Device Development and Signal Feature Extraction of Surface EMG Signals

James D. Justice, *Member, IEEE*, Zachary T. McEachin, and Vineet R. Tiruvadi

Abstract **— Electromyography (EMG) is a pervasive technique employed in a variety of fields, including: medicine, robotics/prosthesis control, and rehabilitation therapy. Given the potential diagnostic/therapeutic benefits associated with EMGs, we conducted this study with two main aims: 1) the design and development of a 2-channel surface EMG device that recorded the myoelectrical activity produced by the bicep & triceps and 2) the development & execution of feature extraction algorithms that could be used to control a robotic arm.**

The myoelectrical signals of the bicep and triceps were detected by two surface electrodes. The signals were than amplified by a custom built instrumentation amp that provided a 350V/V gain. In order to remove noise, the amplified signals were passed through a 20-500Hz bandpass filter with a flat passband. A BeagleBone Black development platform was used for the analog to digital conversion of the signal, the digital processing and the data serving.

I. Introduction

Electromyography (EMG) is an experimental technique that allows for the detection and recording of the intrinsic electrical activity of skeletal muscle. In 1848, using electrodes connected to a galvanometer, Emil Du-Bois Reymond discovered that upon active contraction of muscle, electrical signals were produced [1]. Shortly after, Guillaume Duchenne and other prominent electrophysiologists began investigating this myoelectric activity and it potential for medical uses. Since, EMGs have been proven useful as a clinical tool for the diagnosis of various neuropathies and/or myopathies. In more recent times, EMGs have been exploited as a source input for the control of robotic arms, prosthetics, and computer mouse cursors [2]. In order to properly utilize an EMG, it is important to understand how the EMG signal is generated and detected.

A. Biology of Excitable Tissue-The EMG Signal

Skeletal muscles, like neuronal tissue, are considered "excitable tissue"; as such, neural control of skeletal muscles can be described by the mechanism of action potentials. In order to generate an EMG signal, motor neurons and skeletal muscle must work in synchrony. A single motor neuron and all the muscles fibers that are innervated by it, is referred to as a motor unit. Upon higher level processing of a desired movement or during a reflex, a motor neuron is activated and an action potential ensues. Once the action potential reaches the axon terminal, the neurotransmitter, acetylcholine is released into the neuromuscular junction. Acetylcholine then binds to the nicotinic (ionotropic) acetylcholine receptors present on the skeletal muscle cells. Normally, skeletal muscles are in a state of ionic equilibrium, however once these non-selective cation channels (nAChRs) are opened, an endplate potential is formed. If the endplate potential surpasses a threshold level, an action potential is propagated in both directions down those muscle fibers innervated by the activated motor neuron. This action potential ultimately causes activation of voltage gated calcium channels at the sarcoplasm reticulum, which allows for increased flux of Ca^{2+} into the sarcoplasm. The Ca^{2+} ions bind with troponin proteins and elicit a conformational change that allows for the contractile movement between myosin heads and actin filaments. As with action potentials in neurons, there is both a depolarization and repolarization phase. This depolarization-repolarization cycle creates an electric dipole. The electric dipole thus creates a potential across the electrode dipoles. As the action potential propagates down the muscle, so does this electrical dipole. The varying potential difference "experienced" between the electrodes as the electric dipole propagates down the muscle cell corresponds to the observed EMG signal. It should be noted, however that there are multiple muscle fibers and even motor units activated, thus there are multiple EMG signals produced. The raw EMG data acquired includes the superposition of these multiple single EMG signals.

B. Electrode Design

In order for the myoelectrical activity produced by the contraction of a muscle to be processed, the signal must first be relayed to the processing device via electrodes. Since detection of the biological signal by electrodes is the first step in producing and processing EMG data, it is imperative that the electrodes are designed properly and maintain the fidelity of the biological signal. There are two general types of electrodes commonly used in EMG studies: surface electrodes and fine-wire/needle-like electrodes. Surface electrodes, unlike fine-wire electrode allow for non-invasive measurements due to the fact that electrodes are placed on the surface of the skin. These surface electrodes detect the physiological currents produced by the muscle as described above. In this study, commercially purchased Covidien surface electrodes were used.

C. General Circuit Board Overview

The general outline of the constructed EMG device is depicted in Figure 1. The outline can be subdivided into four divisions: signal input, analog processing, digital processing, and feature extraction. The signal input was accomplished via placement of the Covidien electrodes on the peak surface of the biceps brachii muscle and the triceps brachii lateral head. The signal was then relayed to the analog processing unit which consisted of an instrumentation amplifier and flat-band bandpass filter. Once amplified and filtered, the BeagleBone Black development platform was used to digitize and further process the signal. A python script was implemented to perform feature extraction algorithms on the processed signal and then serve the data through a standardized, flexible system.

II. Design of Analog Components of Device

This section deals with the Analog Processing section from the block diagram in Figure 1.

A. *Pre-Amplifier Design and Implementation*

One of the more challenging aspects of collecting and processing an EMG signal is the amplification of such a small, noisy signal. Surface EMG signals can be anywhere from 0.1mV to 1mV [1] for large muscles, such as biceps and triceps. Initially, the final output voltage needed to be from 0 to 5V. This requires a total gain of 50,000 V/V. Additionally, the frequencies of interest for surface EMG data is typically in the range of 20Hz to 500Hz [1]. Below 20Hz, the signal is noisy due to movement artifacts of the person being measured. Above 500Hz, the signal is noisy due to the analog circuitry and stray electromagnetic signals. Given this upper limit of 500Hz, the amplifier would need a gain-bandwidth product of at least 25MHz which is well outside the range of most commonly used operational amplifiers. For reference, the LM741 has a gain-bandwidth product of about 1.5MHz [2]. Therefore, it was determined that an amplifier with multiple operational amplifiers in series would be needed to get enough gain. Additional design requirements include amplifier input impedance, common-mode rejection ratio, and noise. High input impedance is important for the amplifier to get as much of the voltage across it as possible because the amplifier circuit and the generator resistance act like a voltage divider. High common-mode rejection ratio is important in order to not amplify unwanted signals that are common to both electrodes. This would include 60Hz noise from power lines, motion artifacts from the patient, and other unwanted environmental factors. Low noise is important because when amplifying a small signal it can get covered up by noise and become unintelligible.

After considering all of the design criteria, the instrumentation amplifier topology seen in Figure 2 was chosen. The first stage of the instrumentation amplifier is referred to as the input buffer amplifier. The two operational amplifiers in this stage give the instrumentation amplifier high input impedance. The second stage of the instrumentation amplifier is referred to as the differential amplifier. This stage consists of one operational amplifier which gives a very high common-mode rejection ratio. All of the operational amplifiers in the analog processing section are LM741s. The gain of this instrumentation amplifier is given in Equation 1.

Equation 1 can be simplified significantly by making two assumptions. First, R_1 is much larger than Rg, the electrode resistance and contact resistance. Second the ratio of R_3 and R_2 must be much greater than 1. With these simplifications Equation 2 describes the gain of the instrumentation amplifier and can be easily solved for the appropriate resistor values.

$$\frac{v_{out}}{v_{electrode}} = -\frac{R_5}{R_4}\left[1+\frac{2R_3}{R_2}\right]\frac{2R_1}{R_g+2R_1} \qquad Equation\ 1$$

$$\frac{v_{out}}{v_{electrode}} \approx -\frac{R_5}{R_4}\left[1+\frac{2R_3}{R_2}\right] \approx -2\,\frac{R_5}{R_4}\frac{R_3}{R_2} \qquad Equation\ 2$$

To ensure that the first assumption is correct, the R_{1a} and R_{1b} resistors are made 1MΩ each. The second assumption is always true for an amplifier with at least a moderate gain. Otherwise, it wouldn't really be an amplifier. Next the values of the gain resistors are set. R_2, R_{4a}, and R_{4b} were all set to be equal at 10kΩ. R_{3a}, R_{3b}, R_{5a}, and R_{5b} were all set to be equal at 130kΩ. Obviously, both R_3 (a and b) resistors must be equal to keep the amplifier symmetrical. The same is true for R_4 and R_5. However, R_2 and the R_4 resistors (as well as the R_3 and R_5 resistors) were set to be equal for two reasons. First, this makes collecting the components and building the circuit much easier. Second, if these resistors are the same value it maximizes the gain-bandwidth product of the whole instrumentation amplifier. For example, if one stage was set for a higher gain than the other it would have a low bandwidth which would decrease the gain-bandwidth product of the whole instrumentation amplifier.

With the above resistor values the gain for the pre-amplification stage is about 350 V/V. This is much smaller than the gain listed above for three reasons. First, near the end of the design phase the maximum output voltage changed from 5V to 1.8V due to the fact that the BeagleBone Black board was used because it has some important advantages over the Arduino board. The BeagleBone Black will be discussed later. Second, the input voltage observed was closer to 1mV rather than 0.1mV. Third, the filter stage has some gain which will be discussed in the following section.

The design was confirmed with LTSpice using the appropriate models for the LM741 to get an accurate evaluation of the circuit's performance. The circuit passed the tests in the frequency and time domains and was ready to be built. The circuit was built on a breadboard rather than a printed circuit board. There were three reasons for this design choice. First, the circuit is operating nowhere near the 1 to 10MHz limit of a breadboard. Second, the ease of assembly and modification is vital given the time constraints. Third, the printed circuit board would take too long to design and fabricate even though it would be less noisy.

B. *Bandpass Filtering Design and Implementation*

After the amplification stage it is helpful to discard any part of the signal that isn't wanted. For example, the useful signal is between 20Hz and 500Hz, as mentioned above. This means that anything below 20Hz and above 500Hz acts as useless noise. As an added bonus, the filter stage can also be used to get a small amount of extra gain.

The first design considered for the filtering application was the second-order Sallen-Key bandpass filter. However, it was immediately obvious that this filter wasn't ideal for this application. This filter is a narrowband notch filter with a triangular passband. This means that the center frequency would get amplified more than other frequencies in the passband. This filter would be more useful if had one frequency of interest rather than a range of frequencies.

The second design considered for the filtering application was a second-order Sallen-Key highpass filter in series with a second-order Sallen-Key low pass filter. The topology can be seen in Figure 3. This bandpass filter can be designed to have a flat passband, the cutoff frequencies are easily tuned, and the passband can be as wide as necessary. All of these attributes make this bandpass filter better for the current application and this design was used in the final device. There are a total of two LM741 operation amplifiers used in this filter design. The capacitor values were chosen to be an easily obtained value of 0.1μF. The cutoff frequencies were used to calculate appropriate values for R_{c1}, R_{c2}, R_{d1}, and R_{d2}. The cutoff frequency equations for the highpass and lowpass parts of the filter are given in Equation 3.

$$f_c = \frac{1}{2\pi RC} \qquad \text{Equation 3}$$

Ideally, the gain resistors R_{a1}, R_{a2}, R_{b1}, and R_{b2} follow Equation 4 and are independent of filter shape.

$$\frac{v_{out}}{v_{in}} = \left(1 + \frac{R_{a1}}{R_{b1}}\right)\left(1 + \frac{R_{a2}}{R_{b2}}\right) \qquad \text{Equation 4}$$

However, the gain resistors do heavily influence the shape of the passband. For this reason, specific R_a and R_b values were used to get a flat passband. These resistors gave the bandpass filter a gain of 3V/V. The R_a resistances were set equal for similar reasons listed above in the amplifier section. The same was done for the R_b resistances.

After constructing this filter on a breadboard, it was discovered that there was some 60Hz noise. Several types of operational amplifier bandstop filters were investigated to try to filter this out. However, all of them would have attenuated the useful signal as well as the noise so this noise was taken care of digitally after the data was collected. Other methods for reducing noise include twisting wires, using a minimal number of breadboard wires, and using 9V batteries rather than a DC power supply. However, there is still some slight 60Hz noise probably due to the fact that a breadboard is being used rather than a printed circuit board.

C. Rectification and Voltage Clipper Design and Implementation

The third and final stage of the analog processing circuit is the rectification and voltage clipper stage. The topology of this stage can be seen in Figure 4. The diode D_{rect} is used as a half-wave rectifier to eliminate any negative component. A half-wave rectifier was used rather than a full-wave rectifier because the majority of the signal was already positive and any negative component would have barely been above the noise level, providing limited usefulness.

D_{clip1} and D_{clip2} were used to clip any excess voltage. Voltage clipping is needed in order to assure that the input to the A/D converter isn't above 1.8V to avoid damaging it. Two normal p-n diodes in-series create a voltage clipper with a cutoff of about 1.4V. This is slightly below the 1.8V maximum to give the circuit some room for error. Typically, Zener diodes are used for voltage regulation rather than standard p-n diodes. However, a Zener diode of 1.4V is very difficult to find. Additionally, low breakdown voltage Zener diodes typically have poor performance so there is no loss in performance if standard p-n diodes were used instead. For these reasons two standard p-n diodes are used in series to clip the output voltage of the complete analog circuit at 1.4V.

III. DIGITAL PROCESSING

This section describes the signal processing and feature extraction of EMG signals from the block diagram in Figure 1.

A. Analog to Digital Conversion

The first step in processing the amplified analog signal output from the preprocessing stage is the digitization of the signal. Analog-to-Digital Converters (ADC) are very common components of modern electronics requiring advanced or programmable functions.

A powerful, but cost efficient, Analog-to-Digital Converter (ADC) was vital to the project goals and the major criteria used to select an appropriate ADC consisted of: bit depth, sampling rate, computational capabilities, monetary cost and extensibility.

Three main ADC designs were considered: a) build a system from commercially available ADC chips, b) implement the ADC of an Arduino board then pipe processing to a consumer workstation or c) leverage a full development platform with an onboard ADC and processor. Ultimately, the BeagleBone Black (BBB) was chosen as the digital processing device due to its acceptable bit depth, sampling rate and monetary cost as well as its extraordinary computational capabilities and extensibility.

B. Quantization

A central concept to an ADC is that of quantization. The value of the EMG potential has a continuous real-valued range. After analog processing, due to the limitations imposed by the electronics, the output analog signal from the amplifier, clipper and rectifier can take on any value within a predefined range; in the presented case this range is approximately 0-1.4V. However, the value is still continuous within this range. Digital computing requires discrete values within the signal range and employs quantization of the analog signal to yield an acceptable digital signal.

Bit-depth of an ADC indicates the number of discrete states that can be measured within an input range. Low bit-depth ADCs generally result in coarser reconstructions while high-bit depth ADCs can maintain the fidelity of the analogy input signal. The required bit depth in the case of the presented platform did not have any extraordinary constraints, allowing the use of standard ADCs found in consumer/enthusiast hardware. With an input range of 0 – 1.8V, the 12-bit ADC of the BBB yields a voltage resolution of approximately 400 µV. The bit depth and resultant dynamic range of the BBB ADC is sufficient for presented uses.

C. ADC Sampling rate

Another important consideration for an ADC is sampling rate. While the analog portion of the platform is capable of handling spectral components ranging from 20Hz to 500Hz, the main feature of the presented system extracts low-frequency events such as muscle contractions and flexions in the supra-second range. As such, the required sampling rate of the ADC was low, on the order of 10Hz since repeated muscle contraction and flexion that result in effective gross limb movement do not meaningfully exceed 10Hz.

However, in addressing extensibility and accounting for possible future applications, an ADC capable of sampling at a sufficiently high frequency to capture the 500Hz signal is important. The BBB satisfied the weaker requirement of sampling rate and the stronger requirements of extensibility by having a single ADC that is multiplexed with 7 Analog Inputs (AIs) capable of sampling at 8Mhz aggregate. Split amongst the 7 AIs this results in a per-channel sampling rate of approximately 1Mhz, well above the Nyquist rate of a 500Hz EMG signal.

Another important consideration in using the BBB ADC, in contrast with an ADC chip, is the cost of reading the ADC through the *userspace* of an Operating System (OS). Userspace, where applications and user-interactive functionality exists, is designed to optimize computational ability and function at the cost of reliable timings. An ADC system built from the ground up allows a design with guaranteed sampling intervals without the programmability and flexibility offered by software control. The BBB, however, reads from the ADC through userspace calls, adding uncertainty into when a given sample was actually collected. Increasing computationally intensive processing may increase the variance in the sampling interval and cause problems in accurately digitizing high-frequency signals. This limits the initial investigation to large-timescale phenomena and would require further characterization if future features of interest depend on higher-frequency components of the signal.

D. Digital Processing

After the signal has been sampled and digitized, the digital signal occupies space in the memory of the BBB device. From here, the data can be sent through the BBB Ethernet interface, processed by a user-programmed script or sent to a customizable software/hardware module that performs a user and context defined function (See Figure 5).

The digital processing of the signal utilized in the presented platform are basic and meant to be proofs of concept in the ability of the BBB to utilize mainstay tools of the signal processing world in order to process EMG signals. To that end, the implemented digital processing consisted of a basic digital filter and threshold feature extraction. The filtering and feature extraction was implemented in the Python scripting language utilizing the NumPy libraries. Together, Python and NumPy allow for a full-featured software space capable of reading the AIs, performing matrix-based manipulations of the data and outputting processed signals to a) file I/O, b) the screen c) digital/analog outputs (future implementation).

The digital filter allows for software-controlled, flexible filtering of the input EMG data. In the case of a binary thresholding feature, low frequency data is required and the signal can be digitally filtered with a narrow bandpass filter centered at 30Hz with a FWHM of 10Hz. This filtered sig is then sent to the feature extraction subroutine.

Feature extraction of a signal is the systematic search for patterns and a dimensionality reduction in a signal. Low-level feature extraction algorithms utilize simple patterns, such as binary thresholding of the signal, edge detection of a signal, peak detection of a signal and inflection detection of a signal. Low-level feature extraction algorithms have low computational requirements that would not interfere with the desired sampling rate of the data.

A simple thresholding feature extraction algorithm was demonstrated here; anywhere the amplified EMG signal was above a certain value corresponded to an “event”. These events could be used to determine when the muscle was contracted due to the EMG potential being “high” during a contraction event.

E. Data Delivery

The BBB comes with powerful software and hardware modules that allow it to function as a modern network-capable computer. One goal of the platform was to generate a live stream of EMG data that could be used to control a remote robotic arm. While the live-streaming of the data became beyond the scope of the project, capabilities to transfer the recorded and processed EMG data were incorporated and resulted in robust control of a robotic arm.

Data delivery, in this case of the EMG raw and processed signal, requires file I/O and network I/O functionality which are built-in capabilities of the BBB. Implementing those capabilities required simple Unix scripting and allowed for the transfer of the raw and processed EMG signal through FTP and email.

IV. Experimental Results

This section presents and discusses the results of the developed EMG platform.

A. Raw EMG Signal

The implementation presented utilized two channels, one for the biceps muscle and one for the triceps muscle. The two raw signal read from the electrodes each went to a dedicated amplifier, rectifier and clipper circuit which sent an amplified, preprocessed EMG signal into two AI channels of the BBB. These preprocessed signals read by the BBB are presented in Figure 6.

The input signals are satisfactory for the processing steps utilized in the presented article but more advanced processing may require fine-tuning of the input signal to preserve spectral components or time-domain features that encode important system information. In the presented case, the time points with muscle contraction were compared to video/notes and found to be in full correspondence, indicating that the integrity of the input signals within the context of measuring contraction.

B. Feature Extraction: Thresholds

Extracting the threshold feature resulted in a clear trace of the "state" of each muscle. Samples with voltages higher than 1.0V yield a "positive event" which can be highly correlated to muscle contraction. The resultant State vs Time figure is presented in Figure 7.

Demonstration of a simple thresholding feature extraction is basic but fulfills the first-step goals of the platform in extracting contraction events from muscle activity. This basic information is sufficient to control a robotic arm without many assumptions. Finer control of the arm may require more complex feature extraction dependent on spectral components, wavelet analysis and PCA decomposition; all procedures that are present in the Python library and easy to implement.

C. Control of a Robotic Arm

In collaboration with colleagues within the Department of Robotics at Georgia Institute of Technology, the raw and processed EMG data was used to control a robotic arm. See referenced video for demonstration.

The ability to control the robotic arm with the data collected through the presented platform validates the platform capabilities and design specifications. While there are certain improvements needed, the platform presented is a successful first step in developing a full, mobile and powerful system for EMG-based control and diagnostics.

V. Conclusion

Electromyography has long been utilized in clinical settings as a diagnostic tool; however recent advances in microelectronic, DSP, and robotic technologies have expanded the use of EMGs from a diagnostic tool to an essential component of self-contained prosthetics. There are currently ~2 million below-elbow amputees in the United States with additional increase of approximately 150,000 per year [5]. The ability to exploit EMG signals to control self-contained prostheses/robotic arms would greatly increase the quality of life for these patients.

In this study, we were able to successfully design and construct a 2-channel EMG device. The initial pre-amplifiers and filters were constructed on a bread board using discrete components. Moreover, we utilized the novel BeagleBone Black development platform to digitize and further process the EMG signal. Using python libraries, we were able to extract various characteristics features of the EMG signal after contraction of the bicep and triceps. Furthermore, in collaboration with fellow colleagues in robotics, the EMG data collected allowed us to control and perform basic movements of a robotic arm.

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FIGURES

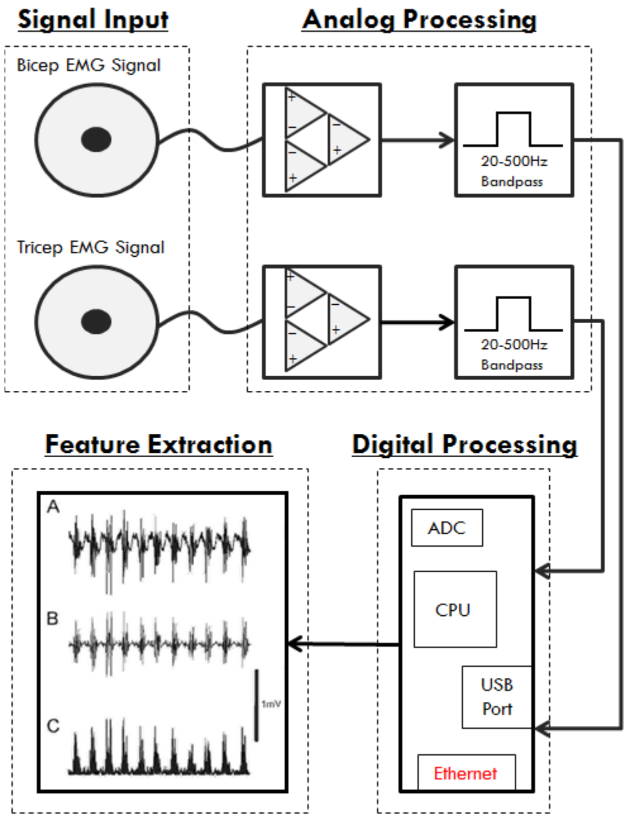

Figure 1. Block diagram of the EMG Measurement and Processing Equipment

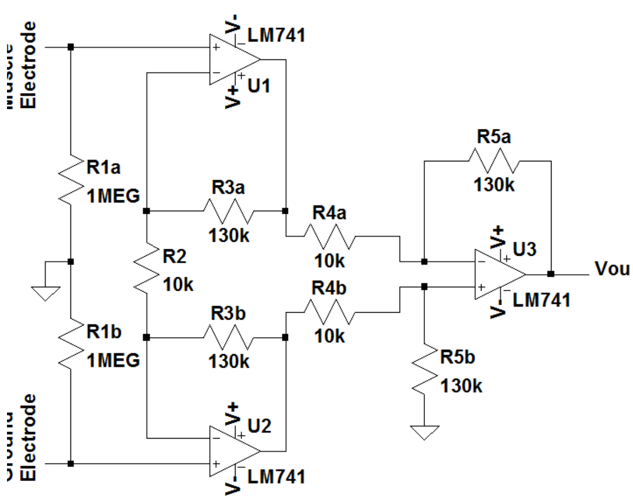

Figure 2. Instrumentation Amplifier Circuit

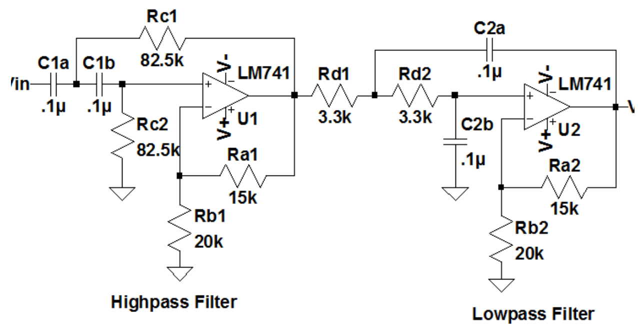

Figure 3. Bandpass Filter Circuit

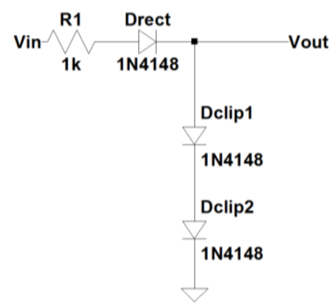

Figure 4. Rectification and Voltage Clipper Circuit

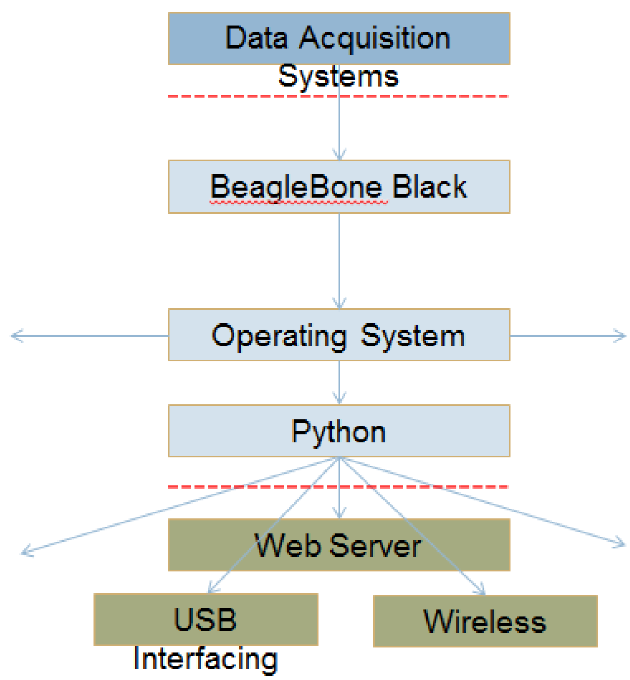

Figure 5. Schematic of BeagleBone Black Digital Processing Framework

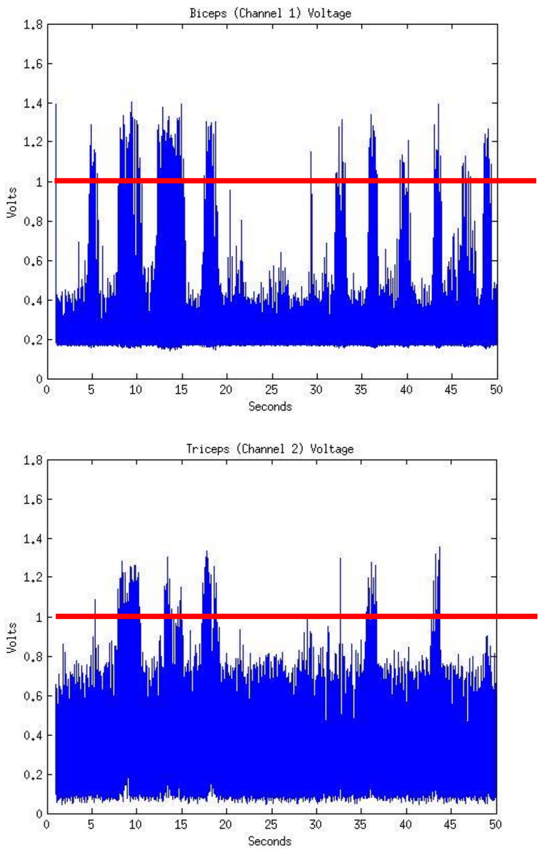

Figure 6. Raw EMG signal from Biceps and Triceps. Threshold for feature selection indicated by red line.

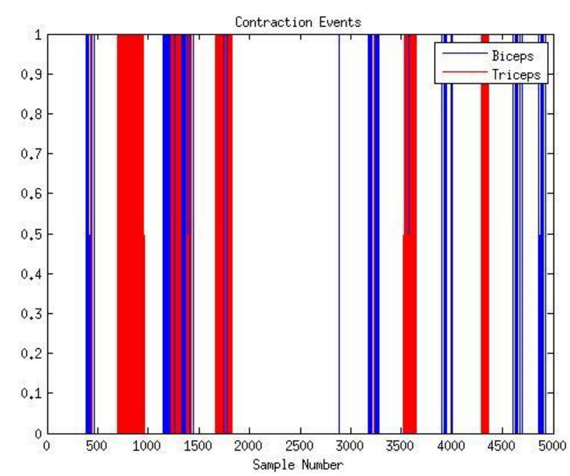

Figure 7. Contraction events for Biceps and Triceps from Thresholding