Framework for EMG Control of a Soft Robotic Exoskeleton

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ABSTRACT

This paper describes research surrounding techniques for an actuator during isotonic movement without the need for a fully-trained neural network. Instead, a control method based on several 4th order Butterworth filters is employed. The method makes a series of educated and updated guesses to actuate a robot in real time with no delay for feature extraction. The proposed method has implications for both rehabilitation and assistive technology. An exploration of EMG amplitude and integral in relation to bicep torque is also presented. Finally future research directions for continued algorithm development are discussed.

INITIAL FINDINGS WITH EMG AMPLITUDE AND INTEGRAL

Setup

All initial experimentation was done with one MyoWare Muscle 4 sensor centered on the bicep. Results were recorded at 30 ms intervals using an microcontroller. The 30 ms interval was chosen to allow for computing time should a computation-heavy control algorithm be implemented. Unless otherwise specified, all output EMG signals are pre-filtered by the MyoWare sensor. The exact filtering and amplification of these signals is not made public by the company.

Isometric vs. Isotonic Contractions and EMG Amplitude

Following the assumption of a correlation between isometric contraction EMG amplitude and isotonic contraction EMG amplitude, relationships were sought (1) between the integrated EMG and expected torque and (2) between the EMG amplitude and expected torque. Unfortunately, as justified in literature (Tax, 1989), many difficulties were encountered in this search.

Without knowing the period of motion, the integral of the EMG cannot be related to muscle activation. The integral reading for a large spike in amplitude could be the same as the integral reading for a relatively constant signal. If the integral is windowed, the integrated reading yields no different results than just examining the EMG amplitude.

Examining the amplitude of the EMG yields other difficulties. A model of expected bicep torque was created using angle and angular velocity gathered from an accelerometer attached to the wrist. The estimated torque value was compared with EMG activation, but no consistent relationship was found.

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Therefore it was determined that with only one surface EMG it was not feasible to relate isometric contraction results to isotonic movements.

ARIMA Models from Integrated Signal

Following previously published work using autoregressive integrated moving average (ARIMA) models for joint angle estimation (Mamikoglu, 2016), EMG signals from the bicep and joint angle values were recorded. The absolute value of the EMG signal was integrated. To remove the trend caused from the accumulating integration, a 4^{th} order polynomial was fitted to the data and then subtracted. This effectively detrended the signal. The integrated and detrended signal was used as the input value in MATLAB's system identification toolbox, while the recorded angles were used as the output. Discrete-time ARX models following the form $A(z)y(t) = B(z)u(t) + e(t)$ were found and then optimized, one using MATLAB's built-in optimization tool and the other according to the Akaike Information Criteria. Sample results are shown in Figure 1.

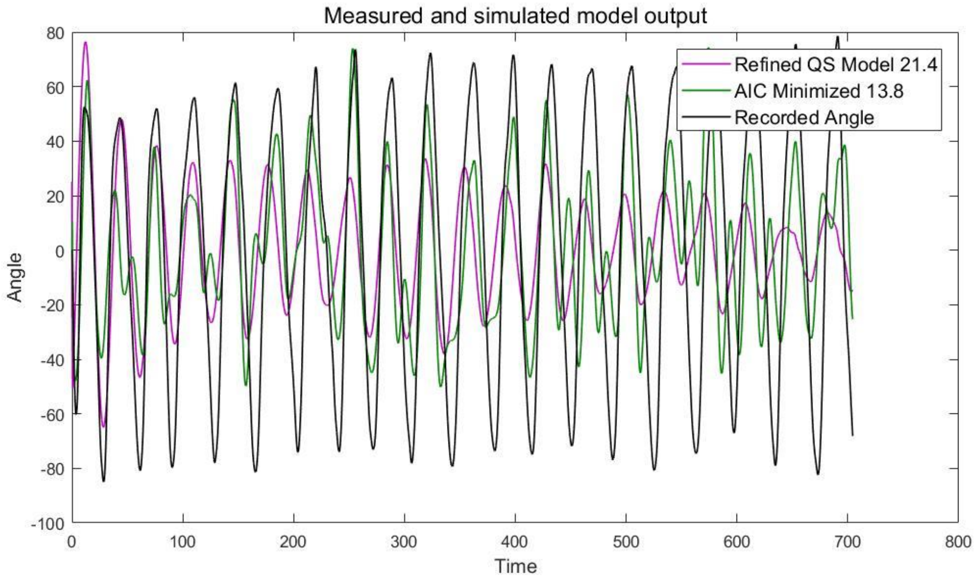

Figure 1. Sample ARIMA Model Output.

For short training and validation datasets, correlations as high as 72% were achieved. However, when the training and validation inputs came from datasets recorded separately, though with the same electrode placement and within 10 minutes of each other, the accuracy of the models noticeably dropped.

This method was moved away from for several reasons. First, it was not possible to find a model that maintained accuracy across different trials on the same day even with the same electrode placement. Second, the integration step required the implementation of a digital filter with a very low cutoff frequency. As described later, this caused great challenges with numerical errors. Finally, as this method had already been published, it was not novel.

PROPOSED CONTROL METHOD

Setup

All experimentation was done with one MyoWare Muscle 4 sensor. A second sensor was briefly added to examine triceps activation during movement, but it was not found to improve the accuracy of the proposed control method. Again, unless otherwise specified, all output EMG signals are pre-filtered by the MyoWare sensor.

EMG Signal Following

Since one of the biggest challenges in relating EMG activation to torque or joint movement is dealing with long-range signal trends and amplitude variations, it is very challenging to define a set of EMG control standards which remain accurate over a long period of time. Therefore, the proposed control method chooses to embrace relative variation instead. It was found that a 4th order bandpass Butterworth filter effectively enveloped the EMG signal for a period of movement such that a series of local maxima and minima occurred within milliseconds of maximal or minimal joint angle.

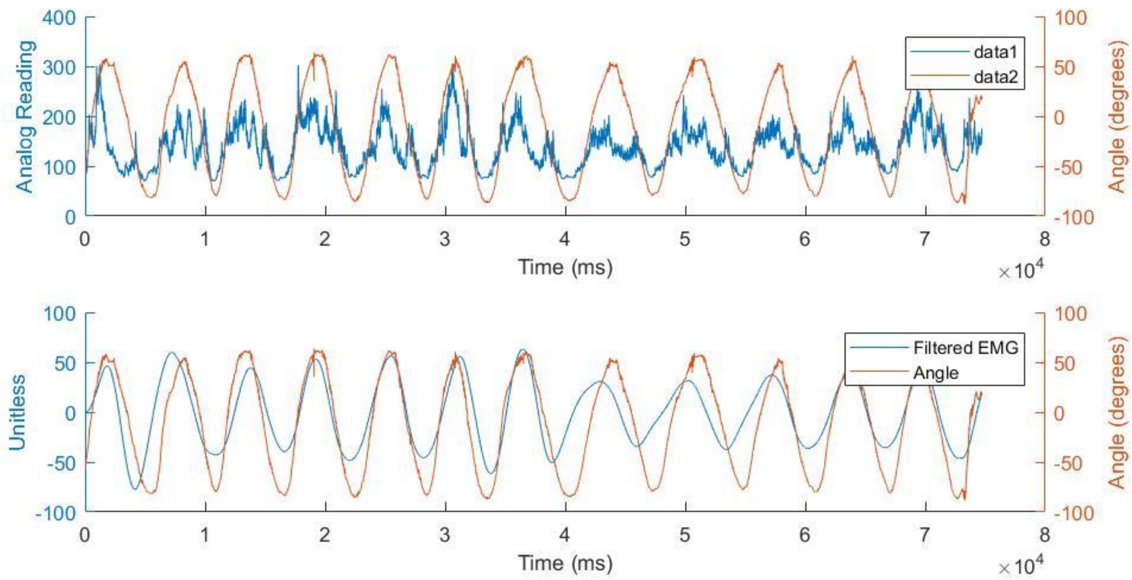

Figure 2. Raw EMG, Arm Angle and Filtered EMG.

Figure 2 shows the MyoWare sensor EMG output and the filtered EMG output using the proposed filtering technique. In this example, the cutoff frequencies of the bandpass Butterworth filter are 0.1 and 0.2 Hz. The ideal cutoff frequencies for the filter depend on the period of joint movement. If they are chosen correctly the EMG signal becomes a smooth oscillation that can be followed for actuator control. The goal in this filtering step is not to output an angle, but to output a smooth oscillation which can be interpreted by the control code.

The control code assumes a set goal amplitude and makes a guess at the period of movement. As the amplitude of the filtered EMG signal increases, the code outputs a linearly increasing angle. At each maxima or minima, the period and angular velocity of the output angle are adjusted.

This algorithm was implemented to demonstrate that continual guessing and updating of the period could work for interpreting intended angle from EMG bicep signal. Two example outputs are shown below. They contain both the real time joint angle input and algorithm’s angle output. Due to the limits of the actuator, the maximum angle output was 140 degrees, while the joint input reached 180 degrees.

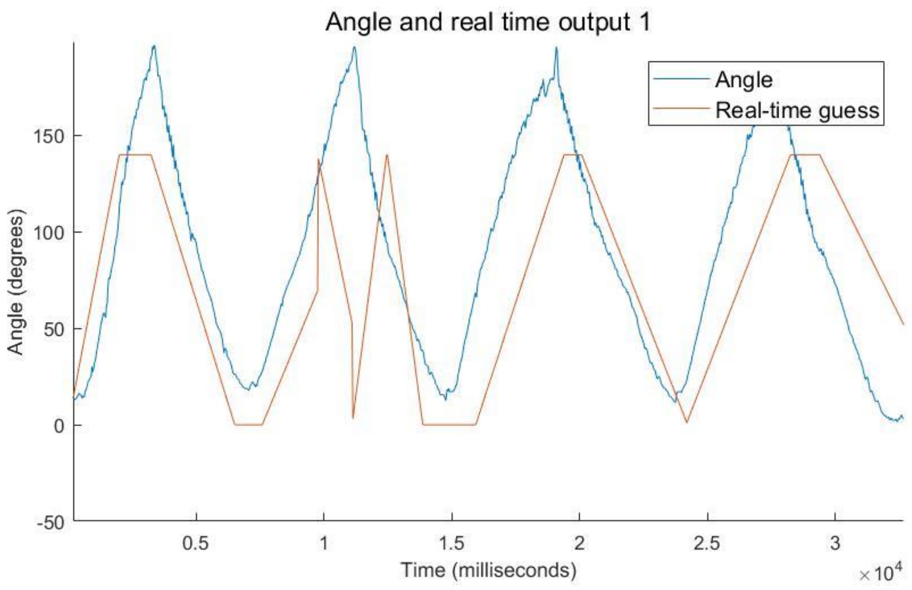

Figure 3. Input and Real Time Output of 750 ms Motion Period.

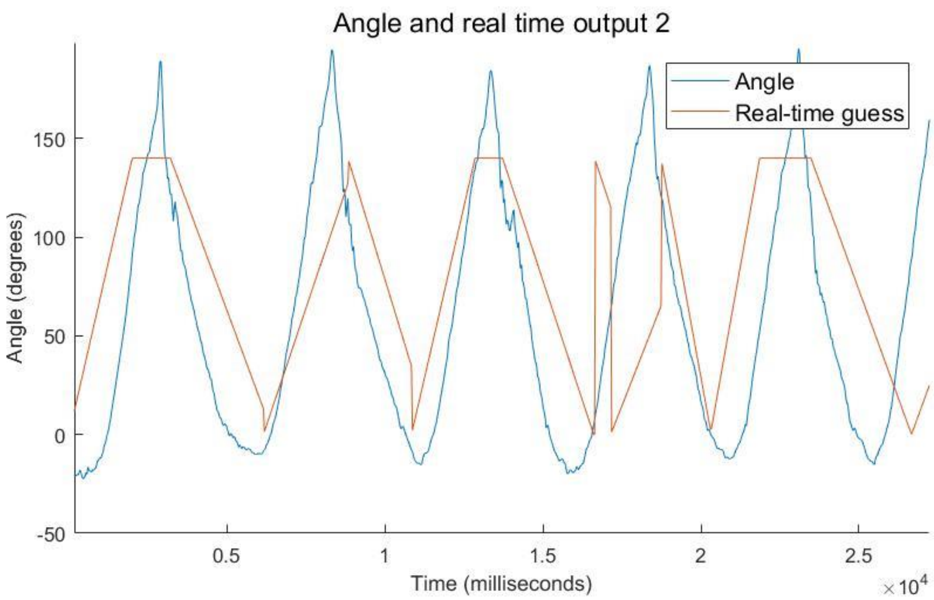

Figure 4. Input and Real Time Output of 500 ms Motion Period.

Figure 3 shows arm angle and the real time angle output as the arm was swung from 0 to 180 degrees. For this period of motion, filter cutoff frequencies of 0.05 and 0.1 Hz were used. The erroneous angle prediction around the 1 second timestamp was caused by an unexpected minima in the filtered signal. Figure 4 shows the arm angle and real time output for a motion period of 500 ms. For this motion, filter cutoff frequencies of 0.1 and 0.2 Hz were used. Similarly, the erroneous prediction around the 1.5 second timestamp was caused by an unexpected minima. Due to the amount of time it takes for the actuator to inflate and deflate, the effects of this mistake are limited. However, this prediction error can be further mitigated with more tailored filtering or code adjustments.

This method of control creates a very natural actuator response to the EMG amplitude that the bicep outputs as it cycles through the pendulum motion. Unlike most other EMG control methods that don't use machine learning, the method does not require unnatural muscle flexing to initiate control of the actuator.

<u>Filter Implementation</u> The Butterworth filter was implemented the microcontroller using a direct form II transposed filter structure. This structure was chosen because of the ease of finding the necessary coefficients in MATLAB, since MATLAB uses the same filter structure. Unfortunately, when implementing filters with cutoff frequencies below .05 Hz on the microcontroller, significant numerical errors caused the filter to become unstable. This hindered the full implementation of this control algorithm. Further research or consultation with an electrical engineer is necessary to design microcontroller-appropriate filters for this control method.

<u>Demonstration Algorithm</u> A demonstration code based purely on event detection was implemented for the purpose of demonstrating the actuator for visitors to the lab. This code demonstrates the feasibility of holding an amplitude constant while guessing and updating the period. Example results can be found at https://youtu.be/Jf-aaltRncA, While this code is not useful for rehabilitation or publishing, for demonstration purposes it is acceptable.

<u>Event Detection</u>

The 4th order Butterworth filter, while it provides a very good signal for the algorithm to follow, responds to a step input with significant overshoot and ringing. This means that should the amplitude of the EMG signal flat line, which was experimentally found to correlate to the stopping of arm movement, the Butterworth filter will still output an oscillating trend for the algorithm to follow. Therefore a form of event detection must be added to the algorithm to control for these false positives.

Rather than looking for a relatively unchanging EMG amplitude, a method of feature extraction was employed. This was chosen for robustness. In the case of rehabilitation, the patient may have a different signal pattern which indicates the stopping of motion. Detrended Fluctuation Analysis (DFA) was the method of feature extraction chosen for novelty. DFA has been used for analysis of self-correlation in EEG signals (Lee, 2002), but a literature search only revealed the use of DFA for pattern classification of hand movements (Phinyomark, 2009). Its strength lies in its ability to mitigate long-term trends.

Detrended Fluctuation Analysis takes a discrete time EMG signal of length N (where N is typically 256 points). The algorithm is as follows: The average value of the EMG signal, $\overline{x(t)}$, is subtracted from the original signal, $x(t)$, and the shifted EMG time is integrated to convert the signal to a random walk, $y(k)$.

$$y(k) = \sum_{t=1}^{k} \left[\left\{x(t) - \overline{x(t)}\right\}\right], k = 1, \ldots, N \tag{1}$$

The integrated series is divided into L equal windows of n points each where $n = int(N/L)$. In each window of length n the integrated time series is fitted with a semi-local trend $y_n(t)$. The root mean square, $F(n)$, of the integrated series and semi-detrended series is calculated.

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N} [y(k) - y_n(k)]^2} \tag{2}$$

The resulting value $F(n)$ is plotted against the value n and then the algorithm repeats with the next value of n, where the number of windows used to find n is chosen by the user. The final result is a graph from which features can be extracted.

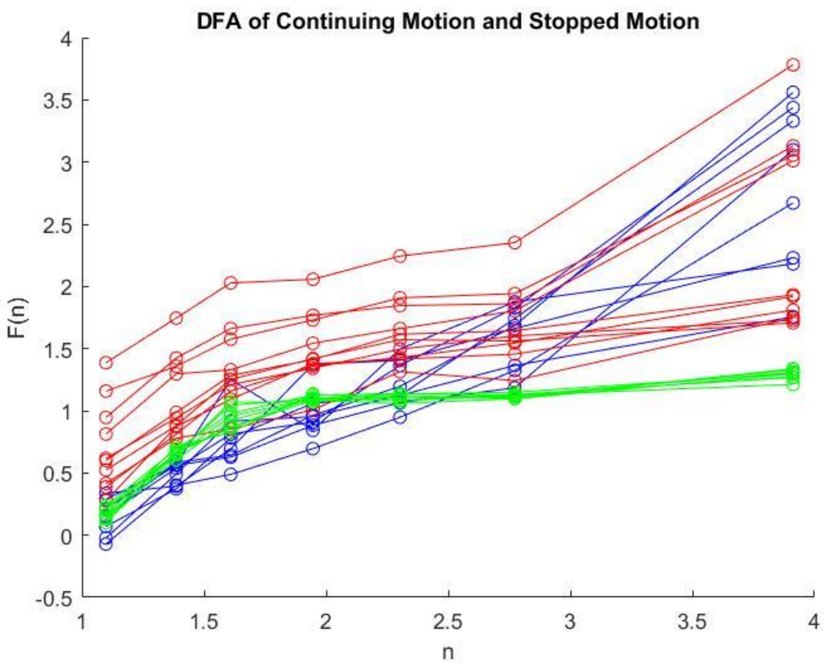

Figure 5. Red: DFA of upward arm movement, Blue: DFA of downward arm movement, Green: DFA of stopped movement.

Figure 5 shows the results of DFA on upward, downward and stationary arm movements. Comparison of the MyoWare pre-filtered signal with the raw output showed that for classification purposes, the raw signal yielded more distinct results.

While other feature extraction methods exist, detrended fluctuation analysis presents a promising method for event detection in the control algorithm, and prevents false interpretations of the Butterworth filtered signal.

Future Additional Improvements

The current implementation of this control algorithm assumes a set range of motion. While this is appropriate for rehabilitation and for simple assistive tasks, it does limit the applications of the code. The following suggestions may be explored to improve the ability of the code to assist a wider variety of tasks.

Amplitude Estimation   As discussed earlier, without knowledge of the angular velocity, the integral and the amplitude of the EMG signal do not yield enough information to control the actuator. However, with the initial guess of period and expected joint angle from the filtered EMG, it may be possible to adapt the motion in real time based on expected amplitude and/or integral. Further exploration of this additional control technique is recommended

Role of Machine Learning   As a certain degree of complication is reached, it may become easier to look for several varieties of events (instead of just the stopping of motion). A combination of this selective event detection and filtered signal following would allow for a quicker data acquisition and training time than implementing a full machine learning algorithm. Further, this combination would retain the novelty of filtered signal following and its real time capabilities. If this implementation is expanded, the fuzzy logic method of learning is recommended. While this form of learning has been implemented for EMG joint angle detection already (Avila, 2015) its robustness and ability to handle the estimated inputs of the filtered EMG signal and period make it a compelling and, in this implementation, novel choice.

NEXT STEPS

Feasibility of Implementation

An important next step for the further development of this control algorithm is to verify the feasibility of implementing several sets of low-frequency discrete-time filters. Once this has been verified, continued exploration of this method can continue.

Further Undergraduate Research

There are many details of this control method which can be explored and perfected, and which would make good research projects in the future. First, finding a relationship between period of movement and Butterworth cutoff frequencies is important. If a linear relationship exists, this would significantly enhance the algorithm since a unique set of filters could be created in real time to best envelope the EMG signal. In addition to determining this relationship, implementing the steps necessary to create each custom Butterworth filter would be a worthwhile undergraduate endeavor. Second, while detrended fluctuation analysis shows promise in feature extraction, it is important to obtain the most useful set of features possible for event detection. Exploring the optimal set of features to extract would also be a good research project.

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