Indian Institute of Technology, Bombay

DH307 Project Report

Jan - May 2023

Arduino based EMG signal acquisition and bio medical signal processing

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Contents

1 Abstract

Amputees who have undergone upper limb amputation face significant restrictions in carrying out their daily activities. One potential solution to restore lost limb function is the use of myoelectric prostheses that utilize signals from residual stump muscles. However, the acquisition and utilization of such myosignals can be complex and require heavy computational power to convert them into user control signals. Moreover, the uniqueness of each amputee's mobility, muscle contraction forces, limb positional variations, and electrode placements presents challenges in developing a practical prosthesis solution that can adapt to individual needs. Modified machine learning techniques for pattern recognition offer promise in reducing the factors affecting traditional electromyography (EMG)-based methods. Despite recent advances in intelligent pattern recognition techniques that can discriminate multiple degrees of freedom with high accuracy, their efficiency and applicability in real-world amputee applications remain limited.
The process can be broken down into various individual steps as depicted below.

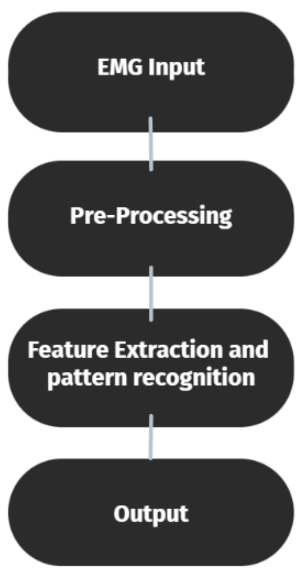


Figure 1: Flow diagram.

2 Introduction and motivation

The human upper limb is a crucial part of the body, and losing it partially or entirely can significantly impact a person's day-to-day activities. It comprises three sections: the hand, forearm, and arm, with coordinating movements between the nervous system, musculoskeletal systems, and surroundings required for each section's movement. To perform various daily activities, coordination of different joints, including the shoulder, elbow, wrist, and finger joints, is essential, which involves a broad range of motions with several degrees of freedom. These coordinated movements are redundant and can be useful in performing complex tasks. However, replicating such control features exactly in a prosthetic hand is highly challenging as the coordinated control of the biological hand is quite complex.

2.1 Literature survey for the current status of the field

- Part 1: **Origin and properties of EMG signals.**

  EMG signals (Electromyography signals) are electrical signals that are generated by the contraction of muscles. The signals are recorded using electrodes placed on the skin above the muscle of interest.

  When a muscle contracts, the muscle fibers are activated and generate electrical signals that propagate through the muscle tissue. These signals are then detected by the electrodes on the skin, and amplified and recorded by an EMG machine. The resulting signal is a representation of the electrical activity of the muscle during the contraction.

  A typical prosthetic hand consists of three main interconnected parts: an input signal acquisition unit, a processing and control unit, and an end effector. Currently, almost all high-performance artificial hands or prostheses use surface electromyography signals (sEMG or myosignals) to control their end effectors. sEMG records the electrical muscle movements from the surface of muscle cells when they are electrically or neurologically activated. The amplitude of sEMG signals ranges from 0 to 10 mV (peak to peak)/0 to 1.5 mV (RMS) with dominant energy in the 20-450 Hz band. To acquire sEMG signals, proper skin preparation is necessary, and EMG electrodes should be placed after confirming the target muscles from which the EMG signal comparable to the predefined limb movement can be produced. With the advancement of technology and miniaturization of sensors, dry electrodes that work as transducers for muscular inputs have replaced traditional gel EMG electrodes and have improved performance. However, muscle fatigue can occur due to the positioning of these dry electrodes on a single target muscle, which affects usability.

- Part 2: **Different approaches to control the prosthetics.**

  Generally, myoelectric prosthetic hands have undergone significant development to overcome the challenges of acquiring myosignals and meet the needs of different types of amputees. However, most myo-activated prosthetic limbs still use the same control principles based on muscle contractions that have been in use for more than half a century. There are two types of technical controls used for these devices: pattern recognition-based control and non-pattern recognition-based control. The traditional non-pattern recognition approach is limited to proportional control (on/off control). To increase the dexterity of myoelectric prosthetic devices and overcome the limitations of conventional proportional control, EMG-PR techniques have been developed. EMG-PR involves extracting multiple features from EMG signals, rather than relying solely on EMG amplitude. A well-designed artificial upper limb requires the use of trajectories of a limb and its associated movement patterns. The control algorithm requires parameters such as kinematics and models of joints, motion, and activity range. By using EMG-based pattern recognition, researchers hypothesize that EMG patterns contain a lot of information about intended movements. Once the EMG patterns are identified using pattern classification, the prosthesis controller will receive the command to execute the movement. Thus, the EMG-PR approach may enable users to control their myoelectric prosthesis more easily with a wider range of control.

- Part 3: **Challenges and application of Machine Learning.**

  Achieving the same level of dexterity and complexity in an artificial hand as in a biological hand is a difficult task. However, pattern recognition (PR) technology has been used for over two decades to control myoelectric prosthetic devices. PR technology provides a more natural and easier-to-learn control for both the user and the machine. It enables independent control of multiple degrees of freedom (DOFs) using simultaneous, sequential, or semi-sequential control, which brings the prosthesis closer to natural arm functions. With the application of appropriate PR-based methods, signal processing techniques, and machine learning algorithms, an amputee's limb movement can be accurately decoded and used to control a prosthetic device. EMG-based PR methods include several approaches such as pre-processing, data segmentation, feature extraction, feature classification, and post-processing.

3 Objective

3.1 Signal acquisition

- Part 1: **Types of EMG recordings.**

  Surface EMG (sEMG) and intramuscular EMG (iEMG) are two methods of recording EMG signals. sEMG uses electrodes placed on the surface of the skin, while iEMG uses fine needle electrodes inserted directly into the muscle tissue.sEMG is less invasive and more comfortable for the patient, and is commonly used for diagnostic and research purposes. However, it is less precise and can be affected by movement or position changes. iEMG, on the other hand, provides a more precise and direct measurement of muscle activity, but is more invasive and uncomfortable for the patient. It is typically used in clinical settings, such as during surgical procedures, or for research purposes requiring high precision measurements of muscle activity. In this project we have mostly focused on sEMG.

- Part 2: **Methods in sEMG.**

  Surface EMG (sEMG) can be recorded using two different methods: gelled electrodes and dry electrodes.
  Gelled electrodes are the traditional method of sEMG recording. They use a gel that is applied to the skin to create a conductive layer between the electrode and the skin. The gel helps to reduce the resistance between the skin and the electrode, resulting in a more accurate and reliable signal. However, the gel can be messy, and may cause skin irritation or allergies in some individuals. Dry electrodes, on the other hand, do not require the use of a gel or other conductive material. They use a different type of electrode that is designed to make contact with the skin directly, without the need for a conductive layer. This makes them less messy and more convenient to use than gelled electrodes. However, dry electrodes are more prone to noise and signal artifacts, and may not provide as accurate or reliable a signal as gelled electrodes.
  Overall, both gelled and dry electrodes have their advantages and disadvantages, and the choice of which to use depends on the specific application and the individual's preferences and needs.

In this project, I have used BioAmp EXG Pill for signal acquisition. Following is the image of the signal acquired for 3 consecutive bicep contraction along with the Arduino code for raw signal acquisition. *Here* is the GitHub link for the Arduino code of raw signal acquisition.

Figure 2: Raw EMG signal.

3.2 Signal Pre-processing

To remove unwanted frequency components from a signal, filters can be used. Filters can be analog, using electrical components, or digital, using software. There are several types of filters including low pass, high pass, band pass, band-stop, notch, and all-pass filters. Each filter type removes a different range of frequencies from the signal, allowing for customization based on the specific needs of the application.

An ideal filter has certain characteristics including complete attenuation in the stop band, full transmission in the pass band, and an abrupt transition between the two bands. Ideal filters have infinite order and latency, but realized filters can be designed for any order. Higher-order filters have a more ideal response, but they also have longer impulse responses, which increase the latency. Therefore, the choice of filter order depends on the specific needs of the application, balancing the need for a more ideal response with the acceptable latency.

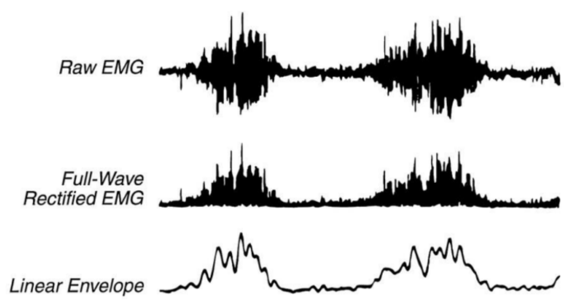


Figure 3: Stages of pre-processing.

- **Envelop detection and smoothing.**

  Smoothing of a signal can be achieved by applying a low pass filter with an appropriate cutoff frequency. Typically, a cutoff frequency around 2-3 Hz is used to obtain the envelope of the signal. This technique is commonly used in signal processing to reduce noise and extract relevant features of the signal.

- **Sampling.**

  Signal discretization is the process of converting a continuous-time signal to a discrete-time signal. This is done by taking the values of the continuous time signal at regular intervals through uniform sampling. The original continuous-time signal can be reconstructed from the discrete-time signal as long as the samples are taken at appropriate intervals. This technique is commonly used in signal processing to facilitate data storage, transmission, and processing.

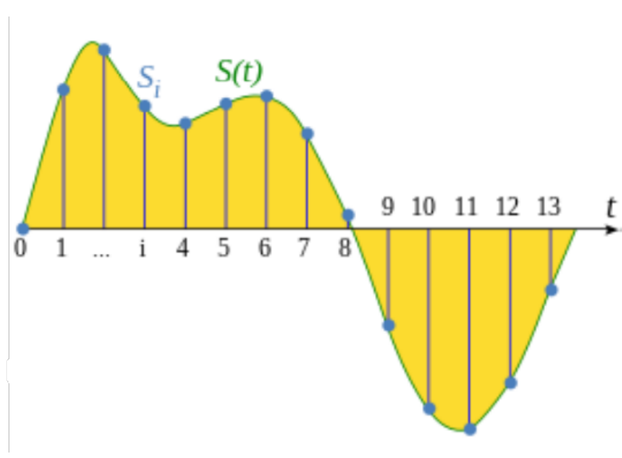


Figure 4: Sampling.

4 Digital processing of raw EMG signal

4.1 Digital Filters

Filtering using mathematical operations refers to the use of digital signal processing techniques to filter signals. Compared to analog filters, this method is not subject to the nonlinearities of the components used in analog filters. Additionally, digital filtering allows for more complex filter transfer functions of higher order to be realized easily.

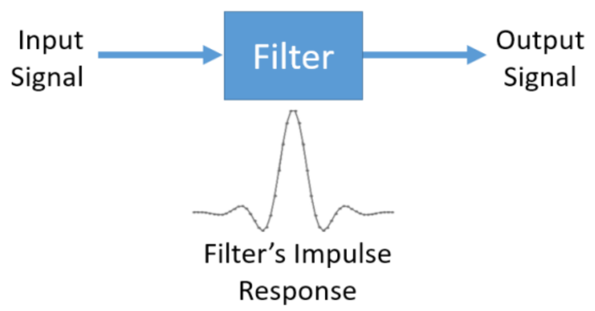


Figure 5: Filter.

- **Important characteristics of digital filters**
    1. Linearity
    2. Causality
    3. Time-Invariance
    4. Stability

- **Digital filter implementation**

  The output signal of a filter with impulse response h[n] is calculated by convolving the input signal x[n] with the impulse response h[n], and denoted as y[n] = x[n] * h[n]. In the Z-domain, this can be represented as Y(z) = X(z) . H(z), where H(z) is the transfer function of the filter. This transfer function describes the relationship between the input and output signals in the frequency domain. By analyzing the transfer function, one can determine the frequency response of the filter, which is useful in designing and optimizing filters for specific applications.

$$H(z) = \frac{B(z)}{A(z)} = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2} + \cdots + b_N z^{-N}}{1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_M z^{-M}}$$

  It is implemented using the Linear Constant-Coefficient Difference Equation (LCCD) as:

$$y[n] = -\sum_{k=1}^{M} a_k y[n-k] + \sum_{k=0}^{N} b_k x[n-k]$$

- **Graphical interpretention of a filter**

General transfer function for an Linear time-invariant (LTI) system is of the form:

$$H(z) = \frac{P(z)}{Q(z)} = \frac{\sum_{m=0}^{M} b_m z^{-m}}{1 + \sum_{n=1}^{N} a_n z^{-n}} = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2} \cdots + b_M z^{-M}}{1 + a_1 z^{-1} + a_2 z^{-2} \cdots + a_N z^{-N}}$$

Numerator has M roots (zeros) and denominator has N roots (poles). Hence eqn can be rewritten as:

$$H(z) = \frac{(1 - q_1 z^{-1})(1 - q_2 z^{-1}) \cdots (1 - q_M z^{-1})}{(1 - p_1 z^{-1})(1 - p_2 z^{-1}) \cdots (1 - p_N z^{-1})}$$

Plotting poles and zeros in the Z-plane, the characteristics of the filter (like stability, causality) can be understood by checking if they are contained within the radius of convergence.

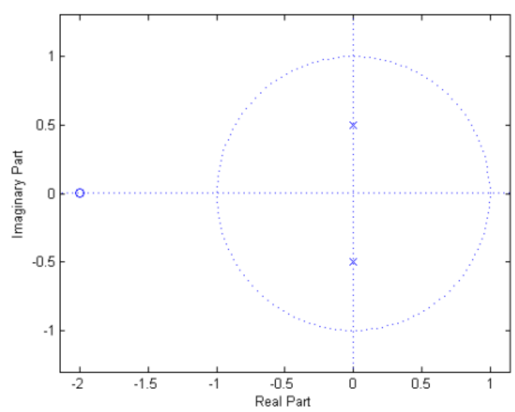


Figure 6: Plot in complex plane

4.2 Types of digital filters

Finite impulse response (FIR) and infinite impulse response (IIR) are two types of digital filters with distinct characteristics.

- Part 1: **Difference between FIR and IIR.**

1. **FIR** FIR filters have a finite-duration impulse response, and their order, or complexity, is determined by the number of impulse response coefficients. FIR filters are inherently stable, meet linear phase criteria, and have an easy design process. However, as the order increases, more delay is introduced, and the computational complexity also increases.

$$\begin{aligned} y[n] &= b_0 x[n] + b_1 x[n-1] + \cdots + b_N x[n-N] \\ &= \sum_{i=0}^{N} b_i \cdot x[n-i], \end{aligned}$$

2. **IIR**

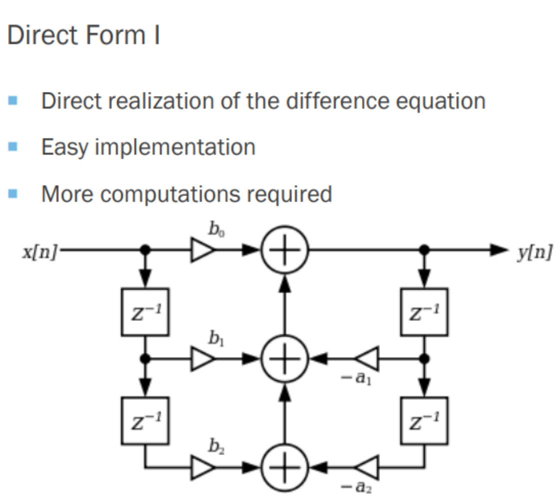
   On the other hand, IIR filters have an impulse response that continues indefinitely due to feedback. Analog filters are usually IIR, and they require less computational complexity in the design process than FIR filters for similar filter specifications. However, IIR filters can be less stable and can have nonlinear phase characteristics.

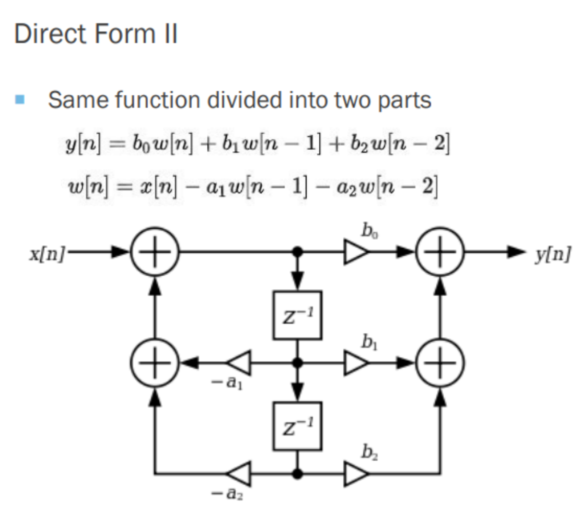
$$y[n] = \frac{1}{a_0}\Big(b_0 x[n] + b_1 x[n-1] + \cdots + b_P x[n-P] \\ - a_1 y[n-1] - a_2 y[n-2] - \cdots - a_Q y[n-Q]\Big)$$

- Part 2: **Conclusion**

  The choice between FIR and IIR filters depends on the specific application requirements and design trade-offs. FIR filters are suitable for applications that require linear phase and high stability, while IIR filters are suitable for applications that require less computational complexity and fast roll-off characteristics.

However, we would use IIR filter. IIR filters are used in signal processing because they are computationally efficient, provide fast transition between passband and stopband, have a compact design, allow for analog filter conversion, and provide greater design flexibility. However, IIR filters can be unstable and have nonlinear phase response, which may limit their use in certain applications. Following are the IIR filter realization:





Higher order IIR filters are often implemented as a cascade of 2nd order filters. These 2nd order filters are typically realized using Direct Form II and multiple sections are cascaded together. This approach is preferred because it allows for a more limited coefficient range and better numerical precision.

4.3 IIR filtering with Arduino

- **Specifications**

  1. Passband: BPF with a passband range of 74.5 Hz to 149.5 Hz.
  2. Filter type: Butterworth filter.
  3. Order: 8th order.

- **Rectification and smoothing**

  Rectification is a process of taking the absolute value of a signal. Envelope detection can be achieved by implementing a low pass filter or by computing the moving average of the rectified signal. *Here* is the GitHub link for the Arduino code for EMG rectification and smoothing.

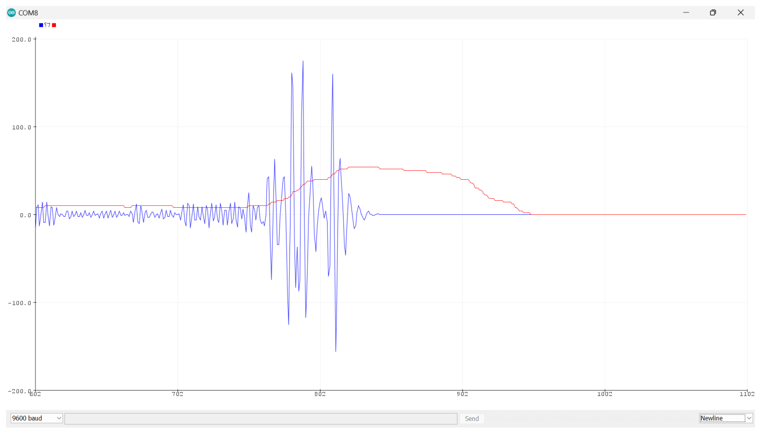


Figure 7: Rectified and smoothed signal

4.4 Driving servo motor with EMG signal

The process involves analyzing a smoothed EMG signal, dividing it into appropriate ranges for thresholding, and using the thresholding output to drive a servo motor using pulse-width modulation (PWM). *Here* is the GitHub link for the Arduino code for driving a servo motor using filtered EMG signal.

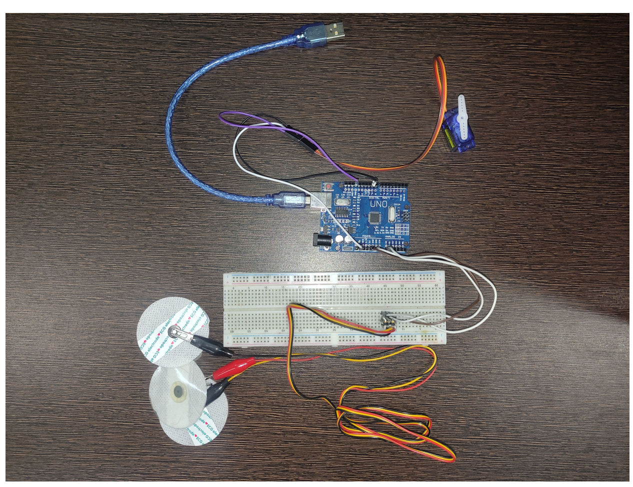


Figure 8: Circuit diagram

5 Future Work

In future work, machine learning techniques could be used for EMG wave pattern detection for a particular user. This would involve using pattern detection algorithms, such as k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), or Artificial Neural Networks (ANN), to train a model on the user's EMG data. The model could then be used to detect specific EMG wave patterns, such as muscle activation or relaxation, in real-time. This approach would have the advantage of being personalized to the user and potentially more accurate than manual thresholding. However, it would require a significant amount of training data and computational resources for model training and inference.