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Analysis of Electromyography Signals for Control Models of Power-Assisted Stroke Rehabilitation Devices of Upper Limb System

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Abstract. Stroke is a significant affliction that can affect people with varying degrees of severity. One of the most common consequences of stroke is the impairment of the muscular motor function to some degree with two-thirds of the patients being affected by upper-limb paralysis. For those cases, the most effective forms of regaining muscular motor function are through rehabilitation therapy, traditionally this must be done in a clinical environment. Developments in robotics, batteries and electronics have made accessible the prototyping, production, and utilization of exoskeleton type devices technically adapted for personal and residential rehabilitation. This paper presents and discusses the results of EMG signals from upper limb of brachial biceps muscle, obtained from a cohort of healthy volunteers. The methodology for testing is presented and explained, additionally, a preliminary discussion is made on the obtained data. Some control considerations, variables and methods are also presented and discussed.

Keywords: Control, Electromyography EMG, Rehabilitation, Stroke, Signals, Upper-Limb.

1 Introduction

Currently, one in four people aged above 25 is expected to have a stroke in their lifetime. Worldwide, over 80 million people are living that have suffered from this affliction [1]. After a stroke has afflicted the patient, the loss of some degree of motor function is common; moreover, more than two-thirds of those have arm paresis [2]. One of the most effective ways of curtailing this loss of mobility comes from technology supported rehabilitation training [3]. Presently, this type of rehabilitation training is typically confined to the clinical environment in hospitals and specialized rehabilitation facilities. Thus, the exercises have a schedule limitation, and the full benefits to the patient can be less than those that could be obtained if the patient had easier access to those kinds of exercises. For this situation to be possible, it is necessary to take these training or assistance aids and move them out of the clinics or rehabilitation centers, inserting them into a domestic environment. On the other side, the rehabilitation device

must possess specific characteristics such as being self-contained, compact and allow for a significant degree of user movement freedom. For example, a device-assisted rehabilitation system for the upper limbs (exoskeleton) can be composed of some electromechanical support located at the shoulder, elbow, forearm, and up-to-hand level. Finger mechanical supports are not common due to their inherent complexity and frailty. Those supports are actuated via an electric motor, being linear, stepper or servo types. Whose control is made via an external system, typically, a desktop computer. This type of system is usually found in the classical-clinical environment [4]. In more recent iterations of this kind of device, the control is placed in an integrated microcontroller board (IC board) built into the exoskeleton's frame and combined with a self-contained power pack for increased patient mobility.

For rehabilitation work, the classical approach is usually focused on an objective-driven therapy, where a computer controls the electromechanical device that assists the patient's reach of objective via a human-machine interface display (HMI) and presents cues to guide the patient's upper extremity movement. In general, this approach has proven successful in improving the patient's daily activities, albeit so far, it has not been clear if it helps improve muscle strength [4]. This type of solution is mainly used for training and must be used under supervision in a clinical environment. Advances in the miniaturization and the large-scale dissemination of cost-effective electronics, actuators, and motors, coupled with the ease of access to 3D printing and advanced prototyping venues, have brought forth a time where it is possible to provide custom-made, patient-related motor-assisted rehabilitation aids at a reasonable cost. Nevertheless, this is also possible due to a resurgence of the do-it-yourself (DIY) paradigm. Thus, after some initial assisted training, a system that performs mainly unsupervised (i.e., at the patients' home) is expected. A rugged system controller with a fair degree of tolerance variation to input signals and a learning capacity is recommended. Figure 1 shows the idealized exoskeleton actuator device.

This paper focuses on the characterization of the brachial biceps' myographic signals during the flexion movements to obtain some initial reference rules for posterior application in a possible fuzzy logic controller for a rehabilitation exoskeleton. This work set the basis for one of the authors' master thesis [5] and is a part of an ongoing research project. The remainder of this paper is composed as follows: after the introduction, the aim of this research project is presented, the experimental methods for sampling the signals are described in section 3; in section 4, the results are compiled and analyzed with a controller topology based on those signals being proposed; finally, the conclusions and the future research work are presented.

2. Aim of the Research

The development of a self-contained exoskeleton-type assistance system can be split into 3 focus areas, biomechanics, electronics, and power electronics. Biomechanics is used to model, design, test-fit the rehabilitation frame (i.e., the exoskeleton's frame); electronics are used for signal sampling and the command and control (C&C) system; finally, power electronics are used for the design and selection of actuators, power supply and power and energy needs. In a daily utilization, control input signals should

be as natural and as robust as possible, so to select the potential muscular areas of interest, a Neuro-Musculo-Skeletal system model was used. This is a two-joint limb system with two pairs of antagonist muscles connected around two hinge joints. The muscle actuators are the brachial biceps, brachial triceps, posterior deltoid, and anterior deltoid, represented in the right image of Figure 1. For simplification, a single joint with a single pair of antagonist's muscles is enough for initial parameter configuration [6]. Thus, for system control, the brachial biceps muscle characterization through electromyography (EMG) signals was chosen in the present work. These muscles are easily accessible, and their EMG can be used to collect enough data to allow for a fair degree of signal repeatability. Quantifying those signals is an essential first step to establish baselines for the control algorithms of the system. As the signal characterization and detection of motion artefacts or other such issues could constrain the type of control strategy that can be applied for exoskeleton C&C.

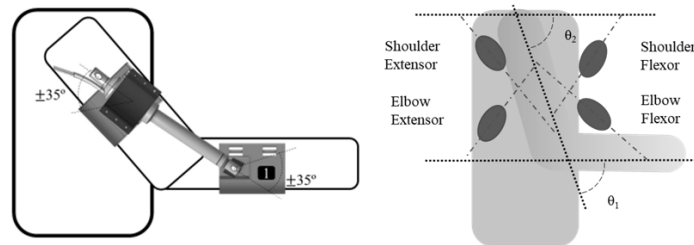


Fig. 1. The proposed 3D printer-ready model with linear actuator (left) [5] Model of Neuro-Musculo-Skeletal two-joint limb system with 2 muscle pairs, (right), adapted from [6].

3. Methods and Basic Assumptions

This research was a preliminary study conducted in the academic environment where the volunteers were mainly healthy, young individuals (i.e., aged <30). Some volunteers with ages above 40 were also used for the reference and posterior analysis. At this first step of the study, the inclusion of stroke-affected volunteers in the test group was not considered. However, it was assumed that presently recorded data will be compared with signals obtained from individuals affected by stroke in future work.

3.1 Study Characterization

The study was conducted with a cohort of 13 volunteers, seven females and six males, aged 17 to 55. The volunteers were generally healthy and presented no physical limitations in the upper extremities that could affect the test procedure (i.e., no limitations at forearm, elbow, or shoulder level that in any form could impair the flexion and extension with the different test loads). Additionally, three volunteers aged 40 were used for comparison, one female and two males aged (44, 43 and 55, respectively). All the volunteers were right dominant arm. Whenever possible, the brachial biceps signals were recorded for biceps of both rights and left arms. For the procedure, volunteers were seated with the elbow supported in a chair armrest and the arm-forearm flexion angle of 130° , approximately. The electrode lead cable was placed so as not to interfere

with the natural forearm movement. Each volunteer's experimental measurements were realized in a single session and lasted no more than 40 min. The experimental protocol was composed of 3 main steps, namely:

- i. The measurement protocol was explained to each volunteer, and the critical parts of the exercise were showed.
- ii. The three disposable electrodes were placed onto the brachial biceps (positive and negative near the muscle insertion) and connected by electrode lead cable to the MP35 unit according to the international EMG guidance protocol [7].
- iii. Calibration and recording of the EMG signals of biceps contraction were performed continuously (based on [8], for forearm flexion movement).

During all the experimental procedure of steps ii) and iii), the volunteer was in the supine sitting position. Before the start of each recording, the system was zeroed and calibrated by doing a full flexion movement (i.e., from 0 to 80°) with the maximum test load, i.e., 2 kg. During a forearm flexion, the EMG signal acquisitions of consequent brachial muscle contraction were performed for three different loads: 0.5, 1 and 2 kg on the volunteer's hand. The load's values were chosen as more suitable for this study since the maximum weight to lift by the forearm of the person after stroke impairments were determined as 2 kg. For each load, the EMG signals were sampled in sets of 3, each group consisting of flexing the forearm at three different angles, 45, 60 and 75°. The angle position was measured by the goniometer. This procedure allows assessing the signals of biceps contraction for various amplitude movements and the different loads. Figure 2 shows the schematic layout of the experiment and a picture of a test setup. The signal acquisition starts with the 0.5 kg and flexion angle of 45° and continue for other angles and increasing the load. The measurements were recorded at each angle, for the repeated movement at least 6 times to allow for signal averaging and variability assessment. Each recording flexion exercise was completed, typically, in less than a minute. Finally, after EMG signals recording from the dominant arm, the same experimental procedure was repeated for another arm of the volunteer.

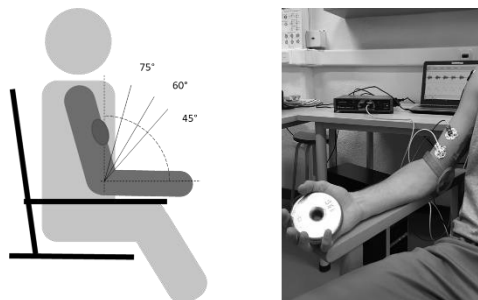


Fig. 2. Subject layout for myographic signal acquisition (left); the placement of the electrodes on the biceps brachial with the weight on the right hand (right image) [5].

Data acquisition was made via an MP35 acquisition unit datalogger from BIOPAC System, Inc., using the BSL PRO 3.7 software with the following channel configuration: EMG signal; AC coupling; no offset; x500 gain and bandpass filter configured to 0.05 Hz to 50 Hz. The sample rate was 1000 Hz. After recording, signals were typically noisy, and automatic post-processing filtering in the 20 Hz band was applied using the BIOPAC tools. Muscular movements, even when explosive, can be

classified as a slow phenomenon, with a relatively low fundamental frequency, more even if those movements are repetitive, as in this study. Considering a repetition rate of 120 movements per minute, those would produce a movement frequency of 0.5 Hz. Using the sampling (Nyquist) theorem, a frequency above 1.5 Hz would be enough to record this periodic movement and obtain viable data. This is a gross underestimation as the interest is in the movement behaviour and not its pure period characteristic, so the objective was to apply a frequency that allowed to oversample in such a way that enough information could be extracted to characterize and classify different stages on a single movement. Using a sampling frequency higher than 1000 Hz was deemed unnecessary for the purpose of this study as the interest was mainly focused on myographic signal trend for time parameter estimation and not a full signal amplitude-time relation [9]. Bandpass filtering was essential, as, at low frequencies, the low amplitude of the recorded signals is susceptible to external noise from electrical sources and motion artefacts.

4. Results and Discussion

A significant amount of data was collected in the present study: 288 recorded files of total 1728 EMG signals of brachial biceps contraction. Statistical analysis of that raw data led to the creation of data sets for better visualization, based on the average of the 6 recorded signals for each flexion movement and each individual condition pairs (i.e., load and angle). Signals were firstly split between female and male, and then right hand and left hand. Figure 3 shows an averaged full data set for a movement of 45° with all the test weights. The top three graphics present the data collected for what was considered as the start of the forearm lift movement, the 1st 400ms; the bottom three graphics present the remainder of the lift action; a small pause at the top of the target angle, followed by the downward movement and breaking muscular action to reach rest position.

To establish the movement definition, time phases where change on the signal trend was visible were obtained from the data and grouped as presented in figure 4. In the left image, there are two main areas of interest where the myographic signal is such that the muscle recruitment is clear. The time slot between 100 to 150ms has a pronounced positive slope. Additionally, the signal strength threshold is such as to allow for the signal to be used as an initial setpoint for movement “start phase”. Considering the next time slot, going from 300 to 350ms, here the signal slope as decreased in relation to the previous time slot; this corresponding to a decrease or stabilization in speed/strength of the recruited muscles. Above 400ms, the movements’ “start phase” can be considered as finished, and the intensification of the signal starts to be less significant as the forearm reaches the maximum height of the movement. Applying the same type of experimental analysis for the right image, several stages of the movement can be defined in time: 400–590ms; 600–750ms; 800ms–1.3s; 1.35–1.65s; +1.7s. These later five stages, clearly indicated by the changes on the characteristics of the myographic signal can be used as set points on control system to be implemented for exoskeleton control. From 400–590ms the signal slope is steadily decreasing as the muscular movement goes from the initial boost to a steady speed and strength until it enters a

slowing motion phase as the maximum height is reached. From 600–750ms occurs the inflection on the slope of the signal, corresponding to muscular relaxation for the beginning of the descent movement of the forearm. From 800ms–1.3s there is a steady slope corresponding to the descent control of the biceps brachial. From 1.35–1.65s, signal slope inflection again changes as muscular recruitment again increases when entering the stopping phase of the movement. Finally, after 1.7s the finalization of the movement occurs. Interestingly, here it can be observed that muscular recruitment varies in duration, becoming dependent of the speed of the movement.

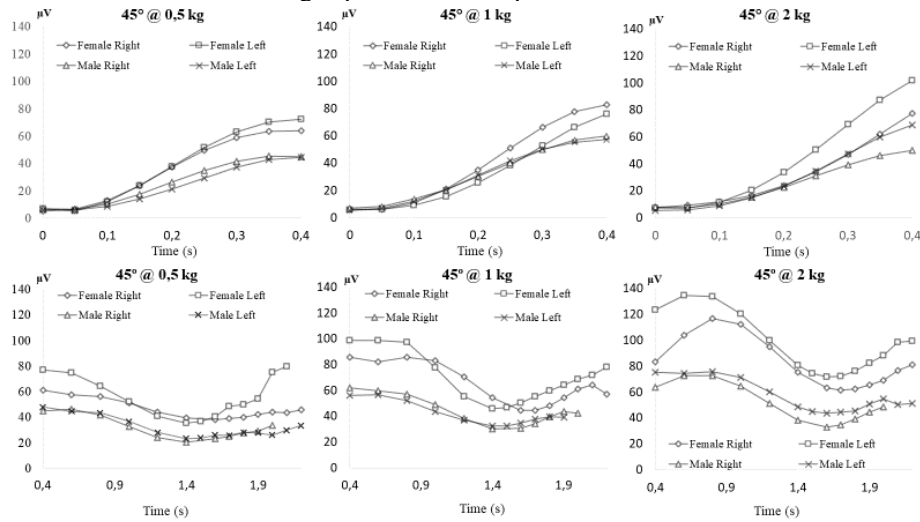


Fig. 3. The full range of averaged male and female data at 45° with the test weights, 0.5, 1 and 2 kg.

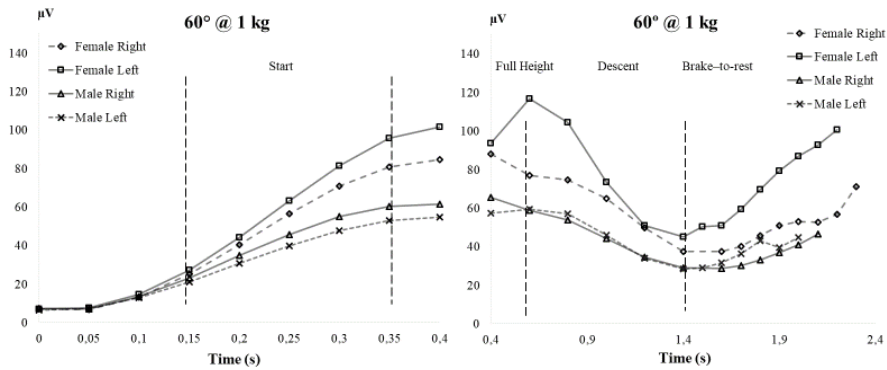


Fig. 4. Sample images used for movement definition phases, full movement for a weight of 1 kg at 60°.

The myographic signal from the brachial biceps presented an inherent amplitude variability with the different loads and angles that, for their contribution, do not allow for the specification of a particular start/stop time for any part of the movement, as can be seen in the signal grouping of figure 5. This intrinsic characteristic of the muscular myographic signals, as already been reported in the literature [9], [10] and brings forth

a specification for a control system that can adapt and accommodate those changes. Increasing the sampling rate for the myographic signal acquisition device will bring an increase in the amplitude, as previously referred. Still, to the nature and variability of myographic signal, this increase will be noticed at all loads and angles. At this stage of the research, it is not clear that a significant distinction between classes can be achieved to allow for a better classification. As an example, considering zone 1 and 2 in figure 5; here, the grouping of signals with different loads and at different angles does not allow for clear control rules to be established; at the point considered to be the start of the movement, 100ms, minimum and maximum values vary meaningfully for each test setup and are contained in a $4 \mu\text{V}$ difference. An analogous situation can be noticed in the second reference point, at 300ms, as the slope change indicates the slowing of the movement as the target height is reached. Where the maximum recorded value of the myographic was measured with the 1 kg weight for 60 and 75°, $54 \mu\text{V}$; with a full voltage swing of $16 \mu\text{V}$ for all the recording, the signal grouping, again, does not allow to establish a clear control rule for single signal control. The critical analysis of the data present in this paper, lead the authors to detect a fault in the test setup, “movement speed” of the forearm on the movement was not correctly considered. As each volunteer unknowing or unwillingly moved at his own natural speed, a variable difficult to control, as a result, that “natural speed” must be considered when recording muscular myographic signals. Practically this issue can be solved with very little impact on the system controller’s footprint. An accelerometer integrated circuit (IC) mounted on the forearm support (figure 1), could provide the necessary signals to complement the biceps brachial myographic signal.

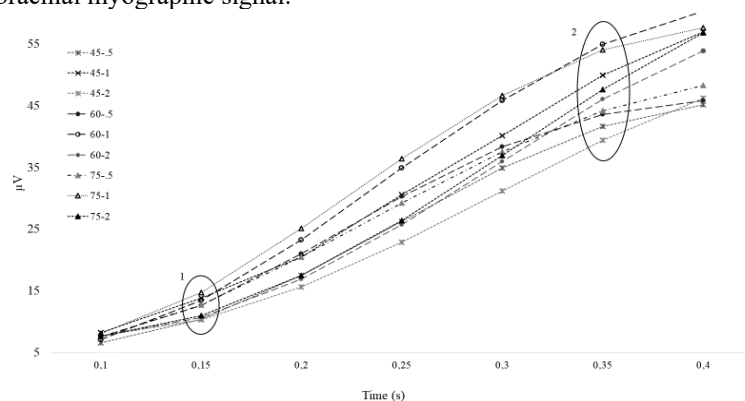


Fig. 5. “Movement start” for the dominant forearm of males for all experimental loads and angles.

5. Conclusions and Future Work

This study evaluated the viability of the myographic biceps brachial muscle response as a control input variable for rehabilitation device control. The detected variability of the signals in the test conditions lead to the conclusion that using a single variable for exoskeleton control would be challenging if not unfeasible, unless the utilization of some type of Artificial Intelligence (AI), controller could be used. Otherwise, the

utilization of accelerometer type IC to complement the muscular signals and/or other control variables (i.e., additional muscular signals) will be necessary to complete the base signals. Future work will refine the experimental procedure, adding acceleration recording and probably, evaluating complementary myographic signals from the forearm and other muscular locations on the upper extremities to complement the muscular base model of [6]. With the collected signals, the review of control topologies and their contrast initially led to the proposal of a fuzzy logic type controller, as the most indicated “classic” control topology to accommodate the signal variabilities, as is further discussed in [5]. Additional work will evaluate the utilization of artificial intelligence on the data to try to obtain an improved set of control rules and gain the ability to accommodate the evolutive changes in the user’s physiological conditions as he grows back to total health or as close as possible to it. It is expected that as the user sample signal database grows AI algorithms will be instrumental in establishing clear control rules. AI algorithms for control and data mining will be evaluated in the next phases of this research. The biceps brachial signals, couple with signals from an accelerometer IC and the proposed controller topology, are expected to be used in a first iteration low-cost stand-alone prototype of a self-power exoskeleton for rehabilitation assistance.

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