Analysis of Myoelectric Signals to Prosthesis Applications

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Abstract. This work presents a myoelectric system measurement incorporated in an arm band device, particularly designed for application in upper-limb myoelectric prosthesis with pattern recognition-based sEMG control. For this particular use, specifications such as low cost, high sampling frequency, size and weight, may be observed. Moreover, it is introduced an acquisition protocol to evaluation of the myoelectric signal in daily activities.

Keywords. Electromyography, Upper-limb Myoelectric Prosthesis, Myoelectric Signal, Wearable sensors

1. Introduction

The perfection of the human body has been motivating engineers and researchers to reproduce it in technologies to enhance human capabilities. One of the most complex pieces of natural engineering are the hands. Characteristics such as opposable thumb and the unique arrangement of muscles give them a great movement versatility going from a power grip to precision manipulation. But their functionality goes beyond just handling objects, they are also involved in communication and tactile sensing. [1]

Therefore, the amputation of a hand by congenital, traumatic or disease causes, has Psychological, Sociological and Ergonomic impacts. However, the active upper-limb prosthesis, considered the best current palliative solution, has high rates of rejection estimated ranging from 25% to 50% [2] especially when compared with a low-limb prosthesis [3]. Indeed it has been more than 70 years since the first concept of the myoelectric prosthesis was introduced by Reinhold Reiter [4], and still, there has not been found a good enough solution for a reasonable price.

The challenges developing an upper limb prosthesis reflect the complexity of the human hand. Further the low acceptance of the currently available devices motivates additional researches. In fact developing effective and intuitive myoelectric control could not just help individuals with amputation, but may further expand possibilities of humans interacting with the environment and controlling other systems.

The myoelectric signal, the classic control signal used on an active prosthesis, is the evoked response by muscle contraction generated by the electrical action potential firing through the muscle fibers. It can be measured in a non-invasive way by the surface electromyography (sEMG) sensors. [5]

The myoelectric prosthesis models, such as i-Limb from Touch Bionics, Bebionic and Michelangelo from Ottobock, has proven the feasibility of mechanically dexterous prostheses, even in a commercial level despite the still high price. Therefore the system-user interface still remains as one of the main issues causing insufficient functionality, rather than the hardware component itself. [6]
These commercial devices use the Direct Control approach, which uses two opposing muscle groups to control each direction of one DoF (degree of freedom) and a voltage threshold-based trigger to the motion. If the prosthesis has multiple DoFs, then the subject through a co-contraction sequentially switch the different setting modes. A rather more sophisticated and intuitive solution is the Pattern Recognition Control, which extracts features from the myoelectric signal aiming to identify patterns associated with the movements, eliminating the need of switching modes. [7] Some of the several parameters common used to quantify the myoelectric signal are Root-Mean-Square (RMS), Mean Absolute Value, Zero Crossings, Slope Sign Changes, Waveform Length, Histogram (HIST), marginal Discrete Wavelet Transform (mDWT). [8]

This work presents a measurement system of the myoelectric signal to be future applied on a pattern recognition-based sEMG control upper limb prosthesis. Also an acquisition protocol is presented to evaluate the myoelectric signal from different muscles in daily activity.

The following Section 2 covers the Methodological Approach of this work presenting the acquisition setup and data acquisition protocol. Section 3 details and discuss the Results. Finally, in Section 4, the conclusions and future works are presented.

2. Methodology

2.1. Acquisition Setup

In this subsection will be described the main hardware parts that composes the measurement system and the software used on the data acquisition process.

Surface Electromyography System: The myoelectric measurement system consist of an elastic and adjustable arm band with three active (indicator) electrodes plus one forth reference electrode as shown in Figure 1 and Figure 2 - Detail D. These are non-invasive dry active differential electrodes formed by a sensor of silver coated with silver-chloride, embed in a pre-processing circuit board. Each electrode was placed in a 3D printed box specially designed to accommodate it and attachable to the arm band.

The pre-processing circuit was divided in three stages: (I) an instrumentation amplifier Burr-Brown INA118P; a bandpass filter with (II) a passive high-pass filter and (III) a first-order inverting low-pass filter. The primary functions of this circuit is signal acquisition, filtering the frequencies between 48.228 ~ 482.28Hz and amplify (G = 2199.5) the signal adjusting within the operating range of the microcontroller’s A/D converter.

![Figure 1 - The myoelectric measurement arm band.](image)

Acquisition Hardware: The Power Supply Circuit has a unique Li-Po battery (Figure 2 - Detail A) of 2 cells, 7.4V. Moreover the power supply board (Figure 2 - Detail B) regulates the voltage in -5V and +5V to properly power the electrodes.

The Microcontroller used was the STM32F103, developed with the ARM Cortex-M3 32-bit RISC core operating at a 72 MHz frequency built in the STM32F103c8t6 board (Figure 2 - Detail C), programed at Mbed OS environment. The pre-processed signal once received by the microcontroller A/D converter, with 12-bit resolution and 0-3.3V operating voltage range, was sampled at 1600Hz frequency forming data chunks containing 512 samples from each of the three sensors.
Moreover to provide a supplementary data, an *Inertial Sensor Xsens MTw Awinda*, which is a wireless motion tracker (Figure 2 - Detail E), was placed in a separated compartment at the bottom of the water bottle providing inertial data of the movement performed by the subject. This data, which includes acceleration, angular velocity and magnetic field (earth), will be used afterwards to validation of the myoelectric data.

**Software:** A Python 2.7.1 application receives through Serial communication data containing the measurements from the three channels. Moreover, a feature of this application allows the researcher manually insert markers corresponding to the executed movement by the voluntary. Therefore during the analysis process, the different tasks are easily identified on the myoelectric signal.

The incoming data is transferred from *Python* to *Matlab* R2015a using the communication protocol *Lab Streaming Layer*. This synchronization of the streaming data enables real-time displaying, live analysis and recording on *Matlab*. This feature of simultaneously tracking all channels during the trial is important to ensure that all electrodes are correctly measuring.

![Figure 2 – Subject wearing the measurement system during trial.](image)

### 2.2. Data Acquisition

The objective of the proposed trial is to collect data to identify common characteristics from the myoelectric signal related to a daily task. This research project was conducted in accordance with the Guidelines and Regulatory Standards for Research Involving Humans (Resolution 196/1996 of the National Health Council and Declaration of Helsinki), and was submitted to the Human Research Ethics Committee from the School of Physical Education and Sport of the University of São Paulo (EEFE-USP).

Each subject signed a consent term agreeing to participate of the research and acknowledging the risks involved. While the physiotherapist prepared the subject to the trial, a series of questions were asked regarding name, birth date, age, gender, weight, height, job, fitness, arm related diseases or previously arm injuries. Moreover an Edinburgh Handedness Inventory was filled in order to assess hand dominance in everyday activities.

The physiotherapist palpating the arm of the subject while he repeatedly contracts the muscle, identified the *Extensor Digitorum* (Channel 1 - Blue), *Brachioradialis* (Channel 2 - Red) and *Flexor Digitorum* (Channel 3 – Yellow) muscles in both arms. This muscle group where selected considering a transradial amputation. Then the position of higher myoelectric activity for each muscle were shaved, cleaned and marked.
The acquisition is made for both arms, but a computational algorithm randomly select the starting side. Then the measurement system is attached to the subject as shown in Figure 2. After inviting the subject to sit at the experimental table observing his posture, a bottle with water is positioned at a distance 80% of his arm length related to the xiphoid process.

The trial for each arm is divided in three sections. Each section, the subject are asked to perform three different movements 10 times following the same random order, previously presented before the beginning of the exercise. The data from each section were recorded separately.

The three movements repeated in a random order each section are:

- M1 - Grab the bottle;
- M2 - Grab and rotate (pronation) the bottle;
- M3 - Pick the bottle up until the shoulder’s height and rotate (pronation) it.

Considering human reaction times and attention spans, the subject was reminded of each movement before executing it and should perform it just when signalized. The research after inserting the corresponding movement marker on Python, would wait around 5 seconds before signaling to the volunteer execute the task to guarantee identification of the beginning of contraction.

3. Results and Discussion

Data from intact subjects were collected as described in Section 2.2 and Figure 3 shows the sample of a myoelectric signal measured during 10 repetitions of the randomly generated sequence M1, M2 and M3, executed with the right hand. It was a male volunteer, left-handed, with 30 years old, height of 1.72m and weighing 80kg. Figure 4 shows the RMS value calculated for each channel.

![Figure 3](image-url) – Example of data collected for motion sequence M1, M2 and M3
The results were compared with a dataset from the Ninapro Project Database of a male intact subject, right-handed, with 29 years old, height of 1.83m and weighing 75Kg, executing a movement similar to M1 (grabbing a bottle) with the right hand. The myoelectric signals from the extensor and flexor muscles were recorded with Delsys Trigno Wireless electrodes and sampled at a frequency rate of 2 kHz. Also different from the presented protocol, he repeated the movements 6 consecutive times in a non-randomized order. [8]

Figure 4 – RMS value

Figure 5 – Myoelectric signal recorded of the subject grabbing a bottle with the developed electrodes and the signal envelope (red line)
The signal envelope was defined for both datasets calculating the Moving Average, which is an amplitude behavior estimator indicating the muscle activation interval. The Figures 5 and 6 shows the signals recorded with both measurement systems with the envelope line. Comparing them it was observed a similar shapes for each muscle. The activation interval of the extensor muscle has a more linear shape. While the activation interval of the flexor muscle has two distinguished peaks in the beginning and at the end of the task. These patterns can be observed for both systems.

![Extensor Digitorum Muscle - Delsys Trigno](image1)

![Flexor Digitorum Muscle - Delsys Trigno](image2)

Figure 6 – Myoelectric signal recorded of the subject grabbing a bottle with the Delsys Trigno Wireless electrodes and the signal envelope (red line)

4. Conclusion

In this project, the proposal of a low cost electrographic signal acquisition system for use in upper limb orthoses was presented. The system proved reliable and with good repeatability of signal reading. In the future stages, the data collected during this research will be further analysed identifying more patterns for each movement considering the same subject and also comparing the variation between different subjects. Then a classifier associated with a control system will be implemented to power an upper-limb prosthesis with two degrees of freedom: flexion/extension and pronation/supination.

References

[1] National Academies of Sciences, Engineering, and Medicine; Health and Medicine Division; Board on Health Care Services; Committee on the Use of Selected Assistive Products and Technologies in Eliminating or Reducing the Effects of Impairments; Flaubert JL, Spicer CM, Jette AM, editors. The Promise of Assistive Technology to Enhance Activity and Work Participation. Washington (DC): National Academies Press (US); 2017 May 9. 4, Upper-Extremity Prostheses. Available from: [https://www.ncbi.nlm.nih.gov/books/NBK453290/](https://www.ncbi.nlm.nih.gov/books/NBK453290/)

[2] Atzori, M; Gijsberts, A; Heynen, S; Hager, AG M.; Deriaz, O; Smagt, vdP; Castellini, C.; Caputo, B, and Müller, H. Building the Ninapro database: A resource for the biorobotics community. 2012 4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob). 2012, pp. 1258-1265. doi: 10.1109/BioRob.2012.6290287
Atzori, M; Gijsberts, A; Kuzborskij, I; Elsig, S; Hager, AG M.; Deriaz, O; Castellini, C; Müller, H; and Caputo, B. Characterization of a Benchmark Database for Myoelectric Movement Classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2015, 23(1): 73-83. doi: 10.1109/TNSRE.2014.2328495.

[3] Raichle KA, Hanley MA, Molton I, Kadel NJ, Campbell K, Phelps E, Ehde D, Smith DG. Prosthesis use in persons with lower- and upper-limb amputation. *J Rehabil Res Dev*. 2008;45(7):961-72. PubMed PMID: 19165686; PubMed Central PMCID: PMC2743731.

[4] Zuo KJ, Olson JL. The evolution of functional hand replacement: From iron prostheses to hand transplantation. *Plast Surg (Oakv)*. 2014 Spring;22(1):44-51. PubMed PMID: 25152647; PubMed Central PMCID: PMC4128433.

[5] Brunelli, D; Tadesse, A M; Vodermayer, B; Nowak, M; and Castellini, C. Low-cost wearable multichannel surface EMG acquisition for prosthetic hand control. *2015 6th International Workshop on Advances in Sensors and Interfaces (IWASI)*, Gallipoli. 2015, pp. 94-99.

[6] Kuzborskij, I; Gijsberts, A; and Caputo, B. On the challenge of classifying 52 hand movements from surface electromyography. *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, San Diego, CA, 2012, pp. 4931-4937. doi: 10.1109/EMBC.2012.6347099

[7] Kuiken T A, Miller L A, Turner K, Hargrove L J. A Comparison of Pattern Recognition Control and Direct Control of a Multiple Degree-of-Freedom Transradial Prosthesis. *IEEE J Transl Eng Health Med*. 2016 Nov 22;4:2100508. doi: 10.1109/JTEHM.2016.2616123. PubMed PMID: 28560117; PubMed Central PMCID: PMC5396910.

[8] Atzori, M; Gijsberts, A; Castellini, C; Caputo, B; Hager, AG M; Elsig, S; Giatsidis, G; Bassetto, F; and Müller, H. Electromyography data for non-invasive naturally-controlled robotic hand prostheses. *Scientific Data*. 2014, 1 - Article number: 140053. DOI: 10.1038/sdata.2014.53