to verify the advantages of the devised system
- A marketing strategy and exploitation plan for the obtained solution
-

Fig. 1. Prosthetic wearer using several degrees of freedom at once to grasp a cup handle efficiently.

C. *First results*

In the first year of the project, the first prototypes of multi-electrode liners have been developed and tested for signal quality and comfortable fit.

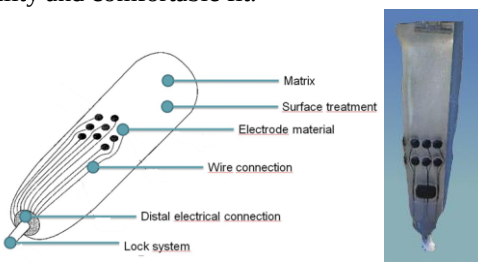

Fig. 2. First prototype of improved electrode liner for multi-channel EMG recording in transradial amputees.

Furthermore the first training concepts have been devised which specifically target improved muscle control of amputees for machine learning driven controls.

We have implemented a deep learning approach with advanced post-processing, which allows for precise control and simultaneous control over 3 degrees of freedom.

In the next year, the prototypes will be miniaturized, ported to portable hardware and be prepared for user testing.

Acknowledgment

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 687795, project Acronym INPUT

References

[1] Biddiss EA and Chau TT. Upper limb prosthesis use and abandonment: a survey of the last 25 years. Prosthet Orthot Int 2007; 31(3): 236–257.

[2] P. J. Kyberd and W. Hill. Survey of upper limb prosthesis users in Sweden, the United Kingdom and Canada. Prosthet. Orthot. Int. 2011, vol. 35, no. 234, pp. 234–241.

[3] Hargrove LJ, Englehart KB, Hudgins B. A training strategy to reduce classification degradation due to electrode displacements in pattern recognition based myoelectric control. 2008, iomedical Signal Processing and Control 3(2):175-180

[4] Jiang N, Muceli S, Graimann B, Farina D. Effect of arm position on the prediction of kinematics from EMG in amputees. Med Biol Eng Comput. 2013, 51(1-2):143-51

[5] Scheme E, Fougner A, Stavdahl Ø, Chan AC, Englehart K. Examining the adverse effects of limb position on pattern recognition based myoelectric control. Conf Proc IEEE Eng Med Biol Soc. 2010; 2010:6337-40.

[6] Lorrain T, Jiang N, Farina D. Influence of the training set on the accuracy of surface EMG classification in dynamic contractions for the control of multifunction prostheses. J Neuroeng Rehabil. 2011 May 9;8:25

Determine socket shift in trans-radial amputees using ultrasound and 3 D motion capture

Unglaube F. , Pobatschnig B. , Kranzl A.

In pattern recognition-based myoelectric control several robustness problems are well known. Different positions of the upper limbs and donning and doffing cause unintended electrode shifts (pistoning) with adverse effects on classification accuracy. To our knowledge the shift of the socket with respect to bony structures has never been assessed. We developed a set up to measure the shift of the socket with ultrasound and 3 D motion capture system in trans-radial amputees. We got obtained accuracy values with .655 mm for our set up. A pilot measurement showed high reliability and a displacement of the socket around 2 mm. We are going to conduct further test measurements and develop parameters to distinguish longitudinal and perpendicular shift of the socket. In future works pistoning parameter should be considered in order improve pattern recognition based myoelectric control.

I. Introduction

Pattern recognition based myoelectric control has the aim to make prosthesis control intuitively and naturally. Several studies have shown classification problems in different limb positions [1]. Further studies have reported classification problems after donning and doffing and weight bearing on the socket as well [2]. The occurring electrode shift (pistoning) of nonstationarities is one of the reasons for the limitation of laboratory performed research. Even a small electrode shift of around 2 cm leads to classification problems[3]. So far electrode shift has quantified only with respect to the skin and with a small number of subjects. To our best knowledge in the literature there are no studies to explore the displacements of the socket and the stump for the upper limbs with respect to underlying bony structures. Several methods are suggested in the literature to measure the movements between the socket and the residual limb, especially for the lower extremities [4], [5]. Most of them were using an x-ray stereography, which is cost-intensive and exposes subjects to radiation. But for clinical outcomes and studies in biomechanics of prosthetic users, the pistoning is an important parameter. Therefore, we developed an accurate setup to evaluate movements between the socket and the stump with respect to underlying bony structures in order to receive quantitative data. In future work these data can be used to improve myoelectric control considering pistoning parameters.

This work was supported by the European Union´s Horizon 2020 research and innovation program under grant agreement number 787795 (project INPUT).

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II. Aim of this Study

The aim of this study was to develop a set up to quantify the shift of the socket with respect to bony landmarks and to determine the shift after donning and doffing, between several quasistatic arm positions and in weight bearing condition.

III. Method

To determine the shift between prosthetic socket and residual limb we developed an accurate measurement set up combining 3 D motion capture system with 14 infrared cameras (Vicon Motion Systems, Oxford, UK) and an ultrasound system (US, Sonosite Titan). Retro reflective markers are attached to the ultrasound probe to receive the position and the orientation of the probe in the global space. With virtual calculated markers we determined the scanning plane of the ultrasound system. In the captured ultrasound picture we detected certain bony landmarks and calculated its global positions. Retro reflective markers were also attached to the prosthetic socket. In order to determine the shift of the socket we calculated the distance between the global coordinate of the bony landmark and the markers attached on the socket.

Fig. 1. Two custom made test sockets. The features of them are the same as the daily used sockets in combination with a prosthetic hand (Michelangelo hand, Otto Bock Healthcare Products GmbH).

To test and improve the accuracy of the developed setup we used an adapted procedure introduced in [6]. A table tennis ball (tt ball) was fixed in a box filled with distilled water and the center of the ball was calculated prior. We determined the global coordinate of the center of the tt ball with our ultrasound system from different scan directions and calculated the rout mean square error (rmse) to the prior calculated center of the tt ball. If the accuracy was at an acceptable level we fixed the probe in a custom made frame with attached markers and saved the positions of the markers attached to on the ultrasound probe and the virtual calculated markers relative to the custom made frame. Due to this saved information we were able to check the correct calibration of the system with the frame in a quick and

uncomplicated manner before measuring a new subject. We performed tests of the accuracy of the set up with one observer in three sessions who determined the center of the tt ball 10 times in three different scanning directions per session. Custom made sockets were equipped with fitted holes to scan through with the ultrasound probe and to detect the bony landmark (see Fig. 1). The sockets had approximately the same spatial features and weight as a daily used socket. We included male subjects from 18 till 60 years of age with unilateral amputation on transradial level due to traumatic reasons. We performed three measurements. 1. During four quasistatic arm positions (1. arm hanging besides body; 2.forearm horizontal to the ground; 3.upper arm horizontal to the ground and elbow 90° flexed; 4. arm abduction at approximately 135 °). 2. Weight bearing with different weights (2-5 kg) on the socket during the four mentioned limb positions. 3. After donning and doffing. We scanned well recognizable bony structures like the proximal radius head and tried to retrieve them between different measurements. Each measurement condition was repeated five times. We analyzed the captured 3 D data and ultrasound videos with Matlab R2011b (The MathWorks, Inc., Natick, Massachusetts, United States).

IV. Preliminary Results

In terms of accuracy we got an rmse value over all three sessions with .655 mm (session 1:.635 mm, session 2:.535 mm, session 3: .795 mm). We conducted a pilot measurement with a prostheses user to get preliminary results. Since we measured only one subject up to now and the pilot character of this measurement the results are depicted in a descriptive manner. Since the socket didn't fitted to the subject as it should be we were only able to perform the measurement with inner socket. Therefore the calculated distances were neglected and we concentrated on reliable issues. Two independent observers analyzed the captured pictures and determined two bony landmarks (distal humerus head and proximal radius head) (Fig. 2). The standard deviation (std.) for the radius head appears even lower than for the humerus head. The range of the std. for conditions except 'after' for both raters is: radius: .1-.4 mm, humerus: .5 – 1 mm. For the condition 'after' the std. for the radius are .9 and .96 mm and for the humerus 1.1 and 1.2 mm.

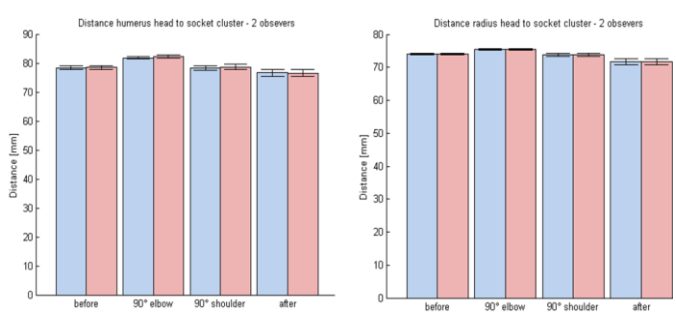

Fig. 2. Distance (mean±standard deviation) between bony landmarks (distal humerus and radius head) and marker attached on the socket determined by two independent observers (blue and red bars).

V. Discussion and Conclusion

Due to the fact, that we performed the measurements only with the inner socket the absolute distance values were negligible. The weight of the inner socket is only around 1/10 of the complete system. Therefore we assume that the measured distances are much smaller than with the complete system. But from the results of the two independent observers we assume that the proximal radius head is better detectable in terms of reliability than the distal humerus. In upcoming works we will perform further measurements with the complete test socket. For this we improved our recruitment procedure. Besides we will work on outcome parameters which describe the shift of the socket more precise in longitudinal and perpendicular directions due to the results of [3]. It appears that the electrode shift in perpendicular directions affects the classification accuracy much more than in the longitudinal direction. Up to now we are limited in the way that we only could describe the shift of a point in the local coordinate system of the socket. But other approaches trying to create a local coordinate system to the stump used either radiation [4] or wasn´t applicable to donning and doffing [5]. Recognition of bony landmarks between different limb positions is a considerable issue. We hope that precise knowledge about the shift of the socket in different conditions, limb positions and after donning and doffing will be considered in the future development of pattern recognition algorithms to make those systems more robust.

VI. Acknowledgment

This work was supported by the European Union´s Horizon 2020 research and innovation program under grant agreement number 787795 (project INPUT).

References

[1] E. Scheme, A. Fougner, A. D. C. Chan, and K. B. Englehart, "Examining the adverse effects of limb position on pattern recognition based myoelectric control." IEEE, IEEE EMBS, 2010.

[2] M. M.-C. Vidovic, H.-J. Hwang, S. Amsuss, J. M. Hahne, D. Farina, and K.-R. Muller, "Improving the Robustness of Myoelectric Pattern Recognition for Upper Limb Prostheses by Covariate Shift Adaptation.," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 24, no. 9, pp. 961–970, Sep. 2016.

[3] A. J. Young, L. J. Hargrove, and T. A. Kuiken, "The effects of electrode size and orientation on the sensitivity of myoelectric pattern recognition systems to electrode shift," *IEEE Trans Biomed Eng*, vol. 58, 2011.

[4] G. Papaioannou, C. Mitrogiannis, G. Nianios, and G. Fiedler, "Assessment of amputee socket-stump-residual bone kinematics during strenuous activities using Dynamic Roentgen Stereogrammetric Analysis.," *J. Biomech.*, vol. 43, no. 5, pp. 871–878, Mar. 2010.

[5] W. L. Childers, K. L. Perell-Gerson, and R. J. Gregor, "Measurement of Motion Between the Residual Limb and the Prosthetic Socket During Cycling," *JPO J. Prosthetics Orthot.*, vol. 24, no. 1, pp. 19–24, Jan. 2012.

[6] B. Brendel, S. Winter, and H. Ermert, "A simple and accurate calibration method for 3D freehand ultrasound," *Biomed. Tech.*, vol. 49, no. Suppl 2, pp. 872–873, 2004.

Machine Learning for Advanced Electromyographic Prosthesis Control

Michael Wand, Klaus Greff, Jürgen Schmidhuber

***Abstract*— We present our work on performing robust simultaneous proportional electromyographic control of a hand prosthesis with multiple degrees of freedom. Our approach is based on state-of-the-art machine learning using a sophisticated neural network. On an offline dataset, we achieve a reduction of the Mean Squared Error by almost 40%, online tests with prosthesis wearers are currently in progress.**

I. INTRODUCTION

Surface electromyographic (sEMG) signals have been considered for control of hand prostheses for decades (see e.g. [1]), and it has been shown that these signals allow to distinguish a large number of different movements for both able-bodied persons and amputees [2]. Yet, the vast majority of hand prostheses which are in practical use are much less versatile than laboratory results suggest to be possible, in particular, simultaneous and proportional control of multiple degrees of freedom (DOF) is typically impossible [3]. This goes along with the observation that commercially available prostheses mostly use rather simple algorithms for sEMG-based prosthesis control, e.g. a small number of sEMG channels is recorded, and signal energy thresholding is used to control a small number of functions.

We present our ongoing research on creating a robust and efficient system for real-time simultaneous control of a prosthesis with 4 DOF. We use a state-of-the-art *neural network* (see sections II and III) to directly perform simultaneous regression of up to seven movement commands (which translate to up to 4 DOF) without explicitly modelling the properties of the EMG signal. Here we report results using an *offline* system based on pre-recorded data. An *online* system is currently being tested on patients, see section IV.

II. MACHINE LEARNING & NEURAL NETWORKS

Machine Learning (ML) deals with automatically solving certain tasks without being given *explicit rules* describing the problem. Instead, the system *learns from examples*: In the *training* stage, the system receives samples of the given task and the desired solution as input; for evaluation, or for practical application, the trained system is then *tested* on *unseen* samples. For example, modern computer vision systems can distinguish hundreds to thousands of image categories [4] without any explicit description on what makes up a certain object: the system learns the correspondence between images and class labels solely from examples.

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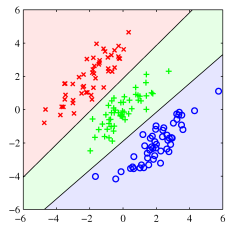

Fig. 1: Fitting straight lines to training data to solve a classification task (source: [5])

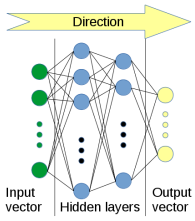

Fig. 2: Schematic diagram of a feedforward neural network

The ML system can be described as a function from the (vector) space of input samples into the output space, likewise represented as a vector space. This allows training algorithms based on fitting a function to the available data, like in figure 1. In contrast to naïve approaches which directly use the input samples, the fitted function can be evaluated efficiently, possibly meeting real-time application constraints, and (if suitably set up) it *generalizes* well, i.e. it works well on unseen data.

Among the variety of machine learning algorithms (see e.g. [5]), *Neural Networks* have recently gained huge popularity for many tasks, including biomedical signal processing. Neural networks perform a *distributed* computation of the mapping from input data to output hypothesis, using a large number of small units (called *neurons*). Each neuron is very simple, it just performs a weighted summation of its input data followed by a nonlinear transformation. The computational power of neural networks lies in the *weighting* of the connections between neurons; these connection weights are optimized during the training stage using the *backpropagation* algorithm [6]. The neurons are commonly organized in layers, as shown in figure 2.

III. SYSTEM, EXPERIMENTS & RESULTS

Data corpus The offline system is based on a dataset of 8-channel sEMG recordings of 11 able-bodied subjects performing seven common movements which are used in prosthesis control: Wrist Flexion/Extension, Wrist Pronation/Supination, Key Grip/Fine Pinch/Hand Open, plus a No Movement baseline. With a proportional control task in mind, these movements were performed in three different target strengths, namely at 30%, 60%, and 90% MVC (maximum voluntary contraction). Each single movement follows a trapezoid structure (1s increase, 3s hold with the target MVC, 1s decrease) Each subject recorded 15 recording sessions with varying electrode positions; each single recording session consists of 5 repetitions of the entire

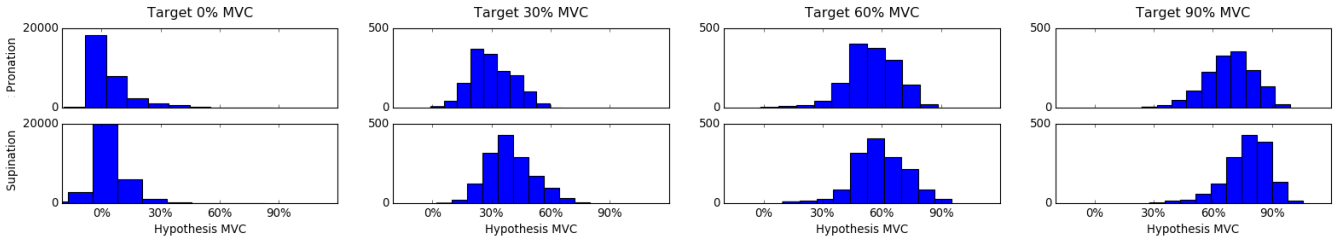

Fig. 3: Histograms of regression results for two complementary classes (subject 1, best neural network). Note that the histograms for 0%MVC also show values for all other movements

set of movements and strengths, i.e. of $5 \times 8 \times 3 = 120$ recordings. The total amount of data per subject is thus 1800 recordings (around 2.5h). The raw EMG data were preprocessed using the standard Hudgins features [7]. For increased exactness, we cut the movement onset and offset of each sample and retained only the part where the subject held the target MVC. Experiments were run *subject-dependently*. From each subject, 10 sessions were chosen for training the regression system, and the remaining 5 sessions were chosen for testing: thus the electrode positioning between recordings varies slightly, which reflects the intended practical usage.

Systems Many current systems for proportional prosthesis control use some sort of linear control scheme, either linear regressor, or a linear classifier (e.g. LDA [8]) combined with a separate estimator for the desired movement speed. In light of this, we use linear regression as our baseline, which is compared with a neural network with the following parameters: The network has two 100-dimensional hidden layers with a $\tanh$ nonlinearity, followed by the seven-dimensional linear output layer (corresponding to the possible movements). The output Mean Squared Error (averaged over all seven movements) is optimized using backpropagation with early stopping.

System	MSE	Correlation
Linear Regression	0.033	0.59
Neural Network	0.020	0.74

TABLE I: Mean Squared Error (MSE) and correlation between target and hypothesis for baseline linear regressor and neural network, on the test data

Results Table I shows the results of our experiments on the test data subset, averaged over all seven movements and all subjects. It is clear that the neural network is substantially better: The reduction of the mean squared error is almost 40% relative. We also computed the correlation between reference target and regressor hypothesis, as a means to quantify the most important parameter for practically controlling a prosthesis, again obtaining an improvement. Finally, figure 3 graphically shows the results of our regressor for a subset of two complementary movements, as a histogram depicting the target MVC (in columns) and the hypothesis, i.e. the output of our system. One sees that the movements are practically always correctly recognized, and that the target strength is quite well estimated. Note that the leftmost column shows the regression output for all other movements, indicating that there are few "false positives" (and that these can easily be removed with thresholding).

IV. CONCLUSION AND ONGOING WORK

We have reported first results on our ongoing work about state-of-the-art prosthesis control. Our current research deals with using these results in a challenging *online* scenario, in particular, in real-life situations with actual prosthesis users. For this purpose, we have developed an online system with the same set of movements and the same training procedure as the offline system. This system is currently undergoing first clinical tests, differences to the offline system described above include the translation of regressor results into movement commands, using versatile postprocessing for improved control. We note in particular that the training data (single muscle contractions) has very different properties from the data accrued in the test situation (real-life movements), a discrepancy which is well-known [9]. In the future, we expect that our neural network paradigm allows an improved training procedure which is closer to the intended usage.

REFERENCES

[1] D. Graupe and W. K. Cline, "Functional Separation of EMG Signals via ARMA Identification Methods for Prosthesis Control Purposes," *IEEE Transactions on Systems, Man and Cybernetics*, vol. SMC-5, no. 2, pp. 252 – 259, 1975.

[2] S. Amsuess, P. M. Goebel, N. Jiang, B. Graimann, L. Paredes, and D. Farina, "Self-Correcting Pattern Recognition System of Surface EMG Signals for Upper Limb Prosthesis Control," *IEEE Trans. Biom. Eng.*, vol. 61, no. 4, pp. 1167 – 1176, 2014.

[3] N. Jiang, S. Dosen, K.-R. Müller, and D. Farina, "Myoelectric Control of Artificial Limbs - Is There a Need to Change Focus?" *IEEE Signal Processing Magazine*, vol. 29, no. 5, pp. 152 – 150, 2012.

[4] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei, "ImageNet Large Scale Visual Recognition Challenge," *International Journal of Computer Vision*, vol. 115, pp. 211 – 252, 2015.

[5] C. M. Bishop, *Pattern Recognition and Machine Learning*. Springer, 2007.

[6] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning Representations by Back-propagating Errors," *Nature*, vol. 323, no. 6088, pp. 533 – 536, 1986.

[7] B. Hudgins, P. Parker, and R. Scott, "A New Strategy for Multifunction Myoelectric Control," *IEEE Transactions on Biomedical Engineering*, vol. 40, pp. 82 – 94, 1993.

[8] E. Scheme, B. Lock, L. Hargrove, W. Hill, U. Kuruganti, and K. Englehart, "Motion Normalized Proportional Control for Improved Pattern Recognition Based Myoelectric Control," *IEEE Transactions on Neual Systems and Rehabilitation Engineering*, vol. 22, no. 1, pp. 149 – 157, 2014.

[9] N. Jiang, I. Vujaklija, H. Rehbaum, B. Graimann, and D. Farina, "Is Accurate Mapping of EMG Signals on Kinematics Needed for Precise Online Myoelectric Control?" *IEEE Transactions on Neural Systems And Rehabilitation Engineering*, vol. 22, no. 3, pp. 549 – 558, 2014.

Preliminary study on the validation of Leap Motion Controller in tetraplegic patients

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***Abstract*—The Leap Motion Controller device has to be validated for its use as rehabilitation purpose. By means of the device SDK, the data acquisition program has been modified to register analytical hand movements. This research is a preliminar study in a sample of 9 healthy people and 5 patients with tetraplegia. The device is validated in terms of the fitting rate between the image captured and the biomechanical model of the hand internal to Leap Motion controller. The hand movements analyzed were the pinch and grasping movements and the flexion-extension of the wrist joint and the index finger. Moreover, a static posture of the hand was registered. In both groups analyzed, the variable analyzed was high in the static posture and the pinch movement. However, in the wrist motion this value was moderate. This study suggests that the device seems to be suitable for quantifying hand movements in tetraplegic patients.**

I. Introduction

IMPAIRED upper limb function is one of the most common sequelae after Spinal Cord Injury. In this situation, patients experiment limitations in the performance of Activities of Daily Living afecting to their autonomy and social participation. For this reason, the treatment over the upper limb that patients receive is very important [1,2].

Within the clinical setting, the upper limb function has been usually quantified in an objective way by means of motion analysis equipments, that are expensive and require qualified staff [3]. However, in last years, several low-cost and markerless motion systems have become commercial devices, available for manipulating applications and videogames. One such system is the Leap Motion Controller (LMC; Leap Motion Inc., San Francisco, CA) [4].

In the literature, two studies have been found that validate the accuracy of the measurements from LMC [5,6]. A recent study analyzed the hand kinematic from LMC, using markered motion capture technology, in relation to the flexion-extension movement of the wrist joint [7]. However, there is no scientific evidence of similar studies in neurological pathologies. Only one study has planned an upper limb therapy using LMC in stroke patients [8].

The aim of this preliminary study is to analyze the feasibility of using LMC for estimating the hand function in an objective way in tetraplegic patients.

This research has been funded by grant from the Spanish Ministry of Economy and Competitivity and cofunded from FEDER, National Plan for Scientific and Technological Research and Innovation. Project RehabHand (Plataforma de bajo coste para rehabilitación del miembro superior basado en Realidad Virtual, ref. DPI2016-77167-R).

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II. Methods

A. Participants

A total of 14 people have participated in the study divided into two groups: 9 healthy people and 5 tetraplegic patients between the metameric levels C5-C8. All the participants had to fulfill the inclusion criteria and sign the corresponding informed consent. The level and severity of the SCI, in relation to the ASIA scale, were determined by a neurological exam [9]. The study was approved by the Local Ethical Committee.

B. The Leap Motion Controller

The LMC is a low-cost device that has been designed to control applications by hand gestures and movements. It contains three infrared lights and two cameras. The device is small, rectangular and its weight is 45 g (Fig. 1). The LMC is connected to the computer via a USB connection.

In this study, the characteristics of the computer used are a i7 processor, 12 GB RAM memory and a graphic card NVIDIA for gaming. The operating system is Windows 10.

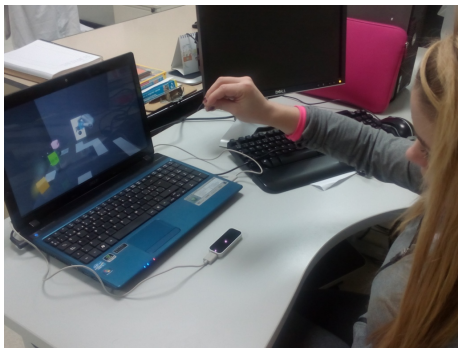

Fig. 1. A healthy subject controls the Virtual Reality application by means of Leap Motion Controller.

C. Data acquisition and kinematic analysis

All the participants performed the experimental session seated in front of a table adjustable in height. Patients performed the session in their own wheelchair following the seating protocol described in our previous publication [3]. The LMC device was placed between the participant and the computer at a standardized distance with the aim of avoiding trunk compensatory movements.

By means of the LMC device SDK (version 2.3.1) the data acquisition software was modified and programmed in C# for quantifying movements performed by the participants. All the movements, frame to frame were saved into a .txt file. The flexion-extension of the wrist joint and the index finger were the movements analyzed. Moreover, the variables *PinchStrength* and *GraspStrength* were used for measuring the level of execution of these movements. The movements were performed with the hand opened and the palm was facing the LMC.

Finally, all the movements were validated in relation to the fitting rate between the hand image captured by LMC and the internal biomechanical model to LMC. This variable ranges between 0 and 1 values.

D. Statistical analysis

A non parametric statistical method, the Kruskal-Wallis test, was applied to find possible differences between both groups analyzed.

For all the movements analyzed, the fitting rate variable was expressed as the median and the interquartile range.

III. Results

The fitting rate obtained for all the hand movements analyzed are shown in Table I. The results have been obtained in both groups analyzed, the healthy people and people with cervical SCI.

TABLE I
FITTING RATE FOR ALL THE HAND MOVEMENTS ANALYZED

Variables	Healthy	SCI patients
Static pose	0.915(0.107)	0.766(0.242)
Pinch	0.807(0.060)	0.734(0.195)
Grasping	0.709(0.103)	0.661(0.110)
Wrist flex-ext	0.640(0.125)	0.582(0.066)
Index finger flex-ext	0.880(0.092)	0.665(0.232)

Significant statistical differences were not found between both groups analyzed in the hand movements in relation to the fitting rate variable.

For all the hand movements, the results were greater in the group of healthy people than in patients. The fitting rate obtained was high in both groups, healthy and patients, during the execution of the pinch movement. However, during the grasping movement and the flexion-extension of the index finger, the variable analyzed was high in the healthy group and moderate in the patients group.

The worst results were obtained in the flexion-extension movement of the wrist joint in both groups. For this movement the fitting rate obtained was moderate.

IV. Discussion

This preliminary study suggests that the LMC device seems to be suitable for quantifying the hand function during the execution of analytical movements that can be rehabilitated after a cervical SCI. The LMC detects the flexion-extension movement of the wrist joint with acceptable reliability.

We investigated the effect of some variables in the movements estimations. The environment lighting conditions, the computer features and the hand postures were analyzed. Hand posture had significant influence in the fitting rate calculated for all the movements analyzed. The optimal results were obtained with the posture *open hand*.

V. Conclusion

For rehabilitation purposes, the reliability in the estimation of the hand movement should be analyzed during the execution of upper limb functional movements oriented to reach a goal.

A more exhaustive study is necessary for analyzing in a greater sample of patients the feasibility of using the Leap Motion Controller in the recovery and rehabilitation of the hand function in tetraplegic patients.

References

[1] M. Beninato, K. S. O'Kane, and P. E. Sullivan. "Relationship between motor FIM and muscle strength in lower cervical-level spinal cord injuries." *Spinal Cord*, 2004,vol. 42, no 9, p. 533.

[2] T. J. Schmitz. Traumatic spinal cord injury. In: S. B. Sullivan and T. J. Schmitz (eds) *Physical Rehabilitation: Assessment and Treatment,* 4th edn. F.A. Davis Company: Philadelphia, pp 873-923.

[3] A. de los Reyes-Guzmán, A. Gil-Agudo, B. Peñasco-Martín, M. Solís-Mozos, A. del Ama-Espinosa, and E.Pérez-Rizo. "Kinematic analysis of the daily activity of drinking from a glass in a population with cervical spinal cord injury". *Journal of neuroengineering and rehabilitation*, 2010, 7(1), 41.

[4] Leap Motion. https://www.leapmotion.com/ (Access: 22/06/2017)

[5] J. Guna, G. Jakus, M. Pogačnik, S. Tomažič, and J. Sodnik. "An analysis of the precision and reliability of the leap motion sensor and its suitability for static and dynamic tracking". *Sensors*, 2014, 14(2), 3702-3720.

[6] F. Weichert, D. Bachmann, B. Rudak, D. Fisseler. "Analysis of the accuracy and robustness of the leap motion controller". *Sensors*, 2013, 13(5), 6380-6393.

[7] A. H. Smeragliuolo, N. J. Hill, L. Disla, and D. Putrino. "Validation of the Leap Motion Controller using markered motion capture technology". *Journal of biomechanics*, 2016, 49(9), 1742-1750.

[8] M. Iosa, G. Morone, A. Fusco, M. Castagnoli, F. R. Fusco, L. Pratesi, and S. Paolucci. "Leap motion controlled videogame-based therapy for rehabilitation of elderly patients with subacute stroke: a feasibility pilot study". *Topics in stroke rehabilitation*, 2015, 22(4), 306-316.

[9] S. C. Kirshblum, S. P. Burns, F. Biering-Sorensen. International standards for neurological classification of spinal cord injury. *The Journal of Spinal Cord Medicine*, 2011, 34(6) 535-546.

Evidence for altered upper limb muscle synergies in cervical spinal cord injury patients

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ABSTRACT: **Background:** After central nervous system (CNS) damage, sensoriomotor coordination can be achieved by muscle synergies. The modular control analysis has shown potential to detect differences in residual gait after incomplete spinal cord injury and in the upper limb performance after a stroke. The objective of the present work is to analyze muscle synergy profile in cervical SCI patients during the activity of daily living (ADL) of drinking. **Methods:** Eighteen subjects were used: healthy group (n=7); C6-SCI (n=7) and C7- SCI (n=4). sEMG data were recorded from 9 muscles and synchronized with trunk and right arm kinematic data, while performing the ADL of drinking. Muscle synergies were extracted from sEMG signal using a non-negative matrix factorialization algorithm. The Kruskal-Wallis test was applied to find possible differences between groups. **Results:** C6 and C7 SCI patients showed a statistically significant increase in the number of upper limb muscle synergies compared with healthy people, during ADL of drinking. **Conclusions:** Muscle synergies analysis is able to detect changes during upper limb motor behaviour after a cervical SCI.

This work is part of the HYPER project "Hybrid Neuroprosthetic and Neurorobotic Devices for Functional Compensation and Rehabilitation of Motor Disorders" (Ref. CSD2009-00067) funded by CONSOLIDER-INGENIO 2010, Spanish Ministry for Science and Innovation and the project "Diseño de electrodos de baja impedancia para interfaces neurales" (Ref. PEII-2014-021-A) funded by Consejería de Educación y Ciencia, Junta Comunidades Castilla La Mancha, Spain..

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I. INTRODUCTION

After central nervous system (CNS) damage, sensoriomotor coordination can be achieved by muscle synergies. The modular organization underlying muscle activity has been extensively investigated, going along with the conclusion that muscle synergies reflect the interaction between the central control and the output of one's motor task[1]. This modular control analysis has demonstrated its potential to detect differences in residual gait after incomplete spinal cord injury, as the VAF could provide an objective quantification of the gait recovery process[2].

The human arm is a hugely complex body structure with an equally refined control system. The brain ought to coordinate over different controls, yet accomplishes this task with apparent skillfulness. How the brain handles real-time control during activities of daily living (ADL) is the subject of much research, whereas the progress in this field has applications in various fields, as motor behavior and rehabilitation, assistive and prosthetic technology, and robotic control[3]. In this sense, muscle synergies represent a feasible, likely control strategy for musculoskeletal modeling. For predicting movements, the number of muscles may be reduced from to the number of muscle synergies, particularly in the search for feasible, rather than optimal recruitment patterns[4], which is the case of the impaired upper extremity due to CNS damage.

Cluster analysis of pooled muscle synergies confirmed that, after mild and moderate stroke, a correlation between the shoulder synergies alteration and the impairment in isometric force generation had been established in an impairment level-dependent manner[5].

There are only a few works that address the upper limb (UL) muscle synergies modifications after cervical spinal cord injury and their physiological significance.

The objective of the present work is to describe the UL muscle synergy profile in subacute and chronic cervical SCI patients during the activity of daily living (ADL) of drinking.

II. MATERIAL AND METHODS

A total of 18 subjects divided into three groups participated in the study: a healthy group (n=7) and two groups of patients with cervical SCI with C6 (n=7) and C7

metameric level (n=4). All participants were right handed and performed the activity with the right arm and fulfilled the following inclusion criteria: age 16 to 65 years, at least 6 months from the injury onset, and level of injury C6 or C7 classified according to the American Spinal Injury Association (ASIA) scale into grades A or B[6]. Surface electromyography (EMG) was recorded using an EMG recording system (Noraxon, Scottdale, Arizona, USA) at a sample frequency of 1500Hz, synchronized online with the photogrammetry system. Bipolar-type, self-adhesive and disposable Ag/AgCl surface electrodes were used. Surface electrodes were positioned on the following nine muscles: upper trapezius (UT), posterior deltoid (PD), middle deltoid (MD), anterior deltoid (AD), pectoralis major (PM), biceps brachium (BB), triceps brachium (TB), wrist extensor (WE) and wrist flexor (WF). The reference electrode was placed on the C7 spinous process. A more accurate description of data adquisition and experimental procedures can be found elsewhere[7]. Muscle synergies were extracted from sEMG signal using a non-negative matrix factorialization algorithm. The Kruskal-Wallis test was applied to find possible differences between groups.

III. RESULTS

When compared with healthy people, the right upper limb (UL) of either C6 or C7 SCI patients showed a statistically significant increment in the number of muscle synergies [3,00 (1,00)[a] in healthy patients versus 4,00(2,00) in C6 SCI patients and 4,00(1,00)[a] in C7 SCI patients) during ADL of drinking (Fig. 1).

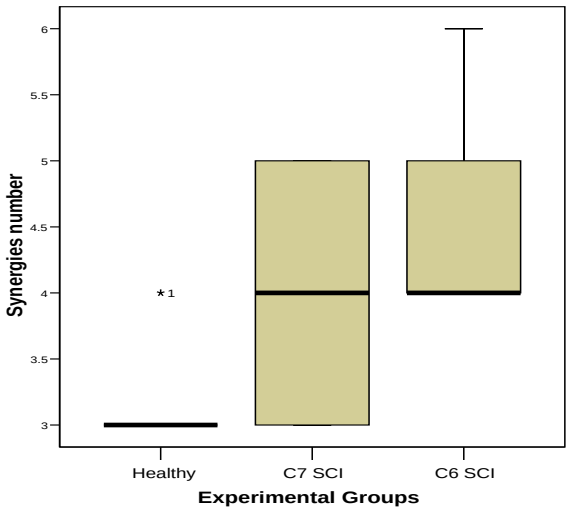

Fig. 1: Number of Muscle Synergies in the three experimental groups. *p<0,05.

With respect to the VAF, no differences were found in the right arm performance of the ADL of drinking, [VAF=0,96(0,02) in healthy patients versus VAF=0,95(0,03) in C6 SCI and VAF=0,96(0,03)in C7 SCI patients]. These results are summarized below in Table I.

TABLE .I
MUSCLE SYNERGIES ANALYSIS

	Healthy	C7 SCI	C6 SCI
Number of Synergies	3,00 (1,00)[a]	4,00 (1,00)[a]	4,00 (2,00)
VAF	0,96 (0,02)	0,96 (0,03)	0,95 (0,03)

[a]p<0,05

IV. DISCUSSION

In the present study, we analyzed the upper limb muscle synergies in healthy an C6 and C7 motor complete tetraplegic patients during the ADL of drinking. The ADL of drinking is particularly suitable for analyzing pathological patterns because it requires UL coordination and control but its execution doesn't require maximal forces.

We found a significant higher number of muscle synergies between C6 and C7 tetraplegic than in healthy subjets. Interestingly, whereas the synergy patterns among the normal subjets were quite fixed, SCI patients showed evident variability. The higher the lesion (C6 in front of C7) the greater the variability was, though a larger morphological and functional spinal damage was expected. Our data are in agreement with other previous works, suggesting that the disruptions and reorganizations of neural circuitry after SCI are reflected by the muscle synergies analysis[8].

V. CONCLUSION

This study provides new evidences about the potential of muscle synergies analysis to detect changes during upper limb motor behaviour after a cervical SCI. This tool could be useful to guide therapeutic interventions and clinical follow up.

REFERENCES

[1] M. COSCIA, V. MONACO, CH.MARTELLONI, B. ROSSI, C. CHISARI and S. MICERA. Muscle synergies and spinal maps are sensitive to the asymmetry induced by a unilateral stroke. J NeuroEngineering and Rehabilitation (2015) 12:39

[2] S. PÉREZ-NOMBELA, F. BARROSO, D. TORRICELLI, A. DE LOS REYES-GUZMÁN, A.J. DEL AMA, J. GÓMEZ-SORIANO, J.L. PONS and A. GIL-AGUDO. Modular control of gait after incomplete spinal cord injury: differences between sides. Spinal Cord, 2017, 55:79-86.

[3] M.K. BURNS, V PATEL, I FLORESCU, K.V. POCHIRAJU and R.VINJAMURI. Low-Dimensional Synergistic Representation of Bilateral Reaching Movements. Front. Bioeng. Biotechnol. 2017, 5:2-15.

[4] L.H. TING, S.A. CHVATAL, S.A. SAFAVYNIA and J. LUCAS MCKAY. Review and Perspective: Neuromechanical considerations for predicting muscle activation patterns for movement. Int J Numer Method Biomed Eng. 2012, 28(10): 1003-14.

[5] J. ROH, W.Z. RYMER and R.F. BEER. Evidence for altered upper extremity muscle synergies in chronic stroke survivors with mild and moderate impairments. Frontiers in Human Neuroscience, 2015, 9:6.

[6] S.C. KIRSHBLUM, S.P. BURNS, F. BIERING-SORENSEN, W. DONOVAN, D.E. GRAVES, A. JHA, et al. International standards for neurological classification of spinal cord injury (revised 2011). J Spinal Cord Med. 2011; 34: 535- 546.

[7] A. DE LOS REYES-GUZMÁN, E. LÓPEZ-DOLADO, V. LOZANO-BERRIO, S. PÉREZ-NOMBELA, D. TORRICELLI, J.L. PONS and A. GIL-AGUDO. Upper Limb Electromyographic Analysis Synchronized with Kinematics in Cervical Spinal Cord Injured Patients during the Activity of Daily Living of Drinking. *JSM Physical Med Rehabil. 2017, 1(1): 1004.*

[8] J. ZARIFFA, J. STEEVES and D.K. PAI. Changes in hand muscle synergies in subjects with spinal cord injury: Characterization and functional implications. *J Spinal Cord Medicine, 2012, 35 (5):310-18.*

Wearable Haptics: Towards a Novel Paradigm of Human-Robot Communication for Assistive and Rehabilitation Robotics

Simone Fani, Simone Ciotti, Manuel G. Catalano, and Matteo Bianchi

***Abstract*— Wearable haptic systems represent a new category of devices that can be easily worn by users and integrated in their everyday-life. The interest on such devices has increased in recent years, as they enable a more natural and effective human robot interaction. In this work, we present a device, namely the CUFF, able to provide both normal and tangential force cues. Here we describe the main features of the system and its psycho-physical characterization. Applications in prosthetics and rehabilitation robotics are finally discussed.**

I. Introduction

HAPTIC devices can be very useful in increasing the acceptance of prosthetic devices. In this work, we propose and study a new device able to generate different cues on the user's arm. These cues can be used to provide different types of feedback for prosthetic devices. Thanks to its versatility, the device can be potentially used in other applications such as rehabilitation systems.

II. The CUFF device

The Clenching Upper-limb Force Feedback (CUFF) device (Fig. 1) is a wearable haptic device capable of generating two different, independent stimuli on the user's arm [1].

A. Mechanical Structure

The CUFF is composed by three main subsystems: the structural frame, the mechanical actuation unit and the feedback interface. For a detailed description please refer to [1].

The structural frame works as main body of the device and permits to fix all the other components such as the control board and the actuation units and the device on the user's arm through two Velcro stripes.

The two actuation units (powered by DC motors) are specular and connected to the main frame with the rotation axis parallel between them and to the arm axis. A cylinder, the rotating part, is placed around the inner frame and fixed with the motor shaft. Each actuation unit is sensorized with a magnetic encoder.

This work is supported in part by the EU H2020 project "SoftPro: Synergy-based Open-source Foundations and Technologies for Prosthetics and RehabilitatiOn" (H2020-ICT-688857), the Advanced Grant SoftHands "A Theory of Soft Synergies for a New Generation of Artificial Hands" no. ERC-291166, and by the EU FP7 project (no. 601165), "WEARable HAPtics for Humans and Robots (WEARHAP)".

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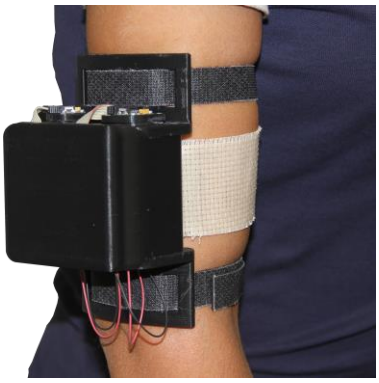

Fig. 1. The CUFF Device applied on a subject's arm (a) and the two applications (b): from the top the use as assistive device for blind people, and rehabilitation device.

Rotating the two motors accordingly, a sliding of the fabric on the arm is generated. If the two motors are rotated in opposite directions, the fabric is stretched or released generating a change in normal force on the arm (see Fig. 2).

The fabric belt is fixed on the rotating cylinder and works as feedback interface. It is a band of non-elastic fabric covered with a biocompatible silicone layer to increase friction.

B. Characterization

The device has been characterized to measure the applied forces on the user. The goal of the characterization was to obtain a relation between motor positions and the normal force exerted by the fabric belt on the arm.

We found that the function that provides the best fit for the dataset is a 3rd order polynomial function

$$P_D = f(F_D) = 0.1138F_D^3 - 5.204F_D^2 + 89.22F_D$$

where P_D is the motor position and F_D the force (Adjusted R-square of 0.9335). This curve have been validated with a second series of experiments obtaining a RMSE between theoretical force values and measured ones of 1.32N.

III. Psychophysical experiments

We used the method of constant stimuli to find the just noticeable difference (JND) of the normal force and tangential displacement perceived by subjects using the CUFF considering the two operating modes of the device, as in Fig. 2.

A. Material and Methods

Paired stimuli were presented to the participants and they were asked to indicate which stimulus in the pair produces a higher normal force or larger tangential displacement.

Normal force, right displacement and left displacement were tested in separate sub-experiments.

Each pair consisted of a reference stimulus (RS) and a comparison stimulus (CS), presented in a random order. We used five and equally spaced stimuli: 3, 6, 9, 12, 15 N (RS 9 N) for the normal force, and 5.97, 11.94, 17.91, 23.88, 29.85 mm (RS 17.91 mm) for the tangential displacement.

Before the experiment, the CUFF was applied to the subject's arm ant the auto-adjustment was performed. The participants wore headphones with white noise to prevent auditory cues. They were asked to not look at the CUFF during all the experiment.

Fig. 2. Scheme of an arm, in section, with a distribution of normal pressure (left) and a distribution of tangential stress (right).

B. Data Analysis

We modeled the responses of each volunteer using the psychometric function

$$\Phi^{-1}\left[P\left(Y_j = 1\right)\right] \sim \beta_0 + \beta_1 x_j$$

where [P(Yj=1)] is the probability that, in trial j, the participant reported a larger stimulus in the comparison than in the reference stimulus, Φ^{-1} is the probit transformation of the response probability, and x_j is the value of the comparison stimulus.

We extended the psychometrics function to all the participants by means of Generalized Linear Mixed Model (GLMM) [2], which enables to consider the analysis of clustered data.

For each experimental condition, we estimated the Just Noticeable Difference (JND), i.e. the amount of stimulus change in order for a difference to be noticeable, and the Point of Subjective Equality (PSE), i.e. the stimulus value yielding a response probability of 0.5.

C. Results

Eleven right handed healthy participants (7 Female, Age mean±SD: 26.64±8.86) gave their informed consent to participate to the experiment. No one had any physical limitation which would have affected the experimental outcomes.

For the normal forces task, we found that the PSE was 9.75N, while the JND was 2.21N.

For the normal displacement task, we found that PSE values for left and right stimuli were 18.27mm and 17.42mm, respectively, while the JND were 2.69mm and 2.91mm respectively.

IV. Applications

A. Prosthetics

The CUFF was originally ideated as grasping force feedback system for prosthetic hands. The device has been used in combination with the prosthetic version of the Pisa/IIT SoftHand [3].

The grasping force can be estimated analyzing the currents absorbed by the motor of the SoftHand [1]. The difference between the current absorbed during environment interactions and the one estimated during free space movement is mapped into the CUFF as positions commands for the two motors. Since the goal is to provide a force feedback, the two motors are moved in opposite directions to provide a normal force.

Another possible application can be as proprioception feedback on the hand closure. Mapping the SoftHand position onto the position of the two motors, it could be possible to give a displacement proportional to the opening of the hand. In this application, the two motors move in the same direction. We are focusing on the comparison between linear and logarithmic mapping.

Since the two motors can be independently controlled, it could be possible to map both grasping force and proprioception on the CUFF. Experiments need to be performed to study the effectiveness of this combined application.

B. Rehabilitation

In the last months, a new application idea was developed. The CUFF has been integrated in a rehabilitation system for the wrist, the Rice University OpenWrist exoskeleton (in [4] a previous version of the exoskeleton). In this system the CUFF is used to guide the user in the rehabilitation process, correcting the movements and bringing the user on the correct movements path.

The point of this integration is that conveying haptic cues for guidance separated from haptic feedback of task dynamics can ensure effective skill transfer from the training environment to the real-world tasks.

V. Conclusion

In this work we showed how it is possible to use the CUFF in different applications, as feedback system for prosthetic devices and as guidance system for rehabilitation systems. Further investigation need to be performed to verify if the device can be used in its fully potential, but the results up to here obtained seems to be positive and promising.

Acknowledgment

Authors would like to thank Simone Ciotti, Federica Barontini, Federica Felici, Giuseppe Averta for their valuable advice and their support in the experimental sessions.

References

[1] Casini, S., Morvidoni, M., Bianchi, M., Catalano, M., Grioli, G. and Bicchi, A., 2015, September. Design and realization of the CUFF-clenching upper-limb force feedback wearable device for distributed mechano-tactile stimulation of normal and tangential skin forces. In Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on (pp. 1186-1193). IEEE.

[2] Moscatelli, A., Mezzetti, M. and Lacquaniti, F., 2012. Modeling psychophysical data at the population-level: the generalized linear mixed model. Journal of vision, 12(11), pp.26-26.

[3] Catalano, M.G., Grioli, G., Farnioli, E., Serio, A., Piazza, C. and Bicchi, A., 2014. Adaptive synergies for the design and control of the Pisa/IIT SoftHand. The International Journal of Robotics Research, 33(5), pp.768-782.

[4] French, J.A., Rose, C.G. and O'malley, M.K., 2014, October. System characterization of MAHI Exo-II: a robotic exoskeleton for upper extremity rehabilitation. In ASME 2014 Dynamic Systems and Control Conference (pp. V003T43A006-V003T43A006). American Society of Mechanical Engineers.

Influence of myoelectric control on finger muscle activation patterns

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***Abstract*—Myoelectric systems allowing for single finger control are used in order to mimic the dexterity of the human hand. The control accuracy of these interfaces is generally tested through offline analysis, even though online testing would be closer to the user's reality. The advantage of online control is the ability of the user to profit from visual feedback. This results in a continuous, closed sensorimotor loop, allowing the subjects to adapt their control strategy during the movement execution. In this case study of a subject trained on single finger movements suggests that people are able to leverage on this while performing combined finger movements. We further investigated the change in motor control by comparing the muscle maps between force and myoelectric controlled movements.**

I. Introduction

In order to mimic the dexterity of the human hand, modern prostheses allow control of individual fingers. Studies including both offline and online single finger control show a similar accuracy for both control scenarios [1], [2]. However, proportional and simultaneous control of individual fingers using myoelectric signals is still to be achieved. For practical application, it is important to minimize the amount of calibration data. The aim of the present study was to test the feasibility of estimating finger forces during both single and combined finger movements using a training set of only single finger movements.

II. Material and Methods

A. Subjects

The preliminary data of this study comes from one healthy right-handed female subject who has no history of neurological disorders.

B. Experimental setup

The index, middle, ring, and little finger of the right hand were loosely placed on top of four individual force sensors (Micro Load Cell CZL635, Phidgets Inc, Calgary, Canada). The placement of the force sensors was adjusted both in the direction of the length and width of the finger and the subject adopted a comfortable position with the elbow in a 90° angle. Finger forces were sampled and transmitted to a host PC running a custom made script in Matlab version 2015b (The Math Works Inc., Massachusetts, United States).

Monopolar high density electromyography (EMG) signals were recorded using 2 8x8 electrode grids with 10mm inter-electrode distance (ELSCH064NM3, OT Bioelettronica, Italy). The electrode grids were positioned lengthwise at the middle of the forearm, and ran from the ulnar bone to the anterior part of the forearm. This placement allowed for the measurement of the muscle bellies of the flexor digitorum superficialis (FDS) as shown in [3] and [4]. The EMG signals were amplified using EMG-USB2 OT Bioelettronica amplifiers, and sampled at 2048Hz. The signals were band-pass filtered at 3-900Hz before being transmitted to the host computer. A reference electrode was placed on the wrist bone.

C. Experimental protocol

The instructions and visual feedback of the different tasks were presented to the subjects on a 26 inch LCD screen. The feedback consisted of four bars, each associated with one of the fingers, filling the screen from top to bottom when the subject applied force to the force sensors.

First, the subject performed a maximum voluntary long-term contraction (MVLC) trial for each finger, which allowed for normalization throughout the rest of the experiment.

Second, the participants performed a set of movements that were used as training data for the linear regressors of the online experiment. Here, they executed 3 trials of single finger movements with each of the 4 instructed fingers. Each trial consisted of an instruction phase, a one second pause, and then a trapezoidal force pattern with 1 second slopes and a 5 second plateau, with that plateau reaching 25% MVLC.

After the execution of the training protocol, a linear regressor with Ridge regularization was trained on the data. For this, the EMG signals were band-pass (20 – 450Hz, 4th order Butterworth filter) and notch filtered (50Hz, 2nd order Butterworth filter), the data was visually cleaned from artefacts, and noisy channels were deleted. Next, the root mean square (RMS) value of 200ms bins with 100ms overlap was calculated for each channel, resulting in a 10Hz signal. The linear regression was based on the obtained signal, and the normalized version of the forces. In order to determine the regularization term lambda, a 3 fold cross-validation based on the trials was used. Finally, the regressors were determined using all of the training data, and the selected lambda. The third part consisted out of a target hitting task. This was repeated with both force and EMG control. In either of the cases, the trials were comprised of 10 repetitions of the 4 single finger movements, and the 6 possible 2-finger

Supported by the European Union Program FP7-PEOPLE-2013-IGN 'HealthPac', grant 604062 – IDP SD

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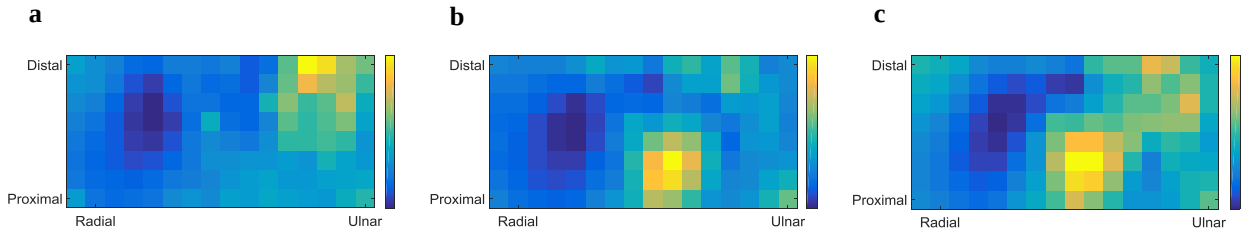

Fig. 1. Activity maps for activity on all 128 EMG channels during movements of the middle finger (a), the ring finger (b), and the combination middle - ring (c).

combinations (2-3, 2-4, 2-5, 3-4, 3-5, 4-5). In order to hit the target, the subjects had to reach between 20-30% MVLC with the instructed fingers, and keep the non-instructed fingers' activation below 10% MVLC. The subjects had to stay in the target range for 0.5sec, and had 15sec to complete the trial. The provided feedback was either the actual forces, or the estimated forces by the linear regression based on the RMS value of 200ms EMG windows, again calculated with a 100ms overlap.

D. Data analysis

During the target hitting task, hit rate, completion time, EMG, and the actual forces were recorded. In order to investigate the motor control properties behind these different tasks, we determined the dissimilarity matrix of pairwise combinations of muscle maps. As a measure of dissimilarity we used 1 – the spearman rank correlation. The muscle maps were determined 250ms before the end of the trial. As we only have 1 subject, no statistics was performed on the data.

III. Results

The hit rate and completion times for the different control strategies and finger movements can be found in table 1. The completion times only include the successful trials. The completion rate in the EMG controlled combined finger movements was dependent on the combinations, where some (e.g. 34) had a 100% hit rate, while others (e.g. 35) had a 0% hit rate.

Fig. 1 shows muscle maps of single finger movements 3 and 4, and the combination 3-4. These maps suggest that for some combinations, linear regression is a sensible way in order to predict combined finger movements that were trained on single finger data.

In order to quantify the similarities between muscle maps, the pairwise distance between all performed trials is shown in fig. 2. The trials along the diagonal demonstrate that the within-movement distance is significantly smaller than the between-movement (0.11 ± 0.08, 0.35 ± 0.20 respectively, $p < 0.001$). Further investigation into the completed trials shows that the Pearson distance between the combined finger movement map, and the maps of the single finger movements included in the combination is lower than the maps of those not represented in the movement (see Fig. 2b).

TABLE I
RESULTS ONLINE TASK

Control strategy, finger movement	Completion rate (%)	Completion time (sec, mean ± std)
Force control, single finger	100	1.21 ± 0.30
Force control, combined fingers	100	1.41 ± 0.54
EMG control, single finger	90	3.62 ± 1.93
EMG control, combined fingers	40	8.89 ± 5.97

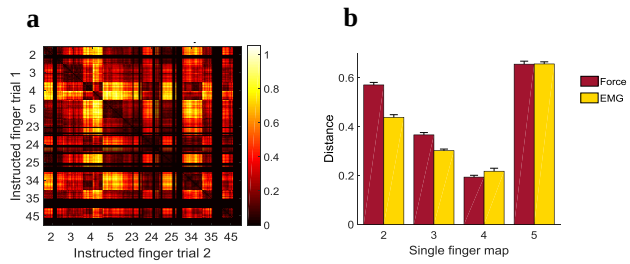

Fig. 2.(a) Pairwise distance between all performed online trials. Failed trials are presented in black. (b) Distance from the muscle map of movement 34 to the different single finger muscle maps.

IV. Discussion

This preliminary study shows that online myoelectric control based on linear regression is possible for both single and combined movements, even if the regressor is trained on only single finger data. The observation during EMG controlled trials that combination movements were either easy to perform, or very hard suggests a non-linear factor might be involved in the neural control of the latter category. However, it is noteworthy that our two subjects had problems executing different combination movements, suggesting that the neural control of complex finger movements is subject-specific. Further research will be necessary to determine which factors determine the linearity of finger combinations.

References

[1] R. N. Khushaba, S. Kodagoda, M. Takruri, and G. Dissanayake, "Expert Systems with Applications Toward improved control of prosthetic fingers using surface electromyogram (EMG) signals," *Expert Syst. Appl.*, vol. 39, no. 12, pp. 10731–10738, 2012.

[2] N. Celadon, S. Došen, I. Binder, P. Ariano, and D. Farina, "Proportional estimation of finger movements from high-density surface electromyography," *J. Neuroeng. Rehabil.*, vol. 13, no. 1, p. 73, 2016.

[3] L. Bickerton, A. Agur, and P. Ashby, "FLEXOR DIGITORUM SUPERFICIALIS : LOCATIONS OF INDIVIDUAL MUSCLE BELLIES FOR BOTULINUM TOXIN INJECTIONS," *Muscle and Nerve*, vol. 20, no. August, pp. 1041–1043, 1997.

[4] M. K. Henzel, M. C. Munin, C. Niyonkuru, E. R. Skidmore, D. J. Weber, and R. D. Zafonte, "Comparison of Surface and Ultrasound Localization to Identify Forearm Flexor Muscles for Botulinum Toxin Injections," *PMRJ*, vol. 2, no. 7, pp. 642–646, 2010.

Effects of Wrist Robot-assisted Rehabilitation on Proximal Upper Limb Segments Recovery in Subacute Stroke Patients: A Preliminary Results

Vi-Do Tran, Paolo Dario, and Stefano Mazzoleni

Abstract—**The study is designed to evaluate the effects of wrist robot-assisted rehabilitation on proximal upper limb recovery in subacute stroke patients. Ten (n=10) subacute stroke subjects were enrolled, they were asked to perform training with InMotion Wrist robotic system. After treatment a decrease in impairment (wrist, shoulder-elbow and upper extremity subsection of FM showed improvements) and increase in motor performance was found. Wrist robot-assisted rehabilitation is effective to reduce motor impairment in subacute stroke patients. The results support the hypothesis that distal-proximal generalization is possible in subacute stroke patient.**

I. Introduction

THE recovery of upper limb represents an important objective in stroke rehabilitation, which contributes to enhancing the quality of life of stroke survivors. In recent years, robot-assisted rehabilitation has been used in order to provide an effective treatment for the patient [1], [2].

Integration of distal (wrist) and proximal arm (shoulder/elbow) training has been demonstrated as an essential to enhance upper limb motor recovery [3], [4]. Training both arm and hand together may provide greater improvement in chronic and subacute stroke patients [5], [6]. However, the role of distal training only on proximal segments still has to be investigated.

Combined distal and proximal training did not show any advantages on the proximal segment in comparison with proximal training only in chronic stroke patients [7]. However, results from the previous study suggested that improvement in more distal segments continues significantly even without further training for that limb segment [8]. Clinical trials are needed in order to better clarify the effects of distal robot-assisted training on proximal upper limb segments in subacute stroke patients.

The main aim of this study is to evaluate the preliminary results of wrist robot-assisted rehabilitation on proximal upper-limb segments recovery in subacute post-stroke patients. The clinical outcome measures and kinematic parameter were used for recovery assessments.

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II. Methods

A. Participants

Ten subacute stroke subjects, nine men and one woman, age range 64-85 (mean age 73.4 ± 7.3 years old), 4 with right hemiparesis and 6 with left hemiparesis were recruited for this study.

The level of the upper limb impairment for each stroke patient at admission was evaluated using the "Stage of Arm" section of the Chedoke-McMaster (CM) Stroke Assessment Scale. The subjects had a CM score of 5.50 ± 0.71 (range from 2 to 6).

The experimental clinical trial was performed at the Neurological Rehabilitation, Auxilium Vitae Rehabilitation Centre, Volterra, Italy.

B. Intervention

The patients performed training with InMotion Wrist robot (Interactive Motion Technologies, Inc., Cambridge, MA, USA). In order to avoid torso compensations during training the patient is seated on a chair provided with seat belts limiting the trunk movements.

Each patient was asked to perform five sessions per week, each session lasted 30 minutes, for 6 weeks of goal-directed planar reaching tasks moving from the centre to each of 8 peripheral targets, which emphasized wrist abduction-adduction, flexion-extension and pronation-supination movement.

C. Clinical outcome measures and kinematic parameters

Clinical scales were used to evaluate upper limb before (Pre-treatment) and after (Post-treatment) the robotic therapy. The clinical outcome measures used in this study were the upper extremity (FM/ue, maximum score = 66), the shoulder-elbow (FM/se, maximum score = 36) and the wrist (FM/w, maximum score = 10) subsections of the Fugl-Meyer Assessment Scale[9].

To evaluate motor performance improvement, data recorded by the robotic system was analyzed. The normalized jerk (NJ), an unit-free metric, was calculated to assess the smoothness of wrist movements. The smaller value of this index represents the smoother movement.

$$NJ = \sqrt{\frac{1}{2}\int J^2 dt * \left(\frac{duration^5}{length^2}\right)} \quad (1)$$

where J is the movement jerk which is the third time derivative of the position vector.

Since North toward (Abduction) is the most difficult task, the robot data analysis was implemented considering this direction. Data processing of kinematic parameters were performed using custom routines developed under Matlab environment (MATLAB, The MathWorks, Inc., Natick, Massachusetts, United States).

III. Results

The values of clinical outcome measures before and after therapy are shown in Table I. Statistically significant improvements in the FM/ue, the FM/se and the FM/w were observed. After training the score of the FM/w increased 2.2 points, the FM/se and FM/ue increased 5.6 and 17.5 points respectively.

TABLE I
PRE- AND POST- TREATMENT VALUES OF CLINICAL OUTCOME MEASURES

	PRE (mean ± SD)	POST (mean ± SD)	Change (mean ± SD)	p
FM/w	6.2 ± 2.1	8.4 ± 1.5	2.2 ± 1.8	0.015
FM/se	25.1 ± 4.8	30.7 ± 3.7	5.6 ± 5.8	0.009
FM/ue	40.0 ± 11.3	57.5 ± 6.6	17.5 ± 11.7	<0.001

The normalized jerk in the North toward direction was decreased in all wrist movement components, significant changes were found in abduction/adduction and flexion/extension. The smoothness improvement of wrist movement was represented by the decrement in normalized jerk metric.

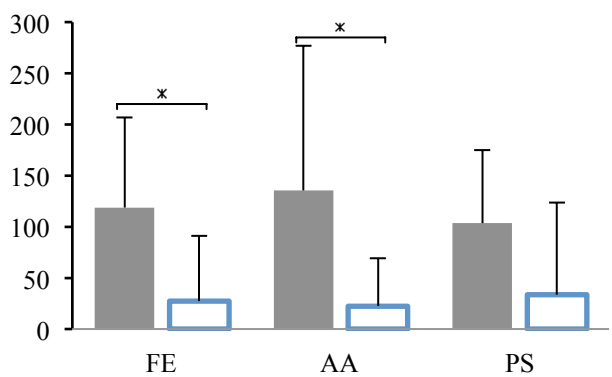

Fig. 1. Normalized jerk on North toward direction at pre- (black) and post- (white) treatment, in flexion/extension (FE), abduction/adduction (AA) and pronation/supination (PS) wrist movements (* indicates p<0.05).

The results from kinematics parameter based on the normalized jerk showed improvements in motor performance, significant changes were observed in the selected direction.

IV. Discussion and Conclusion

Based on the results from the analysis on clinical scales and kinematic parameter, subacute stroke patients may benefit from wrist robot-assisted training. These results provide evidence to demonstrate that robot-assisted rehabilitation provides safe and effective treatment to the patients.

The normalized jerk metric decreased in the selected direction showed the increase in motor performance of patients after therapy. The kinematic parameter confirmed the result of the treatment which was represented by the clinical outcome measures. This is suggested that kinematic parameter should be analyzed and be used as a secondary assessment method following robot-assisted training.

The results from the previous study suggested that a distal-proximal generalization is not possible in chronic stroke patient [7]. The result in this study showed that the FM/ue significant increased after therapy (p<0.001) and achieved the minimal clinically important difference (MCID) score [10] for the upper extremity motor recovery for subacute patients even when the patients only received the wrist training only.

Our preliminary results provide the evidence to support the hypothesis that proximal upper-limb segments recovery can be achieved from distal training. Further studies including a larger pool of patients are needed to verify this.

References

[1] J. Hidler, D. Nichols, M. Pelliccio, and K. Brady, "Advances in the understanding and treatment of stroke impairment using robotic devices.," *Top. Stroke Rehabil.*, vol. 12, no. 2, pp. 22–35, 2005.

[2] S. Mazzoleni, R. Crecchi, F. Posteraro, and M. C. Carrozza, "Effects of robot-assisted wrist therapy in chronic stroke patients: a kinematic approach," *Proc. 4th IEEE RAS/EMBS Int. Conf. Biomed. Robot. Biomechatronics*, pp. 1978–1982, 2012.

[3] A. Basteris, S. M. Nijenhuis, A. H. A. Stienen, J. H. Buurke, G. B. Prange, and F. Amirabdollahian, "Training modalities in robot-mediated upper limb rehabilitation in stroke : a framework for classification based on a systematic review," *J. Neuroeng. Rehabil.*, vol. 11, no. 111, pp. 1–15, 2014.

[4] L. Oujamaa, I. Relave, J. Froger, D. Mottet, and J. Y. Pelissier, "Rehabilitation of arm function after stroke. Literature review," *Ann Phys Rehabil Med*, vol. 52, pp. 269–293, 2009.

[5] A. S. Merians, E. Tunik, and G. G. Fluet, "Innovative approaches to the rehabilitation of upper extremity hemiparesis using virtual environments.," *Eur J Phys Rehabil Med*, vol. 45, no. 1, pp. 123–133, 2009.

[6] R. C. V Loureiro, W. S. Harwin, R. Lamperd, and C. Collin, "Evaluation of reach and grasp robot-assisted therapy suggests similar functional recovery patterns on proximal and distal arm segments in sub-acute Hemiplegia," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 3, pp. 593–602, 2014.

[7] S. Mazzoleni, P. Sale, M. Franceschini, S. Bigazzi, M. C. Carrozza, P. Dario, and F. Posteraro, "Effects of proximal and distal robot-assisted upper limb rehabilitation on chronic stroke recovery," *NeuroRehabilitation*, vol. 33, no. 1, pp. 33–39, 2013.

[8] H. I. Krebs, B. T. Volpe, D. Williams, J. Celestino, S. K. Charles, D. Lynch, and N. Hogan, "Robot-aided neurorehabilitation: A robot for wrist rehabilitation," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 15, no. 1, pp. 327–335, 2007.

[9] A. R. Fugl-Meyer, L. Jääskö, I. Leyman, S. Olsson, and S. Steglind, "The post-stroke hemiplegic patient. 1. a method for evaluation of physical performance," *Scand. J. Rehabil. Med.*, vol. 7, no. 1, p. 13—31, 1975.

[10] K. Narayan Arya, R. Verma, and R. K. Garg, "Estimating the Minimal Clinically Important Difference of an Upper Extremity Recovery Measure in Subacute Stroke Patients," *Top. Stroke Rehabil.*, vol. 18, no. sup1, pp. 599–610, 2011.

EMG based control for elbow joint SMA exoskeleton

Dorin Copaci, David Serrano, Luis Moreno and Dolores Blanco

***Abstract*— A wearable elbow exoskeleton with two degrees of freedom (DOF), actuated with Shape Memory Alloy (SMA) was presented in the past publication (Copaci et al., ICNR2016). This paper presents high level control of the exoskeleton based on surface electromyography (sEMG) signals, for active rehabilitation therapies. The algorithm is capable to generate the reference pattern in two modes: in position and torque, from the biomechanical parameters such a weight and height of the human body. In the two modes before position and torque estimation, the sEMG signals are filtered and normalized and offer the possibility to be combined with the pressure sensors for precise movement intention detection. The preliminary results are obtained over simulations and real tests with the elbow exoskeleton in flexion-extension.**

I. INTRODUCTION

In previews publications, it was presented a wearable SMA exoskeleton with two DOF (for flexion-extension and pronation-supination), actuated with SMAs. In these works, the control algorithm gives the possibility to control the exoskeleton with passive references: only actuating in flexion and recuperating (extension movement) with the aid gravity force [1], and in flexion-extension actuating with two SMAs based actuators in flexion and extension [2]. The reference pattern in these cases represent a repetitive movement (for example a sinusoidal trajectory) defined by the user, which make the rehabilitation passive.

Myoelectric signals (MES) contain information from where can be extracted data about user movement intention in terms of muscular contraction. This information can be detected using surface electrodes (sEMG) [4]. These signals were used in control of prosthetics and rehabilitation devices such a "on-off" control [6], proportional control in position or assistive torque [5], [7], and distinguish between different kind of motion [8], [9].

This paper presents an algorithm capable to generate the reference pattern in position and torque based on sEMG signals and pressures sensors for high level control SMA exoskeleton. The first part of the paper presents an introduction to the current problem, the second part presents the methodology, the third part presents the preliminary results and the last part presents a brief conclusions of this paper.

II. METHODOLOGY

This section present the algorithm used to generate the desired reference in position and torque based on sEMG signals and pressure sensors. The sEMG signals were captured at 1000 Hz frequency with a circuit made in Carlos III University of Madrid. These signals were preprocessed, firstly the raw EMG was filtered with high-pass filter using a zero-lag fourth-order recursive Butterworth filter to remove movement artifact, then full wave rectified, and after in the absolute value was filtered using a Butterworth low-pass filter to cut-off frequency. After this process the algorithm for online calibration override the first two seconds (where the used circuit perturbation happen) and use the next 18 seconds to detect the maximum signal for normalization process. In this time to the patient is required to flex maximum the forearm. The normalized signal, E_{norm}, was calculated with the equation 1:

$$E_{norm} = \frac{E_{act} - E_{min}}{E_{max} - E_{min}} \tag{1}$$

where E_{act} is the actual sEMG signal, E_{min} is the minimum value of the sEMG signal in the first 20 seconds and E_{max} is the maximum value of the sEMG signal in the first 20 seconds.

In order to generate the position reference pattern with a good precision, two types of signals have been used, the sEMG normalized signal and the pressure sensor signal. These two signals were logically compared to detect the intention of movement. The binary result in function of the actual position of the joint generate a position reference using two type of increment: one for fast actuation (used when the actual position of the elbow joint is different to the position of actuator reference) and another increment used to generate the reference pattern following the sEMG normalized signal over threshold value.

The torque reference pattern, is an assist torque for the rehabilitation therapy. In function of the biomechanical model of the human body, with the patient parameters such as weight and height, the necessary torque was calculated to flex the forearm in 90 degrees. In this process, the exoskeleton parameters were included. In function of these torques and the sEMG signal, a percentage of assistance in torque was generate. This is directly proportional with the sEMG signal.

III. PRELIMINARY RESULTS

A. Results in simulation

The first results of the two algorithms were tested in the simulation with the SMA actuator model presented in [3]. For the sEMG data acquisition, the electrodes was placed along the biceps muscle fibers and on the midline of the belly of the muscle, considering that are the sEMG signals with the greatest amplitude.

The research leading to these results has received funding from the RoboHealth (DPI2013-47944-C4-3-R) Spanish research project and from RoboCity2030-II-CM (Comunidad de Madrid) project.

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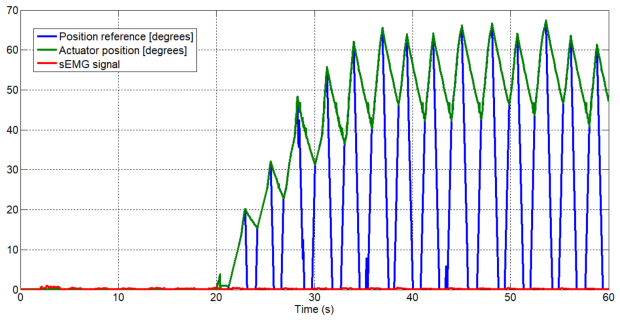

Fig. 1. The generated position reference by the sEmg signal in simulation.

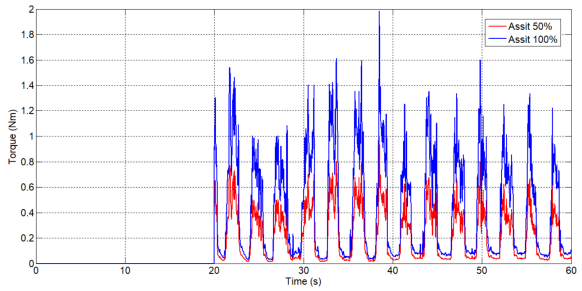

Fig. 2. The generated torque reference by the sEmg signal in simulation.

In Fig. 1 the generated reference in function of the sEMG signal in simulation is shown. Here the red signal is the sEMG signal normalized between 0 and 1. The position reference pattern was generated in function of this sEMG signal and the actual position of the actuator which coincide with the angular position of the SMA exoskeleton. The first $t = 20$ seconds was ignored for online calibration of the algorithm.

In the torque assist movement, the reference was generated in function of the biomechanical model of human body considering that the rehabilitation is executed standing or sitting, and in function of the sEMG signal placed over biceps muscle. A similar idea is presented in [5] but there, they do not take into account the biomechanical structure of the human body.

In Fig. 2 was presented the pattern reference in torque assist for one patient with 70Kg and 1.73 height in two cases: the exoskeleton assist the patient with the total torque, 100% (blue signal) and the exoskeleton assist with 50% of total torque (red signal).

B. Results with the real SMA exoskeleton

The EMG based control algorithm was tested in the real SMA based exoskeleton presented in [1] and [2] generating the position reference. This was tested with a healthy person of 1.73 height and 70 Kg weight. The results of the test can be seen in Fig. 3.

In Fig. 3 was presented the reference position signal (blue signal) generated by the sEMG signal (green signal) and the real position exoskeleton (red signal). In the first $t_c = 20 seconds$ the exoskeleton user calibrate the algorithm doing movements of flexion-extension of the elbow joint.

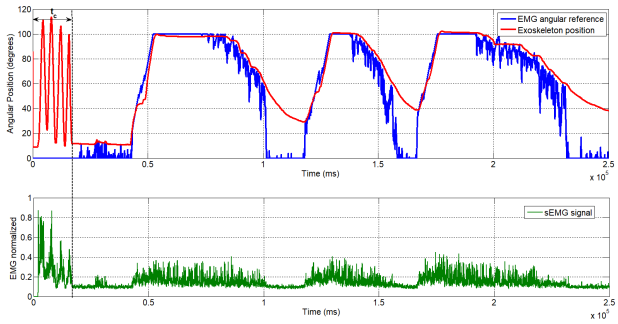

Fig. 3. Position reference and response generated by the sEMG signal

After calibration, when the algorithm detects the movement intention this start to generate the reference position for the control algorithm, which follows the reference with the exoskeleton.

In all these tests the pressure sensor signal missing and the variable algorithm of this was set to "active", which mean that the reference is generated only with the EMG signal. Inserting the pressure signal expect to increase the algorithm precision.

IV. CONCLUSIONS

This work presented an algorithm capable to generate the necessary position reference (or torque) for SMA exoskeleton in active rehabilitation therapies based in EMG signals. The algorithm is tested in the simulation and real applications with healthy people, generating the necessary position reference in function of the movement intention for the rehabilitation therapy.

REFERENCES

[1] D. Copaci, A. Flores, F. Rueda, I. Alguacil, D. Blanco, and L. Moreno. Wearable Elbow Exoskeleton Actuated with Shape Memory Alloy. In Converging Clinical and Engineering Research on Neurorehabilitation II (pp. 477-481) (2017). Springer International Publishing.

[2] D. Copaci, D. Blanco, and L. Moreno. Wearable elbow exoskeleton actuated with Shape Memory Alloy in antagonist movement. Joint Workshop on Wearable Robotics and Assistive Devices, International Conference on Intelligent Robots and Systems. IROS 2016, Daejeon, Korea; 10/2016.

[3] D. Copaci, A. Flores, A. Villoslada y D. Blanco. Modelado y Simulación de Actuadores SMA con Carga Variable. de XXXVI Jornadas de Automática - 2015, Bilbao, 2015.

[4] Mohammadreza Asghari Oskoei, Huosheng Hu, Myoelectric control systemsA survey, Biomedical Signal Processing and Control, Volume 2, Issue 4, 2007, Pages 275-294, ISSN 1746-8094, http://dx.doi.org/10.1016/j.bspc.2007.07.009.

[5] R. Song, K.-y. Tong, X. Hu y L. Li,.Assistive Control System Using Continuous Myoelectric Signal in Robot-Aided Arm Training for Patients After Stroke. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 16, no 4, 2008

[6] C. K. Battye, A. Nightingale, and J. Whillis. The use of myo-electric currents in the operation of prostheses, *J. Bone Joint Surg.*, vol. 37B, pp. 506510, 1955.

[7] A. H. Bottomley. Myo-electric control of powered prostheses. J. Bone Joint Surg., vol. 47B, pp. 411415, 1965.

[8] K. Englehart, B. Hudgins, and P. A. Parker. A wavelet-based continuous classification scheme for multifunction myoelectric control. *IEEE Trans. Biomed.* Eng., vol. 48, no. 3, pp. 302313, Mar. 2001.

[9] B. Hudgins, P. Parker, and R. Scott. A new strategy for multifunction myoelectric control. *IEEE Trans. Biomed.* Eng., vol. 40, no. 1, pp. 8294, Jan. 1993.

Natural management of assistive exoskeleton with crutches

M. Irene de Orbe, Luis J. Barrios, José L. Pons

Abstract— **Lower limb exoskeletons are widly used for rehabilitation and assistance when muscular activity in legs becomes reduced or null due to an accident or illness. The management of commercial exoskeletons is generally performed through wireless devices as remote control. Other approaches, more complex in terms of practicality, involve physiological signals such as EEG or EMG. The main goal of our project is to create a more practical operating interface that can be used in a continuous and natural way. In order to avoid wearing additional devices, our idea takes advantage of the crutches introduced in the system by the subject himself for his postural stability. Thus, our studies focus on recognising the movement intention of the patient by means of the gestures done with his upper limbs. Then, based on the needs of the subject expressed by the upper limbs, a suitable pattern of movement will be generated in the exoskeleton.**

I. Introduction

Lower limb exoskeletons are widely used for rehabilitation and assistance when muscular activity in legs becomes reduced or null due to an accident or illness. The management of outpatient commercial exoskeletons is generally performed through wireless devices as remote control. This is, a priori, a simple and easy handling solution for the subject. However, it imposes to be aware all the time of the movement you want to perform, stop and push a button. While this is not a restriction when standing up or sitting down, it decelerates very much the process of going up or down stairs for instance. Besides, during the walking, this kind of remote control does not allow a dynamic adaptation of speed or step length.

Other approaches involve physiological signals such as EEG or EMG. These may be faster giving orders of movement to the exoskeleton, but are much more complex in terms of practicality. Moreover, it may be challenging to register these physiological signals in patients with spinal cord injury or stroke ones.

This scenario leads to the main goal of our project: create a more practical operating interface that can be used in a continuous and natural way. In order to avoid wearing additional devices, our idea takes advantage of the crutches introduced in the system by the subject for his postural stability. Thus, our studies focus on recognising the movement intention of the patient by means of the gestures done with his upper limbs. Then, based on the needs of the subject expressed by his upper limbs, a suitable pattern of movement will be generated in the exoskeleton.

This research is supported by the grants DPI2014-58431-C4-1-R "A comprehensive and wearable robotics based approach to the rehabilitation and assistance to people with stroke and spinal cord injury" (ASSOCIATE), and DPI2015-69098-REDT "Thematic Network of Research on Neurotechnologies for the Assistance and Rehabilitation" (NEUROTEC), both funded by the Spanish Ministry of Economy and Competiveness.

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II. Material and Methods

A. The system

Our system is provided with a couple of instrumented crutches, in which tri-axial inertial sensors were attached. These inertial measurement units (IMU) are commercial (TECH IMU V.3 from Technaid S.L) but enough configurable for our needs. More precisely, we configured them to acquire data in physical units with a sampling frequency of 50 Hz.

After the acquisition phase, the posterior analysis and processing of the data from the IMUs was performed in MatLab.

B. Data analysis (offline)

The main variable to be measured from crutches is the angle to the vertical in the sagittal plane. Thus, to obtain the angular trajectory drawn by the crutches at any moment, the tri-axial accelerometer and gyroscope signals are merged and filtered with a complementary filter [1] as shown in Fig.1.

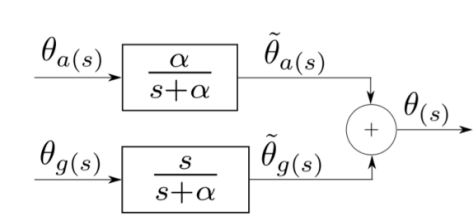

Fig.1. Complementary filter, where θ denotes the variable angle obtained through the accelerometer (subscript a) or the gyroscope (subscript g). α is related to the time constant of both the low-pass filter used for the accelerometer and the high-pass filter used for the angular rate.

To achieve our aim, we classified the process of movement into different states [2]: seated, walking, go up and down stairs and get up and down a ramp. All of them begin and end in a resting state (double stance).

To recognise then the user intention of enter in and exit from each state, we make use of the crutches. It is paramount to underline that the objective is to command the exoskeleton how to move, and not to react with the crutches to the movement of the device. That is, the patient controls the exoskeleton, and no the other way round. Hence, in all of

our experiments, subjects are asked to avoid movements with their lower limbs until they had performed the corresponding movement with the crutches. Furthermore, the gestures performed with the crutches may allow estimate several parameters of some states, such as the stride length, the slope of the ramp or the step height of the stairs.

We registered a test sequence of movements in a real scenario, starting with sitting down, continuing with standing up and ending with taking about five steps forward It is noteworthy that the walking pattern chosen for our study is the contralateral three-point stance phases [3]. Despite being the slowest walking pattern, it provides the subjects with more stability and security against falls.

III. Results

We analysed every gesture with the crutches performed by two healthy subjects during each test sequence of a set of 10. Once the movements are segmented, the main features of each different intention are obtained in an offline way. Consequently, a signal pattern is established for each intention (see Fig.2).

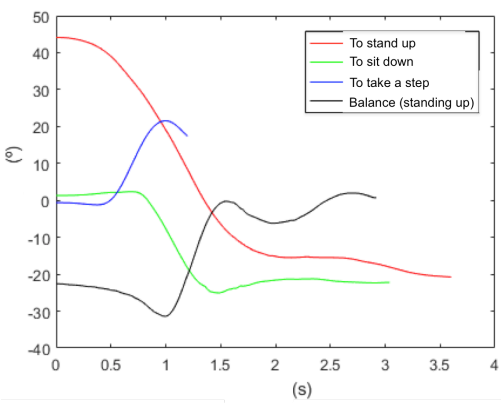

Fig.2. Patterns of movement of the crutches for different intentions. Notice that the balance condition is not an intention itself, but corresponds to a gesture performed during the standing up process that must be taken into account.

The next step was to distinguish each intention inside the sequence of movements, but this time in a semi-online mode. That is, to window the signals obtained from the IMUs as if it was a buffer where the real time samples were stored, and to slide the window iteratively through the whole already registered signal. We set the window length at 1 second and the sliding overlap at 25%.

Each window is processed individually to determine whether or not there is movement. This detection is carried out applying a threshold method to the feature signal magnitude area (SMA) [4].

Once activity is detected, the signal window at issue is compared against the patterns of movement above mentioned. This comparison is performed making use of the dynamic time warping (DTW) method, which relies on the concept of shape similarity between time series, with a specific accent on the robustness to time shifts, and speed variations [5]. The DTW technique leads to a metric of distance between series. Applying a threshold to the given estimation, we were able to classify real time movements into one (or none) of the gestures of the intentions considered.

In order to reduce the computational cost during the comparisons and thinking in terms of scalability, we implemented the state machine shown in Fig.3, so that the time series comparisons are carried out against a reduced group of patterns of movement depending on the currently state.

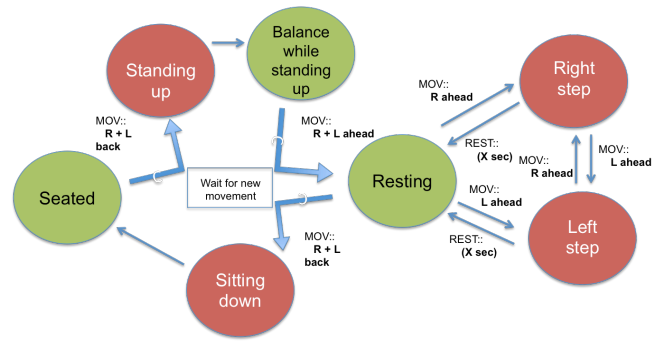

Fig. 3. State machine. Red states represent the intentions of movement to which exoskeleton must respond. The green ones do not imply any movement of the exoskeleton.

With this approach we were able to detect and classify correctly and in semi-real time the movements of the subject associated with the intentions taken into consideration in our experiments.

IV. Discussion and Conclusions

The results of this work suggest the possibility of detect the intention of movement of a patient through the gestures done with the crutches. However, more experiments with a greater amount of subjects should be carried out, altering the order of movements of the test sequence and including the stairs and ramps conditions.

This allows ambulatory clinical studies that can improve the management of assistance devices.

References

[1] Alonge, F., Cucco, E., D'Ippolito, F., & Pulizzotto, A. (2014). The use of accelerometers and gyroscopes to estimate hip and knee angles on gait analysis. Sensors, 14(5), 8430-8446.

[2] Strausser, K. A. (2011). Development of a human machine interface for a wearable exoskeleton for users with spinal cord injury.

[3] Bajd, T., & Kralj, A. (1991). Four-point walking patterns in paralyzed persons. BAM Basic and Applied Myology, 1, 95-100.

[4] Farkas, I., & Doran, E. (2011). Activity Recognition From Acceleration Data Collected With A Tri-Axial Accelerometer. Acta Technica Napocensis, 52(2), 38.

[5] Muscillo, R., Schmid, M., Conforto, S., & D'Alessio, T. (2011). Early recognition of upper limb motor tasks through accelerometers: real-time implementation of a DTW-based algorithm. Computers in biology and medicine, 41(3), 164-172

Brain machine interface and neuroprosthesis for lower limb functional rehabilitation: a corticospinal pathway study in healthy volunteers.

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Abstract— Brain machine interfaces can associate the user´s brain activity with any computer or machine. In healthcare research, devices like neuroprosthesis can be controlled by and linked to the user through these interfaces. Neurobiological data obtained from animal models and humans suggest the potential use of these associative interventions to rehabilitate the neural tissue after a stroke. Other studies indicate that, in healthy and human patients, the movement intention recorded by electro-encephalography precisely timed with functional electrical stimulation increases the excitability of the corticospinal tract as seen by motor evoked potentials.

With non-invasive stimulation techniques, we can now check neural changes in humans elicited by new approaches associating the movement intention with neuroprosthetics like functional electrical stimulation to rehabilitate the lower limb involving bilateral, functional and coordinated tasks. In our research we use these associative approaches in healthy volunteers, to test the improvements that will help stroke patients to regain walking gait in a functional way.

I. Introduction

PREVIOUS studies have shown the importance of accurate association in time of movement intention with peripheral stimulation with neuroprosthesis, emphasizing the need to establish a precise timing to generate changes in excitability of the corticospinal pathway following an associative intervention [1]. This type of associative interventions aims to link motor intention with the stimulation of the limbs to generate lasting physiological changes that could help in the rehabilitation of patients who, due to an acquired lesion, have lost their mobility [2]. In addition, it is true that these previous studies demonstrate the feasibility in this sense to increase the excitability of the projections to specific muscles, but to the knowledge of the authors, no one has managed to increase the bilateral excitability of different muscles involved in a functional task of the lower limb. Therefore, the following proposed study is oriented to apply a brain machine interface (BMI) that uses the movement intention taking as a control signal the Contingent negative variation (CNV) like the studies cited above in healthy subjects, but in this case employing a functional and bilateral task, such as cycling. At the same time, functional electrical stimulation (FES) [3] has been used as a neuroprosthesis for the treatment of stroke patients as a method to assist the pedalling task and to offer the volunteer both assistance and sensory afferents capable of generating changes in the central nervous system thanks to its association with the BMI. For this purpose, as in other studies, a feedback error learning controller (FEL) [4] has been implemented to apply the FES stimulation simultaneously to the pedalling task.

The objective of the present study is to verify if the functional electrical stimulation triggered by slow movement-related cortical potentials (CNV) by the use of a BMI generates changes in the corticospinal excitability of the lower limb in such a way as to aid the rehabilitation of patients with bilateral, distributed and functional stroke.

According to our starting hypothesis, since pedalling shares physiological mechanisms and anatomical structures with walking, thanks to the peripheral stimulation associated with the cortical activity of the motor cortex, it will be possible to increase the excitability of the corticospinal tract involved in the movement of the lower limb, helping the future rehabilitation of patients with stroke.

II. Material and Methods

A. Sample and ethical approval

The present study was approved by the committee in charge of research ethics of the Spanish research council (CSIC). Likewise, all the volunteers who participated in the study were duly informed about the study and evaluated with a screening test to test the suitability of the subject for the test. A total of 16 volunteers participated in the study, 10 for the experimental group and 6 for the control group, in which it was verified whether the pedalling task guided by a visual paradigm generated changes in the corticospinal pathway (without FES stimulation triggered by the BMI).

B. Brain-machine interface

To generate the CNV potential registered in the volunteers, a computer screen showed a synchronous

This work has been done with the financial support of MINECO, project Associate (799158449-58449-45-514; A comprehensive and wearable robotics based approach to the rehabilitation and assistance to people with stroke and spinal cord injury "ASSOCIATE").

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paradigm in which a countdown prepared the volunteer before pedaling. For the application of the BMI, the slow CNV potentials of the volunteers were recorded through the Cz channel of a 32-channel EEG (electroencephalography), and were averaged before the intervention, so that the onset of movement was established at the time of the negative peak of the potential in question. At that precise moment the subject had to pedal and at the same time was stimulated with the FES assisting the movement. This task was carried out during 60 trials in volunteers of the experimental group, and during 90 trials in the control group. The latter received the 30 additional trials of pedaling that correspond to the calibration trials in the experimental group, so that both groups received a very similar number of trials.

C. *Functional electrical stimulation and controller*

The FEL controller was implemented in an electronic card with CAN port to record the pedaling angle, and to apply the FES stimulation to sub- or supra-threshold intensities according to the performance in the cycling task of each volunteer. The mA intensity of the FES stimulation was adjusted according to the thresholds of each individual and the stimulation parameters were 40 hz at 450 µs pulse width.

D. *Ergometer and other materials*

The ergometer used model MOTOmed Viva2 was instrumented with a magnetic encoder to record the pedaling angle used by the FEL controller to apply the FES stimulation. Figure 1 shows a sketch about the setup as a whole.

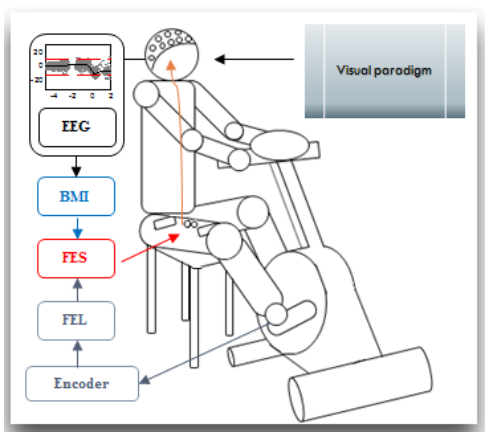

Fig. 1. Setup sketch used for the experiments. (EEG, Electroencephalography), (BMI, Brain-machine interface), (FES, Functional electrical stimulation), and (FEL, Feedback error learning)

E. *Neurophysiological assessment technique (TMS)*

The technique used to assess the changes in the excitability of the corticospinal pathway was the transcranial magnetic stimulation (TMS) whose characteristics are explained in the article [5]. We employed it by recording the MEPs (evoked motor potentials). The equipment was a Magstim 200^2 with a figure of eight conical coil. Single pulse stimulation generated the MEPs that were recorded on the Rectus Femoris and Tibialis Anterior muscle surfaces of both legs with sEMG (Surface electromiography). This assessment was performed on each volunteer Pre-, Post- and Post 30 minutes to associative treatment with the BMI in pedaling, in the same way as in the control group. All measurements were carried out with Matlab and Simulink.

F. *Statistics*

Factorial ANOVA of repeated measurements was applied on normalized data from peak to peak MEP. We analyzed the main and interaction effects of the factors: Leg assessed, time of evaluation, and intensity of TMS stimulation.

All analyzes were carried out using the SPSS software.

III. RESULTS

The results show that changes in MEP amplitude following the implementation of the associative treatment are not as large as expected in the BMI experimental group. However, the results will be discussed in the SSNR.

IV. CONCLUSIONS

Although the scientific literature demonstrates that it is possible to increase corticospinal excitability in distal muscles, the present study with the sample used does not manage to generate such changes with the use of a functional and bilateral task. These results could be due to several reasons, among them the need to apply a BMI that contemplates the changes in the CNV and the movement-related cortical rhythms (Alpha and Beta rhythms), applied in real time trial by trial in each experiment. On the other hand, they may be because of the number of trials applied in the pedalling task is insufficient, and therefore an increase in the number of interventions over several days or the number of trials applied in a session is required.

V. REFERENCES

[1] N. Mrachacz-Kersting, S. Kristensen, I. Niazi and D. Farina, "Precise temporal association between cortical potentials evoked by motor imagination and afference induces cortical plasticity", The Journal of Physiology, vol. 590, no. 7, pp. 1669-1682, 2012.

[2] N. Mrachacz-Kersting, N. Jiang, A. Stevenson, I. Niazi, V. Kostic, A. Pavlovic, S. Radovanovic, M. Djuric-Jovicic, F. Agosta, K. Dremstrup and D. Farina, "Efficient neuroplasticity induction in chronic stroke patients by an associative brain-computer interface", Journal of Neurophysiology, vol. 115, no. 3, pp. 1410-1421, 2015.

[3] L.L. Cheryl, and M.R. Popovic, "Functional electrical stimulation", IEEE Control systems magazine, April, 2008.

[4] F. Resquín, J. Gonzalez-Vargas, J. Ibáñez, F. Brunetti, and J. L. Pons, "Feedback error learning controller for functional electrical stimulation assistance in a hybrid robotic system for reaching rehabilitation.," Eur. J. Transl. Myol., vol. 26, no. 3, 2016.

[5] C.J. McNeil, J.E. Butler, J.L. Taylor, and S.C. Gandevia, "Testing the excitability of human motoneurons", frontiers in human neuroscience, vol 7, 152, 2013.

Robotic Platform including a Visual Paradigm to Promote Motor Learning

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***Abstract*—Recent projects highlight how motor learning and a high level of attention may have the potential to improve sub-maximal strength production during stroke recovery. This study focuses on the evaluation of detailed strength-producing and position-control metrics and the correlation with the learning of submaximal force production control during a new position-maintenance task for early rehabilitation after stroke. Measures are taken during the learning task to determine the time scale of learning. Our purpose is to characterize in a group of healthy subjects the ability to carry out the precision task of position maintenance with a submaximal force production.**

Our hypothesis is that the ability to perform the task of high precision position maintenance with submaximal force production during disturbances at the lower limb over time could promote improvements in ankle control after stroke.

I. Introduction

RECENT projects highlight how motor learning and a high level of attention may have the potential to improve sub-maximal strength production during stroke recovery [1]. This study focuses on the evaluation of detailed strength-producing and position-control metrics and the correlation with the learning of submaximal force production control during a new position-maintenance task for early rehabilitation after stroke [2]. Repeated and frequent measures are taken during the learning task to determine the time scale of learning. The purpose of the study is to characterize in a group of healthy subjects the ability to carry out the precision task of position maintenance with a submaximal force production.

II. Hypothesis

We hypothesize that the ability to perform the high precision task of lower limb position maintenance with production of submaximal torque with disturbances over time would improve ankle motor control function in stroke.

III. Materials and Methods

A. Experimental platform

We have used a Motorized Ankle Foot Orthosis (MAFO) (see Figure 1) with a zero-torque control. This robotic platform is able to provide controlled torque profiles to the subject's ankle joint. It is connected to a BeagleBone Black running Ubuntu and an application to interconnect the robot control board to MathWorks Simulink ® and MATLAB via a CAN bus. The visual paradigm is implemented in Simulink, and the control parameters interface is implemented in MATLAB.

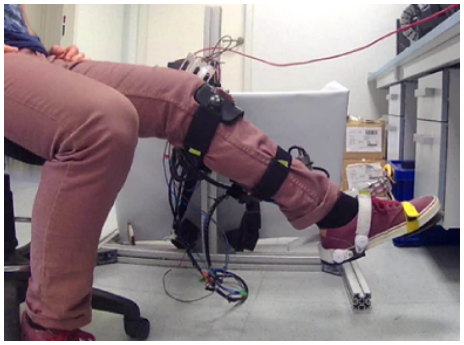

Figure 1 - Subject inside the robotic platform performing the experiment.

B. Participants

Nine male and six female subjects with no history of neuromuscular and/or cardiovascular disorders participated; ages 27.73 ± 3.58, and sport activity of more than 2 and less than 6 hours per week.

C. Task

The experiment consisted in following the trajectories represented in the visual paradigm (see Figure 2), while the robot altered the movement by making torque patterns intercalating plantar and dorsiflexion movements (see Figure 3). The objective of the exercise was to improve the motor control by learning to maintain the position to follow the path shown on the screen, compensating the disturbances made by the robot.

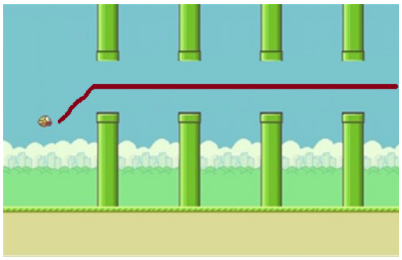

Figure 2 - Visual paradigm. The user controls the position of the bird with the angular.

This study has been funded by grant from the European Commission, within the Seventh Framework Programme (IFP7-ICT-2013-10-611695: BioMot - Smart Wearable Robots with Bioinspired Sensory-Motor Skills).

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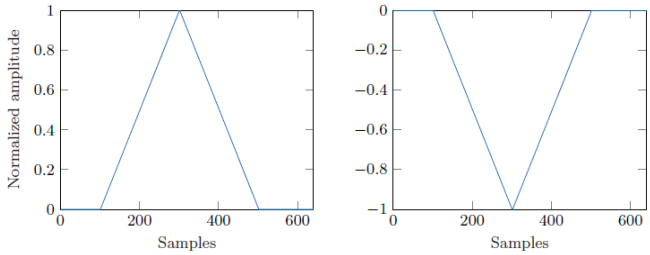

Figure 3 - Torque patterns.

1) *Training paradigms*

Three training paradigms were designed for the experiment:

a) Maximum torque: In this training paradigm, the 30 trajectories are performed at maximum prescribed torque (set at 16 Newton·meter as a technical limitation of the robot - controller set).

b) Progressive: This paradigm, as its name indicates, consists on a progressive increase of the torque exerted by the robot from a minimum of 1 N·m up to 16 N·m.

c) Modulated: the maximum torque exerted on each trajectory increases in steps of 2 N·m if the score in the previous one is 100 %, and decreases to the average torque of the last two trajectories (saturated to at least 1 N·m, and at most 2 N·m compared to the previous torque). For example, if the score was less than 100 %, the previous torque was 8 N·m, and the current torque is 10 N·m, then the next torque will be (8 + 10) / 2 = 9 N·m, since the difference 10-9 = 1 N·m is greater than or equal to 1 and less than or equal to 2 N·m.

2) *Description of the task*

The task consisted of forty trajectories, distributed in this way: 1) the first trajectory allowed the user to move the foot freely to understand the dynamics of the exercise; 2) the next three from 2 to 4 evaluated the performance of the subject in the task before training (at maximum torque); 3) thirty training trajectories were performed (1 of the 3 possible training paradigms was randomly selected for each user); 4) the three trajectories from 35 to 37 evaluated the performance of the subject in the task after training, at 80% of the maximum prescribed torque (to evaluate performance at a torque level different from that used for training); and 5) finally, the last three trajectories from 38 to 40 assessed the performance of the subject in the task after training.

IV. Results

The subjects' scores for the three training paradigms increase after training, and the assessment score at 80 % of peak torque at the end of training is better than the score for the peak torque for all training paradigms.

In Figure 4 we observe that for the average interaction torque for the three training paradigms: 1) in the maximum torque training paradigm, all the tests reach the target of 16 N·m; 2) in the progressive paradigm, this increase is logically progressive in the measured torque; and 3) in the torque modulation training paradigm, the torque increases to a local maximum depending on each subject's score, not reaching the prescribed torque in any case.

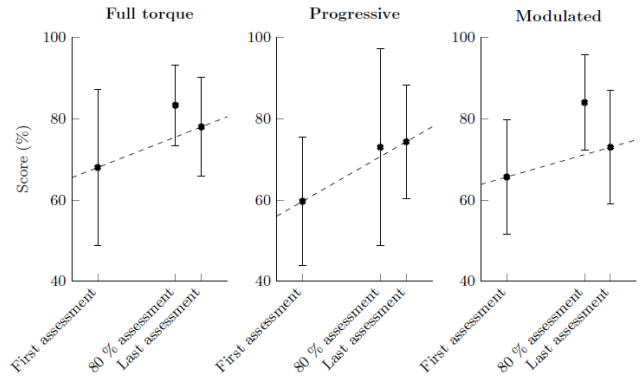

Figure 4 - Scores for the three training paradigms (average and standard deviation), for the three assessments: 1) Before training at fixed torque, 2) after training at 80 % of fixed torque, and 3) after training at fixed torque.

V. Discussion and Conclusion

We observed that all the training paradigms led to an improvement in the score in the comparison pre and post - training, so we can conclude that this platform may induce learning in healthy subjects. All the users in the maximum and progressive torque paradigms obviously reached the prescribed maximum torque, but it was not the case for the torque modulation paradigm, where none of the users reached this prescribed torque during training, so we can conclude that the maximum torque should be customized for each subject. All the subjects stated that they liked the game, and most of them said the task was too easy. This is also observable by looking at the mostly high scores obtained by all the subjects. We will test more difficult trajectories, and different torque profiles, in order to increase the difficulty of the game. In summary, we conclude that this tool may be useful to induce learning in healthy subjects and, therefore, we continue working on these training paradigms, for its transfer to the rehabilitation domain.

References

[1] Steven C Cramer, Mriganka Sur, Bruce H Dobkin, Charles O'brien, Terence D Sanger, John Q Trojanowski, Judith M Rumsey, Ramona Hicks, Judy Cameron, Daofen Chen, et al. "Harnessing neuroplasticity for clinical applications". Brain, 134(6):1591-1609, 2011.

[2] Andrej Panjan, Bostjan Simunic, and Nejc Sarabon. "Maximal voluntary torque and the ability to finely grade submaximal torque are not related/sposobnost nega uravnavanja submaksimalnega navora ni povezana z najvecjim hotenim navorom". Kinesiologia Slovenica, 17(3):5, 2011.

Do activation & synergy of above knee amputees' intact leg change?

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***Abstract*—Amputation is a major public health issue. Due to the functional absence of the amputated leg, excessive joint loads on the amputee's intact limb (IL) have been reported. However, the neural strategy implemented by the central nervous system (CNS) to control transfemoral amputee's (TFA) IL is not properly known during gait. The aim of this study was to identify the differences in muscle activation patterns and muscle synergies between healthy subject's (HS) dominant leg and TFA IL. Two-level analyses were performed on electromyography (EMG) data (1) onset-offset thresholding algorithm and (2) concatenated non-negative matrix factorization (CNMF). The results illustrated a higher period of coactivation in TFA than HS. In addition, similar control complexity by CNS was observed in both groups however, synergy components showed changes in muscle synergies weighting of some modules and activation profiles. This could be due to the compensatory response of IL to support the body mass and to stabilize the knee before prosthetic leg (PL) becomes stance limb.**

I. Introduction

Amputation is a major public health issue and its prevalence in the lower limb is increasing significantly all around the world. Lack of control over the prosthetic leg (PL) joints, i.e. knee and ankle, in transfemoral amputees (TFA) results in higher loading of their intact limb during the stance phase [1, 2]. Little research has been done on electromyography (EMG) of TFA intact limb. Ba et al. [2] showed above knee IL muscles had a larger co-activation than healthy subjects (HS) during gait. Studies in the literature have reported muscle synergy analysis on healthy and pathological populations in various activities [3-7]. Factorization techniques such as concatenated non-negative matrix factorization (CNMF; [4-6, 8]) have been used on EMG signals to extract (1) synergy vector (weighting of each muscle to each module) and (2) activation coefficient (the time activation of each module). Mehryar et al. reported changes in activation patterns of transtibial amputee's PL and IL at different terrains as compared to HS [4-6]. The main goal in this study was to investigate the activation patterns in HS and TFA in two levels: activation and deactivation patterns and muscle synergy analysis. We hypothesized that synergy components of the TFL IL are significantly different to those of HS.

II. Experiments

Four healthy (age: 21.3 ± 0.4) and 1 TFA (age: 53; wearing Ottobock 3R80 with medi panthera CF II) without any neurological or orthopedic disorder (except the amputation) participated in this study. EMG recorded from HS' dominant leg and TFA IL at the self-selected speed over 6 gait cycles (GCs). Electrodes were attached to the muscle bellies of rectus femoris (RF), vastus medialis and lateralis (VM and VL), biceps femoris long head (BFLH), gluteus medius (GMED), tensor fascia latae (TFL), tibialis anterior (TA), gastrocnemius medialis and lateralis (GM and GL) and soleus (SOL) using ultrasound scanner For details of the data collection and processing, refer to [6].

III. Algorithm Description

Two levels of analysis were carried out on EMG signals: high dimensional (HD) and low dimensional (LD). HD is associated with the muscle activation-deactivation patterns to investigate the differences in the muscles onset and offset timing of both groups. The threshold was determined as:

$$\text{Threshold} = 0.5(\max(\text{EMG}) - \min(\text{EMG})) + \min(\text{EMG}). \quad (1)$$

An ensemble average of each muscle for all trials was considered in each group. Threshold was calculated using equation (1) for each trial and an average from all trials was considered to identify onset (≥threshold) and offset (<threshold) pattern of ensemble average signal. In LD level, EMG signals (A^c = n-by-m), where n represents the # of subjects × # of GCs × 101 and m represents the # of muscles, were factorized using CNMF to obtain (1) concatenated coefficient (C^c = n-by-k) and (2) the fixed muscle synergy (S = k-by-m) where k represents the number of synergies or modules [4-6, 8]. A^c represents linear envelope of the EMG data which were normalized to the maximum peak over all trials and were interpolated to 101 points. Functional sorting was performed to match the indices of S and C hence facilitating the between-subject study comparison. Coefficient of determination (R^2), intra-class correlation (ICC) and variance accounted for (VAF) were used to measure the experimental and reconstructed EMG signals., S and C were compared inter-subjectively using R^2 and a two-sample t-test statistical parametric mapping (SPM).

IV. Results and Discussion

Ten muscles from the two groups were analyzed in HD level. It was observed that all muscles (except TA) in TFA had a longer activation period during stance phase as compared to HS (Fig.1). TFA triceps surae were activated in

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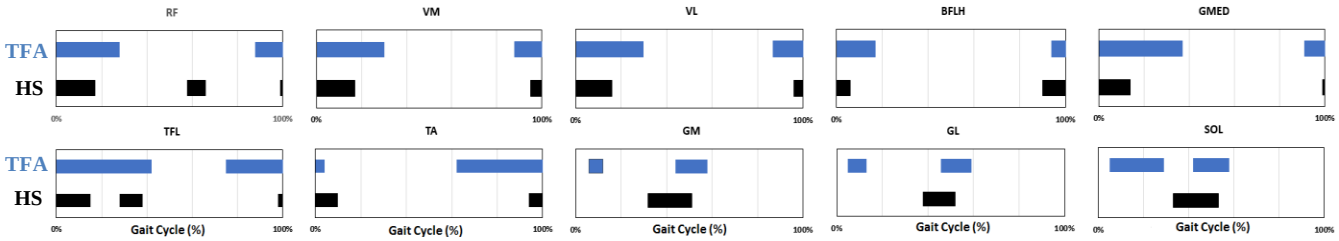

Figure 1. Comparison of muscle activation- deactivation patterns during 0-100% of gait cycle between healthy (black) and TFA (blue) subjects.

early and terminal stance whereas HS triceps surae activation just occurred at the terminal stance. Co-contraction of the TFA quadriceps (RF and vasti) and hamstring (BFLH) was longer than HS during the stance phase. In both groups, 4 modules were accounted for the reconstructed EMG signals to reproduce the experimental ones for all the 10 muscles (VAF > 0.9). Moreover, R^2 and ICC of each muscle showed a high reconstruction quality of the EMG signal (> 0.9).

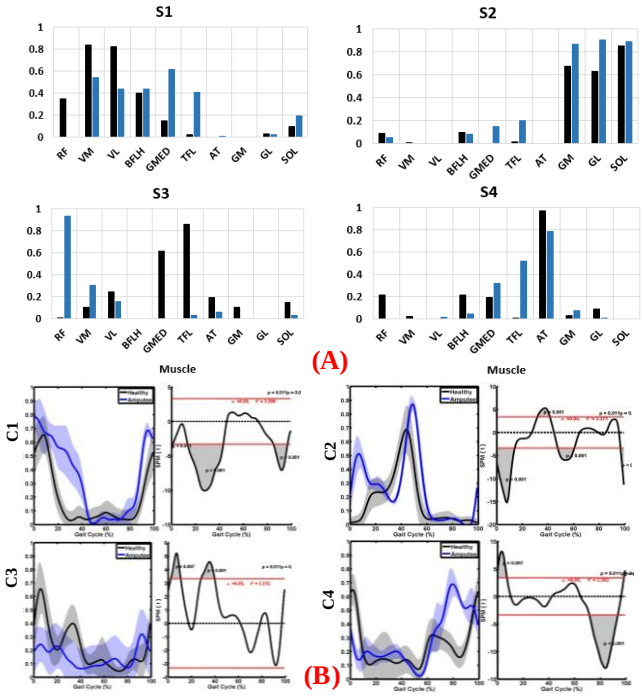

Figure 2. LD test: Muscles weighting within each synergy (A) and activation profiles (B). In B (left), thick black and blue lines with their corresponding shaded areas indicate the average and one standard deviation of *C* (*C1* to *C4*) in HS and TF, respectively. B (right) shows the SPM results of *C1* to *C4* and the grey area is the region where p-value < 0.05.

Similar number of modules between the two groups illustrates that the CNS does not change its control complexity to recruit TFA IL muscles. This is in agreement with the studies conducted on transtibial amputees [4-6] but in contrast with the study associated with post-stroke patients [7]. The difference between the muscle weighting of each module between the two groups (using R^2) showed strong correlation in S2 (0.89), moderate correlation in S1 (0.57) and S4 (0.63) and low correlation in S3 (0.0). SPM results exhibited significant differences at different regions of stance phase in *C*1 to *C*4 of the two groups (Fig. 2 B right). This could be an indication of TF attempts to stabilize the knee joint of IL to support the body mass. In addition, it is evident from the HD test where a longer co-contraction of IL quadriceps and hamstring occurred at the stance phase. At the terminal swing phase, *C*1 and *C*4 showed statistical significant differences intersubjective suggesting gait instability during PL stance which may be due to the fact that the subject tried to prepare the IL for weight transfer. In addition, as shown in Fig. 1, HD test showed earlier and longer activation of quadriceps, GMED, TFL and TA prior to the IL initial contact.

V. CONCLUSION

HD analysis showed a longer activation in TF IL. Similar number of modules were found in both groups indicating analogous complexity implemented by the CNS. Strong correlation in *S* implies the same group of muscles are controlled by the CNS synergistically. Significant differences occurred in *C* at different parts of the GC especially during stance phase indicating the compensatory strategy for stabilization of the TF IL knee. This study can be useful for development of new generation of prostheses.

REFERENCES

[1] P. Mehryar, T. Rezaeian, M. S. Shourijeh, V. Raveendranathan, N. Messenger, R. O'Connor, *et al.*, "Changes in knee joint kinetics of transfemoral amputee's intact leg: An osteoarthritis indication?," *Gait & Posture*, 2017.

[2] T. Bae, K. Choi, and M. Mun, "Level walking and stair climbing gait in above-knee amputees," *Journal of medical engineering & technology*, vol. 33, pp. 130-135, 2009.

[3] G. Serrancolí, J. C. Monllau, and J. M. Font-Llagunes, "Analysis of muscle synergies and activation–deactivation patterns in subjects with anterior cruciate ligament deficiency during walking," *Clinical Biomechanics*, vol. 31, pp. 65-73, 2016.

[4] P. Mehryar, M. Shourijeh, and A. Dehghani-Sanij, "Muscle synergy analysis in transtibial amputee during ramp descending activity," in *Internation Conference on neurorehabilitation* Segovia, Spain, 2016, pp. 945-950.

[5] P. Mehryar, M. Shourijeh, H. Maqbool, M. Torabi, and A. Dehghani-Sanij, "Muscle synergy analysis in transtibial amputee during ramp ascending activity," in *Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the*, 2016, pp. 1676-1679.

[6] P. Mehryar, M. Shourijeh, T. Rezaeian, N. Iqbal, N. Messenger, and A. Dehghani-Sanij, "Changes in synergy of transtibial amputee during gait: A pilot study," presented at the Engineering in Medicine and Biology Society (EMBC), 2017 IEEE International Conference on Biomedical and Health Informatics

[7] D. J. Clark, L. H. Ting, F. E. Zajac, R. R. Neptune, and S. A. Kautz, "Merging of healthy motor modules predicts reduced locomotor performance and muscle coordination complexity post-stroke," *Journal of neurophysiology*, vol. 103, pp. 844-857, 2010.

[8] M. S. Shourijeh, T. E. Flaxman, and D. L. Benoit, "An approach for improving repeatability and reliability of non-negative matrix factorization for muscle synergy analysis," *Journal of Electromyography and Kinesiology*, vol. 26, pp. 36-43, 2016.

Characterizing the effects of soft tissues and physical interfaces in lower limb exoskeletons: a modeling approach

M.C. Sánchez-Villamañán, D. Torricelli, J. L. Pons

***Abstract*—The physical interface of the exoskeleton is the responsible for transmitting the actuation torques to user's lower limbs. Measuring the interaction forces provides a criteria to evaluate the effectiveness of the exoskeleton and it physical interface. We present in this contribution a model that represents force transmission between a lower limb exoskeleton and the shank of the user considering soft tissues and physical interface of the robot.**

I. Introduction

Robotic exoskeletons assist motions by applying forces directly on the user's body [1]. They push or pull limbs through physical interfaces, composed of straps, braces or metallic/plastic cuffs. These components influence the safety and comfortability of the exoskeleton [2]. Skin damage has to be avoided and the exoskeleton has to be comfortable to wear for long periods of time.

Moreover, the effectiveness of the transmission depends on physical interface. Inefficient power transmission is a critical problem for wearable assistive devices [3]. J. Tamez-Duque et al. [4] and A. Rathore et al. [5] presented systems to monitor pressure exerted by the interface. M. B. Yandell et al. [3] went one step further in the study of human-robot interaction through the physical interface as they have presented a methodology for estimating how interfaces absorb and return energy.

Human-robot physical interfaces become popular as a scientific domain within the field of wearable robots research. We present a model for estimating force transmission between a lower limb exoskeleton and the shank of the user. Our goal is to understand the implications of soft tissue and physical interface in the effectiveness of force transmission. This will be a previous stage in the improvement on the mechanical design of future exoskeletons through the optimization of interface components.

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II. Material and Methods

A. Soft tissues

Body segments are considered as rigid bodies in human biomechanics. However, soft tissues are considered as a combination of linear elastic and viscoelastic materials [6]. They can be modelled with different mechanical elements [7]. In our model, we represent soft tissues with a Voigt element, composed by a linear spring with a damper in parallel (see figure 1). This element represents creep and creep recovery of the skin [8].

B. Theoretical model

We represent human-robot interaction as a 2-degree-of-freedom system (see figure 1). The force is applied by the knee actuator of the exoskeleton. It transmits this motion through its frame (m_e) and it reaches user's leg (m_h) through the strap. The strap and the soft tissues covered by the strap are represented by the first Voigt element. The force is applied to the shank and we obtain the force output through the soft tissues in the shank, simulating the user is performing an isometric movement against a rigid structure. This was done in order to study the dynamic behavior of the elements of the system.

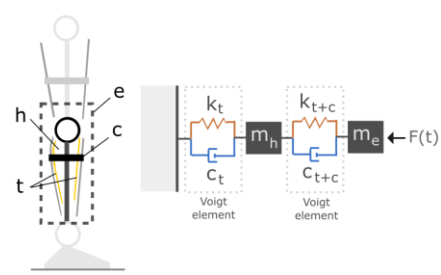

Fig. 1. Human-robot interaction model of a lower limb exoskeleton and user's leg, considering the physical interface and soft tissues in the shank. (k_t: tissues' stiffness value, c_t: tissues' damping value, k_{t+c}: tissues and cuff's stiffness value, c_{c+t}: tissues and cuff's damping value, m_h: shank's mass, m_e: exoskeleton's mass, F(t): input force).

The analytical equations that define the system are:

$$\ddot{x_e} = \frac{F(t)}{m_e} - \frac{k_{t+c}}{m_e} \cdot x_e - \frac{c_{t+c}}{m_e} \cdot \dot{x_e} + \frac{k_{t+c}}{m_e} \cdot x_h + \frac{c_{t+c}}{m_e} \cdot \dot{x_h} \quad (1)$$

$$\ddot{x_h} = -\frac{(k_{t+c}+k_t)}{m_h} \cdot x_h - \frac{(c_{t+c}+c_t)}{m_h} \cdot \dot{x_h} + \frac{k_t}{m_h} \cdot x_e + \frac{c_t}{m_h} \cdot \dot{x_e} \quad (2)$$

We implemented these equations in Simulink, where applying a force, obtaining a dynamic model of the system

(see figure 2). Masses are known and input force is defined as a sinusoidal function with known amplitude. The stiffness and damping parameters of the cuff (strap) and the skin represent the unknowns of the model.

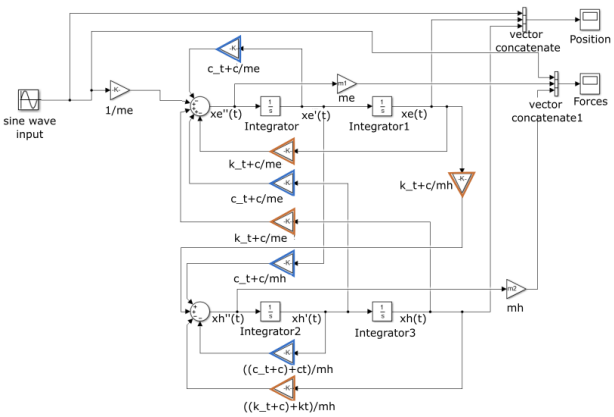

Fig. 2. Simulink model. Orange blocks correspond to springs and blue ones represent dampers of the model.

C. Experiments

The goal of the experiments will be the identification of the stiffness and damping parameters by fitting the data from human experiments into the model. Our experimental setup is composed of a lower limb exoskeleton, an external compression load cell and a rigid structure. The load cell is placed on the shank of the user, just below the strap. The subject remains seated in a passive mode, i.e. without exerting any force on the exoskeleton. The knee actuator will be controlled with a desired force, producing shank motion and the contact with the rigid structure. The force exerted by the exoskeleton will be measured with the strain gauges located in the bar of the mechanical structure of the exoskeleton, while the forces exerted by the subject against the rigid structure will be measured with the external load cell. Thus, the identification will aim at finding suitable stiffness and damping parameters for the model to optimally match the forces data. A scheme of the setting of the experiment is shown in figure 3.

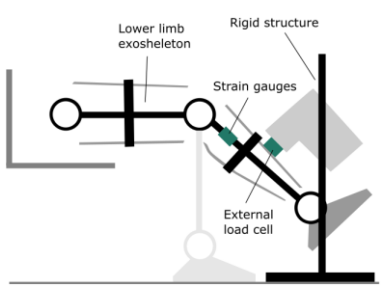

Fig. 3. Preliminary setting of the experiments.

III. Results

Before starting with the experiments, we have modelled human-robot interaction with a simpler model (figure 4) in order to determine a first guess for the parameters of the equations (1) y (2). Blue blocks in the Simulink model (figure 2) were deleted from this configuration. The goal of this simplification is to obtain results for different values of spring stiffness and exoskeleton mass in order to understand the dynamics of the system in ideal conditions, with no energy losses. The input force used was a sine wave with amplitude value of 1 N and human shank mass of 4 kg. These results will be shown and discussed in the symposium, considering the implication of each parameter in the mass-spring system.

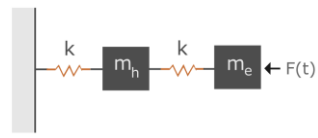

Fig. 4. Simplified model of human-robot interaction.

IV. Conclusions

We presented a model of human-robot interaction to characterize the effect of the physical interface and soft tissues in lower limb wearable robots. We presented the design of the experiment to obtain unknown parameters of the model, as well as a simplified version of the model, considered as a first approach towards the complete study. Joint misalignments have not been considered for simplicity. The long-term goal of this research is to provide the community with quantitative benchmarks of energy efficiency, comfort and safety of wearable robotic devices.

References

[1] J.L. Pons, “Wearable Robots: Biomechatronic Exoskeletons,” John Wiley & Sons, Ltd, 2008.

[2] A. Schiele, “Ergonomics of exoskeletons: subjective performance metrics,” in 2009 IEEE International Conference on Inteligent Robots and Systems, 2009, pp. 480-485.

[3] M. B. Yandell, B. T. Quinlivan, D. Popov, C. Walsh and K. E. Zelik, “Physical interface dynamics alter how robotic exosuits augment human movement: implications for optimizing wearable assistive devices”, Journal of NeuroEngineering and Rehabilitation, 2017, vol. 14, no 1, p. 40.

[4] A. Rathore, M. Wilcox, D. Z. Morgado Ramirez and R. Loureiro, “Quantifying the human-robot interaction forces between a lower limb exoskeleton and healthy users”, in 2016 IEEE Annual International Conference of the Engineering in Medicine and Biology Society, 2016, pp. 586-589.

[5] J. Tamez-Duque, R. Cobian-Ugalde, A. Kilicarslan, A. Venkatakrishnan, R. Soto and J. L. Contreras-Vidal, “Real-time strap pressure sensor system for powered exoskeletons”, Sensors, 2015, vol. 15, p. 4550.

[6] W. Maurel, “3D modeling of the human upper limb including the biomechanics of joints, muscles and soft tissues”, PhD Thesis, Ecole Polytechnique Federale de Lausanne, Switzerland, 1998.

[7] G. Duchemin, P. Maillet, P. Poignet, E. Dombre and F. Pierrot, “A hybrid position/force control approach for identification of deformation models of skin and underlying tissues” in IEEE Transactions on Biomedical Engineering, 2005, vol. 52, no. 2, pp. 160-170.

[8] S. Pal, “Design of artificial human joints & organs,” Springer, 2014.

Technology Assisted Neurorehabilitation as colaborative project

Natalia M Lopez , Elisa Perez , Ricardo Berjano, Valeria Rizo, Julieta Quiroga, Cristian Abelín, Emanuel Tello, Alejandro Rodrigo

Abstract— **This abstract presents the concept of a interdisciplinary project, comprising neurologists, neurosurgeons, biomedical engineers, physiatrists, psychologists, and other health professionals. The main objective is the clinical application and validation of technology assisted neurorehabilitation in post stroke patients, as a systematic research for University and Public Health Institutions.**

The Laboratory of Neurorehabilitation has technological resources such as Kinect® based movement quantification, inertial and electromyographic sensors, specially designed virtual reality and games for cognitive and motor tasks, different accessibility interfaces for personal computers, and a domotized area for Daily Living Activities practice.

At the moment we are in the preliminary stage, with encouraging results in the firsts patients.

I. Introduction

THE rehabilitation process is a fundamental stage in the recovery of the patients, helping them to acquire new abilities for daily activities, improve their independence and recover their social role.

Rehabilitation needs an interdisciplinary staff, especially in stroke recovery, and an analysis of the initial conditions and needs of the patient, suited by a confirmation of clinical change that allows the modification of the rehabilitation plan or the end of treatment. In this context, assessing rehabilitation outcomes depends on measuring the patient performance, usually through tests scores in which the patient/professional condition is decisive (such as experience, fatigue, cooperation, motivation, emotional status, intelligence, etc). This evaluation is performed by physiatrists and medical staff, based in their subjective observations. Recent studies of the mechanisms underlying plasticity and recovery following neurological injuries have originated innovative lines of research in neurorehabilitation. Additionally, the development of new technologies to facilitate the quantitative performance of evaluation and intervention procedures has stimulated research on novel rehabilitation paradigms and more effective strategies that must be translated into clinical practice [1].

We propose an interdisciplinary model of rehabilitation, which is not usual in our country, using technology tools and interventions. The aim of the project is the quantitative assessment and clinical validation of the improvements in overall performance and results in technology assisted rehabilitation. The staff is composed by neurologists, neurosurgeons, psychologists, physiatrists, biomedical engineers and other health and social professionals. The patients get into the study after 6 months of the stroke incident and are clinically, psychologically and physically evaluated with standard tests in order to determine the initial state, selected with ad hoc inclusion criteria. Also RMN images are acquired in the start and after 6 months of treatment for comparison and further analysis. For statistical validation a control group receives conventional rehabilitation and the experimental group complements with special sessions of the technological tools. The software, electronics, and mathematical analysis are developed by biomedical engineers, especially for this project.

All procedures are agreed by the research staff and by the hospital ethical committee, with the aim of obtaining a clinical evidence of the improvement of the technology assisted rehabilitation. We are in the preliminary stage, with encouraging results in the first patients.

II. Materials and Methods

A. Patient History Software

The integral approach proposed in this project needs an special patient's data management system. To accomplish with this requirement, a customized software was designed, that comprises three main areas of evaluation: neurological, functional tests scores and neuropsychological (cognitive and language tests). Also, personal and medical data is included with confidentiality and security considerations. The soft enable the simultaneous evaluation and the storage in a database to statistical and clinical following and can be accessed through cell phones, tablets and computers. Fig. 1 shows the neurological screen, as example, for the "Physiatrist Evaluation Results"

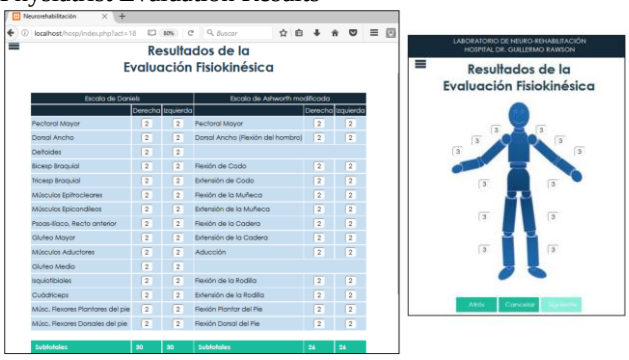

Fig. 1. – Physiatrist Evaluation Results screen for the Clinical Record.

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B. *Movement Analysis Software*

This section describes a tracking platform of the movement made by a patient using Kinect™ sensor, focused in trunk and upper limb [2]. Assessment of the patient's upper limb movement is achieved extracting a quantification of the movement to provide the physiotherapist or attending physician more precise data to carry out an objective diagnosis and, thus, plan a more accurate rehabilitation in accordance with each patient's needs. The software developed implied data processing of the information provided by Kinect™. In the first stage, atypical values were eliminated (outliers). In the second, the trajectory was processed through the application of linear interpolation algorithms and moving average filters. During the last stage, joint position angles were calculated and the graphical interface shows the trajectories performed by the user and joint angles. This is a quantitative measurement of the upper limb mobility, to supervise the rehabilitation evolution trough a graphic interface developed to facilitate data management, acquisition and collection by the medical team. This process enabled easy access to information as well as storage of patients' medical, technical and personal information (Fig. 2)

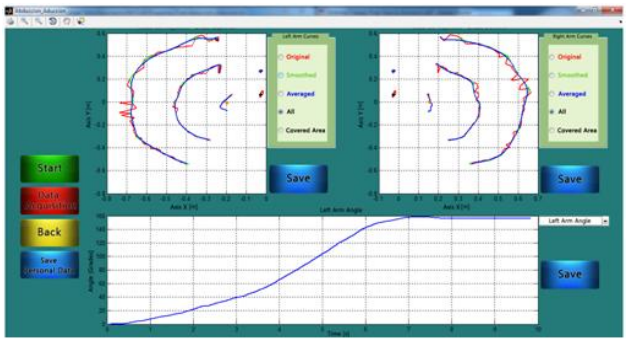

Fig. 2. –Movement analysis software: Graphical interface. Upper limb trajectories can be see in the symmetric squares and joint angles evolution at the bottom.

C. *Virtual Reality*

The systems based on Virtual Reality (VR) provide favorable environments for rehabilitation since they simulate aspects of daily life, for example, cooking, playing the piano, buying, among others. With this tool, a practical task is added to the rehabilitation program, also motivating the patient.This environment implies a computer-generated 3D spatial system where the patient actively participates and KinectTM is the input device. The environment has been designed in the Unity® game development platform.

The scenario created consists of an Avatar (human figure in the VR that represents the user) created to reproduce the movements performed by the patient inside the VR, and an environment where the rehabilitation activity will be carried out. The proposed activity shows a table with different size and color blocks, which the avatar will move or carry to a specific spot on the table in accordance with the movement performed by the user. Other more complex tasks can be incorporated. Others scenarios and activities were designed, such as a basketball ring, stacked boxes, and so on. The most used scenario is a simple game in which the user must catch flying balls a different velocities, laterality and height can be chosen by the physical therapist according to the specific needs and skills of each patient (as shown in Fig. 3).

Fig. 3.-VR Environment with balls game. The Avatar represent the movements of the user who must catch the balls, according to the instructions of the therapist (Corner: Setting Menu)

III. Results

At the moment, the project has incorporated 6 patients for a reduced study, accomplishing the evaluation and rehabilitation process. The group was divided in 4 patients with technology assisted rehabilitation and 2 patients that continue with the classical approach. All of them were evaluated with the same tests for the inclusion to the project and in the next days they will repeat the measurements of 6 months.

However, the patients of experimental group demonstrated a better motivation, and a subjective evaluation clearly shows encouraging results in the technology rehabilitation. Other systems are incorporated, such as inertial, force, electromyographic and other wearable sensors. The entire system is low-cost and easy-to-use, two characteristics that make it suitable for everyday use by physical therapists and physicians. In addition, the movements and tasks can be personalized to the patient's needs by adapting the rehabilitation strategies to the patient's needs.

References

[1] Pájaro-Blázquez M and Pons JL (2014)Research highlights in neurorehabilitation (editorial). J NeuroEngineering and Rehabilitation,11:21; doi10.1186/1743-0003-11-21; https://jneuroengrehab.biomedcentral.com/articles/10.1186/1743-0003-11-21.

[2] Contreras M., Tello E., López N., Echenique A.M. and Perez E. Plataforma de Análisis de Movimiento a Través de Imágenes de Miembro Superior. M. VI Congreso Latinoamericano de Ingeniería Biomédica CLAIB 2014. 29 al 31 de octubre. Paraná, Entre Ríos, Argentina. ISBN 978-950-698-343-7

[3] R. Cano de la Cuerda, S. Collado Vázquez, "Neurorrehabilitación: Métodos específicos de valoración y tratamiento," 1er ed., Ed. Médica Panamericana: 2015.

Transcranial Magnetic Stimulation as a tool for Memory Enhancement Research

A. San Agustín and Jose L. Pons

***Abstract*— Recent studies have used Transcranial Magnetic Stimulation (TMS), a non-invasive cortical stimulation tool, for answering questions related to the functioning of cognition processes such as Memory. In this review, we detail how TMS has being applied in a variety of intervention protocols for memory enhancement.**

I. Introduction

TRANSCRANIAL magnetic stimulation utilizes short high intensity magnetic fields to induce currents that reach the cortex, which depolarize neurons in small regions. Initial reports showed its use to describe impairment on cognitive processes. Other studies have shown that it could also facilitates cognitive capabilities, improving the performance of Memory process [5].

Memory is a complex topic of research because of its multiple forms and classifications, and its relation to different brain areas. However, it is a process of great importance, both in healthy people and in patients with disorders involved in memory malfunction (e.g. Alzheimer's disease or any type of dementia). In this review, we present some of the studies that demonstrate how the use of TMS results in improved memory performance (shown in Table I) and therefore a potential method for future rehabilitation therapy.

II. The Application of TMS in Memory Performance

TMS for memory research has been used in conjunction with tasks that provide performance data of the subjects' memorization capabilities. This task usually consists of three phases. A coding phase in which a stimulus is presented, and the subject must remember it; a retention phase where the subject maintains the information of the presented item; and a recognition phase in which the subject must demonstrate that he/she remembers. Different forms of TMS interventions can be applied in conjunction with the task. The most traditional ones in this field are single pulse TMS, Paired Pulse TMS and repetitive TMS.

A. Single Pulse TMS

The Single Pulse TMS intervention is based on the application of one pulse, occurring immediately before the onset of any presented item in the task. Catteneo et al. [1] used this TMS intervention to determine whether TMS intervention increases the primary visual cortex excitability. A visual stimulus was presented, followed by a 2000ms retention phase for the subject to memorize it. Then, the TMS pulse was given immediately before the onset of the response phase. The generated effect on memory performance was a decrease of the Reaction Time (RT) during the response phase, but no changes in the performance accuracy were found.

Similar results were found by Hannula et al. [3] although the stimulation was performed on the Middle Frontal Gyrus and applied in the retention period of the task. Facilitation occurred when TMS in this period was applied early (at 300 ms from the start of the phase) but did not happen if it was later on the phase (at 1200 ms after onset).

B. Paired Pulse TMS

The Paired Pulse TMS intervention is the application of a conditioning stimulus given at variable intervals of time prior to the task stimulus. This kind of intervention has been applied by Gagnon et al. [2]. In this study, TMS stimuli were applied every 15ms during 4s. The results revealed that the RT was shorter when the stimulation in the coding phase was applied in the Left Dorsolateral Prefrontal Cortex (DLPFC) and when the stimulation in the recognition phase was applied in the Right DLPFC.

C. Repetitive TMS

The TMS intervention is called Repetitive TMS (rTMS) when frequency of pulses is equal or higher than 1Hz. Different studies have described RT facilitation in memory performance applying a frequency of 5Hz at the retention period in Middle Parietal Cortex [4] and Right Parietal Cortex [10]. At the same phase of the task but giving three pulses at 10Hz, Rademarker et al. [7] described a memory facilitation at early visual cortex improving accuracy.

Another paradigm of rTMS to facilitate memory is based on basal assessment at a first day, an application of rTMS for at least five consecutive days and a memory task on the final day. A comparison between the basal state and the performance on the final day is used to assess improvement in accuracy and RT. Wang et al. [9] and Nilakantan et al. [6] followed this experimental methodology in their studies, applying consecutive blocks of 20Hz of 2s with a period of 28s of no stimulation between trials (1600 pulses per session) during each day and for 5 days. Results indicate a facilitation

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TABLE I
STUDIES REPORTING MEMORY ENHANCEMENT RELATED TO A TMS INTERVENTION

TMS Intervention	Reference	Type of Memory	Stimulation location	Performance Effect
Single pulse	Cattaneo et al. (2009)	Non-verbal Working Memory	Early Visual Cortex (V1/V2)	Decreased RT
	Hannula et al. (2010)	Tactile Working Memory	Middle Frontal Gyrus	Decreased RT
	Rose et al. (2016)	Latent Working Memory	Right Precuneus	Reactivation
Paired pulse	Gagnon et al. (2011)	Episodic Memory	Left/Right Dorsolateral Prefrontal Cortex	Decreased RT
Repetitive pulses	Luber et al. (2006)	Verbal Working Memory	Middle Parietal Cortex	Decreased RT
	Yamanaka et al. (2009)	Spatial Working Memory	Right Parietal Cortex	Decresed RT
	Wang et al. (2014)	Associative Memory	Left Lateral Parietal Cortex	Increased Capacity
	Rademaker et al. (2016)	Visual Working Memory	Early Visual Cortex (V1/V2)	Increased Accuracy
	Nilakantan et al. (2017)	Episodic Memory	Left Lateral Parietal Cortex	Increased Accuracy

in capacity [9] and accuracy (memorization of more detailed data) [6] when TMS is applied at Left Lateral Parietal Cortex. No effects were found when TMS was applied in Right Lateral Parietal Cortex, neither in a Motor Cortex region.

III. CONCLUSION

These findings suggest that TMS interventions have a potential use for improving memory performance. This improvement is specific to the timing of stimulation relative to the memory task and to the TMS application site taking into account the stimulated hemisphere. For rTMS protocol, the specificity of the effects is related as well to the stimulation frequency.

Research in this area is a complex work because it is necessary to take into account the physiological pathway of the stimulation location, the TMS protocol intervention that is applied and the stimulation moment during the task performance. Besides, it is important to take into account the type of memory forms (e.g. visual memory, tactile memory, verbal memory…) that could be facilitated in diverse ways (e.g. RT, the capacity or the accuracy). The theories underling the phenomenon described in this review could determine the steps to follow in future studies: Hebbian principles [5], Frontoparietal network theory [10] or Posterior Cortical-Hippocampal network theory [9]. Thus, it provides a better understanding of physiological mechanisms of memory facilitation to utilize TMS in healthy subjects or as a therapy for disabled patients.

ACKNOWLEDGMENT

We would like to thank Dr. Jose Gonzalez for revising the text. This work was supported by European social funds through the Youth Employment Operational Program and the Youth Employment Initiative (YEI) of the Community of Madrid and the Cajal Institute of the Spanish National Research Council, Madrid, Spain.

REFERENCES

[1] Cattaneo, Z., Vecchi, T., Pascual-Leone, A., & Silvanto, J. (2009). Contrasting early visual cortical activation states causally involved in visual imagery and short-term memory. European Journal of Neuroscience, 30(7), 1393–1400.

[2] Gagnon, G., Schneider, C., Grondin, S., & Blanchet, S. (2011). Enhancement of episodic memory in young and healthy adults: A paired-pulse TMS study on encoding and retrieval performance. Neuroscience Letters, 488(2), 138–142.

[3] Hannula, H., Neuvonen, T., Savolainen, P., Hiltunen, J., Ma, Y. Y., Antila, H., … Pertovaara, A. (2010). Increasing top-down suppression from prefrontal cortex facilitates tactile working memory. NeuroImage, 49(1), 1091–1098.

[4] Luber, B., Kinnunen, L. H., Rakitin, B. C., Ellsasser, R., Stern, Y., & Lisanby, S. H. (2007). Facilitation of performance in a working memory task with rTMS stimulation of the precuneus: Frequency- and time-dependent effects. Brain Research, 1128(1), 120–129.

[5] Luber, B., & Lisanby, S. H. (2014). Enhancement of human cognitive performance using transcranial magnetic stimulation (TMS). NeuroImage, 85, 961–970.

[6] Nilakantan, A. S., Bridge, D. J., Gagnon, E. P., VanHaerents, S. A., & Voss, J. L. (2017). Stimulation of the Posterior Cortical-Hippocampal Network Enhances Precision of Memory Recollection. Current Biology, 27(3), 465–470.

[7] Rademaker, R., van de Ven, V. G., Tong, F., & Sack, A. T. (2016). How Transcranial Magnetic Stimulation over Early Visual Cortex impacts short-term memory precision and guess rate. bioRxiv, 1–19.

[8] Rose, N. S., LaRocque, J. J., Riggall, A. C., Gosseries, O., Starrett, M. J., Meyering, E. E., & Postle, B. R. (2016). Reactivation of latent working memories with transcranial magnetic stimulation. Science, 354(6316), 1136 LP-1139.

[9] Wang, J. X., Rogers, L. M., Gross, E. Z., Ryals, A. J., Dokucu, M. E., Brandstatt, K. L., … Voss, J. L. (2014). Targeted enhancement of cortical-hippocampal brain networks and associative memory. Science, 345(6200), 1054–1057.

[10] Yamanaka, K., Yamagata, B., Tomioka, H., Kawasaki, S., & Mimura, M. (2010). Transcranial magnetic stimulation of the parietal cortex facilitates spatial working memory: Near-infrared spectroscopy study. Cerebral Cortex, 20(5), 1037–1045.

A Plug-and-Train Robotic Kit for Hand Rehabilitation- Preliminary Design

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***Abstract*— Hand rehabilitation requires an intensive training with many gross and fine movements. Wrist rehabilitation robots are expensive and complex to accommodate for the different degrees of freedom (DOF). In this work, we have designed a portable plug and train robot (PLUTO) to overcome the problem by having a single actuator but have different passive mechanisms for each DOF. The system has attachments/mechanism is plugged into the actuator which could train wrist flexion-extension, ulnar and radial deviation, hand opening closing and wrist pronation and supination. To give feedback to the patients and to motivate them during training, the robot is linked to performance adaptive computer games. The robot would be able to provide training in active and passive regimes. In this paper, we present the preliminary design and control of the robot.**

I. INTRODUCTION

Rehabilitation robots are excellent tools for assisted sensorimotor training and have several potential advantages. Robots can provide intense task-oriented therapy and assessment under the intermittent supervision of a trained human therapist[1]. Thus, resulting in an effective and efficient process for delivering continued therapy and care, in both hospital and home environments, in a scalable and sustainable manner. However, in spite of the deluge of research activity in therapeutic robots, their infiltration into clinical practice has been minimal; the primary reason being their high cost-to-benefit (CB) ratio.

The overall objective of this work is to address this limitation of robotic devices for hand training, by designing a modular, plug-and-train robotic kit for hand rehabilitation. The most expensive part of any robot is its actuator, thus reducing the number of actuators can significantly reduce the overall cost. The proposed device – the plug-and-train robotic kit for hand rehabilitation (PLUTO) – uses a single actuator (a DC motor) along with a set of pluggable passive kinematic mechanisms (which can be easily attached/detached from the actuator) designed to train specific hand functions. Such a device would be significantly cheaper than a set of individual robots (each with its actuators) training different functions. In this work we present the preliminary design of the proposed hand rehabilitation robot, control and its associated computer games for hand rehabilitation.

This project is funded by DBT, India

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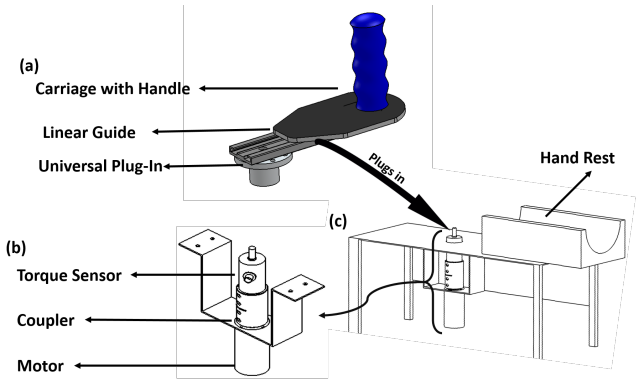

Fig. 1. (a) Wrist flexion extension Plug-in. (b) Actuator-torque sensor assembly. (C) Robot Housing.

II. DESIGN AND CONTROL

A. Robot Hardware Design

The primary design feature of PLUTO was to make it portable and compact. To acheive this, we chose a compact brushless DC motor (Maxon, Brushless EC Flat45) with a planetary gear head (26:1 speed reduction ratio), resulting in an arrangement producing 3.5Nm at 384rpm. Since the gearhead introduced friction, we coupled a rotary torque sensor (Forsentek, FYF: max torque 5Nm) on the motor shaft using an in-line shaft coupler (Ruland,MCLX-12-8-F), as shown in Fig. 1 (c). An admittance controller was implemented to improve the backdrivablity of the system. An incremental optical quadrature encoder (Maxon MILE 1024 encoder) and a Hall sensor provide position and speed measurements of the motor shaft.

The second important design feature of PLUTO was to have simple and fast way to mount/unmount the passive mechanisms from the actuator. The passive mechanism get mounted to the shaft of the torque sensor (as shown in Fig. 1), which was acheived through a commercial universal mounting hub with two nuts to mount.

Our current aim is to develop four passive mechanisms for training: wrist flexion/extention (WFE), ulnar/radial deviation, forearm prono-supination and opening/closing. We have currently completed implemented of the WFE mechanism, which is shown in Fig. 1(a). The plug-in mount is attached to the rail of a linear guide and the handle of the mechanism is attached to a carriage that is free to slide along the linear guide. The purpose of the linear guide is to account for the offset between the axis of rotation of the wrist and the actuator. The same setup with a modified handle would be

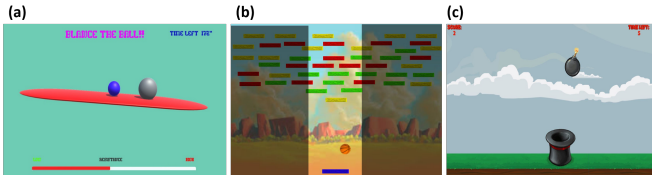

Fig. 2. Screenshot of the games. (a)Passive training: Ball Balance.(b) "Brick breaker" (c) "Egg catcher"

suitable for ulnar/radial deviation training.

B. Robot Control

The low level control for the robot is implemented through speed control. At the higher level, two control modes are implemented which could train for active and passive movements of the subject.

1) Passive training: The aim of passive is stretching of soft tissue and to help train the relax active muscles. The robot moves the subject's hand to required position with the minimum jerk trajectory (MJT) [2]. The resistance offered by the user to passive stretching, measured by the torque sensor, is used for controlling a game to make this training more interesting.

2) Active training: The objective of the active training is to train the subject to make precise and fast movements. The active training regime is implemented with the admittance controller as shown in (1) by sensing the torque applied to the shaft. The torque sensor senses the interaction torque applied by the subject and the controller moves the actuator with a speed proportional to the torque. As the subject actively moves and the subject's position was used to control a game.

C. Therapy games

The training regimes were gamified to avoid boredom and also to provide a feedback of their performance. The games were developed with Unity (Unity Technologies) game engine. The games were divided into passive and active games.

1) Passive game: One game was designed for passive training. In the game, player's goal is to balance a ball on a board which tits in proportion to the sensed torque. The robot moves smoothly to different positions at different speeds (max. speed and passive range of motion will be set by the therapist), and the subject must provide as little resistance as posisble to the movements. Each training trial lasts for three minutes.

2) Active Games: The two games were developed for active training: "Brick Breaker" and "Egg Catcher" games."Brick Breaker" is a simple paddle and a ball game, where the objective is to break as many bricks as possible in a single trial that lasts 3 minutes. The subject would have control of the position of the paddle and should move the paddle to the required position and intercept the ball from falling through the bottom of the screen. A point is awarded for every successful brick break and player losses if he is unable to intercept the ball with the paddle. In the Egg Catcher game, similar to the Brick breaker game, theplayer attempts to move the hat and to catch as many falling eggs as possible in a trial lasting 3 minutes. Player scores one point for a catch and loses the game if an egg is missed.

The difficulty of both these games depends on two parameters: 1) the range of motion θ_{ROM} required to cover the game space; and 2) the speed of the movements ω necessary to intercept the target. The game difficulty is adapted at the start of each trial (offline adaptation), and also within a given trial (online trial). The online adaptation rule within a given trial is as follows,

$$\begin{aligned} \theta^n_{ROM}[t] &= S^n_r[t] \times \theta^{max}_{ROM} \\ \omega^n[t] &= S^n_r \times \omega_{max} \end{aligned} \tag{1}$$

where, $\theta^n_{ROM}[t]$, $\omega^n[t]$ are the range of motion and speed parameters for the nth trial at the current trial time t; $S^n_r[t] = \frac{S_n[t]}{S_{max}}$ is ratio of current score $S^n[t]$ to the maximum score S_{max}.Each game trial starts with zero score $S[0] = 0$; $\theta^{max}_{ROM} = 120\,\text{deg}$ and $\omega_{max} = 120\,\text{deg}/s$.

The offline adpatation algorithm changes the starting values for the two parameters for the nth trial based on the starting and ending values of the corresponding parameters for the $(n-1)^{th}$ trial. This adaptation rule is given as follows,

$$\begin{aligned} \theta^n_{ROM}[0] &= \theta^{n-1}_{ROM}[0] + k(\theta^{n-1}_{ROM}[T_{n-1}] - \theta^{n-1}_{ROM}[0]) \\ \omega^n[0] &= \omega^{n-1}[0] + k(\omega^n[T_{n-1}] - \omega^{n-1}[0]) \end{aligned} \tag{2}$$

where, T_{n-1} is the time t at the end of the $(n-1)^{th}$ trial; k is a randomly chosen from the interval $[0.02, 0.06]$; the sign of k is determined by the success or failure of the $(n-1)^{th}$ trial. If $T_{n-1} < T$, then the trial is a failure, else it is a successful trial, where T is the maximum possible trial duration.

The proposed adaptation rule changes difficulty in a finely graded manner removing the need for artificially defined difficulty levels. This might allow subjects to explore/experience different speeds and range of movements during training.

III. Conclusion

Preliminary work in the design and development of a simple, portable hand rehabilitation robotic kit was presented. The current version of the system can train WFE movements in passive and active mode using a set of custom designed rehabilitation games. Our current work is focused on the implementation of an adaptive "assist-as-needed" training regime, development of other passive mechanisms and development of additional games for evaluation with stroke patients.

References

[1] P. Maciejasz et al., Effects of Robot-assisted therapy on upper limb recovery after stroke: A Systematic Review, IEEE Int. Conf. Rehabil. Robot., vol. 7, no. 1, pp. 421434, 2013.

[2] N. Hogan, The Coordination of Arm Movements: Mathematical Model, vol. 5, no. 7, pp. 16881703, 1985.

[3] L. Marchal-Crespo and D. J. Reinkensmeyer, Review of control strategies for robotic movement training after neurologic injury., J. Neuroeng. Rehabil., vol. 6, no. 1, p. 20, 2009.