Anticipatory Electromyogram-Torque Estimation
and Effect of Whitening Bandwidth
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Abstract

The electromyogram has numerous applications in engineering and science. One specific application is to model a system for the torque generated by the elbow joint. This application has been long studied and applied in controller designs for artificial prosthetics limbs. Previous research had shown that nonlinear and multiple channel whitened EMG signal models gave the best EMG to torque estimates compared to linear un-whitened models. This thesis describes the methodologies for predicting the torque into the future up to 1 second. Four specific types of finite impulse response models (linear and nonlinear, single channel un-whitened and multi-channel whitened) are compared based on the EMG-based predicted torque and the actual torque. The errors were measured as the difference between actual and predicted torque. It was observed that the error was mostly constant at the minimum error value between 0 and 80 ms for all four models, with the lowest error being 5.48 % maximum voluntary contraction (MVC) flexion. Further comparison was performed between different lower order models and a Butterworth second order model for predicting torque ahead in time. Such models are common in the literature.

This thesis separately investigates the effect of band limiting the whitened EMG signal and using the advanced EMG processors for estimating the torque. Whitened EMG data were passed through a low pass filter with selectable cutoff frequency from 2048 Hz down to 20 Hz to limit the whitened band width. It was observed that the error was not significantly different for bandwidths down to approximately 400–600 Hz, grew gradually as the band width further decreased to 200 Hz, beyond which the error increased sharply. It can be inferred that for this particular study consisting of lower contraction levels, there is no significant power usable for whitening in the EMG signal at higher frequencies, providing an opportunity for lower sampling rate, effective noise suppression, better signal to noise ratio and implementation of low cost electrodes.

This research work lead to two conference paper publications at the 2013 IEEE 39th Annual Northeast Bioengineering Conference. Two journal papers are in the writing and preparation stage which will be submitted after their completion.
Acknowledgement

I would like to thank Professor Edward A. Clancy for providing me and our team with an opportunity for this research work under his guidance. He has been a great research adviser throughout my 2 years at Worcester Polytechnic Institute and without his help this thesis would not have been possible. The amount of time he devoted to this research, advising and the writing part of the Journal and Conference papers have been significant value despite the fact of his busy course and other research schedule.

I would also like to thank my team mate Meera Dasog for providing significant effort in this combined research and PhD candidate Pu Liu for the supervision and guidance during the entire research period.

Finally I would like to thank my wife Shruti Khadka for helping me and motivating throughout my graduate studies. She is the only reason for me being at WPI for my Master’s degree.
Contributions

This research work is a combined effort of two Master’s Degree seeking students Kishor Koirala and Meera Dasog with the supervision of Ph.D. candidate Pu Liu with direction from our research advisor Professor Dr. Edward A. Clancy. During the first part of the research, Meera was involved in the initial evaluation and preprocessing of the EMG signals. I was involved in the system identification of the EMG to torque model. During the next stage of research, I was involved in investigating the lower order FIR and IIR models and Meera was involved in the whitening bandwidth part of the research. The statistical tests and collection of results were done with a combined effort during all the research work. To be concise, the whole research had equal contribution from both Meera and I.
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Chapter 1: Introduction

Background Introduction

This research continues past research conducted at WPI and throughout the world, focusing on modeling human elbow torques. A simple model of the elbow is studied in which the electrical signals generated by the biceps (flexion) and triceps (extension) muscles are related to joint torque during constant-posture, force-varying contractions. Applications of EMG signal processing is an ongoing area of research with a long history; however due to the complex nature of human physiology, it still remains an active area of research. One significant application is estimating the torque generated from EMG signals, which is applicable to control of artificial prosthetic limbs [1], orthotics control, and virtual environment applications (e.g., head mounted displays [2]). These applications provide us with a motivation to develop models that can estimate the torque generated via observation of the EMG signal. In particular, each of the above applications would benefit if EMG could be used to estimate the torque that will occur a few tens of milliseconds into the future. Doing so would provide better control of these various mechanisms based on EMG muscle signals.

It has been long known that movement of the human body exhibits a combination of electrical and mechanical properties. For example, elbow movement can be defined by the simultaneous mechanical contraction and extension of those muscles that cross the elbow joint, including the biceps and the triceps muscles. Figure 1 shows a simple mechanical model of human elbow movement with the shoulder fixed. The overall torque can be represented as the absolute difference between the torque generated by the flexion and extension muscles. The mechanical movements are initiated by electrical firing of different motor units within each muscle—hence these contractions exhibit electrical activation that can be recorded at the surface of the skin.

![Figure 1 : A simple mechanical model of human elbow [Clancy, 1991]](image)

The surface electromyogram (EMG) is the recording of the electrical activity of the skeletal muscle at the surface of the skin. Figure 2 shows a general model of surface EMG signal generation at the motor unit (MU) level. Each motor unit firing can be viewed as the output of
the pulse shaping filter with the input modeled as a random time-varying Dirac delta impulse train. The EMG signal is the sum of these time-varying individual firings. At the surface of the skin, many motor units are viewed by the electrodes, so individual spikes are not distinguishable.

Figure 2: Individual motor unit firing [De Luca, IEE Trans Biomed Eng., 1979]

Figure 3 shows the triceps (extensor) muscle EMG recorded at the surface of the skin. The surface EMG signal can be modeled as an amplitude varying random signal with zero mean. The effort level produced by the elbow is assumed to be coded in the time-varying standard deviation of the random signal. The figure shows the change in the amplitude of the random signal with decrease in effort level as time progresses.

Figure 3: EMG signal amplitude vs effort level [Clancy, 1991]
Figure 4 shows a general breakdown of the overall EMG to torque estimation. It is divided into three distinct segments: Data Acquisition, Signal Pre-processing and System Identification. Both parts of this research project have the same signal processing steps for EMG-torque estimation, with slight variations in the signal Pre-processing stages and the System identification stage. The raw flexion and the extension EMG signal are processed separately to estimate their individual torques, and finally the overall torque is estimated as the difference between the two individual torques. In the figure, $S_F$ and $S_E$ are the standard deviation estimates (EMGσ) of the flexion and extension EMG signals.

**Figure 4 : EMG-Torque Estimation Model**

**Data Acquisition**

Experimental data consisted of 54 subjects (30 male and 24 female) from three distinct experiments with identical setup for the collection of data utilized in this project. Figure 5 shows the basic diagram for data collection setup. Subjects were seated with their shoulder securely fastened at 90 degrees. Four active bi-polar electrode amplifiers were placed transversely across the biceps and the triceps muscle separately. The wrist was cuffed with a load cell (dynamometer) for recording the actual torque generated by the elbow. Subjects performed various torque varying-contractions tracking a 1 Hz bandwidth random target that was displayed on a computer screen shown in Figure 5. A total of 30 seconds of data were collected. The EMG signals were sampled at 4096 Hz with a 16 bit resolution analog to digital converter. More on data collection is described in Appendix A.
Signal Pre-Processing

Figure 6 shows the general block diagram for the signal pre-processing stages involved in the EMG signal estimation. Both the flexion and extension EMG signals are processed separately. Also, for multiple channel signals, each channel was processed individually.

**Power Line Notch filter**

Figure 7 shows the power spectral density for one of a randomly chosen EMG signal. It can be observed that there are several large magnitude spikes. Close examination of these frequencies showed that these spikes were a result of 60 Hz power line harmonics. Second order IIR notch filters were implemented to remove the power line interference. More detailed analysis of power line notch filtering and the frequency selection is explained in Appendix C.
Adaptive Signal Whitening

It has been shown that adaptive whitening improves the EMG estimates [5]. Whitening a signal distributes the power evenly across the entire bandwidth for a band limited signal, decorrelating the signal in time domain. Implementation of whitening also increases the statistical bandwidth of the signal, which makes the approximation of standard deviation more accurate. A decorrelated EMG signal is essential in the system identification stage where the optimal performance models can be designed which are based on individual contributions of the estimated EMGσ samples. Figure 8 shows whitening in the time and frequency domains for one EMG signal and its whitened signal. It can be seen that the power spectral density of the whitened signal is comparatively flat.
The adaptive whitening algorithm \cite{5} implements a fixed whitening filter followed by an adaptive low pass FIR filter to reduce the gains for the high frequency noise. Figure 9 shows example time domain and the frequency domain plots of a fixed whitening filter. It can be observed that the whitening filter applies the inverse power estimate of the incoming raw signal.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig9.png}
\caption{Whitening filter [Clancy and Hogan, 1994]}
\end{figure}

\textbf{Rectification and Spatially Channel Average}

The overall torque generated by the elbow is the difference between the flexion and the extension torque. To estimate the difference between the torques generated, the whitened EMG from each electrode is rectified. For multiple channel inputs, all the channels are averaged to produce an equivalent single average of flexion and (separately) extension EMGσ.

\textbf{Low-pass filter and Decimation}

The rectification that was done in the previous stage changes the mean of both the extension and flexion EMG signals which is no longer zero. The signal information is now contained in the time-varying mean of the signal. The power of the signal is mostly concentrated below 16 Hz. All the higher frequency content contributes noise. Also, the high sampling frequency does not serve any benefit, so both the flexion and extension EMGσ signal are downsampled to a frequency of 40.96 Hz. A low pass anti-aliasing filter is applied with cutoff frequency at 16.8 Hz for down-sampling of the signal. The lower sampling frequency also decreases the memory requirements for the system identification filters that are implemented in the following stages.
**Start-up Transient Removal**

The signal pre-processing stages have implemented three separate filtering operations: power line notch filters, adaptive whitening filters and the decimator low pass filter. After visual inspection of the impulse response of these filters individually, a collective total of 2 seconds were removed as start-up transients from the 30 seconds of data.

**System Identification**

Figure 10 shows the general overview of the system identification modeling. The system identification involves training of the unknown system and then testing the performance with a different data set. Flexion and extension EMG estimates from the previous section are the inputs to the system and the known actual torque is the output, which is measured directly during the data collection stage. For this research, two models are implemented: Finite Impulse Response (FIR) filter models which require estimating the filter coefficients and second order Butterworth filters at cutoff of 1.5 Hz which requires estimating gains of the filter.

After training the system, a different data set is chosen which estimates the flexion and extension EMG signals following the procedure described above. Based on the trained model, output torque is estimated. By using the future values of actual torque during training, we train the system to predict the torque ahead in time during testing.

For this research work, we have focused mostly on four different EMG-torque processors based on two system identification models (linear and non-linear) and two signal processing methods (multiple channel whitened and single channel un-whitened). These four models are referred to as advanced EMGσ processors [3] throughout the paper. It has been shown that advanced EMGσ processors which implement multiple channel adaptive signal whitening techniques [5] produce better torque estimates based on the flexion and extension EMG signals. In creating system identification models, 54 seconds of training data (from two combined trials) were used and the resulting models were tested on distinct test data.

This research was focused in two distinct areas of EMG-torque modeling which are described in the following sub-sections. The first part of this research work investigates FIR and Butterworth system identification models and the ability of EMG signals to estimate the torque generated by the human elbow up to 1000 ms ahead in time. The second part deals with the
investigation of the bandwidth requirement for whitening the EMG signal. For both areas of research, previously collected data from 54 subjects were available, which is described in detail in Appendix A.

**EMG- Torque Estimation at Future Times with FIR and Butterworth models**

This area of research (Chapter 2 and Chapter 4) was focused on estimating human elbow torque ahead in time, using the EMG signal and advanced EMG processors [3]. It has been shown that the peak of the EMG signal precedes the peak force [4] produced by approximately 40–100 ms. The applications described in the earlier section require estimating the torque ahead of time for implementing better control mechanisms. Some of these applications have focused on developing models that take account of electromechanical delays in EMG-torque modeling [1, 2], but those works were focused on use of a fixed delay. In our research work, we have been able to show that advanced EMG processors are capable of self-adapting to the delays that are introduced in other types of processors.

Most commercial EMG-torque applications, including prosthetics and biomechanical modeling, apply a second order Butterworth filter with gain calibration in order to model the torque based on the processed EMG signals (with delay added, in some cases). A comparison of optimized FIR vs. Butterworth models were evaluated in this research. We optimized our FIR models by fitting their entire response (magnitude and phase) to calibration data. The resulting FIR models exhibited characteristics of a low pass filter with cutoff frequency in between 1 to 2 Hz. This cut-off frequency (1.5 Hz) was chosen for the Butterworth system identification model.

The lowest error obtained was for a nonlinear, four EMG channel model, which exhibited an average error (across the 54 subjects) of 5.48% maximum voluntary contraction (MVC) flexion. For all the four FIR models (linear and nonlinear; single channel un-whitened and four-channel whitened), it was observed that the error was not significantly different between 0 ms to approximately 80 ms.

Nine different order FIR models were investigated starting from 3rd to 25th order. The lowest model (order =3) exhibited a decrease in error as the prediction time increased from 0 ms to about 80 to 100 milliseconds (see figures in the journal paper draft), after which the error grew quite large. As the model order was increased, the error between 0 ms and 80 ms became flat, at a level below the order 3 model. Again, the error climbed after a prediction time of 80–100 ms. Model performance for orders greater than or equal to 15 did not differ. Similar results were observed for the single channel un-whitened model. Hence, the low order models were optimum only at one time location (in the range between 35 and 75 ms), but the higher order models were optimum over the complete time range from 0 to 80 ms. And, all errors associated with the higher order models were lower.

To investigate this behavior, estimated torque and the actual torque were examined in the time domain for the lower model order at different anticipatory times. At a 0 ms prediction time,
the estimated torque shapes followed the actual torque; however they lagged the actual torque considerably. At prediction times beyond 100 ms, the estimated torque shapes were also a close match, but the estimated signal led the actual torque. It was inferred that implementing higher order models captures both magnitude and phase, whereas the lower order models could not properly model the phase response. The Butterworth model exhibited time-domain errors similar to the low order FIR models. Analysis of Variance testing was performed for statistically verifying the observed results.

**EMG-Torque Estimation with Band limited EMG Whitened Signal**

Most of the electrodes used for commercial application of EMG have a bandwidth of around 500 Hz. In this second research area, we used a sampling frequency of 4096 Hz for electrodes with a bandwidth of approximately 1,800 Hz. This research area was to investigate the performance changes in the estimated torque signal from the EMG signal when the bandwidth of the whitened EMG signal is limited to the frequency content requirement of the regular electrodes. More generally, we investigated the EMG-torque performance as a function of the bandwidth used in whitening. Bandwidth was restricted offline with a digital low-pass filter.

A lower bandwidth requirement for EMG signal whitening would show that regular commercial electrodes could be used even for the advanced EMG processors, which in turn would save considerable cost associated with the general electrodes versus the specially build electrodes. Also, a lower sampling frequency could be used which can be a significant factor when implementing these algorithms and models in real-time operating hardware allowing more signal processing time between samples.

The methods for obtaining EMG amplitude estimates were similar to the previous area of research work using the advanced EMG processors. The only difference was that after whitening the EMG flexion and extension signals, a low pass filter was applied to each in order to limit the power contribution at the higher frequencies. Thirty seven different cutoff frequencies were implemented for the study. A step size of 100 Hz was implemented in decreasing order from 2000 Hz to 200 Hz, and after that a smaller step size of 10 Hz was chosen down to 20 Hz. Most of the EMG signal power extends out to 300–500 Hz, with a mode frequency that is typically near 100 Hz. Least squares modeling was implemented for the system identification, which was similar to the previous area.

Results showed that there was no substantial change in the EMG-torque estimation error as the whitening bandwidth is progressively limited to about 400–600 Hz. A rapid decrease in performance occurred for bandwidths below 200 Hz. These results showed that for this type of experimental study, simpler electrodes can be used instead of custom wide-band electrodes. Previously, [5] had shown that utilizing the entire bandwidth (1,800 Hz) for whitening improved the performance of EMG processors. However, these prior results utilized higher contraction levels, which are known to have more power at all frequencies—including the higher frequencies.
Conference Papers Published


Journal Papers in Preparation


References


Chapter 2: Copy of Conference paper - 1

EMG-Torque Estimation at Future Times

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Abstract—This paper investigates the ability of surface electromyogram (EMG) to estimate joint torque at future times, up to 1 s. EMG was recorded from the biceps and triceps muscles of 54 subjects during constant-posture, force-varying contractions and related to the torque produced about the elbow. EMG to joint torque was predicted up to 80 ms into the future without any changes in the minimum least square error of 5.48% of maximum voluntary contraction for the best estimation model investigated: whitened, multiple-channel EMG used with a non-linear model. Error progressively increased for prediction times above 80 ms.

I. INTRODUCTION

Real-time applications such as myoelectric prosthesis control [7], teleoperations and control of exoskeletons require minimization of time delays introduced between intention sensing and actuator activation. Similarly, virtual environment applications [8] employing head mounted displays need to reduce the latency between movement and scene generation. These applications motivate the need to anticipate torque ahead of time. In this regard, EMG is an attractive control source, since peak electrical activation of a muscle precedes peak twitch force by 40–100 ms. It has previously been shown that EMG-torque performance is improved by advanced (i.e., with feedback) EMG processing [4]. Thus, this processor was used to estimate torque at future times up to 1 second and the change in maximum voluntary contraction (MVC) flexion error was observed. Linear and non-linear models were investigated using the pseudo-inverse to regularized the least squares model fit.

II. METHODS

A. Experimental Data and Methods

Experimental data from 54 subjects (30 male, 24 female, aged 37±16.5 years) from three prior studies were utilized. The study was approved by the WPI IRB. Subjects had previously provided written informed consent. The three studies had nearly identical apparatus and protocols with respect to the data reanalyzed [1], [3]. Subjects were seated and secured with their shoulder abducted 90°, forearm oriented in a parasagittal plane, wrist fully supinated and elbow flexed 90°. Their right wrist was rigidly cuffed to a load cell (Biodex dynamometer; or Vishay Tedex-Huntleigh Model 1042, 75 kg capacity). Skin above the muscles under investigation was scrubbed with an alcohol wipe. In one study, a small bend of electrode gel was massaged into the skin. Four bipolar electrode-amplifiers were placed transversely across each of the biceps and triceps muscles, midway between the elbow and the midpoint of the upper arm, centered on the muscle midline. Custom electronics amplified each EMG signal (CMRR of ~90 dB at 60 Hz) followed by bandpass filtering (either a 2nd-order, 10–2000 Hz bandpass filter; or 8th-order highpass at 15 Hz followed by a 4th-order lowpass at 1800 Hz). All signals were sampled at 4096 Hz with 16-bit resolution.

After a warm-up period, MVC torque was measured in both elbow extension and flexion. Five-second, constant-posture constant-force contractions at 50% MVC extension, 50% MVC flexion and rest were recorded for calibration of advanced EMG estimation [5], [6]. Then, a real-time feedback signal consisting of either the load cell voltage or a four-channel whitened EMG\(\text{processor (formed by subtracting the extensor EMG) from the flexor EMG)}\) was provided on a computer screen. Thirty-second duration, constant-posture force-varying contraction trials were then recorded. The subjects used the feedback signal to track a computer-generated target that moved on the screen in the pattern of a band-limited (1 Hz) uniform random process, spanning 50% MVC extension to 50% MVC flexion. Three trials were collected.

B. Methods of Analysis

All analysis was performed offline in MATLAB. Two distinct EMG\(\text{processors were used: single-channel unwhitened (using a centrally located electrode) and four-channel whitened [2], [3]. Each processor used a 15 Hz highpass filter (causal, 5th-order, Butterworth) and first-order (i.e., absolute value) demodulation. The four-channel processor whitened each channel prior to demodulation [6] and then averaged the four channels after demodulation. Finally, the EMG signal was formed by decimated this signal by a factor of 100 to a sampling rate of 40.96. To do so, the signal was decimated twice by a factor of ten (effective lowpass filter prior to down sampling of 16.4 Hz, causal, 9th-order, Chebyshev Type 1). The torque signal was similarly decimated, yielding a bandwidth approximately one tenth that of the input EMG signals [5]. Extension and flexion EMG\(\text{s were related to joint torque via the parametric model [4]:}\)

\[
T[m] = \sum_{d=1}^{D} \sum_{q=0}^{Q} e_d \sigma_d[m-q] + \sum_{d=1}^{D} \sum_{q=0}^{Q} f_d \sigma_d[m-q]
\]

where \(T[m]\) is the decimated torque signal, \(e_d\) is the extension EMG, \(\sigma_d\) is the flexion EMG, \(e_d\) and \(\sigma_d\) are extension fit coefficients and \(f_d\) and \(\sigma_d\) are flexion fit coefficients. Integer \(D\) sets the number of signal lags. When integer \(D=1\), the model is linear. When integer \(D=2\), a nonlinear dynamic model is facilitated. Parameter \(Q\) was set to 30 for our linear model and 15 for our non-linear model. The pseudo-inverse tolerance values for varied combinations of EMG estimates were chosen based on performance results of torque estimates using the singular value decomposition pseudo-inverse technique [4]. A 5 ms time resolution was used to advance the EMG. Two seconds of data were excluded from the beginning of each 30s trial to account for filter start-up transients.
III. RESULTS

Fig. 1 shows the average error for four processing combinations: single-channel unwhitened EMG estimates, whitened EMG estimates, and multiple-channel whitened EMG estimates, all with a linear vs. non-linear model structure. The lowest error was 5.48% referenced to MVC flexion. Achieving the multiple-channel whitened EMG estimates and the non-linear model structure. The error does not vary for prediction times up to approximately 80 ms. This result suggests that EMG-based torque estimation at 80 ms into the future has an error that is no different than estimating torque at the current time. Table 1 shows the lowest average MVC error of the predicted torque for each of the four processing combinations.

<table>
<thead>
<tr>
<th>System Identification Model</th>
<th>EMG Technique</th>
<th>Lowest Average Error (% MVC Flexion)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Single Channel, Unwhitened</td>
<td>8.62%</td>
<td></td>
</tr>
<tr>
<td>Non-linear Single Channel, Unwhitened</td>
<td>7.55%</td>
<td></td>
</tr>
<tr>
<td>Linear Multiple Channel, Whitened</td>
<td>5.44%</td>
<td></td>
</tr>
<tr>
<td>Non-linear Multiple Channel, Whitened</td>
<td>5.48%</td>
<td></td>
</tr>
</tbody>
</table>

IV. DISCUSSION

EMG to torque prediction was performed to investigate error as a function of future time. Error varied with processing technique. Multiple-channel whitened EMG estimates provided lower errors than single-channel unwhitened. A second-degree non-linear model provided lower error than a linear model. These results are consistent with past observation in EMG-torque models [4]. We observed no differences in torque estimation errors for the range of prediction times between 0–80 ms. This result is unexpected, as most researchers explicitly model delays of 40–100 ms to improve EMG-torque performance. However, these other models tend to apply fixed dynamics (e.g., first- or second-order Butterworth lowpass filter with cut-off frequency between 1–3 Hz). Our models adapt their dynamics to each subject. After prediction times of 80 ms, error grew with the amount of time into the future, until errors leveled off at approximately 600 ms with a worst-case value of approximately 18% MVC flexion. At this error, EMGs no longer indicate the specific torques being produced in this experiment. The lowest error occurred at any future time between 0–80 ms using the multiple-channel whitened EMG estimates and a non-linear model structure. The error corresponding to these conditions was 5.48% MVC flexion.

REFERENCES


Fig. 1. Error (percent maximum voluntary contraction) vs. time predicted into the future for EMG-torque processing. Error is shown for the four combinations of EMG estimates (single-channel unwhitened and multiple-channel whitened) and model structures (linear and non-linear). Torque estimates were computed every 5 ms. Each estimate is the average result from 54 subjects.
EMG Bandwidth Used in Signal Whitening

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Abstract—It has been demonstrated that whitening the surface electromyogram (EMG) improves EMG amplitude (EMG) estimation. But, due to the wide bandwidth range often used when whitening, custom high-cost electrodes (bandwidth of \~{}2000 Hz) have been used. This paper investigates the effect of limiting the bandwidth for the whitened EMG data. The change in the average error of EMG to torque estimation was observed for 54 subjects over different whitening bandwidths ranging from 20–2000 Hz. We found that the average error remained the same for bandwidth limits between 600 Hz to 2000 Hz, suggesting that wider EMG electrodes were not helpful with this data set.

I. INTRODUCTION

Whitening of the surface electromyogram (EMG) has been shown to improve EMG amplitude estimation and to lower EMG-torque errors [1], [2]. The current adaptive whitening approach used in our laboratory [3] utilizes more signal bandwidth when EMG is large (SNR is high) but less signal bandwidth when EMG is low (more noise than signal only exists at the lower frequencies). This strategy has been shown advantageous when contraction levels extend to 50–75% of maximum voluntary contraction (MVC) [1], [3]. To take advantage of the broader bandwidth during higher contraction levels, our work has utilized custom-designed electrodes with a passband to nearly 2000 Hz. As a result, we typically sample the incoming EMG signal at 4096 Hz and implement adaptive signal whitening over the entire Nyquist bandwidth (2048 Hz). However, most day-to-day contractions occur at average levels below 25% MVC. At these contraction levels, the adaptive whitening may be discarding much of the higher frequencies in the signal. Given the cost and effort required for custom electrodes, we wanted to rigorously investigate the role of bandwidth on EMG processing at more modest contraction levels. In this work, the maximum frequency out to which whitening was applied was limited using digital lowpass filtering. We examined bandwidth limiting for frequencies ranging from 20 Hz to the full whitening bandwidth of 2048 Hz. For each of these bandwidths, EMG to torque estimation was performed for 54 subjects and the average error in percent MVC flexion was computed.

II. METHODS

A. Experimental Data and Methods

Experimental data from 54 subjects (30 male, 24 female; aged 37.6\pm16.5 years) from three prior experimental studies were analyzed. This study was approved and supervised by the WPI IRB. All subjects had previously provided written informed consent. The three studies had nearly identical experimental apparatus and protocols (fully described in [3] and [4]). Subjects were seated and secured with their shoulder abducted 90\(^\circ\), forearm oriented in a pronansial plane, wrist fully supinated and elbow flexed 90\(^\circ\). Their right wrist was tightly cuffed to a load cell (Biodex dynamometer; or Vishay Teddington Technical Model 1042, 75 kg capacity) at the styloid process. Skin above the muscles under investigation was scrubbed with an alcohol wipe. In one study, a small bead of electrode gel was massaged into the skin. Four bipolar electrode-amplifiers were placed transversely across each of the biceps and triceps muscles, midway between the elbow and the midpoint of the upper arm, centered on the muscle midline. Each electrode-amplifier had a pair of 4 mm (or 8 mm) diameter, stainless steel, hemispherical contacts separated by 10 mm edge-to-edge, oriented along the muscle’s long axis. The distance between adjacent electrode-amplifiers was 1.75 cm. A single ground electrode was gelled and secured above the acromion process or on the upper arm. Custom electronics amplified each EMG signal (CMRR of approximately 90 dB at 60 Hz) followed by bandpass filtering (either a second-order, 10-2000 Hz bandpass filter, or 8th-order highpass at 15 Hz followed by a 4th-order lowpass at 1800 Hz). All signals were sampled at 4096 Hz with 16-bit resolution. After a warm-up period, MVC torque was measured in both elbow extension and flexion. Two repetitions of five-second duration, constant-posture constant-force contractions at 50% MVC extension, 50% MVC flexion and rest were recorded. A real-time feedback signal consisting of either the load cell voltage or a four-channel whitened EMG processor (formed by subtracting the extensor EMGs from the flexor EMGs) was provided on a computer screen. Thirty-second duration, constant-posture force-varying contraction trials were then recorded. The subjects used the feedback signal to track a computer-generated target that moved on the screen as a band-limited (1 Hz) uniform random process, spanning 50% MVC extension to 50% MVC flexion. Three trials were collected. At least three minutes of rest was provided between contractions to prevent cumulative fatigue. Additional sensors were applied and tracking trials collected, but not used in this study.

B. Methods of Analysis

All analysis was performed offline in MATLAB. A four-channel whitened (but bandwidth restricted) EMG processor was used. Each processor used a 15 Hz highpass filter (causal, 5th-order, Butterworth) and first-order (i.e., absolute value) demodulation. The four-channel processor whitened each channel (causal algorithm of Clancy and colleagues [3], [5], [6]). Whitening filters were calibrated from one of the constant-force contraction sets, comprised of a 50% MVC extension, 50% MVC flexion and a rest recording. To restrict bandwidth, the whitened signal was lowpass filtered using a causal, 9th-order, Chebyshev Type 1 whose cutoff frequency was selectable. Cutoff frequencies incremented by 10 Hz between 20 and 200 Hz, and then incremented by 100 Hz up to 2000 Hz. After bandwidth restriction, each signal was demodulated and then the four EMG channels were averaged.
Finally, the EMG signal was formed by decimating this signal by a factor of 100 to a sampling rate of 40.96. To do so, the signal was decimated twice by a factor of ten (effective lowpass filter prior to downsampling of 16.4 Hz, causal, 6th-order, Chebychev Type 1). The torque signal was similarly decimated, yielding a bandwidth approximately one-tenth that of the input EMGs signals [7]. Extension and flexion EMG signals were related to joint torque via the parametric model [2]:

\[ T[m] = \sum_{d=1}^{D} \sum_{q=0}^{Q} e_{q,d} \sigma_{e}^{d}[m-\theta_{q}] + \sum_{d=1}^{D} \sum_{q=0}^{Q} f_{q,d} \sigma_{f}^{d}[m-\theta_{q}] \]

where \( T[m] \) is the decimated torque signal, \( \sigma_{e} \) is the extension EMG, \( \sigma_{f} \) is the flexion EMG, \( e_{q,d} \) are extension fit coefficients and \( f_{q,d} \) are flexion fit coefficients. Integer \( Q \) sets the number of signal lags. When integer \( D=1 \), the model is linear. When integer \( D=2 \), a nonlinear dynamic model is facilitated. Parameter \( Q \) was set to 30 for our linear model and 15 for our non-linear model. Fit parameters were found via least squares, regularized via the pseudo-inverse approach [2].

III. RESULTS

Fig. 1 shows the average error (difference in the estimated vs. actual torque) from all 54 subjects for whitened multiple channel EMG, using the linear and non-linear models, as a function of maximum frequency used for whitening. The average error remains at almost constant value of 5.48% (non-linear) and 6.24% (linear) for maximum frequencies between -600 Hz and 2000 Hz. Below maximum frequencies of -600 Hz, the error increases. A steep error increase occurs for maximum whitening frequencies below 200 Hz.

IV. DISCUSSION

EMG estimation was performed using different bandwidths of the whitened EMG in order to observe the change in error. It was observed that the error both for linear and non-linear models remained relatively constant over a wide range of maximum frequencies, i.e. 600 Hz up to 2000 Hz. This result questions the need for adaptive whitening over such a wide frequency range as 2048 Hz, at least for contractions at these levels. These data ranged in contraction from 50% MVC flexion to 50% MVC flexion, with an average contraction level below 25%. This result also supports eliminating the requirement to use custom high bandwidth electrodes when acquiring data with these contraction characteristics, as most off-the-shelf EMG hardware has a bandwidth up to -500 Hz.

REFERENCES

Using the Electromyogram to Anticipate Torques About the Elbow

Kishor Koirala, Meera Dasog, Pu Liu, and Edward A. Clancy, Senior Member, IEEE

Abstract— Electromyogram (EMG) activity from skeletal muscles precedes mechanical tension by 50–100 ms. This property can be exploited to anticipate muscle mechanical activity. Thus, we investigated the ability of surface EMG to estimate joint torque at future times, up to 750 ms. EMG recorded from the biceps and triceps muscles of 54 subjects during constant-posture, force-varying contractions was related to elbow torques. Higher-order FIR models, combined with advanced EMG processing (whitening; four EMG channels per muscle), provided a nearly identical minimum error of 5.48 ± 2.21% MVC<sub>f</sub> (flexion maximum voluntary contraction) over the time advance range of 0–50 ms. Error grew thereafter for larger time advances. The more common method of filtering EMG amplitude with a Butterworth filter (2nd-order, 1.5 Hz cutoff frequency) produced a statistically inferior (p<0.05) minimum torque error of 6.50 ± 2.99% MVC<sub>f</sub>, with an error nadir at a time advance of 60 ms. Error was progressively poorer at all other time advances. Lower-order FIR models mimicked the poorer performance of the Butterworth models. The more advanced models provide lower estimation error, require no selection of an electromechanical delay term and maintain their lowest error over a substantial range of time advances.

Index Terms—Biological system modeling, biomedical signal processing, electromyography, EMG amplitude estimation, EMG signal processing, EMG-force.

I. INTRODUCTION

It has long been known that electromyogram (EMG) activity from skeletal muscles precedes the associated mechanical activity [Inman et al., 1952]. This electromechanical delay may vary with the condition, but is typically measured as a pure delay between peak surface EMG amplitude (e.g., rectified, smoothed EMG) and peak mechanical activity of approximately 50–100 ms [Howatson, 2010; Inman et al., 1952; Li and Baum, 2004]. In many biomechanical models that relate EMG to force/joint torque, it is common to include a model term that accounts for this pure delay [Eggert et al., 2005; Staudenmann et al., 2005, 2010; Thelen et al., 1994]. Such models can also account additionally for frequency-dependent delay via a dynamical system model.

A related use of electromechanical delay is to predict muscle forces/joint torques at future times from EMG. Applications that do, or could, benefit from this property include: anticipating head motion in virtual environments to reduce scene vs. sensory alignment errors [Barniv et al., 2005], optimizing controller delay in myoelectric prostheses [Farrell and Weir, 2007], user control of exoskeleton suits [Dollar and Herr, 2008; Kiguchi et al., 2004; Lenzi et al., 2012] and the actuation of rehabilitation devices from impaired limbs [Delph et al., 2012; Dipietro et al., 2005; Khoshkar et al., 2010; Lukas et al., 2004; Mulas et al., 2005; Stein et al., 2007]. In many of these cases, estimating forces 50–100 ms into the future permits better temporal matching of user motor intent in the presence of computational delays and inherent delays within mechanical actuators.

Since numerous applications might benefit from “anticipatory” EMG-torque estimates, we performed a systematic evaluation of the errors associated with doing so over a broad range of times. No such detailed analysis had been previously identified in the literature. In addition, more advanced EMG-torque models can now incorporate multiple EMG channels per muscle, EMG signal whitening, as well as advanced model identification that is subject-specific [Clancy and Furry, 2000; Clancy et al., 2012; Potvin and Brown, 2004; Staudenmann et al., 2010]. These techniques have been shown to reduce EMG-torque errors and might influence the realization of electromechanical delay within EMG-torque models. Thus, we have investigated the performance of these advanced EMG-torque algorithms when estimating as much as 750 ms into the future. Preliminary results of this work were presented in Koirala et al. [2013].

II. METHODS

A. Experimental Data and Methods

Experimental data from 54 subjects (30 male, 24 female; aged 37.6±16.5 years) from three prior experimental studies were utilized. This reanalysis study was approved and supervised by the WPI IRB. All subjects had previously provided written informed consent. The three studies had nearly identical experimental apparatus and protocols with respect to the data reanalyzed (fully described in Clancy [1999] and Clancy and Furry [2000]). Subjects were seated and secured with their shoulder abducted 90°, forearm oriented in a parasagittal plane, wrist fully supinated and elbow flexed 90°. Their right wrist was rigidly cuffed to a load cell (Biodex dynamometer, or Vishay Tedea-Huntleigh Model 1042, 75 kg capacity) at the stylion process. Skin above the muscles under
investigation was scrubbed with an alcohol wipe. In one study, a small bead of electrode gel was also massaged into the skin. Four bipolar electrode-amplifiers were placed transversely across each of the biceps and triceps muscles, midway between the elbow and the midpoint of the upper arm, centered on the muscle midline. Each electrode-amplifier had a pair of 4-mm (or 8-mm) diameter, stainless steel, hemispherical contacts separated by 10 mm (edge to edge), oriented along the muscle’s long axis. The distance between adjacent electrode-amplifiers was ~1.75 cm. A single ground electrode was gelled and secured above the acromion process or on the upper arm. Custom electronics amplified each EMG signal (CMRR of approximately 90 dB at 60 Hz) followed by bandpass filtering (either a 2nd-order, 10–2000 Hz bandpass filter, or 8th-order highpass at 15 Hz followed by a 4th-order lowpass at 1800 Hz). All signals were sampled at 4096 Hz with 16-bit resolution.

After a warm-up period, maximum voluntary contraction (MVC) torque was measured in both elbow extension and flexion. Five-second duration, constant-posture constant-force contractions at 50% MVC extension, 50% MVC flexion and rest were recorded for calibration of advanced EMG amplitude (EMG) estimation algorithms [Clancy and Farry, 2000; Prakash et al., 2005]. Then, a real-time feedback signal consisting of either the load cell voltage or four-channel whitened EMG signal from the flexor EMG was provided on a computer screen. Thirty-second duration, constant-posture force-varying contraction trials were then recorded. The subjects used the feedback signal to track a computer-generated target that moved on the screen in the pattern of a band-limited 1 Hz uniform random process, spanning 50% MVC extension to 50% MVC flexion. Three trials were collected. At least three minutes of rest was provided between contractions to prevent cumulative fatigue.

B. Methods of Analysis

All analysis was performed offline in MATLAB. Two distinct EMG processors were used: single-channel unwhitened (using a centrally located electrode) and four-channel whitened (EMG Toolbox; Clancy and Farry; Prakash et al.). Each processor used a 15 Hz highpass filter (causal, 5th-order, Butterworth filter), notch filters at the power-line and each harmonic frequency (2nd-order IIR filter, notch bandwidth ≤ 1.5 Hz), and first-order (i.e., absolute value) demodulation. The four-channel processor whitened each channel prior to demodulation (causal algorithm of Clancy and colleagues [EMG Toolbox; Clancy and Farry; Prakash et al.]) and averaged the four channels after demodulation. Finally, the EMG signal was formed by decimating this signal by a factor of 100 to a sampling rate of 40.96 Hz. To do so, the signal was decimated twice by a factor of ten (effective lowpass filter prior to downsampling of 16.4 Hz, causal, 9th-order, Chebychev Type I). The torque signal was similarly decimated, yielding a data set with bandwidth approximately ten times that of the torque signal being estimated [Ljung, 1999].

Initially, extension and flexion EMGs were related to joint torque via the parametric model [Clancy et al., 2012]:

\[ T[m+1] = \sum_{i=1}^{Q} \sum_{k=1}^{K} a_{ik} e_{ik}[m-q] + \sum_{i=1}^{Q} \sum_{k=1}^{K} f_{ik} e_{ik}[m-q]. \]  

where \( T \) is the decimated torque signal, \( m \) is the current sample, \( i \) is the future time advance in samples, \( e \) is the extension EMG, \( f \) is the flexion EMG, \( e_m \) are extension fit coefficients and \( f_m \) are flexion fit coefficients. Integer \( Q \) sets the number of signal lags. When 

\( Q=2 \), a nonlinear dynamic model is facilitated. Model parameters were fit using the pseudo-inverse technique to regularize a least squares minimization [Clancy et al., 2012; Press et al., 1994]. The tolerance (Tol) for removal of singular values was the ratio of the largest singular value to each singular value in the design matrix. Based on a prior model optimization study utilizing non-causal processing [Clancy et al., 2012], two optimal model forms (30th-order linear, 15th-order nonlinear) were selected for both EMG processors, with the Tol for each as listed in Table 1.

In addition to these optimal models, two groups of other models were examined for comparison. First, many investigators cascade a fixed low-order Butterworth filter after each of the extension and flexion EMG signals, setting their difference as the estimated torque. Thus, we utilized 2nd-order Butterworth filters with cut-off frequencies at 1.5 Hz. The gains of both filters, representing the fit coefficients for the Butterworth model, were simultaneously calibrated for each subject in the training stage via least squares. These gains were fit separately for each time advance. Both EMG processors were investigated. Second, our linear FIR models, specified in (1), use a large number of lag values compared to what might be commonly found in the literature. Thus, we also investigated the linear model form with lag values of: \( Q=3, 5, 7, 9, 12 \) and 15. Only the four-channel whitened processor was investigated. The pseudo-inverse tolerance was 0.0056 for all lag values.

All models estimated torque for future time advances between 0 and 750 ms, at an increment of 5 ms. Models were calibrated (trained) from two of the trials [Clancy et al., 2012] and tested on the third trial per subject. This set of three trials utilized the same real-time feedback signal. The RMS error between the measured torque from the load cell and the EMG-estimated torque on the test trial from each subject was expressed as a fraction of twice the torque at 50% MVC flexion (MVCx) of each subject. The first 25 ms of signal was omitted from the RMS error computation to account for filter startup transients. Mean and standard deviation (\( \bar{\mu} \pm \sigma \)) errors from the 54 subjects are reported. Statistical comparisons utilized ANOVA when comparing across time advances within a particular combination of model and EMG processor. Pair-wise comparison between distinct models or EMG processors was performed at the best time advance and utilized pairwise sign tests [Miller and Freund, 1977].
III. RESULTS

Fig. 1 shows μ2 error results from 54 subjects vs. future time advance for the two optimal-order (i.e., high-order) FIR models and the two EMG processors. The minimum average error for each model-EMG processor combination, listed in Table 1, occurred at a time advance of 0 ms. At this optimal time advance, paired sign tests showed that each model-EMG processor pair was significantly different from the other (p<10^{-4}). Thus, the nonlinear model using four channel whitened EMG processing exhibited the lowest error. ANOVAs applied separately to each of the four plots in Fig. 1 each showed a significant change in error vs. time advance over the full 750 ms (p<10^{-6}). More importantly, however, was to test when error results first significantly departed from the minimum error at zero time advance. Thus, we applied a forward progressive ANOVA to the results of each plot condition. Our forward progressive technique began with an ANOVA using data from the time location of the error minimum and one forward time increment (i.e., 0 and 5 ms). If this result was non-significant (p>0.05), we increased the time range forward to include 0, 5 and 10 ms and recomputed the ANOVA. The time range was progressively increased until a significant difference (p<0.05) was achieved. This corresponding time advance indicated when the upward trend became statistically significant. For all four plots, the time advance for a statistically significant change was between 140-170 ms, with individual results shown in Table I.

Fig. 2 shows a sample time-series plot of the actual and EMG-estimated torque using the nonlinear model with four channel whitened EMG processing, at three distinct time advances. At time advances of 0 ms and 4007 ms, both the shape and phase of the estimated torque closely matched that of the actual torque, yielding a low RMS error. At a time advance of 84007 ms, the shape of the estimated torque matches that of the actual torque, but the estimated torque lags in phase. In addition, the estimated torque exhibits higher variance. Substantially higher RMS error results.

Fig. 3 shows μ2 error results from the Butterworth models for both EMG processors. With single channel unwhitened EMG processing, the minimum error of 9.16 ± 4.58% MVC occurred at a time advance of 60 ms. This value did not differ significantly (p>0.30, ANOVA) from the results at a time advance of 0 ms. A forward progressive ANOVA starting at the minimum error advance time (60 ms) showed that the upward trend became statistically significant at 160 ms. With four channel whitened EMG processing, the minimum error of 6.90 ± 2.93% MVC also occurred at a time advance of 60 ms. This value did differ significantly (p<0.02, ANOVA) from the results at a time advance of 0 ms. A forward progressive ANOVA starting at the minimum error advance time (60 ms) showed that the upward trend became statistically significant at 120 ms. The optimal error locations between Butterworth plots were compared using a paired sign test, and these values differed (p<10^{-4}). Finally, the best Butterworth model (four channel whitened EMG processor, 60 ms time advance) was compared to (i) the best linear model (30th-order, four channel whitened EMG processor, 0 ms time advance) and, separately, (ii) the best nonlinear model (15th-order, four channel whitened EMG processor, 0 ms time advance) using paired sign tests. Both comparisons were significant (p<10^{-4}), thus this best Butterworth model had inferior RMS error performance compared to each.

Fig. 4 shows sample time-series results (actual vs. EMG-estimated torque) using the Butterworth model with four channel whitened EMG processing, for the same time advances as Fig. 2. In all cases, the shape of the estimated torque matches that of the actual torque, but at a 0 ms time advance the estimated torque leads (somewhat) in phase while at the 60 ms time advance the estimated torque lags in phase (and exhibits increased variance). The RMS error is lowest at the 60 ms time advance.

Fig. 5 shows mean error results from each of the lower-order linear FIR models using the four channel whitened EMG processor. Model order 3 and 5 exhibit a substantial nadir in RMS error near 100 ms, whereas model orders above 9 demonstrate no noticeable dip in this error. Each of the lower-order models achieves a minimum average error at an advance time above 0 ms, but that time approaches 0 ms as the order increases. Similarly, RMS error decreases as model order increases, although the error decrease slows with increasing order. (At order 30, the error is 6.24 ± 2.21, as shown in Table I and Fig. 1.) Fig. 5 lists the location and value of the minimum average error for each model order. Fig. 5 also lists the ANOVA p-value comparing the results at each order's minimum error location to the within-order results at a time advance of 0 ms. For model orders 3 and 5, these differences were significant. Next, for each adjacent model order pair, a paired sign test was conducted at the respective location of the minimum error. All five paired comparisons were significant (p<10^{-5}). Time-series results for model orders 3 and 5 (not shown) exhibited phase trends similar to the Butterworth models—the estimated phase led at 0 ms, was appropriate at the time advance corresponding to the lowest average error and lagged at 60 ms.

IV. DISCUSSION

Our interest in this work was to exploit the electromechanical delay between surface EMG and joint torque, in order to estimate torque in advance of its occurrence. Applications that might benefit from torque estimation at advanced times include: anticipatory head motion in virtual environments, myoelectric prosthesis control, control of exoskeleton suits and powered rehabilitation devices. The observed delay between peak EMG amplitude and peak force is typically 50–100 ms [Howatson, 2010; Inman et al., 1952; Li and Baum, 2004]. Many biomechanical models, particularly those based on 1st- or 2nd-order Butterworth filter dynamics, include a pure delay term of this time duration. We systematically studied time advances ranging from 0–750 ms, using high-order linear (30th-order) and nonlinear (15th-order) models with and without advanced EMG processing (whitening and multiple channel combination). The selection of these model orders, and the pseudo-inverse tolerance used in the associated least squares
training, was optimized based on a prior study of a subset of these data [Clancy et al., 2012]. We also studied Butterworth models and lower-order FIR models, as these forms are commonly found in the literature.

For each of the high-order optimal models, Fig. 3 shows that torque could be estimated for time advances of ~50 ms with no discernible change in minimum error, and out to 140-170 ms before a statistically significant change in error occurred. Thus, these EMG-torque models would not benefit from the use of a pure delay term, which simply shifts the location of the x-axis in this plot. At very large time advances, the error consistently approached an average error of ~18% MVC. This error is comparable to the error that would be achieved if the input EMG were ignored and a constant torque, set in the mid-range of all experimental torques, was used; implying that EMG is no longer providing any useful predictive information at these advance times. The errors for all of the models display this same maximum average error. Consistent with prior research [Clancy and Pardy, 2000; Clancy et al., 2012; Potvin and Brown, 2004; Staudennann et al., 2010], the high-order models also showed that the nonlinear models produced lower error than the linear models and that advanced EMG processing (multiple-channel, whitened) produced lower error than standard EMG processing.

The Butterworth models (Fig. 3) and the low-order FIR models (Fig. 5) each exhibited error that contained a single nadir as a function of advance time. This error nadir occurred at a time advance of 60 ms for the Butterworth models and 135 ms for the FIR model. The average error at each of these locations was significantly lower than the respective error at a time advance of 0 ms. Figs. 2 and 4 suggest that the primary reason for an increasing error as the advance time moved away from the nadir was improper phase alignment of the EMG-based estimated torque. The Butterworth model has a fixed phase response that cannot adjust to the subject or time advance. The low-order FIR models likely do not have a sufficient number of degrees of freedom in order to accommodate the necessary phase. Each, the result is an estimated torque that leads the actual torque for short time advances but lags the actual torque for long time advances. Additionally, the existence of an error nadir explains why these models can benefit from a pure delay term; the delay term attempts to time shift the torque to the advance time corresponding to the error nadir. As the model order increased, the nadir in the FIR models disappeared—concomitant with an overall decrease in error.

Note that our constrained (constant-posture) contractions and limited bandwidth (1 Hz) will not be representative of all possible contraction profiles. Certainly, ballistic motions can easily exceed 1 Hz and may have implications for the desired phase response in an EMG-torque model. Unconstrained motions will necessarily add complexity to the models to account for changes in joint angle.

Overall, our results show that the higher-order models are clearly superior to the Butterworth models and the low-order FIR models. First, the best error in the higher-order models is significantly lower than that of the other model forms, with the nonlinear 15th-order model exhibiting the lowest error of all. Second, a range of times spanning at least 50 ms is available in which the error maintains this minimum, whereas the other models only exhibit their minimum average error at one specific time advance. Third, no delay term need be determined; the complete model is calibrated through the least squares fit of the model parameters. And, fourth, most Butterworth models are not calibrated to dynamic contraction trials as we have done here. If constant-force trials are used to calibrate the Butterworth filter gains, then significantly higher errors result (approaching 20% MVC), as demonstrated previously on a subset of these data [Clancy et al., 2012]. If force-averaging data are available for calibration, researchers might as well choose the higher-order models which can be calibrated from these same data. Our 15th-order nonlinear model, using four channel whitened EMG, provided the lowest error of 5.48 ± 2.21% MVC over the time advance range from approximately 0–50 ms. Errors increased at the time advance was increased further.

REFERENCES

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### TABLE I

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<tr>
<th>Model Linearity</th>
<th>EMG Processor</th>
<th>Q</th>
<th>Tol</th>
<th>Min μ ± σ Error (as % MVC)</th>
<th>Advance (ms)</th>
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<tr>
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<td>1 Channel, Unwhitened</td>
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<td>0.00032</td>
<td>8.65 ± 3.08</td>
<td>170</td>
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<td>6.24 ± 2.33</td>
<td>145</td>
</tr>
<tr>
<td>Nonlinear</td>
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<td>0.02</td>
<td>5.49 ± 2.21</td>
<td>140</td>
</tr>
</tbody>
</table>

**Fig. 1.** Mean errors (one-sided standard deviations shown for two of the models) from 54 subjects vs. future time advance for the two optimal-order models and two EMG processors. Mean values computed every 5 ms, std. dev. values only shown every 50 ms.

**Fig. 2.** Sample time-series plot of the actual (solid) and EMG-estimated (dashed) torque using the 15th-order order nonlinear model with four channel whitened EMG processing, at three distinct time advances. Approximately 7 s segments shown in each plot. Subject WX13. (For these plots and for Fig. 4, can we get the EMG error corresponding to each plot? Full 2 s second error is probably fine.)

**Fig. 3.** Mean and one-sided standard deviation errors from 54 subjects vs. future time advance for the Butterworth filter model. Separate plot for each EMG processor. Mean values computed every 5 ms, std. dev. values only shown every 50 ms.
Fig. 4: Sample time-series plot of the actual (solid) and EMG-estimated (dashed) torque using the Butterworth model with four channel whited EMG processing, at three distinct time advances. Approximately 7 s segments shown in each plot. Subject WX15.

Fig. 5: Mean errors from 34 subjects vs. future time advance for the lower-order linear FIR models. EMG processing used four whited channels in each case. Table shows the advance time value and error value (deg) corresponding to the minimum location of each plot, as well as the ANOVA p-value comparing the results at each minimum location to the results at an advance time of 0 ms, within each plot.
Electromyogram Bandwidth Requirements
When the Signal is Whitened

Meera Dasog, Kishor Koizala, Pu Liu, and Edward A. Clancy, Senior Member, IEEE

Abstract—Whitening the surface electromyogram (EMG) improves EMG amplitude (EMGA) and EMG-torque estimation. Laboratory studies utilizing contraction levels up to maximum voluntary contraction (MVC) show that whitening is useful over a frequency band extending to 1000–2000 Hz. However, EMG electrode systems with such wide bandwidth are uncommon, particularly in real-time applications; and these contraction levels are also not common. Thus, we studied the influence of the frequency band over which whitening was performed vs. resulting performance. Low-level, torque-varying contractions (average torque level of 13.5% flexion MVC) of the elbow were contrasted with medium-level 50% MVC constant-torque contractions. For each, the maximum whitening bandwidth was varied between 30–2000 Hz. The low-level contractions (which incorporate the contraction range of most daily tasks) showed that performance utilizing frequencies out to 400–500 Hz was not statistically different (p<0.01) than results out to the full available frequency (2000 Hz). For the medium-level (50% MVC) contractions, frequencies out to 800–900 Hz were statistically equivalent to the full bandwidth. These results suggest that conventional electrodes with a typical passband of ~50 Hz are appropriate when whitening data from contraction levels typically experienced in many applications. Wider bandwidths may be advantageous for strenuous activities.

Index Terms—Biological system modeling, biomedical signal processing, electromyography, EMG amplitude estimation, EMG signal processing, whitening.

I. INTRODUCTION

White noise is the electromyogram (EMG) signal that has been performed for several decades, dating back at least to the work of Kaiser and Peterson [1974]. Whitening temporally decorrelates EMG samples, reducing the variance of parameters that are extracted from it [Clancy and Hogan, 1993; D’Alessio, 1984; Farina and Merletti, 2000; Filigoi and Mandarini, 1984; Harba and Lynn, 1991; Hogan and Mann, 1980a, 1980b; Liu et al., in press; Zhang et al., 1990]. These parameters are used in various applications, including: myoelectric prosthesis control [Parker et al., 2006], ergonomic assessment [Ejgå et al., 2004; Kumar and Bihal, 1995], clinical biomechanics [Benedetti et al., 1999; Dixelius et al., 2009, 2009], motor control research [Costley and Feldman, 2003] control of powered exoskeletons [Kiguchi et al., 2004, 2005] and others. The whitening process is important for extracting meaningful information from the EMG signal. It helps in reducing the noise component and enhances the signal-to-noise ratio, making it easier to analyze and interpret the EMG data. This can be achieved using various techniques such as spectral analysis, filtering, and whitening algorithms. The choice of technique depends on the specific application and the characteristics of the EMG signal.
these filters whiten out to 2048 Hz (the Nyquist frequency).

In each of the above adaptive filtering methods, the EMG acquisition system incorporated a passband from just above DC out to 1000–2000 Hz. Such a wide passband is not characteristic of many commercially-available electrode systems (particularly when also considering the real-time computational requirements of some applications) and, thus, were custom-built by the respective investigators. Many commercial passbands for surface EMG systems only extend to ~500–600 Hz, limited either by the analog electrodes or by sampling rates/processor computation power (e.g., the standard Delays Inc Bagno! Desktop EMG Systems are limited by their acquisition system to a maximum frequency of 450 Hz). This bandwidth limit is consistent with the frequency band containing most of the EMG signal power (see Fig. 1 and Hogan and Mann, 1985). While the wider passbands appear useful when whitening at high effort contractions, the vast majority of contraction levels in most EMG applications are relatively low (e.g., [Jeavons et al., 1993]). Thus, the benefit of the custom passband and increased computation throughput is unclear in these applications, particularly weighed vs. their cost. In fact, the desire for custom or high throughput electrode systems can be an impediment to adoption of whitening into these applications.

Thus, this project investigated the role of whitening bandwidth, contrasting low- and medium-intensity contractions from the same data set. The low-intensity contractions consisted of constant-posture, torque-varying contractions of the elbow, limited in effort over the range from 50% MVC extension to 50% MVC flexion. The μSIS instantaneous contraction level was 18.5 ± 11.1% MVC flexion (MVC0). EMG was related to joint torque, with the rms error between actual torque and EMG-estimated torque serving as our performance measure. Medium-intensity contractions consisted of constant-posture, constant-torque contractions at 50% MVC. In this case, the more customary signal to noise ratio (SNR) was used as the performance measure. In each case, we characterized performance as a function of the whitening bandwidth. Preliminary results of this work appeared in Dasog et al. [2013].

II. METHODS

A. Experimental Data and Experimental Methods

Experimental data from 54 subjects (30 male, 24 female; aged 37.6±16.5 years) from three prior experimental studies were analyzed. This study was approved and supervised by the WPI IRB. All subjects had previously provided written informed consent. The three studies had nearly identical experimental apparatus and protocols (fully described in Clancy [1999] and Clancy and Farry [2000]). Subjects were seated and secured with their shoulder abducted 90°, forearm oriented in a parasagittal plane, wrist fully supinated and elbow flexed 90°. Their right wrist was tightly cuffed to a load cell (Biodesx dynamometer, or Vishay Tedea-Huntleigh Model 1042, 75 kg capacity) at the styloid process. Skin above the muscles under investigation was scrubbed with an alcohol wipe. In one study, a small bead of electrode gel was massaged into the skin. Four bipolar electrode-amplifiers were placed transversely across each of the biceps and triceps muscles, midway between the elbow and the midpoint of the upper arm, centered on the muscle midline. Each electrode-amplifier had a pair of 4-mm (or 8-mm) diameter, stainless steel, hemispherical contacts separated by 10 mm edge-to-edge, oriented along the muscle’s long axis. The distance between adjacent electrode-amplifiers was ~1.75 cm. A single ground electrode was gelled and secured above the acromion process or on the upper arm. Custom electronics amplified each EMG signal (CMRR of approximately 90 dB at 60 Hz) followed by bandpass filtering (either a second-order, 10–2000 Hz bandpass filter, or 8th-order highpass at 15 Hz followed by a 4th-order lowpass at 1800 Hz). All signals were sampled at 4096 Hz with 16-bit resolution.

After a warm-up period, MVC torque was measured in both elbow extension and flexion. Two repetitions of five-second duration, constant-posture constant-torque contractions at 50% MVC extension, 50% MVC flexion and rest were recorded. A real-time feedback signal consisting of either the load cell voltage or a four-channel whitened EMG processor (formed by subtracting the extensor EMGs from the flexor EMGs [Clancy, 1999]) was provided on a computer screen. Thirty-second duration, constant-posture torque-varying contraction trials were then recorded. The subjects used the feedback signal to track a computer-generated target that moved on the screen as a band-limited (1 Hz) uniform random process, spanning 50% MVC extension to 50% MVC flexion. Three trials were collected. At least three minutes of rest was provided between contractions to prevent cumulative fatigue.

B. Methods of Analysis

All analysis was performed offline in MATLAB. For all analyses, a single-channel, whitened (but bandwidth limited) EMG amplitude (EMGref—the time-varying standard deviation of the EMG signal) processor was used, formed from a centrally located electrode. The processor used a 15 Hz highpass filter (causal, 5th-order, Butterworth filter) and notch filters at the power-line and each harmonic frequency (2nd-order IIR filter, notch bandwidth ≤ 1.5 Hz). The signal was then whitened across all frequencies (causal) algorithm of Clancy and colleagues [EMG Toolbox, Clancy and Farry, Prakash et al.]. Whitening filters were calibrated from one of the constant-torque contraction sets, comprised of a 50% MVC extension, 50% MVC flexion and a rest recording. To restrict bandwidth, the (full-band) whitened signal was lowpass filtered using a causal, 9th-order, Chebyshev Type I filter whose cutoff frequency was selectable. Cutoff frequencies investigated were 30–200 Hz in increments of 10 Hz and 300–2000 Hz in increments of 100 Hz. After bandwidth restriction, the signal was first-order demodulated (i.e., absolute value).

The torque-varying contractions served as the low-intensity data set. For these data, each EMG signal was formed by decimating the demodulated EMG signal by a factor of 100
(effective lowpass filter prior to downsampling of 16.4 Hz, causal, 9th-order, Chebychev Type I) to a sampling rate of 40.96 Hz. The torque signal was similarly decimated to 40.96 Hz, yielding EMGs (input) data with bandwidth approximately ten times that of the (output) torque signal [Ljung, 1999]. Extension and flexion EMGs were related to joint torque via the parametric model [Clancy et al., 2012]:

$$T[m] = \sum_{k=0}^{p} T_k \cdot \sigma_k^2[m-k] + \sum_{k=0}^{s} f_k \cdot \sigma_k^2[m-k],$$

where $T$ is the decimated torque signal at samples $m$, $\sigma_k$ is the extension EMG, $\sigma_k$ is the flexion EMG, $\sigma_k$ are extension fit coefficients and $f_k$ are flexion fit coefficients. Integer $Q$ denotes the number of signal lags. When integer $D=1$, the model is linear. When integer $D=2$, a nonlinear model is facilitated. Model parameters were fit using the pseudo-inverse technique to regularize at least squares minimization [Clancy et al., 2012; Press et al., 1994]. The tolerance (Tol) for removal of singular values was the ratio of the largest singular value to each singular value in the design matrix. Based on a prior model optimization study utilizing non-causal processing [Clancy et al., 2012], two optimal model forms (30th-order linear, Tol=0.00032, 15th-order nonlinear, Tol=0.0056) were implemented. Models were calibrated (trained) from two of the varying trials [Clancy et al., 2012] and tested on the third trial per subject. This set of three trials utilized the same real-time feedback signal. The RMS error between the measured torque from the load cell and the EMG-estimated torque on the test trial from each subject was expressed as a fraction of twice the torque at 50% MVC flexion (MVCf) of each subject. The first 2 s of signal were omitted from the RMS error computation to account for filter startup transients. Error was evaluated as a function of whitening cut-off frequency, with full bandwidth (200 Hz) serving as the reference.

The second set of 50% MVCs served as the medium-intensity data set. Extension electrodes from extension contractions and flexion electrodes from flexion contractions were analyzed separately. Initial EMG processing, through the demodulation stage, was the same as above. After demodulation, EMGs were formed by performing a moving average, using a 125 ms smoothing window. For constant-torque contractions, it is customary to compare performance via the EMG SNR [Clancy et al., 2012]. Thus, the SNR of each EMG was computed as the sample mean divided by the sample standard deviation. The first 250 ms of the signal was ignored, to account for filter startup transients. SNR was evaluated as a function of whitening cut-off frequency. All statistical comparisons were between pairs of data values and were computed using the paired sign test [Miller and Freund, 1977].

III. RESULTS

Fig. 2 shows \(\mu \sigma\) error results from 54 subjects vs. whitening cut-off frequency for the two parametric models (linear and nonlinear), corresponding to the low-intensity contractions. Lower errors correspond to superior performance. For both models, the error remained essentially flat for cut-off frequencies extending from 2000 Hz down to \(\sim 400-500\) Hz. Error rose slowly thereafter as the cut-off frequency was reduced towards zero, until a rapid rise occurred for frequencies below approximately 50 Hz. Since the data were highpass filtered at 15 Hz, there is little bandwidth available below 50 Hz. For the linear model, the minimum error of 0.09% MVC occurred at a cut-off frequency of 700 Hz, but this error did not differ significantly from the error at the maximum cut-off frequency of 2000 Hz (\(p=0.77\)). More importantly, however, was to test when error results first significantly departed from the minimum error at the 700 Hz cut-off frequency. Thus, we applied a backward progressive paired sign test. Our backward progressive technique began with a paired sign test using data from the cut-off frequency of the error minimum and one backward frequency increment (i.e., 700 Hz and 600 Hz). If this result was non-significant (\(p>0.01\)), we widened the frequency span backward to 700 Hz and 500 Hz and recomputed the paired sign test. The frequency span was progressively increased until a significant difference (\(p<0.01\)) was achieved. That corresponding cut-off frequency indicated when the increasing error became statistically significant. This statistically significant change occurred at 400 Hz. For the nonlinear model, the minimum error of 5.39% MVC occurred at a cut-off frequency of 900 Hz, but this error did not differ significantly from the error at the maximum cut-off frequency of 2000 Hz (\(p=0.93\)). A backward progressive paired sign test found that the error first significantly deviated from the location of the minimum error (900 Hz) to the maximum error (500 Hz). Lastly, we contrasted the linear vs. nonlinear model performances, pairing data from the minimum error location of each, respectively. The nonlinear model had statistically significant lower error (\(p<10^{-5}\)).

Fig. 3 shows \(\mu \sigma\) SNR results from 54 subjects vs. whitening cut-off frequency for the 50% MVC constant-torque contractions, corresponding to the medium-intensity contractions. Higher SNRs correspond to superior performance. For both models, the error remained somewhat flat for cut-off frequencies extending from 2000 Hz down to \(-800-900\) Hz. The SNR decayed progressively thereafter as the cut-off frequency was reduced towards zero. For extension contractions, the maximum SNR of 14.74 occurred at a cut-off frequency of 1100 Hz, but this error did not differ significantly from the error at 2000 Hz (\(p=0.25\)). A backward progressive paired sign test found that the error first significantly deviated from the location of the maximum SNR (1100 Hz) at a cut-off frequency of 800 Hz. For flexion contractions, the maximum SNR of 14.81 occurred at a cut-off frequency of 1300 Hz, but this error did not differ significantly from the error at 2000 Hz (\(p=0.34\)). A backward progressive paired sign test found that the error first significantly deviated from the location of the maximum SNR (1300 Hz) at a cut-off frequency of 900 Hz. Lastly, we contrasted the extension vs. flexion performances, pairing data from the maximum SNR location of each, respectively. The results did not differ (\(p=0.55\)).
IV. DISCUSSION

Signal whitening has been used in laboratory settings to reduce the variability of parameters extracted from the EMG signal since at least the work of Kaiser and Petersen in 1974 [Kaiser and Petersen, 1974]. Their work implemented a form of adaptive whitening (based on effort level) in an analog filter. Harba and Lynn [1981] implemented whitening off-line in software, continuing advances have been reported in the literature over the intervening years (see Clancy et al. [2002] and Stauderman et al. [2010] for related reviews). Unfortunately, few of these advances seem to have transitioned far outside of those research groups who have developed the techniques, and none have seemed to transition to commercial devices. One issue has been the historically limited amount of computation performed on microprocessor-controlled commercial devices in prosthetics, orthotics and related areas. [Barr, 2006; Lake and Miguelez, 2002], although manufacturer experience and increases in microprocessor performance over time are likely mitigating this issue. Another issue is the complexity of whitening algorithms, particularly time-adaptive processing to attenuate noise [Clancy and Farry, 2000]. To combat the challenge in algorithm complexity, Poulton and Brown [2004] implemented whitening with an efficient, low-order FIR highpass filter. Of interest, their system sampled EMG at 1024 Hz, hence whitening only occurred out to a frequency of 512 Hz (the Nyquist frequency). Their implementation was inherently bandwidth limited.

The issue investigated in this paper was that of the bandwidth (maximum frequency) required when whitening. Whitening of 1000–2000 Hz have been successfully implemented in the laboratory [Kaiser and Petersen, 1974; Clancy and Farry, 2000]. But these wide bandwidths can require the development of custom wideband electrodes and necessitate more powerful microprocessors—factors which can impede the transition of whitening into real-time commercial devices. The literature suggests that the primary advantage of the wider bandwidths is at high contraction levels; such levels have been commonly tested in laboratory studies. However, most routine tasks and most applications of EMG processing primarily utilize the low range of muscle contraction force.

Our results in this study from the low-level contractions (Fig. 2) suggest that conventional electrodes with passbands out to 700–900 Hz capture all of the relevant EMG-torque information in our data, at least if EMG is the parameter of interest. Joint torque estimation is a common usage of EMG, as is EMG directly. Further, we found that a cut-off frequency as low as 400–500 Hz was the first to exhibit errors that were significantly different from that of the full-band signal (at least as defined using a significance level of p<0.01). Although we termed our torque-varying contractions as “low level,” they span 50% MVC extension to 50% MVC flexion, with approximately equal use of each contraction level in between (uniform distribution). The average instantaneous contraction level was 18.5% MVC. Hence, these contractions are representative of a wide class of daily muscle usages and, thus, EMG applications.

To contrast these results, we compared to (medium-level) static 50% MVC contractions (Fig. 3). Since these contractions were constant-torque and non-fatiguing, SNR was used as the performance measure. This measure assumes that EMG is unchanging during the trial, but takes advantage of not having to assume/estimate a relationship between EMG and joint torque. At this higher contraction level, somewhat wider bandwidth proved advantageous, out to approximately 1100–1300 Hz. SNRs at cut-off frequencies of 800–900 Hz were first to differ from the highest SNRs. This result is consistent with the model shown in Fig. 1 in which recorded EMG is represented as the sum of an amplitude modulated “true” EMG (i.e., noise-free) and background noise. As the EMG signal strength is increased, the frequency region over which there exists more signal than noise also increases. These regions can be successfully whitened.

Hence, the required bandwidth for whitening seems largely related to the noise power relative to the true EMG power, as a function of frequency. Logically, increased bandwidth could be utilized if noise power can be reduced. However, noise power due to the acquisition electronics is typically only a few µVs RMS [Metting van Rijn and Peper, 1991] or about 1% of the RMS level at MVC [Clancy and Farry, 2000]. Additional noise sources, including electrode-skin interface noise, only increase the total RMS noise to approximately 3% of the RMS level at MVC [Clancy and Farry, 2000]. Hence, large reductions in noise are unlikely, at least for conventional surface EMG with standard skin preparation.

Although we contrasted results from two different contraction levels, the actual comparison measure varied (EMG-torque error and SNR). However, each measure is applicable to the contraction type studied. For constant-torque contractions, use of the SNR avoids the need for a model relating EMG to torque. Since torque is largely held constant (no dynamics or even any change in torque level), a model serves little purpose other than to set a system gain. SNR is gain invariant, thereby avoiding the issue altogether. For dynamic (torque-varying) trials, a dynamic EMG-torque model is required. In either case, we studied relative changes in performance, which should be more robust to variations in the performance measure. Other factors that might influence the interpretation of these results include the use of alternative electrode shapes and inter-electrode distances, and the extraction of other features from the EMG signal (e.g., zero crossing rate and average signal length).

In this off-line study, we limited whitening bandwidth via the use of a lowpass filter inserted after EMG had been whitened to the full Nyquist frequency (2048 Hz). This method was convenient for off-line study of performance vs. whitening bandwidth. In practice, anti-aliasing lowpass filters would be applied at the desired whitening cut-off frequency and the signal appropriately sampled at a rate that is at least twice this frequency. Whitening would then be performed in its normal manner, over the full Nyquist frequency, without further bandwidth restriction.
From this work, we conclude that the torque-varying contractions studied in these experiments only require a frequency bandwidth of 400–500 Hz when whitening is applied, at least when EMG-torque is studied. These contractions uniformly occupied the torque range from 50% MVC to 70% MVC flexion (average instantaneous contraction level of 13.5% MVC)—thus they include contraction levels at or above typical muscular exertions. Medium-level contractions (e.g., constant-torque 50% MVC contractions) benefit from a bandwidth out to approximately 800–900 Hz. Contractions at even higher levels would presumably benefit from an even wider frequency band.

REFERENCES

Basic format for books:

Examples:

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Examples:

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Examples:

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Examples:

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Examples:

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Examples:

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[24] Name of the invention, by inventor's name. (year, month day). Patent Number (Type of medium) Available: site/path/file

Examples:

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Examples:

Example for papers presented at conferences (unpublished):

Basic format for patents:

Examples:
Examples:
[34] N. Kawasaki, "Parametric study of thermal and chemical nonequilibrium

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references:
Examples:
[40] A. Linhams, "Representation error for real numbers in binary computer

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Fig. 2. Low-intensity torque-varying contraction results. Average plus (or minus) one standard deviation error 95% maximum voluntary flexion contraction—%MVC0) from 64 subjects vs. whitening cut-off frequency for the linear and non-linear models.

Fig. 3. Medium-intensity contraction results. Average plus (or minus) one standard deviation signal to noise ratio (SNR) from 64 subjects vs. whitening cut-off frequency for the extension and flexion 50% maximum voluntary contractions.
Appendix A : Subjects used for the research

LA Experiment:
Subjects used:  01, 02, 03, 04, 05, 06, 07, 10, 13, 14, 15, 16, 17, 18, 19, 20, 21

LB Experiment:
Subjects used:  02, 03, 05, 07, 08, 09, 10, 12, 13, 16, 17, 18, 19, 20, 21

WX Experiment:
Subjects used:  01, 02, 04, 05, 06, 07, 08, 09, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, 22, 23, 24, 25

<table>
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<th>LB</th>
<th>WX</th>
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<td>15</td>
<td>22</td>
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<tr>
<td>Total number of female subjects</td>
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<td>6</td>
<td>10</td>
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<tr>
<td>Total number of male subjects</td>
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<td>9</td>
<td>12</td>
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<tr>
<td>Range of ages of female subjects</td>
<td>28-62</td>
<td>31-62</td>
<td>18-47</td>
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<tr>
<td>mean</td>
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<td>49</td>
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<tr>
<td>standard deviation</td>
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<td>12.4</td>
<td>11.30</td>
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<td>Range of ages of male subjects</td>
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<tr>
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<td>49.3</td>
<td>25</td>
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<tr>
<td>standard deviation</td>
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<td>15.85</td>
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<td>Range of ages of total subjects</td>
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<td>23-65</td>
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<tr>
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<td>49.2</td>
<td>25.36</td>
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<tr>
<td>standard deviation</td>
<td>14.92</td>
<td>13.62</td>
<td>10.50</td>
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Appendix B : Noise in Torque of LA subjects

The torque of LA subjects had noise spikes for all the trials used in this project (10, 12, 15, 25, 45, and 65). Following figures (1-2) show these spikes for LA subject 01, trials 12 and 25 (50% and 100% MVC respectively).

![Fig 1: Plot of torque data of subject LA01 trial 12 (50% MVC)](image1)

![Fig 2: Plot of torque data of subject LA01 trial 25 (100% MVC)](image2)
Figure 3a shows the plot of five seconds of torque data (trial 12) having 12 such spikes. The next two figures show enlarged views of one of these spikes. When closely observed, each of these noise spikes appeared as a repetitive, cluster of spikes ranging from 5 ms to 8 ms wide (figure 3b) and each of these spikes was observed to be as narrow as 0.8 ms (figure 3c). Hence two ranges of frequencies appear in the noise. The first one is the narrow spikes occurring at about 1250 Hz and the second is the lower frequency modulation that ranged from 160 Hz to 200 Hz across all the LA subjects.

Fig3 (a) LA torque data (trial 12), (b) Enlarged view showing the cluster of noise spike appearing in torque data (c) Enlarged view of each spike from one of the clusters
The torque is decimated in two passes in the later processing stages for the torque estimation and the decimation function uses an 8th order Chebyshev Type I low pass filter. The cut-off frequencies used for the two passes are 163.84 Hz and 16.384 Hz. Since the noise spikes can be filtered in these ranges, no extra filtering stage was used in order to filter the noise spikes. But it was observed that a type I Chebyshev filter with order that is an even number produced a slight DC shift (see: http://www.mathworks.com/support/solutions/en/data/1-2YWEQD/index.html?solution=1-2YWEQD).

Hence, performance of the decimation function was observed using odd number filter orders ranging from 5 to 11. The results looked better for higher orders i.e. 9 and 11. Also, there was no difference in the performance for the filter orders higher than 9. Hence the 9th order Chebyshev filter was chosen in the modified decimate function. Figure 4 shows the first pass decimation stage results. Most of the high frequency content is filtered. However there is a slight time shift of about 6-10 ms. This is because Chebyshev filters exhibit phase delay.

![Fig 4 Plot of torque with noise and decimated torque with a time shift of ~6-10 ms](image)

As mentioned previously the noise is also in the lower range of 200 Hz, which requires another stage of filtering. This is evident from Figure 5 showing the torque data after the first pass decimation stage where some noise still exists.
The second pass decimation function uses a cut-off frequency of 16.384 Hz which implies that most of the noise should be filtered out. Figure 6 shows the second pass decimation results. We can observe that all the noise has been removed and there is a time shift of about 50 ms.
Appendix C : Notch filtering for power line harmonics

For the EMG anticipation research, we used subjects from three different experiments - LA, LB and WX. The power spectrum plots of the flexion and extension data showed huge spikes of width ranging from 0.6 to 1.5 Hz. Figure 1 shows spikes present in the power spectrum plot for extension data of subject WX19.

Fig1 Power spectrum plot of extension data - subject WX19 (channel 4, trial 53)

The locations of these spikes were noted in a spreadsheet for each subject and each trial (100% MVC). It was observed that the frequencies at which they were present were consistent across all the subjects of the WX experiment. These spikes appeared to be the power harmonics, present mostly at odd multiples of 60Hz. The locations (in Hertz) of the harmonics noted for one of the subjects (WX19, trial 53) are as follows:
59.99, 780, 1019.9, 1139.9, 1259.9, 1379.9, 1499.9, 1619.9, 1739.9, 1859.9 [Hz].

We can observe that these frequencies are odd multiples i.e. 13, 17, 19, 21, 23, 25, 27, 29 and 31 of 59.99Hz respectively. It should be noted that the power is not exactly at 60 Hz. It differs by a small amount due to inaccurate frequency of the ADC clock in the equipment, among other factors.

For the LA subjects, the spike appeared at a single location i.e. at 1638.9 Hz around 0.5 Hz bandwidth (refer Figure 2). This frequency is not a power harmonic and could be present due to some noise in the instrument.
LA subjects had noise spikes too, but were not present at the power harmonics. For experiment LB, the harmonics were present for only a few subjects and was not consistent across all the subjects. There was also noise observed for LB subjects at random frequency points.

![Welch Power Spectral Density Estimate](image)

**Fig2 Power spectrum plot of extension data - subject LA01 (channel 4, trial 25)**

In LB subjects, the spikes were present at random frequency locations and could be due to some noise in the equipment. A few of the LB subjects (3 to 4) showed the presence of power harmonics.

Notch filters were used to remove the power harmonics/noise-spikes of varying width. Since multiple harmonics existed across each channel, a single cascaded second order IIR notch filter, of narrow bandwidths ranging 0.25 to 1.5 Hz was designed for each experiment. The bandwidths selected for the power harmonics located at different frequencies were as follows:

<table>
<thead>
<tr>
<th>Frequency range</th>
<th>Width of notch filter</th>
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<td>1-500 Hz</td>
<td>0.25 Hz</td>
</tr>
<tr>
<td>500-1000 Hz</td>
<td>0.8 Hz</td>
</tr>
<tr>
<td>1000-1500 Hz</td>
<td>1.2 Hz</td>
</tr>
<tr>
<td>1500-2048 Hz</td>
<td>1.5 Hz</td>
</tr>
</tbody>
</table>

The numerator and denominator coefficients (b, a) were convolved as follows:

\[ b = b_1 \times b_2 \times b_3 \times \ldots \times b_n \]
\[ a = a_1 \times a_2 \times a_3 \times \ldots \times a_n \]

where \( n \) is the number of harmonics to be filtered for each trial.
The resulting coefficients b, a are of that of a cascaded notch filter. The following figures show the power spectrum of filtered data for one of the subjects from each experiment i.e. LA, LB and WX.

**Fig 3** Notch filtered data for LA01 at frequency 1638.9 Hz

Power harmonics present at 59.97, 299.8, 419.8, 539.6, 659.6, 779.5, 899.5, 1019.4, 1139.3, 1259.2, 1379.1, 1499 Hz

Noise spikes other than power harmonics present at frequencies - 1757.8, 1784.3, 1877.4 and 1997.3 Hz

**Fig 4** Notch filtered data for subject LB19
Fig 5 (a) Notch filtered data for subject WX19
(b) Enlarged view of the harmonics at frequencies – 1139.5, 1259.4 and 1379.4 Hz