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Development of a Haptic Feedback Device Based on Electromyography Signals and an Arduino

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Abstract
The objective of this project was to build, using an Arduino microcontroller, a device integrating a generator of haptic feedback and an electromyography (EMG) sensor. The development of such device led to research in the expected areas of EMG signal processing and EMS design, and also to research on unexpected related areas such as machine learning, Bluetooth communication and GUI design. This paper describes the main research paths explored: EMG and the Myo Armband; EMS toolkit and haptic feedback; classification and machine learning; open source repository development. Each section outlines the underlying reasoning for the research theme, describes its main point and presents some example results. The overall general results were both the completion of the proposed device, making future studies involving the integration of haptic feedback in human-computer (HC) interfaces possible, and the development of an open source repository. The accompanying video exemplifies them both.

KeyWords*: EMG, EMS, Classification*

1. Introduction

The project proposed to build, using an Arduino microcontroller, a device integrating a generator of haptic feedback and an electromyography (EMG) sensor. More specifically, it proposed to build a human-machine-human interface, capable of measuring a biosignal (electromyogram), filtering and extracting relevant information, and using this information as input to a control system. This system, in turn, should generate a haptic force on a user, using electric stimulation, as a feedback mechanism. In this pursuit, the project spanned over several fronts (Figure 1), some planed from the start and others added as necessity dictated, exploring different aspects of the multiple technologies needed to complete it. This paper will briefly describe each of the studied fronts, presenting its bases, exploring its reasoning and main avenues and exemplifying the results obtained and how they contributed to other fronts and the main projects goals.

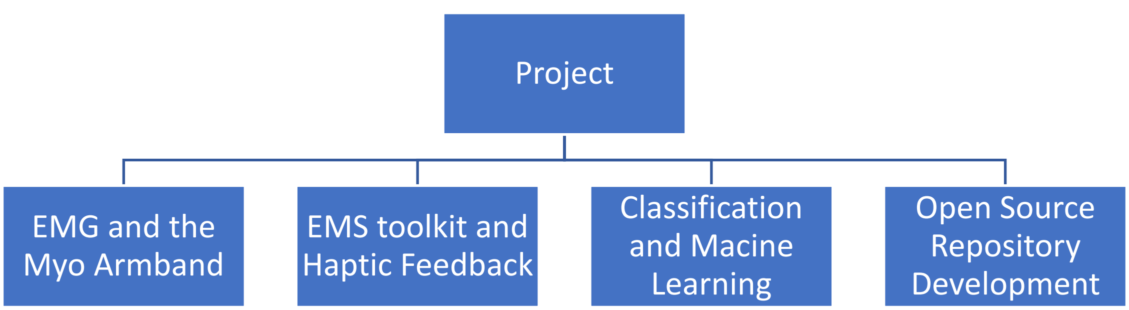


Figure 1. Breakdown of different studied facets in the project.

2. EMG and the Myo Armband

Electromyography (EMG) is the electrodiagnostic technique that measures the electrical signals produced during the contraction of the skeletal musculature. In its core the EMG signal is the action potential produced by the motor units (MU) distributed around the muscular fibers. These units receive signals form the nervous systems and distribute them via numerous enervations to the muscular cells, causing the contraction of the muscle. When groups of MU are activated the resulting signal is called the Motor Unit Action Potential (MUAP) [1].

While EMG can be measured invasively via needle electrodes, surface EMG, with electrodes on the surface of the skin, is the norm for IoT applications, due to simpler, hassle-free usage. One device that takes on this ideal, being simple to set and use, small and virtually risk free, is the Myo armband, our choice for EMG sensor on this project (Figure 2).

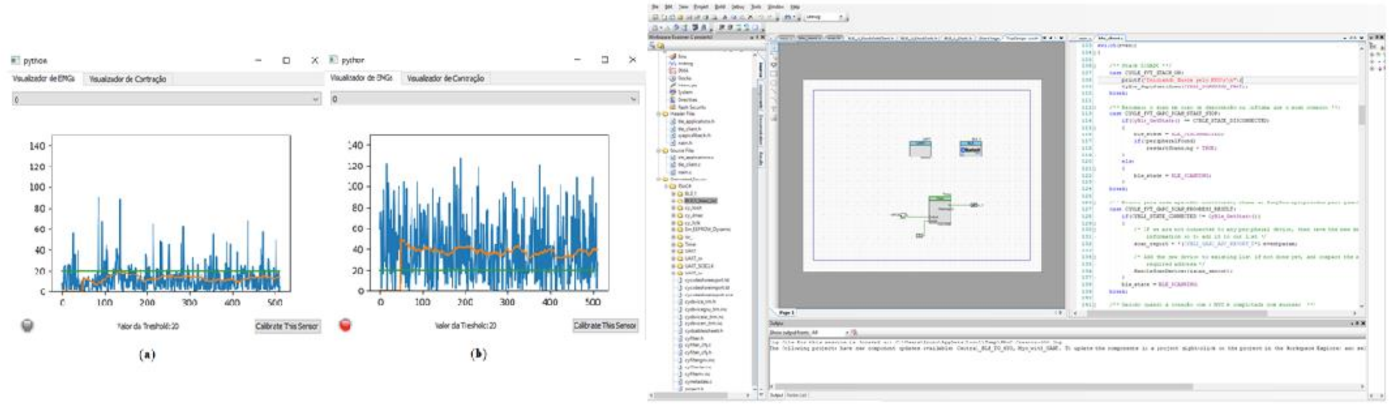
(a) (b)

Figure 2. (a) The Myo Armband. (b) Screen capture of the program used to perform the data acquisition of EMG signals to perform the first classification experiment.

The Myo armband (Thalmic Labs, Canada), was released in 2013 as a commercial device with eight medical grade stainless steel single differential electrodes. The device also includes a nine-axis inertial measurement unit (IMU) and a Bluetooth Low Energy (BLE) unit, all controlled by an ARM Cortex-M4 based microcontroller. Being a commercial grade product, a Myo Armband used to cost a few hundred dollars while, other, commonly used research sensors, such as the Delsys Trigno (www.delsys.com/trigno/sensors), may cost up to several thousand dollars.

The Myo armband should be positioned on the arm just below the elbow. This approach to sensor positioning is called untargeted, as the sensors are not directly positioned on specific muscles but are positioned in relation to each other. As a result, the information each sensor reads is a compound readout from various muscles around the sensor.

On the other side, this choice also created challenges. While the presence of eight EMG sensors allows for the introduction of complex gesture classification via machine learning techniques (Section 4), the low sampling frequency (200 Hz), low bit resolution (±127 values) and low precision on sensor positioning complicate the implementation of a reliable classification system. On the more technical side, the challenge was using the BLE protocol, since while, on Windows there exists the MyoConnect C++ IDE and a variety of bindings to translate its functions to other languages (Figure 2b), on other platforms, such as the Arduino, the problem becomes more complex and more work was required for a full implementation (Figure 3).



(a) (b)

Figure 3. (a) Screen capture of the first experiments on real time threshold control of EMG signals via a Python code with the QtPy GUI interface. (b) Screen capture of a part of the coding process done on the PSoC Creator IDE, the first workable solution for BLE communication between the Myo and the Arduino.

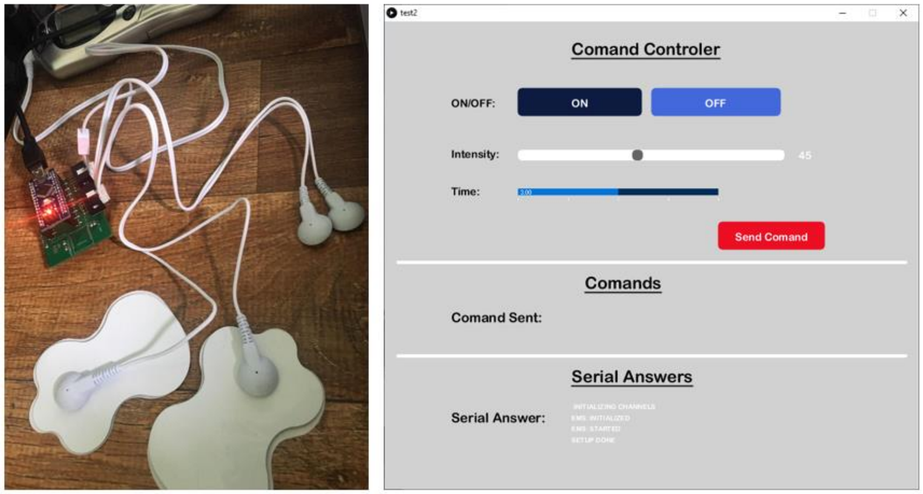
3. EMS Toolkit and Haptic Feedback

The Electrical Muscular Stimulation (EMS) technique functions in a very similar way to EMG. While EMG uses electrodes as sensors to measure the MUAPs, EMS is performed by creating a potential difference between the electrodes, carrying a small current (mA) that artificially activates the MUs causing the underlying muscles to contract.

EMS has been studied as a way to provide feedback in human-computer interfaces (HCI) under haptics technology, or as a way to recreate somatosensorial perceptions. These sensations can be divided into tactile sensations, related to the perception of temperature, textures and vibrations; and kinesthetic sensations, related to the perception of force and resistance. For example, while holding a small wood box, the tactile sensors inform you about its temperature and the feeling of its texture, while the kinesthetic receptors inform you about its weight and its hardness (on the opposite extreme of a rubber box softness). EMS has been shown to be especially useful to emulate kinesthetic feedback via coordinated stimulation of antagonist musculature.

Our main goal while designing the system was its security, as a badly designed EMS may cause harm to its users. For this our project aimed at reproducing a toolkit project called "*Letyourbodymove*", developed by M. Pfeiffer [2]. By producing the stimulation current not internally, but controlling the flow of current from a medical grade, off the shelf, stimulator, via a digital potentiometer, and by maintaining galvanic isolation between the user and the Arduino microcontroller (and its battery), the systems allows for a safe stimulation.

On the hardware part, our version (Figure 4a) of the toolkit only had some slight alterations compared to the original design. It was printed as a two-layer printed circuit board (PCB) and had surface mounted components soldered on it. We also took advantage of the newly released Arduino BLE, instead of the classic model. The firmware, while based on the original, was heavily altered resulting in two different versions; one that communicates directly with the Myo, being more IoT focused, handling all processing; and another that depends on a middle device (laptop or smartphone) to process the EMG information and generate a control command (Figure 4b).



(a) (b)

Figure 4. (a) Photo of the toolkit connected to a laptop, both electrodes and the medical grade stimulator. (b) Screen capture of a basic GUI, made with the Processing programming language, to control the stimulation toolkit.

4. Classification and Machine Learning

While processing an EMG signal to create a control signal is a tradeoff of many different variables, newer methods continue to push the boundaries, especially in the last few years. Our project implemented many of the possible approaches starting from on/off controllers, using a threshold to determine a two-state controller (Figure 5a) and similar proportional controllers [3].

Our first attempts at proper classification used the data acquired from 7 subjects on 5 distinct classes (XTReMe - CAAE 58592916.9.1001.5404) (Figure 2b). This work explored a feature extraction experiment using time domain features and a Linear Discriminant Analysis (LDA) classifier [4]. Using the same dataset, an improvement on the concept was developed, using other classical methods such as support vector machines and k nearest neighbors, and introducing our studies on the newer Neural Networks based classifiers (1D convolutional neural networks and long-short term memory architectures) [5].

While reviewing the literature for the previous experiments we found research performing a more unique method of classification called Hyperdimensional (HD) Computing. This technique takes advantage of mathematical properties of high dimensionality vectors (with dimensions greater than 10,000). These properties are used in conjunction with well-defined mathematical vector operations to perform cognitive-like operations and to codify the sEMG data (temporally and spatially) into the high dimension. On the process of implementing and validating the algorithm, we performed a full study which, to the best of our knowledge, is the first comparison between HD classification and more common classifiers (SVM and CNN) on a public benchmark dataset [6]. The study concluded that while HD classification is still unrefined, this technique shows promise in dealing with sEMG, being able to learn from few examples, being resistant to noise and highly adaptable to newer subjects [6].

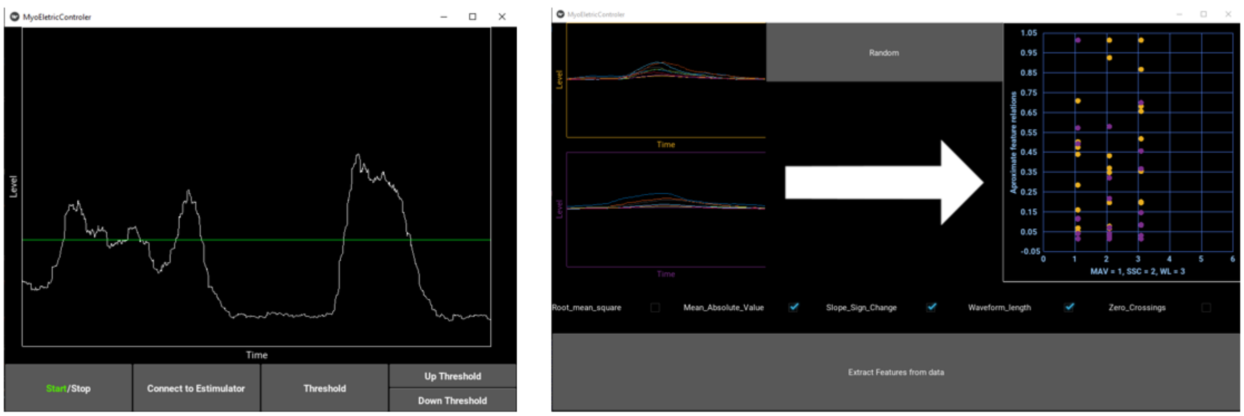
5. Open Source Repository Development

Our initial plan was to end the project by performing an experiment to validate the workings of the full sEMG controlled stimulation device. However, such experiment was not possible due to the present sanitary conditions. Instead, we focused on building an open source repository with a variety of content steaming from the many different fronts researched, such as sEMG, BLE technology and devices, EMS devices, haptic feedback, and control and classification techniques. The repository is being constructed with an educational view; as such, the content assumes little knowledge of the specifics and proposes a road from simpler programs and methods to more complex ones. It also aims at archiving the produced content and guiding any interested individual in reproducing the project for personal use and research.

While some of the programs are designed for use with the Myo armband and the toolkit (Figure 5a), others are made for standalone usage, such as the one on Figure 5b, which guides the user over each major process in a classical machine learning process, providing feedback on the user choices and how they affect the final classification result.

Besides its open source programs, the repository also contains a wiki with a series of short articles, that either explain or contain references, to the main subjects necessary for the understanding of the project.

During the writing of this paper the repository is under active development and construction.



(a) (b)

Figure 5. Screen captures of early versions of (a) a On/Off paradigm to control the stimulation and (b) a standalone software that explores the process of segmentation, preprocessing, feature extraction, classificatory selection and training with visual support and exemplification.

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