Project Phase 1: EMG Report

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Background

The main source of EMG signals comes from muscle fiber action potentials or MFAPs. These excitations travel along muscle fibers and are affected by fiber properties like diameter and electrode location. Multiple muscle fibers get activated together as part of motor unit. The motor unit action potential (MUAP) is generally what gets detected. [1] The recorded MUAP size is mostly affected by the fibers closest to the detection electrode. Variability in MUAP signals can come from muscle fiber failure and the varying depolarization time of the muscle fibers. Electrode and tissue act as filters to the MUAP signal. A train of MUAPs (MUAPT) is what creates muscle contraction force.

The EMG signal comes from summing the MUAPT from every motor unit involved in a contraction. The EMG signal amplitude ranges from $1mV - 10mV$ and has a bandwidth from $0Hz - 500Hz$ with the most power in the range $50Hz - 150Hz$. The firing rate of motor units is in the range of $0Hz - 20Hz$. [2] Ambient electrical noise, motion artifacts, and noise from the electrode skin interface can impact the signal significantly since it is fairly low amplitude. [3] A larger electrode picks up more low frequency activity from more muscle fibers but also loses some ability to distinguish individual motor units which smaller electrodes are better at. To tap into both sources of information, two or more channels can be used with different electrode sizes. Doing so can give new insights like combining the MUAP area detected from macro electrodes with average motor unit firing rate (FR) to calculate an estimate of average force produced by the muscle. [1] A decomposition algorithm should be able to identify several motor units and, deal with the effect of small electrode position changes on MUAPs, and deal with shape, noise, and variability in MUAP shape from biological phenomenon like those mentioned earlier.

To sort MUAPs by motor unit, assume that the same motor unit produces MUAPs that are self-similar and that motor units activate enough times independently to identify their shapes. When detecting a signal, make MUAP signal amplitude and slope as high as possible by adjusting electrode position. The sampling rate must be at least 10kHz but a higher rate gives greater freedom for analyzing the signals.

A threshold value can be used to identify candidate MUAPs, though this may miss signals from more distant fibers which have smaller amplitudes. A certain portion of the signal around detection is selected for further processing to determine whether they truly contain one or more MUAP signals. Filtering can be used to help separate different MUAPs. They can be validated by looking at features like variance, slope, and amplitude. Analyzing the signal to noise ratio can help determine threshold values. Spikes can be aligned by peak values and after which features can be extracted from the signal.

There are many different ways to select and analyze signal features i.e peak to peak voltages, number of phases (biphasic, triphasic), Fourier/wavelet transform coefficients, time samples.[1] A technique like PCA can be used to help determine what features are important and reduce the dimensions of the feature space. ICA can be used to remove artifacts and uninteresting signals.

The obtained features can be used to form groups in a process called clustering which would assign MUAPs to a specific motor unit. Clustering depends on the self-similarity assumption mentioned earlier. Every member of a cluster should be more similar to its cluster members than other cluster members. There are many different clustering methods like hierarchical techniques vs partition techniques. K-means clustering is one common partition technique which creates clusters by guessing cluster means, clustering by distance, recalculating cluster means, and iterating till convergence. The template of a cluster is the archetypal group member which is determined after clustering.

After group templates have been obtained, they can be used to classify additional spikes using supervised classification methods. For example, a neural network can be trained using classified MUAPs. Classification methods from communication systems can be used by treating EMG signals as symbols to be sent over a noisy channel with intersymbol-interference. The well tested technique of maximum a posteriori (MAP) estimation can be used with this approach. [4] Templates can be updated iteratively as these methods are used. This classification must be robust to interunit and intraunit noise and be able to merge and split classes. Firing rate information can be carefully used to help improve performance.

A certainty classifier is considered to be a robust method of classification which combines various decision functions to get a certainty measure. A classification is made by finding the certainty value for each candidate MUAP and choosing the highest candidate if its certainty is greater than a threshold. It can incorporate more information in later stages like firing rate to improve performance accuracy. It deals with intraunit noise and superpositions of MUAPs well. [1]

Separating MUAPs is important for the analysis of firing rate patterns. To deal with superposition of MUAPs, templates can be matched to a section of the signal and then subtracted if they match. The residual waveform then goes through the same process. This doesn't work as well for MUAPs that interfere destructively as it will be harder to match a small signal to the high amplitude MUAPs. Another method is to create templates of superpositions by adding together combinations of waveforms which can then be used for matching. These methods can be combined to make use of the benefits of both. The relationship between MUAPT can be incorporated to help with MUAP identification. [1]

An EMG signal decomposition system must be evaluated for classification accuracy, percentage of MUAPs detected, and speed. Manual decomposition results through graphical analysis by an operator can be used as a benchmark for comparison. Simulated EMG signals be used for decomposition. This allows for getting a measure of true accuracy but simulations don't perfectly match real data. Important properties of a MUAPT are the interdischarge intervals (IDI) distribution and IDI statistics like mean and standard deviation, mean IDI. The IDIs can also be used to calculate the firing rate (FR) which impacts the force delivered. These characteristics can be used to evaluate decomposition results like by creating raster plots of a MUAPT and viewing IDI distribution and firing rate evolution over time.

EMG can be used to gain information about muscle operation and the impact of factors like aging and fatigue on the system. It can also be useful for the analysis of neuromuscular disorders. In myopathic diseases fibers become smaller and less numerous within a motor unit. In neuropathic diseases, motor units have more fibers and become less numerous. EMG signals can be used to estimate fiber density and study MUAP properties. This can be useful in the diagnosis and treatment of the aforementioned disorders. Firing rate statistics can give information on the ability the neuromuscular system to deliver force. For example, the FR covariance acts as a measure of neural control stability and consistency which could be used to identify ill-functioning units. [1]

Better decomposition methods allow for more complex firing rate analyses. This can give insight into the science behind muscles. An example of this science are results suggesting that muscles follow an onion skin control scheme in voluntary contraction. In this scheme, the higher threshold units have lower firing rates leading the principle that firing rates of motor units activated earlier will be higher than the firing rates of later activated units.[5] This scheme provides energy efficient force generation and reduces fatigue for later activated units leaving muscle reserve capacity for extreme situations like the flight-or-fight response.[6]. To do such detailed analysis EMG signal decomposition must be very robust. De Luca (2012) mentioned that their algorithm from the paper Nawab et al. (2010) used Artificial Intelligence and had very high accuracy and no bias. There is a tradeoff for this performance as speed is fairly slow and performance declines if the algorithm is sped up. up.[7]

There are several open source software packages for analyzing EMG signals. EMGLAB works in Matlab to view and decompose EMG signals. [8] It has a GUI and algorithms for template matching and resolving superimposed MUAPs. There is also software for simulating EMGs in MATLAB by Hamilton-Wright and Stashuk. [9] This could be used for testing the validity of the program we will create. The site emglab.net also contains sample datasets from real EMG data that was decomposed by an operator and could be used for validation. [10]

Project Plan

Figure 1 shows the project framework given by Professor Liu. In the first stage, the given EMG file will be read into MATLAB. The next stage filters the signal using a low pass filter adjusted to make action potential more clear. Likely a second-order low pass filter will be used.[1] The action potential spikes should now be visible. These spikes can then be detected using a threshold. At first I plan on pre-setting the thresholds. Depending on the end results, the threshold can be adjusted by analyzing the signal to noise characteristics.

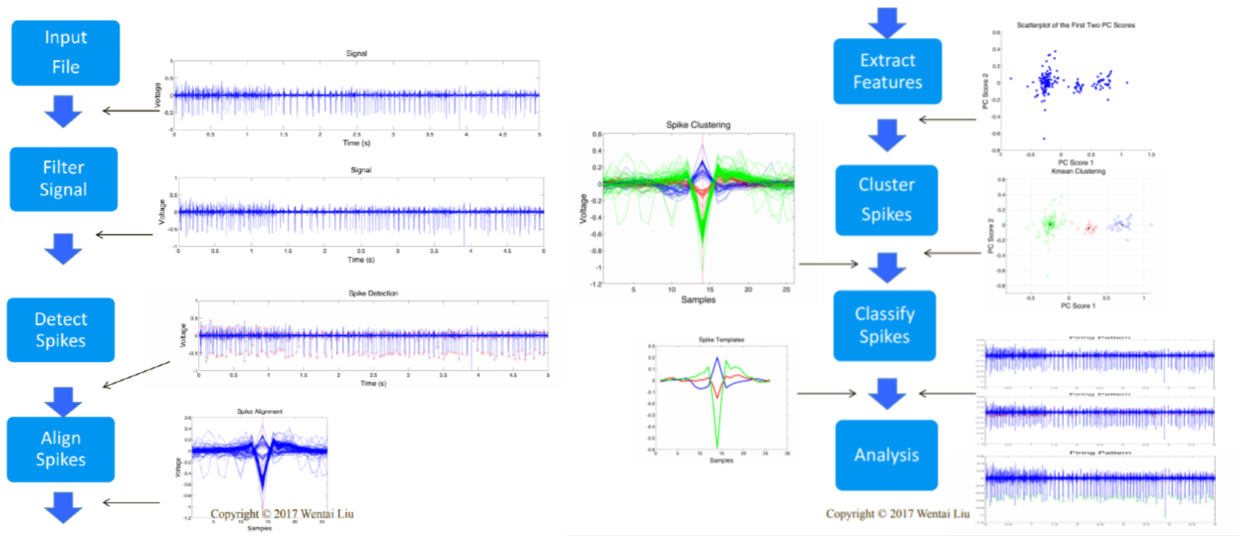

Figure 1: Provided by Professor Wentai Liu. First half pipeline. Second half pipeline (right). This figure shows the pipeline to get from raw EMG data to decomposed MUAPs

[1]. The next stage will align the spikes using peak values and store a fixed length section around the peak.

Features can now be extracted from the aligned spikes. I plan to extract time samples of the signal in my first iteration. Afterwards I can apply PCA to reduce the dimensions of the features space after verifying that the first 2 or 3 principal components contain a significant percentage of the overall variability. Now the spikes can be clustered using an unsupervised learning algorithm. I plan on using k-mean clustering in my first iteration, adjusting the number of clusters after observing results. A template for each MUAP can now be obtained be looking at the cluster mean. Templates should look like real MUAP signals if clustering is working properly. In the next stage, the rest of the spikes can get classified using a supervised learning algorithm. I plan to use a Support Vector Machine trained on the clustered spikes to do this in my first iteration. Now all the spikes should be assigned. Performance can be analyzed visually and by running simulated and operator sorted data through the pipeline to test accuracy, extent, and speed.

If decomposition performance is not very high, additionally complexity can be added to improve the various stages. Optimization will be focused on accuracy and extent since the algorithm is not designed to be used in a real-time application where speed would be more important. In the detection stage, different methods of setting the threshold can be tested. In the alignment stage, variable length sections could be tried if the fixed section is missing out on important signal components.

At the extraction stage, Fourier transform coefficients could be tried instead of time samples. Statistics like peak-to-peak voltage and number of phases could also be extracted. The clustering could be tried without reducing the feature space to see if accuracy improves. More complex clustering algorithms could also be used like DBSCAN, GMMs, and Hierarchical Clustering. The algorithm can be chosen by studying visually estimated cluster shapes in a lower dimensional space and choosing the best algorithm suited to that shape. If supervised classification is inaccurate, a more advanced decoder like a neural network could be used. Other options are using communication systems decoding techniques, using certainty-based classification, or removing the supervised classification step altogether and only using clustering. Firing pattern statistics could also be incorporated into the algorithm. To determine the first potential target for improvement, the variables and outputs in each stage will be studied and analyzed for errors or inaccuracy.

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