CHANGES IN MUSCLE ACTIVITY PATTERN FOR HAND-ARM MOVEMENTS OF AMPUTEES AND NON-AMPUTEES

I. C. M. da Silva* and L. B. Bagesteiro* e **

*Pós-Graduação em Neurociências e Cognição, Universidade Federal do ABC, Santo André, SP, Brasil

**Escola de Engenharia, Depto. Engenharia Elétrica, Universidade Federal do Rio Grande do Sul, Porto Alegre, RS, Brasil

email: leia.bagesteiro@ufrgs.br

Abstract: Limb amputation causes impact in quality of life and professional aspects. Over the past few years, several progresses have being made in myoelectric control but the rejection rates of robotic prostheses are still high. This study evaluate muscle activation pattern of hand-arm movements. Participated of the study six volunteers (three amputees (AG) and three healthy individuals (CG)). Surface electromyography (EMG) was used to collect the patterns of muscle activation. Eight channels were placement in stump (AG) and upper limb (CG): four channels were equidistant positioned around the upper arm and the other four channels were equidistant positioned around the forearm. All participants performed two sequences of 18 continuous movements and each channel data was analyzed comparing groups and the complexity of movements. CG presents most channels activated with higher activation in extensor and flexor areas, always in accordance with analyzed movement. The channel activation in AG was not necessarily related to the targeted movements. The data suggest that the modification on muscles disposition, absence of muscle insertion and metabolic chance after amputation can alter the muscle activation in amputee limb during continuous movements.

Keywords: amputee, muscle activity, hand-arm movements.

Introduction

Upper-limb amputation produces some day-to-day limitations in the ability to carry and manipulate objects, therefore restraining quality of life and professional aspects of amputees [1, 2, 3]. Myoelectric prostheses technology have greatly advanced in the last years, although the rejection rates are still high [1, 4, 5], and this is one of the reason for improving the performance of robotic prostheses allowing amputees with a more natural man-machine interface. The use electromyography (EMG) represents a promising research area in the development of intelligent prosthesis with finer control and greater realism in motion. There are many available works with EMG and upper limb control [2, 6, 7] but until now no functioning system developed features equivalent to natural systems.

The relationship between myoelectric signal and movement has been studied for many years; nevertheless, amputation can alters the muscles disposition and the functional changes of the residual muscles [7, 9]. In these cases, it can be difficult to extract sufficient information from the EMG signals to control the upper limb prostheses [9]. Some researchers [6, 7, 8] have observed that the electrodes uniform distribution around the stump can capture the largest possible number of muscles groups with a degree of accuracy between 79-94% during upper limb movements. Ordinary limb movement involves simultaneous and combined wrist/hand motions during everyday activities [8]. For the analysis of simultaneous movements, it is important to understand the action of the synergist and antagonist muscles to move, as well as aspects of muscle co-activation. Hence, the present challenge is to establish how EMG patterns can represent a set of synergies for continuous upper limb movements. The purpose of this work is to evaluate and compare muscle activation patterns of residual upper limb from amputees (Amputee Group – AG) and a healthy control group (CG) during specific hand-arm movements.

Materials and methods

Six individuals participated in the study. Three amputees (wrist disarticulation amputation level - AG) and three healthy subjects (control group - CG), matched for gender, age, height and weight with the amputee subjects. All participants signed the informed consent and answered an anamnesis. Table 1 summarizes the characteristics of each subject group. No subject in AG has used myoelectric prosthesis. The exclusion criteria for the AG was: amputation of upper limb transhumeral level and above; amputation with less than one year due to immaturity of stump and the possibility of edema or changes in volume; whereas, for the CG were neurological disorders that result in chance of motion and acquired or congenital abnormalities involving the upper limb.

Surface EMG was collected using an 8-channel EMG system (EMG System do Brasil Ltda.). Four channels (C1, C3, C5 and C7) were equidistant positioned around the circumference of the midportion of the arm and the other four channels (C2, C4, C6 and C8) were equidistant positioned around the midportion of the forearm. For best electrodes positions, the muscles regions were initially found by palpation and confirmed by performing contractions looking at the EMG signal. The electrodes position was chosen according to [2, 6, 7]. A ground electrode was placed on the clavicle, away from the muscles of interest. Figure 1 illustrates the electrodes positioning on an amputee volunteer.

Table 1: Summary of participants' information (mean ± SD).

Group	Amputee	Control
Age (years)	37 ± 0,6	37 ± 0,6
Height (m)	1.72 ± 0.08	1.74 ± 0.08
Body Mass (kg)	79.3 ± 9.0	77.7 ± 8.4

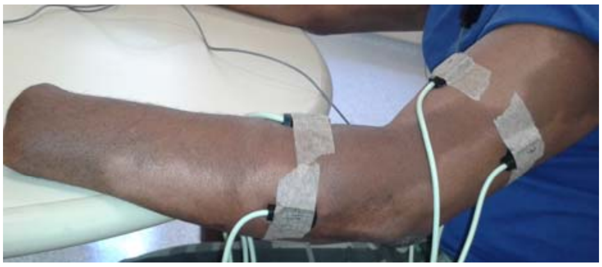

Figure 1: Electrodes setup.

Subjects sat in front of a computer with their limb in a comfortable position resting on the table. The movements performed by the subjects were standardized using a virtual model previously developed [10]. All participants were instructed to imitate the movements of the virtual model in a synchronous way. Two sequences of 18-targeted movements were performed replicating the virtual humanoid model animation. In each sequence there were nine different movements repeated twice taking approximately 250s for the whole session. A rest period of 3 seconds was provided between each movement in each sequence to prevent muscle fatigue. Table 2 shows the 18-targeted movements which were divided in three groups: (1) Simple (Wrist Flexion (WF) and Wrist Extension (WE)); (2) Double (Supination and Pronation (S+P), Wrist Extension and Wrist flexion (WF+WE), Elbow extension and Elbow flexion (EE+EF), and Hand closed and Hand opened (HC+HO)); and (3) Complex (Supination, Elbow flexion, Elbow Extension and Pronation (S+EF+EE+P); Hand closed, Elbow flexion, Elbow extension and Hand opened (HC+EF+EE+HO), and Supination, Hand closed, Pronation and Hand opened (S+HC+P+HO)).

EMG signals were recorded at 1000Hz and filtered with a second-order Butterworth band-pass filter at 23 and 500Hz cut-off frequencies. EMG signals were normalized to the maximum voluntary contraction (MVC). The MVC was measured at the end of the experiment session. Subjects were asked to maintain maximal flexor and extensor forces at each joint, over a 5-s recording time. Each of these maximum force trials was scanned using a computer algorithm to find the highest root-mean-square (RMS) EMG magnitude for each muscle. Data was analyzed shifting window with a time length matching and depending on the specific targeted-movement been performed, and then obtaining the corresponding segment of muscle contraction captured by each of the eight channels. Subsequently the RMS was calculated for each channel related to every movement. Each data channel was analyzed comparing groups and the complexity of movements (simple, double or complex). The statistical analysis verified the mean and standard deviation of RMS values for each channel. Statistical significance was tested using an alpha value of 0.05.

Table 2: Targeted movements performed.

Movements	Abbreviation
Wrist Extension	WE
Wrist Flexion	WF
Supination	S
Pronation	P
Elbow Extension	EE
Elbow Flexion	EF
Hand Opened	HO
Hand Closed	HC

Results

Data from both groups was collected and analyzed using custom computer algorithms written in MATLAB (The MathWorks, Inc.) and IgorPro (Wavemetrics, Inc.). Figure 2 and 3 show representative EMG data from C1 (red) and C8 (blue) channels during the first sequence of movements for a subject from each group. It is possible to identify different antagonist muscles activation along the sequence between these channels, even in continuous movements.

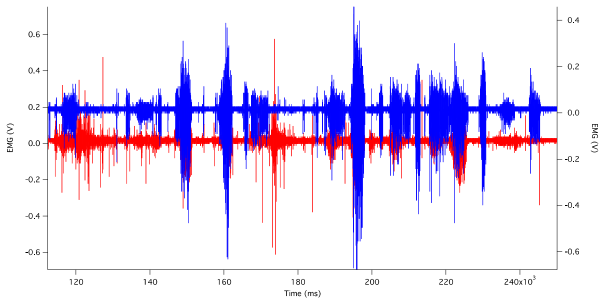

Figure 2: EMG data for a representative control subject.

For the analysis it was considered the average RMS of each channel in each of the two sequences of movements performed by each subject. Each movement was completed four times per subject. In each group with three subjects, the same movement was accomplished 12 times. When comparing each channel, there are differences statistically significant between groups.

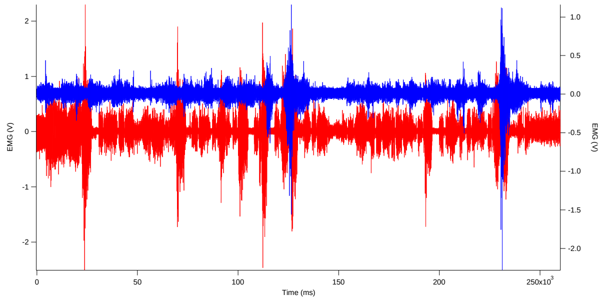

Figure 3: EMG data for a representative amputee subject.

Table 3 shows the comparisons for each channel in the movements. The arm channels present more statistical significance between groups than the forearm channels. Some differences showed a larger pattern of activation in CG than AG. On the other hand, some differences were also shown in the larger pattern of activation in AG than CG. For WE movement, it was observed difference in extensor region (C7) with a larger pattern of activation on CG (p=0.037). In WF was observed a larger pattern of activation in flexor region (C1) of CG (p=0.019) and in the arm and a larger pattern of activation in extensor region (C6) in forearm of AG (p=0.044). Movement of elbow (EF+EE) presented difference in the extensor region in the arm, channel C5 with a larger pattern of activation in AG (p=0.024) and channel C7 more activated in CG (p=0.035). For hand movement (HO+HC) a larger pattern of activation was shown in channel C1 (p=0.011), representing the flexor region (brachial biceps) in the arm and in radial extensor carp region in C4 (p=0.027), both for CG. HC+EF+EE+HO movement presented flexor region in C1 (p=0.019) in the arm more activated in CG and extensor region in C8 (p=0.021) more activated in the AG. S+EF+EE+HO movement had a larger pattern of activation on extensor region (C7) in CG (p=0.023) and pronator region in C6 more activated in AG (p=0.020). S+HC+P+HO movement presented difference only in flexor region in the arm, C1 (p=0.011) and C3 (p=0.038), with a larger pattern of activation for CG.

Control group present most channels activated according to analyzed movement. Table 3 shows movements with extension with a higher activation in extensor areas (C4 and C7). When the movements involved flexion, there was greater activation of C1 and C3. For the AG, activation of extensor and pronator regions (C5, C6, C8) was predominant, as compared to the CG subjects. However, channel activation in AG was not necessarily related to the targeted movement. Complexity of movement showed difference in C1 for single and double movements in both group (p=0.034). Double movements present a larger pattern of activation as compared to the single movements. However this difference was shown in channel C5 only for the CG (p=0.029), with greater activation for double movements.

Table 3: Comparison between AG and CG for each movement and EMG channels.

Movements	**Arm EMG channels**	**Forearm EMG channels**
WE	C7 (p=0.045)	-
WF	C1 (p=0.031)	C6 (p=0.040)*
EF+EE	C5 (p=0.026)*, C7 (p=0.015)	-
WF+WE	-	-
HO+HC	C1 (p=0.011)	C4 (p=0.027)
S+P	-	-
HC+EF+EE+HO	C1 (p=0.018)	C8 (p=0.022)*
S+EF+EE+P	C7 (p=0.033)	C6 (p=0.012)*
S+HC+P+HO	C1 (p=0.019), C3 (p=0.048)	-

*larger pattern of activation in AG than CG.

Discussion

In this study, EMG signals for wrist disarticulation amputees were compared with individuals without amputation. Sequences with single, double and complex movements were evaluated in order to characterize the complexity of the upper limb movement and better understand its functional performance.

Placing the electrodes around the stump and upper limb allowed EMG data collection and analysis for both groups. Others researchers [2, 6, 7] have had encouraging results with the same methodology. So, even in the absence of physiologically appropriate musculature it is possible to analyze the intended motion in amputees. As shown in Figure 3, there is a complete sequence of movements completed by an amputee. It is possible see the patterns of activation of agonist and antagonistic muscles, even for hand/wrist movements. Sheme and Englebart [8] reported that it is necessary a sufficient number of channels and spatial coverage of EMG for characterizing information available from the underlying musculature. Although a non-standard EMG electrodes' position was employed, and the crosstalk between muscles may be an issue, the trend of muscle activities over time should contribute to the development of effective rehabilitation programs.

For the RMS analysis, two movements do not show statistical different in any channel (see Table 3). These movements were wrist flexion and extension (WF+WE) and supination and pronation (S+P). For both group, the patterns of activation was similar according to the statistical analysis. Young et al. [2] studied these movements and found no difference between transhumeral amputees and non-amputees. It is possible that S+P and WF+WE movements can be performed even after amputation, in different situations that involved some stump action [2]. The present study, observed that after upper-limb amputation, the related muscles involved in wrist extension and flexion and upper-limb supination and pronation are activated at the same intensity that in individuals without amputation.

Analysis of movement complexity is very important for functionality; several elbow/wrist/hand motions are involved in activities of daily living [1]. According to previous studies [2, 6, 7] no difference between amputee and non-amputees was found. In this study, double movements showed statistical difference compared with single movements for two arm channels. Yet, there is a lack of previous work with combined movements. Consequently, further investigation is needed to improve our understanding of EMG signals in continuous movements.

In addition, classification strategies as pattern recognition algorithms can also be applied to expand our knowledge in this field, as well as advance prosthetics design [11]. Additional investigation implementing simultaneous pattern recognition can offer various benefits for the development of upper limb prosthetics being more functional and lower the rejection rates.

Conclusion

This study analyzed continuous movement and used eight EMG channels to compare amputee and non-amputee volunteers. The results demonstrate difference between both groups while performing some specific movements. These data emphasize the anatomical and functional changes after amputation, thus more studies with amputees are needed to a better understanding of how the myoelectric prostheses can be more functional.

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