Effect of Joint Angle on EMG-Torque Model During Constant-Posture, Quasi-Constant-Torque Contractions

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Effect of Joint Angle on EMG-Torque Model During Constant-Posture, Quasi-Constant-Torque Contractions

by

Pu Liu

A Thesis
Submitted to the Faculty
of the
WORCESTER POLYTECHNIC INSTITUTE
in partial fulfillment of the requirements for the
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in
Electrical and Computer Engineering
by

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APPROVED:

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Abstract

The electrical activity of skeletal muscle—the electromyogram (EMG)—is of value to many different application areas, including ergonomics, clinical biomechanics and prosthesis control. For many applications the EMG is related to muscular tension, joint torque and/or applied forces. In these cases, a goal is for an EMG-torque model to emulate the natural relationship between the central nervous system and peripheral joints and muscles. This thesis mainly describes an experimental study which relates the simultaneous biceps/triceps surface EMG of 12 subjects to elbow torque at seven joint angles (ranging from 45° to 135°) during constant-posture, quasi-constant-torque contractions. The contractions ranged between 50% maximum voluntary contractions (MVC) extension and 50% MVC flexion. Advanced EMG amplitude (EMGσ) estimation processors were investigated, and three nonlinear EMGσ-torque models were evaluated. Results show that advanced (i.e., whitened, multiple-channel) EMGσ processors lead to improved joint torque estimation, compared to unwhitened, single-channel EMGσ processors. Depending on the joint angle, use of the multiple-channel whitened EMGσ processor with higher polynomial degrees produced a median error that was 50%-66% that found when using the single-channel, unwhitened EMGσ processor with a polynomial degree of 1. The best angle-specific model achieved a minimum error of 3.39% MVC_F90 (i.e., error referenced to MVC at 90° flexion), yet it does not allow interpolation across angles. The best model which parameterizes the angle dependence achieved an error of 3.55% MVC_F90.

This thesis also summarizes other collaborative research contributions performed as part of this thesis. (1) Decomposition of needle EMG data was performed as part of a study to characterize motor unit behavior in patients with amyotrophic lateral sclerosis (ALS) [with Spaulding Rehabilitation Hospital, Boston, MA]. (2) EMG-force modeling of force produced at the finger tips was studied with the purpose of assessing the ability to determine two or more independent, continuous degrees of freedom of control from the muscles of the forearm [with WPI and Sherbrooke University]. (3) Identification of a nonlinear, dynamic EMG-torque relationship about the elbow was studied [WPI]. (4) Signal whitening preprocessing for improved classification accuracies in myoelectric control of a prosthesis was studied [with WPI and the University of New Brunswick].
Acknowledgements

Foremost, I am greatly thankful to my thesis advisor, Dr. Edward A. Clancy, not only for his guidance, support in academics and research, but also enlightening me with the general philosophy of life. His insight, knowledge and experience helped me attain the objectives of this research.

I am extremely grateful to members of the thesis committee, Dr. D. Richard Brown III and Dr. Denis Rancourt. I appreciate their advice and feedback in spite of tight schedules.

Many thanks go to Lukai Liu for his help with the experiment, discussion and comments through this research.

I would also like to thank Dr. Fred Looft as the department head of Electrical and Computer Engineering department in WPI who gave me the opportunity of continue my studies here in WPI as a TA.

Simply, I could not have reached where I am today without my father, Mr. Yuanqiu Liu, my mother, Ms. Jianhua Pan. Without their unconditional love and support, this work wouldn’t have been possible.
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CHAPTER 1—INTRODUCTION

During my M.S. degree studies, I have been working on electromyogram (EMG) signal processing and modeling under the direction of Dr. Ted Clancy. Most of my work concentrated on investigating the relationship between surface EMG and the torque/force produced by the associated muscles. This topic has application in many different fields, such as myoelectrically-controlled powered prosthesis, clinical biomechanics and ergonomics. I served as project principle investigator for a study of the slowly torque-varying EMG-torque relationship in the elbow, as a function of various joint angles. I also participated as a co-investigator on a project to determine the EMG-torque relationship in the elbow when the torque varied dynamically, and in a study of the slowly force-varying EMG-force relationship between the muscles of the forearm and forces at the tip of the fingers. I supported a project that compares the performance of whitened vs. unwhitened EMG signals used to classify hand/wrist motions in healthy and amputee subjects. The goal of the project was to improve classification accuracy in myoelectric control of prostheses. Additionally, I was involved as a co-investigator in needle EMG decomposition in clinical and scientific studies, in which invasive needle electrodes were used to detect the activity of individual motor units (the functional unit of the neuromuscular system [Liddell and Sherrington, 1925]). An overview of these contributions is provided below. Each project has resulted in archival publications/submissions. This introduction overviews each project, with relevant details provided in the publications/submissions (which form the remaining chapters of this thesis).

EMG-Torque at Various Joint Angles: The primary work presented in this thesis (Chapter 5 and 8) is the influence of joint angle on EMG-torque modeling during constant-posture, quasi-constant-torque contractions. The EMG-torque relationship should emulate the natural relationship between the central nervous system and peripheral joints and muscles. More accurate models should lead to better estimates of joint loading and muscle tension at varied joint angles in the studies of worker tasks, biomechanical evaluations and prosthesis control. Also, joint stiffness can be directly obtained by analytic differentiation of the EMG-torque model with respect to joint angle [Shin et al., 2009]. Thus, establishing a reliable EMG-torque model across joint angles will allow joint stiffness to be estimated simultaneously directly from EMG signals without using the more complex conventional perturbation method [Shin et al, 2009]. Previous studies indicated a systematic influence of joint angle on the relationship between EMG and torque [Heckathorne and Childress, 1981; Vredenbregt and Rau, 1973]. One study of biceps muscles [Vredenbregt and Rau, 1973] suggested that the EMG-torque model may only change by a (multiplicative) scaling factor as a function of joint angle. However, the study did not account for muscle
co-contraction; it assumed that an agonist muscle can be contracted while the antagonist muscle is inhibited. Another study of biceps and triceps muscles [Solomonow et al., 1986] indicated that the EMG-torque relationship of antagonist muscles vary considerably for three different elbow angles. Also, advanced EMGσ processing techniques have been developed over the last few years [Clancy et al., 2002; Clancy and Farry, 2000; Clancy and Hogan, 1994; Clancy and Hogan, 1995; Hogan and Mann, 1980a; Hogan and Mann, 1980b]. State of the art EMGσ processing incorporating multiple-channel EMG and EMG whitening has been demonstrated to substantially improve EMGσ estimates (lower signal variance) [Clancy et al., 2002]. However, few of these advances have been applied to EMG-torque modeling at varied joint angles. The above studies suggest that an EMG-torque model should include both agonist and antagonist muscles to account for co-contraction, and advanced EMGσ processing techniques should also be applied. In the study conducted within this thesis, we assembled a custom experimental apparatus (the design and construction of the apparatus is detailed in Appendix A) with the help of Dr. Denis Rancourt and Francois Martel from the University of Sherbrooke in Canada. We collected surface EMG from biceps and triceps muscles simultaneously from 12 healthy subjects (9 male, 3 female; aged 18–52 years) at seven different joint angles (from 45° to 135°, 15° apart). Advanced EMG amplitude (EMGσ) estimation processors were investigated, and three nonlinear EMG-torque models considering agonist and antagonist co-contractions and the influence of joint angle were evaluated. Results show that advanced (i.e., whitened, multiple-channel) EMGσ processors lead to improved joint torque estimation. An angle-specific model with a fourth-degree polynomial function of EMGσ, using the four-channel whitened EMGσ processor achieved the minimum error of 3.39% MVC$_{F90}$ (maximum voluntary contraction flexion at 90°), yet it does not allow interpolation across angles. A flexion-extension multiplicative model with second- or third-degree polynomial functions modeling an angle multiplier, third-degree polynomial function of EMGσ, and the four-channel whitened EMGσ processor achieved an error of 3.55% MVC$_{F90}$. This model allows interpolation of all angles between 45° to 135°. It should be noted that the number of subjects recruited in this study was relatively small and the number of joint angles was limited. Also, our experiment was designed to examine constant-posture, quasi-constant-torque, nonfatiguing contractions about the human elbow, while most contractions in real-life are more fully dynamic.

**Decomposition of Needle EMG in Healthy Subjects and ALS Patients:** My earliest work (Chapter 2) was collaborative with Spaulding Rehabilitation Hospital in Boston, MA and the Department of Physical Medicine and Rehabilitation, Harvard Medical School in Boston. The study aimed to characterize motor unit behavior in patients with amyotrophic lateral sclerosis (ALS). ALS, also known as Lou Gehrig’s disease, is a neurodegenerative disease that affects both the lower (LMN) and upper (UMN)
motor neurons. It is a progressive, fatal, neurodegenerative disease with most affected patients dying of respiratory compromise and pneumonia after two to three years. [Kasi et al., 2009] To date, the cause of ALS has not been determined thus making the search for a cure very difficult. In this study, needle EMG signals were collected from control subjects and patients with both LMN and UMN dominant forms of ALS. Needle EMG decomposition, the process of breaking down the complex EMG signal into individual motor unit trains that comprise the signal, was performed on the collected data. Mean motor unit firing rate differences, motor unit substitution, and increasing complexity in motor unit action potential (MUAP) waveforms were observed from ALS patients, compared with control subjects. My contribution to the work was decomposing parts of the needle EMG signal collected both from healthy control subjects and ALS patients. The decomposition was challenging in patient recordings because MUAP waveforms in patients were typically more complex than in healthy control subjects. In addition, changes over time in MUAP waveform shape in patient recordings were more dramatic than in control recordings, which made the data difficult to decompose. Therefore, I had to combine the use of automated decomposition software [Florestal et al., 2009] with editing tools [McGill et al., 2005], and also visually inspect/edit each recording to assure reliability of the results. The complexity of the EMG decomposition further increased when waveform superimpositions occurred. Data were analyzed using an algorithm designed to automatically resolve superimpositions [McGill, 2002]. Instances that were not resolved by the automated algorithm were resolved manually.

**EMG-Force at the Finger Tips:** After this study was completed, I began to work on relating the surface EMG signal from forearm flexors and extensors to the flexion-extension forces generated at the finger tips during constant-posture, slowly force-varying contractions (Chapter 6). This project was performed in conjunction with Dr. Rick Brown from Worcester Polytechnic Institute, and Dr. Denis Rancourt and Francois Martel from the University of Sherbrooke in Canada. Existing commercial EMG-controlled powered hand prostheses are limited to rudimentary control capabilities of either three discrete states (open, close, off) or one degree of freedom of proportional control [Parker et al., 2006]. Only a few studies of finger movement have begun to consider multi-finger proportional control via EMG-based estimation of finger forces or finger joint angles [Castellini and van der Smagt, 2009; Smith et al., 2009]. Through our study, we hope to assess the ability to determine two or more independent, continuous degrees of freedom of control from the muscles of the forearm. We collected surface EMG signals from four healthy subjects, utilizing a high resolution EMG array (up to 64 channels) over the flexion and extension muscles of the forearm. Twenty three distinct conventional spatial filters were separately evaluated to enhance signal separation. The EMG standard deviation (EMGσ; a.k.a. EMG amplitude
estimate) of each spatially filtered channel was related to finger tip force via linear least squares. Separate training and testing records were used. Preliminary results identified some amount of independent EMG-force control among four fingers (index, middle, ring and pinky) and the “pinky” finger seems to have the most independent control, although some amount of EMG cross talk/muscle co-activation is visible in EMG-force estimates. This exploratory study was intended as an initial assessment of EMG-force estimation in the finger tips. As such, several study limitations should be noted. Data were only successfully collected from four subjects and subjects only produced constant-posture, slowly force-varying contractions. Our EMG-force models did not account for the influences of localized muscle fatigue, electrode movement and day-to-day variations.

**System Identification Methods, Dynamic EMG-Torque at the Elbow:** Then, I worked on identification of a nonlinear, dynamic EMG-torque relationship about the elbow during constant-posture, force-varying contractions (Chapter 4 and 7). This work was collaborative with my colleagues, Lukai Liu and Daniel V. Moyer. The goal of this study was to incorporate nonlinear model structures into the dynamic EMG-torque problem to further reduce joint torque error. However, nonlinear models typically require additional parameters, which can lead to over-fitting [Ljung, 1999]. A complex interplay exists between the number of fit parameters in the model, the available training data size and the system identification method [Ljung, 1999; Liu et al., 2011]. This study reanalyzed surface EMG signals collected from biceps and triceps muscles of 33 subjects (18 male and 15 female, aged 18 – 65 years) and compared different dynamic EMG-torque models (linear time invariant, nonlinear polynomial, Hammerstein and Weiner models), various system identification methods (pseudo-inverse least squares approach, ridge regression [Hoerl and Kennard, 1970; Jones, 1972; Marquardt and Snee, 1975], and longer duration training data sets), and distinct EMGσ processors (“conventional” single-channel unwithened and “advanced” multi-channel whitened). The results show that the merging of the advanced EMGσ processor (multiple-channel and whitening combination), more complex EMG-torque models (e.g., nonlinear polynomial model) and robust system identification techniques (pseudo-inverse/ridge regression, longer duration training sets) have led to a substantial performance improvement (lowering the EMG-torque error to 4.65% of MVC flexion). My contribution to the work was: 1) investigating the fitting of model parameters through the singular value decomposition-based pseudo-inverse least squares approach in which the reciprocals of small singular values were replaced with the value zero [Press et al., 1994]. The tolerance for replacement was based on the ratio of each singular value to the maximum singular value, ranging over 40 values spanning $10^{-16}$ to 0.5 in logarithmic increments; 2) comparing linear time invariant and nonlinear polynomial dynamic EMG-torque models; 3) examining the effect of
increasing the duration of data available to train the least squares; and 4) helping to form advanced multiple-channel, whitened EMGσ processors. While our experimental situation is limited and does not mimic fully dynamic, unconstrained motion, its results should still be informative to applications such as clinical biomechanics, EMG/neural control of powered prostheses and ergonomic analyses.

**EMG Whitening for Prosthesis Control:** Meanwhile, I was involved in another study, in collaboration with my colleague Lukai Liu, and with Erik Scheme and Dr. Kevin Englehart from the University of New Brunswick. This work investigated signal whitening preprocessing for improved classification accuracies in myoelectric control (Chapter 3 and 9). EMG-based motion classification is one common method proposed for controlling upper-limb prostheses, in which time and frequency features derived from the EMG have been investigated. Since whitening decorrelates the EMG signal and has been shown to be advantageous in other EMG applications, we hypothesized that the use of EMG signal whitening as a preprocessing step in EMG-based motion classification would provide a decrease in the in-class variation of features leading to improved classification accuracy. In a ten-subject study of up to 11 motion classes and ten electrode channels, we found that whitening improved classification accuracy by approximately 5% when small window length durations (<100ms) were considered. My contribution to this study concentrated on the whitening of raw EMG signals.
**Published Conference Manuscripts:**


**Journal Manuscripts In Review or In Preparation:**


- Edward A. Clancy, Pu Liu, Donald R. Brown, Francois Martel and Denis Rancourt, “Continuous, Proportional EMG-Force Estimation at the Finger Tips” (or similar title). In preparation. (Not included in this thesis.)
References:


CHAPTER 2

Copy of published conference paper:

Characterization of Motor Unit Behavior in Patients with Amyotrophic Lateral Sclerosis

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Abstract— In this study, we investigated the behavior of active motor units identified via analysis of electromyographic (EMG) signals recorded from the first dorsal interosseous (FDI) muscle using a quadripolar needle electrode. Data was collected from control subjects and patients with both lower (LMN) and upper (UMN) motor neuron dominant forms of amyotrophic lateral sclerosis (ALS). EMG recordings were gathered during isometric contractions reaching 20 or 50% of the force output produced during a maximum voluntary contraction (MVC). Recordings were analyzed using available EMG decomposition software (EMGlab). Results showed differences in mean motor unit firing rates between patients with ALS and control subjects. Differences were also observed between patients with LMN- and UMN-dominant forms of ALS. Motor unit substitution was observed in patients despite the contractions lasting just a few seconds. Finally, we observed that motor unit action potential (MUAP) waveforms recorded from patients were more complex than those recorded from control subjects as often observed in motor neuron diseases.

Keywords: Amyotrophic lateral sclerosis; motor units; motor unit firing rate; motor unit decomposition

I. INTRODUCTION

Amyotrophic lateral sclerosis (ALS), also known as Lou Gehrig’s disease, is a neurodegenerative disease that affects both the lower (LMN) and upper (UMN) motor neurons. ALS is typically seen in individuals 40 to 70 years old, with a slight male predominance. It is estimated that in the US alone, about 30,000 people are affected by ALS and more than 5,000 people are newly diagnosed each year. It can be difficult to diagnose ALS in the early stages of the disease because its symptoms may mimic other disorders. To date, the cause of ALS has not been determined thus making the search for a cure very difficult.

In order to detect small changes in the rate of disease progression, multiple outcome measures are normally used[1]. The neurophysiologic measures that have been utilized to date are: (1) the compound motor action potential (CMAP) amplitude, (2) the motor unit number estimate (MUNE), and (3) the neurophysiologic index derived from motor nerve conduction study parameters [2]. Both the CMAP amplitude and the MUNE decline over time in ALS [1]. All of the measures mentioned above are sensitive to changes in the number of motor units, which decreases as the disease progresses. However, these measures do not allow one to assess the firing characteristics of the motor units. Since functional impairment in ALS is caused by muscle weakness (i.e., the inability to generate force), and given that in addition to motor unit number, the motor unit firing rate characteristics influence the generation of muscle force, it is important to study the firing rate characteristics of the remaining motor units (in addition to their number) in order to fully understand the etiology of muscle weakness in ALS.

II. METHODS

A. Subject Recruitment

Eight control subjects, 56.6 ± 7.7 years of age (mean ± SD) were enrolled in the study. Each control subject was examined by a practicing physiatrist for exclusion criteria including neuromuscular disorders and the use of medications that could affect muscle activity. Six subjects 52 ± 5.3 years of age (mean ± SD) with ALS were also recruited in the study. Individuals with ALS were recruited among patients routinely examined at the EMG clinic, Massachusetts General Hospital. Patients met clinic and electro-diagnostic criteria for definite ALS. Four patients had dominant LMN dysfunction and two had dominant UMN dysfunction. The Revised ALS Functional Rating scale (ALSFRS-R), a standard clinical assessment tool based on interviewing and clinically observing patients, was administered. Also, a muscle stretch reflex assessment was performed. Biceps, triceps, brachioradialis, knee and ankle reflexes were tested using standard physical examination techniques and graded using a scale ranging from 0 to 4. The modified Ashworth scale, a standard clinical assessment tool for assessing spasticity, was used to evaluate elbow flexor spasticity. Finally, a nerve conduction test was performed on all subjects (including both control subjects and ALS patients).

This work was supported by the Harvard Neurolony Center under the project entitled “Motor Unit Behavior in Amyotrophic Lateral Sclerosis”. The authors would like to thank Rita Illesgara for her help in performing some of the data analysis utilized in this study.

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B. Experimental Setup

A device to monitor index finger abduction force was used (Figure 1). The device was adjustable and accommodated different hand sizes. Two force transducers were used to provide subjects with feedback concerning abduction and flexion of the index finger. The acquisition system was set up with a first screen utilized to help the researcher conducting the data collection to inspect the quality of the data and a second screen to provide subjects with a template of the force trajectory to be followed during testing. A set of speakers was used for feedback to the researcher as well. Sound generated by the EMG signal, in addition to visual feedback, was used to assess whether we were recording high quality EMG data.

A 25-gauge stainless steel quadrifilar needle electrode was used to record electromyographic (EMG) signals. The quadrifilar needle electrode was composed of four electrodes made of platinum wires with diameter of 50 μm. The wires were fed through the cannula of the needle and reached a side port where the electrodes were arranged in a 2x2 array with inter-electrode distance of 200 μm (Figure 2). Four channels (differentially amplified) of EMG data were recorded.

Data was sampled at 25 kHz using a 16-bit acquisition card (NI6035E). When active muscle fibers were within the detection volume of the quadrifilar needle electrode, motor unit action potential (MUAP) waveforms were recorded. MUAPs related to different motor units were marked by different shapes and amplitude values, due to the orientation of each recording area relative to the propagation of the electric field associated with the presence of depolarized zones traveling along the muscle fibers.

C. Protocol

All study procedures were approved by the local ethical committee. All subjects provided written informed consent before taking part in the study. EMG data was recorded from the first dorsal interosseous (FDI) muscle of the right hand. A quadrifilar needle electrode was inserted into the FDI muscle (approximately 0.25-0.5 cm deep) and positioned in a manner so as to obtain MUAP recordings that were assessed (via visual inspection) to be suitable for the analysis of motor unit firing rate characteristics. Based on our experience, we considered the uniqueness of the MUAP waveforms associated with each motor unit and the consistency of the MUAP shapes over time to predict the number of motor units whose firing rate characteristics could be derived. Subjects abducted their index finger in order to activate the FDI muscle while tracing a trapezoidal template (a ramp up and a ramp down were set with a slope of 10% MVC/s) displayed on a computer screen as shown in Figure 1. The plateau of the trapezoidal trajectory lasted for 15 s for the 20% MVC tests and 5 s for the 50% MVC tests. Subjects rested for at least one minute after each contraction.
D. Data Analysis

We analyzed the EMG signals by relying on a procedure known as "motor unit decomposition technique". The motor unit decomposition technique is a method designed to identify the occurrence of MUAP waveforms related to the activity of a given set of motor units. We utilized a software tool (EMGLAB) developed by McGill et al. [3].

During the decomposition process, visual inspection of the recordings and results of the automated analysis were performed to assure reliability of the results. Estimation of the firing rate of a specific motor unit was based on associating a specific MUAP waveform shape with a given motor unit.

The analysis of the EMG data was challenging in recordings from patients because MUAP waveforms in patients were typically more complex than in healthy control subjects. In addition, changes over time in MUAP waveform shape in recordings from patients were more dramatic than in recordings from control subjects. Figure 3 shows two examples of MUAP waveforms recorded from a control subject and a patient with ALS. The complexity of the polyphasic waveform recorded from the patient compared to the relatively simple waveform recorded from the control subject is apparent. The complexity of the MUAP waveform made the data difficult to decompose because the shape of the waveform changed over time. Therefore, we had to combine the use of automated decomposition software [4] with editing tools [3]. The complexity of the EMG decomposition further increased when waveform superpositions occurred. Data were analyzed using an algorithm designed to automatically resolve superpositions [5]. Instances that were not resolved by the automated algorithm were resolved manually.

After the decomposition process, we derived the instantaneous motor unit firing rate time series from occurrences of MUAP waveforms that belonged to a given motor unit. Firing rate time series were defined taking the inverse of the inter-pulse intervals of MUAP waveform occurrences.

III. RESULTS

Examples of motor unit firing rate time series are shown in Figures 4 and 5. These examples demonstrate one of the main observations we performed in this study, namely the fact that motor unit substitution occurred in individuals with ALS despite the short duration of the contractions performed in the study. This observation was made in patients with dominant UMN dysfunction. Motor unit substitution has been observed before in healthy subjects, but only when contractions of long duration (i.e. minutes) were performed [5]. The observation of motor unit substitution during contractions of short duration suggests an early onset of fatigue in individuals with ALS with dominant UMN dysfunction. Comparison of the results we obtained from control subjects and individuals with ALS and comparison of the results we obtained from subjects with dominant LMN dysfunction and subjects with dominant UMN dysfunction revealed other interesting characteristics of motor unit behavior (Figures 6 and 7). Mean firing rate values in control subjects were generally in the range between 15 and 20 Hz with slightly lower values for motor unit recordings performed at 20% MVC compared to motor unit recordings performed at 50% MVC. Larger variability was observed in motor unit recordings from individuals with dominant LMN dysfunction. Besides, a difference in mean firing rate was observed in patients with ALS compared to controls. We observed a higher mean firing rate value in patients with dominant LMN dysfunction likely due to a compensatory mechanism aimed at producing the desired force output despite the loss of motor units. We observed a lower mean firing rate value in patients with dominant UMN dysfunction likely due to a lack of "central drive". Finally, we observed a decrease in variability of the motor unit firing rate time series in patients with dominant LMN dysfunction compared to both control subjects and patients with dominant UMN dysfunction. This observation is likely due to spasticity in patients that have dominant LMN dysfunction.

![Figure 4](image4.png)

**Figure 4.** Firing rate time series from a 50% MVC contraction (control subject). The green trajectory is the index abduction force measured by a force transducer, and the blue trajectories are the motor unit firing rate time series of two of the detected motor units.

![Figure 5](image5.png)

**Figure 5.** Firing rate time series from a 50% MVC contraction (patients with ALS). The green trajectory is the index abduction force measured by a force transducer, and the blue trajectories are the motor unit firing rate time series of two of the detected motor units. This figure shows a motor unit substitution. Thin dashed line is force trajectory and the others represent motor units.
IV. Conclusions

To our knowledge, this is the first report concerning the characteristics of motor unit behavior in individuals with ALS. Our study identified several unique features of motor unit behavior in individuals with ALS compared to control subjects. Besides, we identified differences between recordings performed in patients with dominant LMN dysfunction and recordings performed in patients with dominant UMN dysfunction. MUAP waveforms recorded from patients were generally more complex than MUAP waveforms recorded from control subjects. The firing rate time series recorded in patients with dominant UMN dysfunction showed motor unit substitution despite the short duration of the contractions. Greater variability in the mean motor unit firing rate was observed in patients with dominant LMN dysfunction compared to control subjects. Decreased variability in motor unit firing was observed in patients with dominant UMN dysfunction. Elevated motor unit firing rate values were observed in patients with dominant LMN dysfunction likely due to a compensatory mechanism to cope with the loss of motor units. Decreased motor unit firing rate was observed in patients with dominant UMN dysfunction likely because of lack of "central drive". Decreased variability in the firing rate time series was observed in recordings from patients with dominant UMN dysfunction likely because of spasticity.

REFERENCES

CHAPTER 3

Copy of published conference paper:

Signal Whitening Preprocessing for Improved Classification Accuracies in Myoelectric Control

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Abstract— The surface electromyogram (EMG) signal collected from multiple channels has frequently been investigated for use in controlling upper-limb prostheses. One common control method is EMG-based motion classification. Time and frequency features derived from the EMG have been investigated. We propose the use of EMG signal whitening as a preprocessing step in EMG-based motion classification. Whitening decorrelates the EMG signal, and has been shown to be advantageous in other EMG applications. In a ten-subject study of up to 11 motion classes and ten electrode channels, we found that whitening improved classification accuracy by approximately 5% when small window length durations (< 100ms) were considered.

I. INTRODUCTION

The surface EMG has often been used in prosthesis control, ergonomics analysis and clinical biomechancis. Whitening has been used as a preprocess to decorrelate the EMG signal. In the context of EMG-based motion selection for prosthetic control, we hypothesized that whitening would provide a decrease in the in-class variation of features leading to improved classification accuracy. The present study examined the influence of whitening on classification using time and frequency features of the EMG, in particular at shorter time durations. Three time domain features: mean absolute value (MAV), signal waveform length and zero-crossing rate, and 7th order autoregressive (AR) coefficients as frequency features, were used in our study. We observed an accuracy improvement of about 5% at smaller window lengths (less than 100 ms) with diminishing returns at longer window durations.

II. METHODS

A. Experimental Data and Methods

Data from a prior study [1] were reanalyzed. The WPI IRB approved and supervised this reanalysis. Briefly, ten electrodes were applied transversely about the entire circumference of the proximal forearm. A custom electrode amplifier system provided a frequency response spanning approximately 30–450 Hz. Ten subjects with intact upper limbs began and ended each trial at “rest” with their elbow supported on an armrest. Each trial consisted of two repetitions of 11 sequential motion classes: 1) wrist pronation/supination; 2) wrist flexion/extension; 3) hand open; 6) key grip; 7) chuck grip; 8) power grip; 9) fine pinch grip; 10) tool grip; and 11) no motion. Each motion within a trial was maintained for 4 s, after which the subject returned to no motion for a specified inter-motion delay period. Trials 1–4 used an inter-motion delay of 3, 2, 1 and 0 s, respectively, and trials 5–8 used an inter-motion delay of 2 s. A minimum 2-min rest was given between trials. EMG data were sampled at 1000 Hz with a 16-bit ADC. Notch filters were used to attenuate power-line interference at the fundamental frequency and its harmonics.

B. Methods of Analysis

The inter-trial delay segments were removed from the data recordings, resulting in 22, four-second epochs per electrode, per trial (two repetitions of 11 motion classes). For all features, 0.5 seconds of data were truncated from the beginning and end of each epoch. Contiguous, non-overlapping windows were formed from the remaining 3-second epoch segments.

Feature sets were computed for each window within an epoch. A time-domain feature set consisting of three features per window—MAV, signal length and zero-crossing [2] rate—was evaluated. A frequency domain feature set consisted of seven features per window, comprised of the coefficients of a seventh order autoregressive (AR) power spectral density estimate [3]. A third feature set concatenating the seven frequency domain features and the MAV was also evaluated.

Trials 1–4 were used to train the coefficients of the classifier, and trials 5–8 were used to test classifier performance. Initially, all channels and all motions were included in the classifier. The models were trained and tested for each individual subject. Only the test results are reported.

Ten window durations were used: 25, 50, 75, 100, 150, 200, 250, 300, 400 and 500 ms. The analysis was then repeated after the data had been whitened. When doing so, each epoch was high-pass filtered at 15Hz, then adaptively whitened using an algorithm that is tuned to the power spectrum of each EMG channel [4]. Two global variants were also considered. First, the entire analysis was repeated using only nine pre-selected motion classes (the classes denoted above as numbers 1–8 and 11), and again using only seven pre-selected motion classes (1–5, 8 and 11). Second, the entire analysis was repeated using a preselected set of six of the electrode channels. A linear discriminant classifier was used for the recognition task.
III. RESULTS

Fig. 1 shows the averaged test accuracies for the motion-channel combinations with lowest (left) and highest (right) overall performance. Classifying with more channels and fewer motion types (right) produced better overall performance. The concatenated (AR-MAV) feature set gave the highest overall classification accuracy, and the frequency domain feature set the lowest. A consistent 4-5% classification performance increase can be seen at shorter window durations for all three feature sets due to whitening, although the improvement decreases with longer window duration. Paired t-tests (p<0.05) at all window lengths suggest that use of whitening as a preprocessing stage provides a statistically significant performance improvement.

IV. DISCUSSION

We have shown that the use of signal whitening prior to classification analysis of the EMG system consistently improves the recognition accuracy, especially at shorter time durations. This improvement is modest (~5% for window durations less than 100 ms), but may help improve the accuracy of EMG-based artificial limb controllers. The fact that the most substantial improvement is seen with small window lengths is important, as it may allow a control system to use less data, and therefore improve response time.

Further work may apply to other EMG processing techniques, such as universal principal components analysis [1] and more sophisticated classifiers to further improve classification performance.

REFERENCES

CHAPTER 4

Copy of published conference paper:

System Identification of Non-Linear, Dynamic EMG-Torque Relationship About the Elbow

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Abstract— The surface electromyogram (EMG) from biceps/triceps muscles of 33 subjects was related to elbow torque, contrasting EMG amplitude (EMGΔ) estimation processors, linear/non-linear model structures and system identification techniques. EMG-torque performance was improved by: advanced (i.e., whitened, multiple-channel) EMGΔ processors; longer duration training sets (52 s vs. 26 s); and determination of model parameters via the use of the pseudo-inverse and ridge regression methods. Best performance provided an error of 4.65% maximum voluntary contraction (MVC) flexion.

I. INTRODUCTION
The surface EMG has often been used in prosthesis control, ergonomics analysis and clinical biomechanics. We applied advanced EMGΔ estimates (whitening, multiple-channel combination) and different parametric model structures to the EMG-torque problem to reduce torque estimation error. The present study examined system identification methods for non-linear, dynamic EMG-torque models which utilized advanced EMGΔ processors and explicitly addressed model over-fitting. Four system identification concepts were compared. First, Hammerstein and Weiner model structures were specifically selected to have a small number of parameters [1]. Second, we investigated the fitting of model parameters via least squares, utilizing the singular value decomposition-based pseudo-inverse approach [2]. Third, we evaluated least squares estimation using ridge regression [3]. Fourth, we increased the duration of the training data.

II. METHODS
A. Experimental Data and Methods
Experimental data from 33 subjects from two prior studies ([4] and [5]) were reanalyzed. The WPI IRB stipulated that supervision was not required. A subject was secured into the seat of a Biokin exercise machine with their right shoulder abducted 90°, their forearm oriented in a parasagittal plane, the wrist fully supinated and the elbow flexed 90°. The subject was rigidly attached to the Biokin dynamometer with a cuff at the styloid process. An array of four EMG electrod-amplifiers was placed transversely across each of the biceps and triceps muscles. Signals were sampled at 4096 Hz at 16-bit resolution. Twelve force-varying contraction trials of 30 s duration were recorded during which the subjects used a feedback signal to track a computer-generated target that moved on a screen as a band-limited (1 Hz) uniform random process, spanning 50% MVC extension to 50% MVC flexion. Eight trials per subject were used to fit model coefficients and four distinct trials were used for testing. Only test trial results are presented.

B. Methods of Analysis
Two distinct EMGΔ processors were created from each of the extension and flexion muscle groups for each 30 s trial—single-channel unwhitened and four-channel whitened [5]. EMGΔ and torque signals were decimated by a factor of 100 to a sampling rate of 40.96 Hz.

Extension and flexion EMGΔs were related to joint torque using four parametric, dynamic model structures. For each structure, m was the decimated discrete-time sample index; \( T[m] \) was the measured torque; \( \alpha_0 \) was an offset parameter; \( e_k \) and \( f_k \) were the extension and flexion fit parameters, respectively; and \( \sigma_k[m] \) and \( \sigma_k'[m] \) were the extension and flexion EMGΔ estimates, respectively. The model structures were:

1) Linear time invariant (LTI) FIR system of order Q:
   \[
   T[m] = a_0 + \sum_{q=1}^{Q} \sum_{k=0}^{Q} e_{k,q} \sigma_k'[m-q] + \sum_{q=1}^{Q} \sum_{k=0}^{Q} f_{k,q} \sigma_k[m-q]. 
   \]

2) Polynomial non-linear model of degree D, order Q:
   \[
   T[m] = a_0 + \sum_{q=1}^{Q} \sum_{k=0}^{D} e_{k,q} \sigma_k'[m-q] + \sum_{q=1}^{Q} \sum_{k=0}^{D} f_{k,q} \sigma_k[m-q]. 
   \]

3) Hammerstein model (\( D^0 \)-order polynomial static non-linearity cascaded with a \( D^0 \)-order, LTI, FIR system).

4) Weiner model (\( D^0 \)-order, LTI, FIR system cascaded with a \( D^0 \)-degree polynomial static non-linearity).

The LTI system order ranged from 1≤Q≤30 and the polynomial degree ranged from 1≤D≤4. Two seconds of data were excluded from the beginning and end of each 30 s trial.

Three approaches were evaluated to reduce least squares over-fitting. First, the singular value decomposition-based pseudo-inverse was used, in which the reciprocals of small singular values were replaced with zero. Forty tolerance values ranged logarithmically from \( 10^{-8} \) to 0.5. The offset term \( \alpha_0 \) was not used. Second, ridge regression [3] was used and the offset term \( \alpha_0 \) was included in the model. Ridge parameter \( k \) ranged logarithmically from \( 10^{-7} \) to \( 10^{6} \) in 112 values. Third, the duration of data available to the least squares fit was altered between 26 s or 52 s.
III. RESULTS

Figs. 1–2 show representative aspects of the overall results. Models which utilized a low linear model order (e.g., Q=5) exhibited high error. High model order often also led to higher error, particularly for high polynomial model degrees and with single-channel unwhitened EMGσ processors (or their combination). Excessively large pseudo-inverse tolerance values and ridge λ values exhibited poor performance.

Although results are not shown here, the Weiner models were clearly inferior to the polynomial non-linear model. Hammerstein model results were also inferior to the pseudo-inverse and ridge regression results, but only mildly so. The best pseudo-inverse results (4.65% MVC flexion; D=3, Q=28, Tol=5.6×10⁻³, 52 s training set, multiple whitened EMGσ) were not statistically different (p=0.5; paired sign test) than the best ridge regression results. Error was consistently reduced by fitting with a longer duration training set (52 s).

IV. DISCUSSION

The multiple-channel whitened EMGσ processor was again demonstrated to improve EMG-torque estimation. Increasing training set duration from 26 s to 52 s provided a clear improvement, with less sensitivity to the number of model parameters. Surprisingly, this improvement occurred even if the corresponding 26 s duration error did not vary much as a function of model order. Even though Weiner models contained the same number of coefficients as equivalent Hammerstein models, their results were consistently poorer. Hammerstein models exhibited performance close to that of the non-linear polynomial models. With the non-linear polynomial model, the best pseudo-inverse tolerance gave performance similar to that of the best ridge method. However, the range of pseudo-inverse tolerances over which a nearly optimal fit occurred (10⁻¹⁵<Tol<10⁻¹⁰) was wider than the range of ridge values for its near optimal fit (1<λ<10³).

The merging of advanced EMGσ processors (whitening, multiple-channel combination), more complex EMG-torque models (e.g., non-linear polynomial model) and robust system identification techniques (pseudo-inverse/ridge regression, longer duration training sets) has reduced the EMG-torque error to 4.65% of MVC flexion—a substantial improvement over previous EMG-torque models.

REFERENCES

Copy of published conference paper:

EMG-Torque Estimation of Constant-Posture, Quasi-Constant-Torque Contractions at Varied Joint Angles

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Abstract— This paper describes an experimental study which relates the simultaneous biceps/triceps surface electromyogram (EMG) of 12 subjects to elbow torque at seven joint angles during constant-posture, quasi-constant-torque contractions. Advanced EMG amplitude (EMGₐ) estimation processors were investigated, and an EMG-torque model considering agonist and antagonist co-contractions was evaluated at each joint angle. Preliminary results show that advanced (i.e., whitened, multiple-channel) EMGₐ processors lead to improved joint torque estimation and that the EMGₐ torque relationship may only change by a scaling factor as a function of joint angle.

I. INTRODUCTION

A significant literature has developed around the problem of relating the surface EMG to muscle tensions and joint torque. However, most investigators have not accounted for muscle co-contractions by assuming that an agonist muscle can be contracted while the antagonist muscle is inhibited [1], [2]. Also, there are clear advances in EMGₐ processing techniques over the last few years [3], yet little have been incorporated into EMGₐ-torque estimation. The present study investigated the EMG-torque problem by modeling agonist-antagonist co-contractions over a wide range of joint torques at seven different angles, and also applied advanced EMGₐ processing techniques (whitening, multiple-channel combination).

II. METHODS

A. Experimental Data and Methods

Similar experimental apparatus and methods are described in detail elsewhere [3], [4]. Briefly, experimental data from 12 healthy subjects (9 male, 3 female; aged 18–52 years) were analyzed. A subject was secured into a custom-built straight-back chair with their right shoulder abducted 90°, their forearm oriented in a parasagittal plane, the wrist fully supinated (palm perpendicular to the floor) and the wrist tightly cuffed to a load cell (Vishay Tedea-Huntleigh Model 1042). The angle between the upper arm and the forearm was selectable, but fixed. An array of six EMG electrodes-amplifiers was placed transversely across each of the biceps and triceps muscle groups to record EMG signals. Signals were sampled at 4096 Hz at 16-bit resolution. A sequence of constant-posture, quasi-constant-torque contractions was conducted at elbow angles of 45°, 60°, 75°, 90°, 105°, 120° and 135°. The order of the angles was randomized. At each angle, three tracking trials of forty-five second duration were recorded during which the subjects used a feedback signal to track a computer-generated target linearly ramping slowly in time between 50% MVC flexion and 50% MVC extension. Additionally, subjects performed ten second duration 50% MVC and rest trials (0% MVC), used to calibrate the advanced EMGₐ processors.

B. Methods of Analysis

The sampled EMGₐ data were notch filtered at the power line frequency and all harmonics, and then two different EMGₐ processors were contrasted. Processor 1 was the "conventional" single-channel, whitened processor which used EMG recordings from a centrally located electrode. The EMG signal was high-pass filtered at 15 Hz and then rectified. Processor 2 was a four-channel, whitened processor. Each channel was similarly high-pass filtered, adaptively whitened prior to rectification [3], and then normalized and ensemble averaged. Prior to use in model fits, EMGₐ and torque signals were effectively low-pass filtered at 3.3 Hz and decimated by a factor of 1000 (resulting sampling rate of 4.096 Hz).

The decimated extension and flexion EMGₐs (inputs) were related to joint torque (output) using a degree D polynomial non-linear model:

\[ T[m] = \sum_{d=0}^{\infty} c_{d,0} \sigma_{d}[m] + \sum_{d=0}^{\infty} f_{d,0} \sigma_{d}[m] \]  \hspace{1cm} (1)

where \( m \) was the decimated discrete-time sample index, \( T[m] \) was the measured torque, \( c_{d,0} \) and \( f_{d,0} \) were the extension and flexion fit parameters at joint angle \( \theta \), respectively; and \( \sigma_{d}[m] \) and \( \sigma_{d}[m] \) were the extension and flexion EMGₐ estimates, respectively. The polynomial degree ranged from 1≤D≤5 and 7.5 seconds of data were excluded from the beginning and end of each 45 s trial to account for filter transients.

A train-test paradigm was utilized in which the model coefficients were determined using linear least squares from a training trial and then used to "predict" the torque from a distinct test trial [5]. An error signal was obtained from the difference between the predicted and actual test trial torque. All errors were normalized to twice the torque at 50% flexion MVC at joint angle 90°. To quantify these errors, we used the mean absolute error (MAE) computed for each testing trial.
Fig. 1: EMG\textsubscript{torque} estimation shown as a function of normalized extension (top) and flexion (bottom) dominant joint torque at seven joint angles for subject WY04. The dots are real data and the solid lines are the second-degree polynomial fits, using multiple-channel, whitened EMG\textsubscript{torque} processor.

<table>
<thead>
<tr>
<th>Joint Angle/EMG\textsubscript{torque} Processor</th>
<th>Polynomial Degree (D)</th>
<th>D = 1</th>
<th>D = 2</th>
<th>D = 3</th>
<th>D = 4</th>
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<tr>
<td>45° Single, Unwhitened</td>
<td></td>
<td>6.79%</td>
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<td>4.32%</td>
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<tr>
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<td>5.09%</td>
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<td>4.73%</td>
</tr>
<tr>
<td></td>
<td>Multiple, White</td>
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<td>4.23%</td>
<td>3.96%</td>
<td>4.08%</td>
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<td>4.10%</td>
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<td></td>
<td>Multiple, White</td>
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<td>4.18%</td>
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<td>3.91%</td>
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<td>4.78%</td>
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<td></td>
<td>Multiple, White</td>
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<td>3.22%</td>
<td>3.16%</td>
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</tr>
<tr>
<td>120° Single, Unwhitened</td>
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<td>2.86%</td>
<td>2.79%</td>
<td>2.69%</td>
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<td>2.26%</td>
<td>2.24%</td>
<td>2.23%</td>
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</tr>
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</table>

...and took the median of 24 MAEs (12 subjects x 2 test trials per angle) at each joint angle.

III. PRELIMINARY RESULTS

Fig. 1 shows the normalized joint torque vs. EMG\textsubscript{torque} during extension-dominant (top) and flexion-dominant (bottom) portions of the tracking task at seven different joint angles for subject WY04. The EMG\textsubscript{torque} curves at different joint angles exhibit a similar shape but different gains. The EMG\textsubscript{torque} curves were also generated for the other 11 subjects, and this observation was consistent across the subjects.

Table 1 provides the summary results of analysis of median errors between the predicted and actual torques from all subjects, at seven different joint angles, when the polynomial degree ranged from 1 ≤ D ≤ 5, and using two distinct EMG\textsubscript{torque} processors. For each joint angle and polynomial degree, the four-channel whitened processor produced a lower median error than the single-channel unwhitened processor.

IV. DISCUSSION

First, advanced EMG\textsubscript{torque} estimation was applied to the EMG\textsubscript{torque} problem at multiple joint angles for constant-posture, quasi-constant-torque contractions about the elbow. Results from 12 subjects showed that the multiple-channel whitened EMG\textsubscript{torque} processor consistently produced improved EMG\textsubscript{torque} estimation. Depending on the joint angle, use of the multiple-channel whitened EMG\textsubscript{torque} processor with higher polynomial degrees produced a median error that was 50%–66% that found when using the single-channel, unwhitened EMG\textsubscript{torque} processor with a polynomial degree of D = 1. Second, the EMG\textsubscript{torque} curves of individual subjects, viewed across multiple joint angles, indicated that the relationship between EMG\textsubscript{force} and joint torque might be multiplicative as a function of angle [1]. Therefore, EMG\textsubscript{torque} models might be calibrated at certain joint angles and then applied to other angles via only a change in model gain.

REFERENCES

Copy of published conference paper:

EMG-to-Force Modeling for Multiple Fingers

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Abstract—We provide a preliminary report on work to relate the EMG activity from forearm flexors and extensors to the flexion-extension forces generated at the finger tips during constant-posture, slowly force-varying contractions. EMG electrode arrays (up to 64 channels) were applied over the flexor and, separately, extensor musculature of the forearm. Spatial filters were used to create derived EMG channels that were then related to finger tip force (via least squares models). Preliminary results identify the “pink” finger as having the most independent EMG-force control, with moderate control available from some combinations of the other fingers.

I. INTRODUCTION

Existing commercial EMG-controlled powered hand prostheses are limited to rudimentary control capabilities of either three discrete states (open, close, off) or one degree of freedom of proportional control [1]. Some studies of finger movement have considered multi-finger proportional control via EMG-based estimation of finger tip forces or finger joint angles [2], [3]. In this report, we describe preliminary findings of an exploratory study to relate forearm flexor and extensor EMG to flexion-extension force generated at the tips of the four fingers during constant-posture, slowly force-varying contractions. A high resolution EMG array was utilized over the flexion and extension muscles of the forearm, and spatial filters were formed to enhance signal separation. The project goal was to assess the ability to determine two or more independent, continuous degrees of freedom of control from the antagonist muscles of the forearm.

II. METHODS

A. Experimental Apparatus and Methods

Experimental procedures were approved by the New England IRB. Subjects provided written informed consent. A custom-built restraint, shown in Fig. 1, was rigidly clamped to a table. The palm of the seated subject’s hand was secured to the restraint with the thumb directed upwards, the four remaining digits were passively extended beyond the restraint and the elbow angle was 90°. The distal phalange of any one digit was secured to a load cell.

Two, 64-channel monopolar electrode arrays acquired the EMG (ELSCH64R3S Adhesive Electrode Arrays, EMG-USB Amplifier, OT Bioelectronica, Torino, Italy). Each array was a 13x5 matrix of electrodes (one corner electrode omitted), utilizing 2 mm diameter electrodes (gel-filled) separated by 8 mm. The “flexion” array was oriented along the medial aspect of the forearm, the “extension” array along the lateral aspect. Eight extension electrodes were unused. Each electrode channel had a bandwidth from 10–750 Hz. EMG data were sampled at 2048 Hz (12-bits). A PC sampled the finger tip flexion-extension load cell data (128 Hz sampling rate, 16 bits) and served as a subject display.

Four subjects completed one experiment. Each subject performed separate maximum voluntary contraction (MVC) flexion, then extension trials for each of the four digits. Thereafter, subjects performed a series of slowly force-varying tracking trials, with their force ranging between 30% MVC flexion and 30% MVC flexion. Four tracking trials of 30 s duration were completed per digit.

B. Methods of Analysis

Data Preprocessing: Each monopolar EMG signal from the electrode arrays was band-pass filtered (15–700 Hz) and notch filtered at the power line frequency and all harmonics. Then, each trial was manually reviewed. EMG signals with anomalous data (e.g., obviously corrupted by excessive power line noise or motion artifact) were removed.

Formation of Classic Spatial Filters: Classic spatially filtered channels, using known (pre-selected) spatial filter weights [4], were formed. A spatial filter is a memory-less weighted sum of the monopolar signals. First, L (preprocessed) monopolar signals were extracted for each of

![Fig. 1. Photograph of hand/arm secured into finger restraint. Velcro strap is wrapped around one finger (not visible) to secure it to the load cell. Gloved hand is held to the restraint upright using Velcro. Electrode arrays are mounted over the medial (flexion array—not visible) and lateral (extension array) aspects of forearm.](image-url)
the extensor and flexor muscle groups. These extracted channels served as a baseline set of spatially filtered channels. Separate such channel sets were formed for \( L = 13, 7, 5, 4, 3 \) and 2 signals (spread transversely about the muscles). Second, bipolar channels and, third, linear double difference (LDD) channels were formed. Separate channel sets were again formed for \( L = 13, 7, 5, 4, 3 \) and 2 signals. Lastly, normal double difference (NDD) filters were formed for \( L = 11, 6, 4, 3 \) and 2. In total, 23 distinct spatially filtered channels were created for each of the flexor and extensor muscle groups.

**EMG-Force Estimation:** A separate EMG-force analysis was conducted for each of the 23 distinct spatially filtered channel sets. The EMG standard deviation (EMGsd; a.k.a. EMG amplitude estimate) of each spatially filtered channel was computed and then deconvolved to 20.48 Hz. The first and last 10 signals of each 50 s tracking trial were discarded, to eliminate filter startup transients. Four trials, representing data from each of the four digits, were combined to form an analysis record. When one finger tip was active in the load cell, the finger tip force of the three remaining unmeasured finger tips was set to zero. Linear least squares was used to simultaneously relate the L extension EMGsd's and L flexion EMGsd's to the four finger tip forces. Separate training and testing records were used.

**III. PRELIMINARY RESULTS**

Only preliminary results are available at this time. Fig. 2 shows results using a bipolar montage of 13 derived electrode channels from each of the flexion and extension arrays. In these results, the “pinky” finger seems to exhibit excellent independent control and the “index” finger the least independent control. Some amount of EMG cross talk/muscle co-activation is visible in the EMG-force estimates for the index, middle and ring fingers.

Although statistical comparisons are not yet available, there did not seem to be an obvious advantage to use of the more complex spatial filter montages (LDD, NDD). One concern is that formation of these montages in software from monopolar electrodes is technically more challenging than doing so in hardware, and may lead to inferior comparisons.

**IV. DISCUSSION**

In this study, we are concentrating on determining available degrees of freedom of independent, proportional control, expecting that future research would determine how these signals might be fully utilized to control a hand prosthesis. This study was intended as an initial assessment of EMG-force estimation in the finger tips. As such, several study limitations should be noted. First, data were only successfully collected from four subjects. Additional subjects would improve generalizability of the results. Second, subjects only produced constant-posture, slowly force-varying contractions. Third, the performance of EMG-force models has seen little testing relative to the influences of localized muscle fatigue, electrode movement and day-to-day variations.

The electrode arrays used in this project are not appropriate for use in reusable systems (such as prosthetics) that are routinely donned and doffed by their user. The system was selected for its large number of active electrodes, with the understanding that knowledge learned in this study might direct research towards a more deployable electrode solution in the future. Future EMG-based prosthesis control systems might achieve high selectivity and better noise/interference performance via indwelling electrodes.

**REFERENCES**


Copy of submitted journal paper:

Identification of Nonlinear, Dynamic EMG-Torque Relationship About the Elbow

Edward A. Clancy, Senior Member, IEEE, Lukai Liu, Pu Liu and Daniel V. Moyer

Abstract—The surface electromyogram (EMG) from biceps and triceps muscles of 33 subjects was related to elbow torque, contrasting EMG amplitude (EMGa) estimation processors, linear/nonlinear model structures and system identification techniques. Torque estimation was improved by: advanced EMGa processors (i.e., whitened, multiple-channel signals); longer duration training sets (52 s vs 26 s); and determination of model parameters via pseudo-inverse and ridge regression methods. Dynamic, nonlinear parametric models that included second- or third-degree polynomial functions of EMGs outperformed linear models and Hammerstein/Weiner models. A minimum error of 4.67% maximum voluntary contraction (MVC) flexion was attained using a third-degree polynomial, 28th-order dynamic model, with model parameters determined using the pseudo-inverse method with tolerance $5.6 \times 10^{-5}$ on 52 s of four-channel whitened EMG data. Similar performance (4.67% MVC flexion error) was realized using a second-degree, 18th-order ridge regression model with ridge parameter 50.1.

Index Terms—Biological system modeling, biomechanical signal processing, electromyography, EMG amplitude estimation, EMG signal processing

I. INTRODUCTION

The surface electromyogram (EMG) reflects the neural activity of the underlying musculature, and has often been used to estimate torque produced about joints [1], [2]. Typically, EMG amplitude (EMGa)—the time-varying standard deviation of the EMG waveform—is related to joint torque through parametric models determined via system identification techniques. Both agonist and antagonist muscles are included in these models to account for co-contraction (particularly at higher contraction levels) [3], [4].

Low error EMG-torque estimation has several applications. In prosthetics control, it would be expected to provide more accurate emulation of the natural command relationship between the central nervous system and peripheral joints/muscles. In ergonomics and clinical biomechanics, it should lead to better estimates of joint loading and muscle tension in studies of worker tasks and biomechanical evaluations.

Numerous authors have contributed to the advanced signal processing techniques of multiple-channel combination and EMG whitening for estimating EMGa (e.g. [5]-[9]). Substantially improved EMGa estimates (lower signal variance) result from these techniques. However, few of these advances have been applied to the EMG-torque problem.

We applied advanced EMGa estimates as well as different parametric model structures to the EMG-torque problem to reduce torque estimation error. We initially studied constant-posture, quasi-constant-torque contractions about the elbow using nonlinear polynomial EMG-torque relationships [10]. The combination of multiple-channel whitened EMGa estimates with a third-degree polynomial model reduced joint torque estimation error by half, compared to single-channel unwhitened EMGa linear model estimates. Approximately half of this improvement was due to the advanced EMGa estimates and half to the nonlinear (polynomial) model structure. Constant-posture, torque-varying contractions were subsequently studied, using linear, dynamic models [11], [12]. Compared to single-channel unwhitened EMGa estimates, multiple-channel whitened EMGa estimates decreased joint torque error by 23%. A 15th-order, linear, FIR EMG-torque model provided an average error of 7.3% of the maximum voluntary contraction (MVC) flexion torque. Nonlinear models were not examined in that study.

Based on the above results, we hypothesized that incorporating nonlinear model structures into the dynamic EMG-torque problem would further reduce joint torque error. However, nonlinear models typically require additional parameters, which can lead to over-fitting [13]. There exists a complex interplay between the number of fit parameters in the model, the available training data size and the system identification method [13].

Accordingly, the present study compared system identification methods for nonlinear, dynamic EMG-torque models using advanced EMGa processors, and explicitly addressed model over-fitting. Hammerstein and Weiner models were specifically examined due to their small number of parameters [13]. We investigated the fitting of model parameters through the singular-value-decomposition-based least squares pseudo-inverse approach, in which certain linear combinations of the training data—those that likely provide little information, but contain considerable noise—are omitted from the training solution [14]. We evaluated least squares
estimation of the training parameters using ridge regression [15]-[17]. Finally, we studied the effect of training data duration, as longer training data sets support models with more parameters.

II. METHODS

A. Experimental Data and Methods

A subset of experimental data from 33 subjects (18 male and 15 female, ranging in age from 18 to 65 years) from two prior studies of the upper arm (fully described in [18] and [19]) were reanalyzed. Because these data had been de-identified and unlinked, the WPI IRB stipulated that supervision of this reanalysis was not required. In these studies, each subject was secured into the seat of a Biodex exercise machine with his/her shoulder abducted 90°, forearm oriented in a pampasagittal plane, wrist fully supinated and elbow flexed 90°. The subject was rigidly attached to the Biodex dynamometer with a cuff at the styloid process. The skin above the muscles under investigation was cleaned with an alcohol wipe. An array of four Liberty Technology MYO115 EMG electrode-amplifiers was 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 diameter, stainless steel, hemispherical contacts separated by 15 mm (center to center), oriented along the muscle's long axis. The distance between adjacent electrode-amplifiers was approximately 1.75 cm. A single ground electrode was placed and secured above the acromion process. Custom electronics amplified and filtered each EMG signal (CMRR of approximately 90 dB at 60 Hz; second-order, 10–2000 Hz bandpass filter) before being sampled at 4096 Hz with 16-bit resolution.

Each subject was provided a warm-up period, after which MVC torque was measured in both elbow extension and flexion. Five-second duration, constant-force contractions at 50% MVC extension, 50% MVC flexion and rest were recorded. These contractions were used to calibrate the advanced EMGσ estimation algorithms [19], [20]. Then, a real-time feedback signal consisting of one of four EMGσ processors (formed by subtracting the extensor EMGσ from the flexor EMGσ) was provided on a computer screen. Thirty-second duration, 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. Twelve trials (three per feedback signal) were collected in a randomized order. Additional tracking trials not used in this study were also collected. Rest was provided between trials to prevent cumulative fatigue.

B. Methods of Analysis

All analysis was performed in MATLAB. Two distinct EMGσ processors were created from each of the extension and flexion muscle groups for each 30 s trial using our open-source MATLAB toolbox [21]. The estimates were either single-channel unwhitened (using an electrode located centrally on the muscle) or four-channel whitened [9]. Each estimator utilized a 15 Hz high pass filter (5th-order Butterworth applied in the forward and reverse time directions to achieve zero phase) and a first-order demodulator (rectifier). Whitened channels used the non-causal adaptive whitening algorithm of Clancy and Farry [19], [20]. After demodulation, signals were decimated by a factor of 100 to a sampling rate of 40.96 Hz using a low pass filter with cut-off frequency of 16.4 Hz (which also served as the smoothing stage of the amplitude estimate). The torque signal was similarly decimated, producing a data set with a bandwidth approximately 10 times that of the torque signal being estimated [13], [12].

Extension and flexion EMGσs were related to joint torque using four parameters, dynamic model structures. For each structure: \( T[m] \) was the measured torque at the \( m^{th} \) decimated sample; \( a_0 \) was an offset parameter (not used in all system identification techniques); \( e_r \) and \( f_r \) were the extension and flexion fit parameters, respectively; and \( \sigma_{EMG} \) were the extension and flexion EMGσ estimates, respectively. The model structures were:

1) Linear, time invariant (LTI) system of dynamic order \( Q \):
\[
T[m] = a_0 + \sum_{q=1}^{Q} e_r \sigma_{EMG}[m-q] + \sum_{q=1}^{Q} f_r \sigma_{EMG}[m-q].
\]

2) Polynomial nonlinear model of degree \( D \), dynamic order \( Q \):
\[
T[m] = a_0 + \sum_{d=1}^{D} \sum_{q=1}^{Q} e_r^{d} \sigma_{EMG}[m-q] + \sum_{d=1}^{D} \sum_{q=1}^{Q} f_r^{d} \sigma_{EMG}[m-q].
\]

3) Hammerstein model: This model was comprised of a \( D^{th} \)-degree polynomial static nonlinearity cascaded with a \( Q^{th} \)-order, LTI, FIR system, for each of the extension and flexion EMGσ inputs. The sum of the extension and flexion outputs was related to joint torque.

4) Weiner model: This model was comprised of a \( Q^{th} \)-order, LTI, FIR system cascaded with a \( D^{th} \)-degree polynomial static nonlinearity, for each of the extension and flexion EMGσ inputs. The sum of the extension and flexion outputs was related to joint torque.

In these four model structures, the LTI system order ranged from 1 to 30 and the polynomial degree ranged from 1 to 4. Two seconds of data were excluded from the beginning and end of each 30 s signal to mitigate filter start-up transients.

The parameters of the LTI and polynomial models were estimated using linear least squares. Three approaches were evaluated to reduce over-fitting during parameter estimation. First, the singular value decomposition-based pseudo-inverse was used, in which the reciprocals of small singular values were replaced with the value zero [14]. The tolerance for replacement was based on the ratio of each singular value to the maximum singular value, ranging over 40 values spanning \( 10^{9} \) to 0.5 in logarithmic scale. The pseudo-inverse model did not include an offset term \( a_0 \). Second, ridge
regression [15]-[17] was investigated, including an offset term \( a_0 \) in the model. The ridge parameter, \( k \), ranged from \( 10^{-7} \) to \( 10^3 \) in 112 logarithmic increments. Third, we examined the effect of increasing the duration of data available to train the least squares, as described in detail below. Parameters of the Hammerstein and Weiner models were determined via nonlinear least squares using the MATLAB System Identification Toolbox.

As noted above, each subject completed 12 tracking trials, consisting of three repetitions each of four different feedback options. Each set of three repetitions was used to produce one test result. In the single-trial calibration method, the first trial was used as training data and the second as a test set. Then, the third trial was used as training data and the second was again used as the test set. The average mean absolute value error (between the actual torque and that predicted by the EMG-torque model) of these two test results is reported as the test error value. In the dual-trial calibration method, the first and third trials were simultaneously used to train one set of parameters (effective sequence duration of 52 seconds), and then tested on the second trial. In all cases, error is reported as a percent of the MVC flexion torque. Only test trial results are presented. For statistical analysis, the four test trial results from each subject were averaged, and these average values subjected to a paired sign test [22].

III. RESULTS

EMG-torque performance was studied as a function of two EMG\( \varepsilon \) processors, four model structures and three system identification techniques. Figs. 1-4 graphically depict representative aspects of the overall test results. Fig. 1 concentrates on results from the pseudo-inverse approach. Fig. 2 on ridge regression results. Fig. 3 on Hammerstein/Weiner model results. Fig. 4 on results using the longer-duration training data (52 s). Figs. 1, 2, 4 show results only from dynamic model orders \( Q=5, 8, 15, 20 \) and 30, which form a representative sub-set of the 30 model orders evaluated. Table 1 lists the lowest test error, along with the corresponding model parameters, for the pseudo-inverse approach. Overall, models which utilized a low model order (e.g., \( Q=5 \)) exhibited high error, presumably because this low model order did not sufficiently capture the system's true dynamic behavior. Exceptionally high dynamic model order often also led to higher error, particularly for high polynomial model degrees and with single-channel unwhitened EMG\( \varepsilon \) processors (or their combination), presumably due to over-fitting. Excessively large pseudo-inverse tolerance values or ridge \( k \) values exhibited poor performance, and should be avoided.

Figs. 1 and 2 each provide direct comparison between the EMG\( \varepsilon \) processors. Excluding tolerance values above \( 10^{-2} \) (Fig. 1) and ridge \( k \) values below \( 1 \) (Fig. 2)—regions that users would avoid due to very high error—multiple-channel whitened processors consistently performed better than single-channel unwhitened. Statistically, the results for parameters of best performance (see Table 1) for the pseudo-inverse method, 26 s training duration, were compared between the two EMG\( \varepsilon \) methods for each polynomial degree. This comparison was repeated for the ridge regression results and for the 52 s training duration. Each comparison was significant (\( p<6.8 \times 10^{-5} \)).

Fig. 3 shows that the Weiner models were clearly inferior to the best polynomial nonlinear model. The results for parameters of best performance for the Weiner model (\( D=2, Q=18 \), multiple whitened EMG\( \varepsilon \)) were statistically different from those of the best pseudo-inverse-based polynomial nonlinear model (\( p<10^{-6} \)). The Hammerstein model's performance was closer to that of the pseudo-inverse and ridge regression methods. Comparing the results for parameters of best performance for the Hammerstein model (\( D=2, Q=10 \), multiple whitened EMG\( \varepsilon \)) to results from the best pseudo-inverse-based polynomial nonlinear model was marginally significant (\( p=0.0175 \)). With the available MATLAB toolbox, it was not possible to produce results that combined two training trials into a 52 s training duration for the Hammerstein and Weiner models.

The best pseudo-inverse results (4.65% MVC flexion, \( D=3, Q=28, \) \( Tol=5.6 \times 10^{-3} \), 52 s training set, multiple whitened EMG\( \varepsilon \)) were not statistically different (\( p=0.5 \)) from the best ridge regression results (4.67% MVC flexion; \( D=2, Q=18 \), \( k=50.1 \), 52 s training set, multiple whitened EMG\( \varepsilon \)). Differences between results were most consistent when using multiple-channel whitened EMG\( \varepsilon \) processing. The pseudo-inverse results for a linear model (\( D=1 \)) differed from each of the three nonlinear degrees (\( D=2, 3, 4 \)) when using either single unwhitened or multiple white EMG\( \varepsilon \) processors (\( p<1.8 \times 10^{-5} \)). Results were less consistent with the 26 s training duration.

Finally, comparison of the results shown in Fig. 4 to those in Fig. 1 clearly demonstrates that error is reduced by a longer duration training set (52 s). Statistically, the results for parameters of best performance for the pseudo-inverse method, single-channel unwhitened EMG\( \varepsilon \) were compared between the two training durations for each polynomial degree. This comparison was repeated for the ridge regression results and for the multiple-channel whitened EMG\( \varepsilon \) method. All differences were significant (\( p<1.6 \times 10^{-5} \)).

IV. DISCUSSION

Though models with a small number of parameters risk missing significant relationships in the data, over-fitting poses an obstacle to parameter identification in models with a large number of parameters. Factors known to decrease the severity of over-fitting include: training sets with higher SNR, larger training sets, model structures with fewer parameters, and system identification techniques that are robust with respect to training set noise and correlated features. In this study,
several clear trends emerged from the methodological comparisons performed.

First, the multiple-channel whitened EMGσ processor was again demonstrated to improve EMG-torque estimation. It is well established that these methods decrease the variability of the EMGσ estimate [5]-[9], hence increasing the SNR in the training and testing sets. Anecdotally, whitening seemed to provide the clearest performance improvement in this study. While multiple-channel EMGσ processors offer improved performance in many situations, problems can arise if even one of the raw EMG signals contains a large amount of noise [8].

Second, increasing the training set duration from 26 s to 52 s provided a clearer improvement, with considerably lower test errors and reduced sensitivity to the number of model parameters. A larger data set helps to reduce the influence of training set noise, because parameter estimates are averaged over more training samples. For example, the single-channel whitened results based on a 26 s training duration (Fig. 1) show that test set error grows as dynamic model order is increased above approximately 15th order, for nonlinear polynomial degrees of D=3 and 4. However, when a 52 s training duration was used with the single-channel unwhitened data (Fig. 4), the error was lower and remained so at higher model orders. Interestingly, the multiple-channel whitened results for first- and second-degree polynomial models with 26 s training duration (Fig. 1) do not exhibit the upward trend in error at high model orders. Thus, one might be convinced that adequate training had occurred without over-fitting. However, the corresponding 52 s training set results shown in Fig. 4 still exhibit substantially lower errors. Thus, the fact that error ceases to vary as model order increases does not necessarily indicate that an optimal model has been found. Further reduction in EMG-torque error might be realized using even longer training sets.

Third, the Weiner model results were consistently poorer than those of the nonlinear polynomial models. The Hammerstein models exhibited performance close to, but not as good as, the best nonlinear polynomial models. Because the Hammerstein and Weiner models contain fewer coefficients, it is possible that they simply did not capture the full complexity of the true EMG-torque relationship. These reduced parameter models might be advantageous in situations where only short durations of training data (i.e., less than 26 s) are available.

Fourth, with the nonlinear polynomial model (D=2 or 3), system identification using the best pseudo-inverse tolerance gave performance similar to that of the best ridge method. However, the range of pseudo-inverse tolerances over which a nearly optimal fit occurred (10^-15 < Tol < 10^-9) was much wider than the range of ridge k values for its near-optimal fit (1.4x10^-3). Hence, the pseudo-inverse method may be less sensitive and easier to tune. Results also indicate tolerance/ridge k value tuning is more critical when the data are more susceptible to over-fitting, i.e., for short duration training sets, single-channel unwhitened EMGσ processing, high nonlinear degree and high dynamic model order. Note that the tolerance value and ridge k value were fixed in this analysis, then studied as a function of the fixed value. It is possible that better performance is available by adapting the tolerance/ridge k value based on information within each training set. Anecdotal analysis suggests that the optimal ridge k value is not linear across five orders of magnitude. Indeed, selection of a ridge k value is often performed based on case-by-case (graphical) evaluation of a “ridge trace” [15]-[17]. Herein, manual evaluation of the ridge trace was not compatible with automatic calibration of the EMG-torque relationship. But, automated algorithms for ridge trace evaluation might be considered in the future.

Taken together, the several techniques utilized in this study provide a substantial improvement over typical EMG-torque performance. A typical EMG-torque technique might rectify, then low pass filter the EMG waveform (commonly with a cut off frequency of approximately 2 Hz). This technique would be expected to demonstrate poorer performance than even the single-channel unwhitened LTI models evaluated in this study. The merging of advanced EMGσ processors (whitening and multiple-channel combination), more complex EMG-torque models (e.g., nonlinear polynomial model) and robust system identification techniques (pseudo-inverse/ridge regression, longer duration training sets) have reduced the EMG-torque error to 4.65% of MVC flexion, a substantial performance improvement. While our experimental situation is limited and does not mimic fully dynamic, unconstrained motion, its results are still informative to applications such as clinical biomechanics, EMG/neural control of powered prostheses and ergonomic analyses.

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Fig. 2. EMG-torque error as a function of ridge “k” value, using the ridge regression system identification method, with 26 s of training data. Results for “k” values below $10^{-2}$ not shown, but follow similar trend. Each row shows results from the two EMG processors, columns distinguish the different polynomial model degrees ($D$). Each plot shows the results for representative dynamic model orders ($Q$) 5, 8, 15, 20 and 30, as labeled. Each result is the average of 132 test trials (33 subjects x 4 test trials/subject).

Fig. 3. EMG-torque error as a function of dynamic model order ($Q$), using the Hammerstein and Weiner system identification methods, with 26 s of training data and multiple-channel whitened EMG processor. Polynomial degree ($D$) is labeled on each plot. (Degree one not shown, since it is equivalent to the linear model, shown elsewhere.) Also shown is best results using the pseudo-inverse method (polynomial degree $D=2$, tolerance $=5.0 \times 10^{-7}$). Each result is the average of 132 test trials (33 subjects x 4 test trials/subject).
Fig 4.  EMG-torque error as a function of tolerance value, using the pseudo-inverse system identification method, with 52 s of training data. Results for tolerance values below $10^{-5}$ not shown, but follow similar trend. Each row shows results from the two EMG6 processors, columns distinguish the different polynomial model degrees ($\phi$). Each plot shows the results for representative dynamic model orders ($\phi$): 5, 8, 15, 20 and 30, as labeled. Each result is the average of 132 test trials (33 subjects x 4 test trials/subject).
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Influence of Joint Angle on EMG-Torque Model During Constant-Posture, Quasi-Constant-Torque Contractions

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Abstract— The electrical activity of skeletal muscle—the electromyogram (EMG)—is of value to many different application areas, including ergonomics, clinical biomechanics and prosthesis control. For many applications the EMG is related to muscular tension, joint torque and/or applied forces. In these cases, a goal is for an EMG-torque model to emulate the natural relationship between the central nervous system and peripheral joints and muscles. This thesis mainly describes an experimental study which relates the simultaneous biceps/triceps surface EMG of 12 subjects to elbow torque at seven joint angles (ranging from 45° to 135°) during constant-posture, quasi-constant-torque contractions. Advanced EMG amplitude (EMGα) estimation processors were investigated, and three nonlinear EMGα-torque models were evaluated. Results show that advanced (i.e., whitened, multiple-channel) EMGα processors lead to improved joint torque estimation. The best angle-specific model achieved a minimum error of 3.39% MVC70 (i.e., error referenced to maximum voluntary contraction at 10° flexion), yet it does not allow interpolation across angles. The best model which parameterizes the angle dependence achieved an error of 3.55% MVC70.

Index Terms—Biological system modeling, biomedical signal processing, electromyography, EMG amplitude estimation, EMG signal processing, joint angle influence

I. INTRODUCTION

The surface electromyogram (EMG) provides a non-invasive method to obtain information on muscle activity and hence muscle force production during functional movements. Therefore, surface EMG has often been used to estimate torque produced about joints [nn], [oo]. Also, muscle fiber length and the associated joint angle have a significant impact on the maximum force that a muscle can generate, as described by the well established force-length relationship [ww]. It has been found that altering joint angle affects neural activity during isometric contractions, such as motoneuron stimulation rate [xx], [yy] and motor unit recruitment thresholds [zz]. Therefore, in order to accurately model surface EMG to joint torque, an understanding of the influence of joint angle is necessary.

EMG-torque models that account for various joint angles should be of value to many different application areas, such as ergonomics, clinical biomechanics and prosthesis control. These models should emulate the natural relationship between the central nervous system and peripheral joints/muscles. Also, it has recently been shown that joint stiffness can be directly estimated by analytic differentiation of the EMG-torque relationship with respect to joint angle [ab]. Thus, establishing a reliable EMG-torque model across joint angles will allow joint stiffness to be estimated simultaneously, directly from EMG signals without using the more complex conventional perturbation method [ab].

A systematic influence of joint angle on the EMG-torque relationship has been previously presented [ac], [ad]. One previous study of biceps muscles [ac] suggested that the EMG-torque model may only change by a (multiplicative) scaling factor as a function of joint angle. This study did not account for muscular co-contraction; it assumed that an agonist muscle can be contracted while the antagonist muscle is inhibited. Another previous study of biceps and triceps muscles [ad] indicated that the EMG-torque relationship of antagonists vary considerably for three different elbow angles. These studies suggest that an EMG-torque model should include both agonist and antagonist muscles.

Advanced EMG amplitude (EMGα) processing techniques have been developed over the last few years [kk], [ll], [ss], [jj], [bb], [ee]. State of the art EMGα processors incorporating multiple-channel combination and EMG whitening has been demonstrated to substantially improve EMGα estimates. These advances have not been incorporated into EMG-torque modeling at various joint angles.

The purpose of this study was to systematically investigate the influence of elbow angle on EMG-torque modeling during constant-posture, quasi-constant-torque contractions. We examined three non-linear polynomial model structures and utilized advanced EMGα processing techniques to improve the model performance.

II. METHODS

A. Experimental Data and Methods

The experimental work was approved and supervised by the WPI IRB. All subjects provided written informed consent prior to participation. Similar experimental apparatus and methods are described in detail elsewhere [bb], [hh]. Experimental data from 12 healthy subjects (9 male, 3 female, aged 18–52 years) were analyzed. A subject was secured into a custom-built straight-back chair with their right shoulder
abducted 90°, their forearm oriented in a parasagittal plane, the wrist fully supinated (palm perpendicular to the floor) and the wrist tightly cuffed to a load cell (Visjay Tedes–Huntleigh Model 1042). The angle between the upper arm and the forearm was selectable, but fixed. The skin above the muscles under investigation was cleaned with an alcohol wipe and an array of six EMG electrode-amplifiers was placed transversely across each of the biceps and triceps muscle groups, midway between the elbow and the midpoint of the upper arm, centered on the muscle midline. Each electrode-amplifier had a pair of 8-mm diameter, stainless steel, hemispherical contacts separated by 18 mm (center to center). The distance between adjacent electrode-amplifiers was approximately 1.75 cm. A single ground electrode was gelled and secured on the right wrist. Custom electronics amplified and filtered each EMG signal before being sampled at 4096 Hz with 16-bit resolution.

Each subject was provided a warm-up period, after which MVC torque was measured in both elbow extension and flexion (at a joint angle of 90°). Ten second duration, constant-force contractions at 50% MVC extension, 50% MVC flexion and at rest (arm removed from the wrist cuff) where next recorded. These contractions were used to calibrate advanced EMG estimation algorithms [bb, [cc]. Then, a sequence of constant-posture, quasi-constant-torque contractions was conducted at elbow angles of 45°, 60°, 75°, 90°, 105°, 120° and 135°. Elbow angle was the included angle between the forearm and upper arm. The order of the angles was randomized. At each angle, MVC torque was measured in both elbow extension and flexion. Then, three tracking trials of forty-five seconds duration were recorded during which the subjects used a feedback signal to track a computer-generated target linearly ramping slowly in time (6.67° MVC per second) between 50% MVC flexion and 50% MVC extension [with MVC referred to that specific angle and effort direction (extension vs. flexion)]. Two-three minutes of rest was provided between trials to avoid cumulative fatigue.

B. Methods of Analysis

All analysis was performed in MATLAB. The sampled EMG data were notch filtered at the power line frequency and all harmonics, and then two distinct EMG processors were created from each of the extension and flexion muscle groups for each 45 s trial using our open-source MATLAB toolbox [dd]. The estimates were either “conventional” single-channel, unwhitened (using an electrode located centrally on the muscle) or four-channel whitened (using the four centrally located electrodes) [ee]. Each estimator utilized a 15 Hz high pass filter (5th-order Butterworth applied in the forward and reverse time directions to achieve zero phase) and a first-order demodulator (e.g., rectifier). Whitened channels used the non-causal adaptive whitening algorithm of Clancy and Farry [bb, [cc]. After demodulation, signals were effectively low-pass filtered at 3.3 Hz and decimated by a factor of 1000 to a sampling rate of 4.096 Hz. The torque signal was similarly decimated, producing a data set with a bandwidth approximately 10 times that of the torque signal being estimated [gg, [ff].

The decimated extension and flexion EMG estimates were related to joint torque (output) using three non-linear polynomial models:

1) Angle-specific model:

\[ T[m] = \sum_{i=1}^{n} e_i \alpha_i [m] + \sum_{j=1}^{n} f_j \sigma_j [m] \]  

(61)

2) Flex-extend multiplicative model:

\[ T[m] = \left( \sum_{i=1}^{n} e_i \alpha_i [m] \right) \left( \sum_{j=1}^{n} f_j \sigma_j [m] \right) \]  

(62)

3) Single multiplicative model:

\[ T[m] = \left( \sum_{i=1}^{n} e_i \alpha_i [m] \right) \sum_{j=1}^{n} f_j \sigma_j [m] \]  

(63)

where \( m \) was the decimated discrete-time sample index, \( T[m] \) was the measured torque, \( e_i, f_j \) were the extension and flexion fit parameters, respectively, \( \sigma_j [m] \) and \( \alpha_i [m] \) were the extension and flexion EMG estimates, respectively, \( g_s \) was the angle fit parameters, and \( a \) was the elbow joint angle. These three model structures, the EMG polynomial degree was varied as \( 1 \leq d \leq 5 \), and the angle polynomial degree was varied as \( 1 \leq c \leq 5 \). The first and last 7.5 seconds of data were excluded from each 45 s trial to account for filter start-up transients.

The angle-specific model estimated the extension and flexion fit parameters at the seven elbow joint angles separately, using linear least squares. The flex-extend multiplicative model contained two sets of gains (one each for extension and flexion activities) which were functions of elbow joint angle, and simultaneously estimated the extension and flexion fit parameters across the seven elbow joint angles. The single multiplicative model was similar to the flex-extend multiplicative model except that it contained only one multiplicative gain function. The parameters of flex-extend and single multiplicative models were estimated using non-linear least squares.

Each subject completed three repeated tracking trials with the duration of 45 seconds at each of the seven angles mentioned above. Seven trials, representing data from each of the seven angles, were combined to form an analysis record. Thus, for each subject, there were three repeated combined analysis records. The first analysis record was used as training data and the second record was used as a test set. Then, the third record was used as training data and the second record was again used as the test set. The average mean absolute value error (between the actual torque and that predicted by the EMG-torque model) of these two test results was reported as the test error value. All error values were normalized to twice the torque at 50% MVC at elbow joint angle 90°. Only test trial results are presented. For statistical analysis, these test error values were subjected to a paired sign test [vv].
III. RESULTS

Influence of joint angle on EMG-torque model was studied via three nonlinear polynomial model structures and two EMG\textsuperscript{p} processors were applied. Fig. 1 shows one example of the relationship between EMG\textsuperscript{p} and normalized joint torque for various elbow angles. Fig. 2 illustrates the estimated and actual torque in time domain for various elbow angles using three model structures. Figs. 3–4 graphically depict various representative aspects of the overall test results. Fig. 3 concentrates on results from the angle-specific model structure, and Fig. 4 on the flex-extend/single multiplicative models.

Fig. 1 shows the normalized joint torque vs. EMG\textsuperscript{p} during extension-dominant (top) and flexion-dominant (bottom) portions of the tracking task at seven different joint angles for subject WY04. The EMG\textsuperscript{p}-torque curves at different joint angles exhibit a similar shape but different gains. The EMG\textsuperscript{p}-torque curves were also generated for the other 11 subjects, and this observation was consistent across the subjects. The results are similar to those presented in previous study [12] and indicate that the relationship between EMG\textsuperscript{p} and joint torque might be multiplicative as a function of angle (the flex-extend multiplicative model and the single multiplicative model).

Fig. 2 shows the estimated torque (dotted red line) and actual torque (solid black line) vs. time for seven elbow angles using three model structures for subject WY01 whose performance was close to the median of all subjects. In these results, the angle-specific model has the least test error value and the single multiplicative model has the highest error value. The angle-specific model optimized the model coefficients at each particular joint angle, thus does not interpolation across joint angles. The results of the angle-specific model are used as the reference for the other two models which parameterize the angle dependence.

Fig. 3 provides direct comparison between the EMG\textsuperscript{p} processors. For joint angles from 45° to 135° and the EMG\textsuperscript{p} polynomial degree varied as $1\leq D\leq 5$, multiple-channel whitened processors consistently performed better than single-channel unwhitened. Statistical results, for the tests on two of the seven joint angles were compared between the two EMG\textsuperscript{p} processors for each EMG\textsuperscript{p} polynomial degree $D$. When $D=1$, comparison between two EMG\textsuperscript{p} processors was marginally significant ($p=0.0193$). When $2\leq D\leq 5$, comparisons were significant ($p<2.48\times 10^{-3}$).

Fig. 4 shows the test error values for the flex-extension and single multiplicative models, with the EMG\textsuperscript{p} polynomial degree was varied as $1\leq D\leq 5$, and the angle polynomial degree was varied as $1\leq A\leq 5$, using multiple-channel whitened EMG\textsuperscript{p} processor. For both of the models, when $D$ is high (≥4), the error becomes larger as $A$ becomes higher, which might due to the over-fitting problem. When $1\leq D\leq 3$, there did not seem to be any obvious difference for different $A$ and $D$ values. The best performance of the flex-extension multiplicative model ($D=3$, $A=2$ or 3) was 3.58% MVC\textsubscript{p} (i.e., error referenced to maximum voluntary contraction at 90° flexion), very close to the best angle-specific model (3.39% MVC\textsubscript{p}) when $D=4$.

The best performance of the single multiplicative model ($D=2$, $A=3$) was 5.61% MVC\textsubscript{p}.

IV. DISCUSSION [TO BE WRITTEN]

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Fig. 1. EMG estimation shown as a function of normalized extension (top) and flexion (bottom) dominant joint torque at seven joint angles for subject WY04. The dots are real data and the solid lines are the second-degree polynomial fits, using multi-channel, whitened EMG preprocessor.

Fig. 2. EMG-torque test results of estimated (jagged red line) and actual torque (black line) vs. time for seven elbow angles using three model structures for subject WY01. Upward is in the extension direction.
Fig. 3. EMG-torque error as a function of joint angle, using the angle-specific model and two EMGα processors. Each plot shows the results for representative EMGα polynomial degree 1≤D≤5, as labeled. Each result is the median of 12 test results.

Fig. 4. EMG-torque error as a function of angle polynomial degree (A), using the flex-extension and single multiplicative models and multi-channel whitened EMGα processor. Each plot shows the results for representative EMGα polynomial degree 1≤D≤5, as labeled. Each result is the median of 12 test results.
CHAPTER 9

Copy of drafted journal paper:

Electromyogram Whitening for Improved Classification Accuracy in Prosthesis Control

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Abstract—Time and frequency domain features of the surface electromyogram (EMG) signal acquired from multiple channels have frequently been investigated for use in controlling upper-limb prostheses. A common control method is EMG-based motion classification. We propose the use of EMG signal whitening as a preprocessing step in EMG-based motion classification. Whitening decorrelates the EMG signal, and has been shown to be advantageous in other EMG applications including EMG amplitude estimation and EMG-force processing. In a study of ten intact subjects and five amputees with up to 11 motion classes and ten electrode channels, we found that whitening increased classification accuracy by approximately 5% when small window lengths (<100 ms) were considered.

Index Terms—coefficient of variation, electromyography, EMG, myoelectric, prosthesis, whitening.

I. INTRODUCTION

APPROXIMATELY two million people are living with limb loss, with 150,000 new amputations occurring each year in the United States [8], [9]. Surface electromyogram (EMG) controlled powered hand/wrist/elbow prostheses are used by some of these amputees to return partial upper-limb function. Conventional transradial prostheses, for example, can use surface EMG amplitudes from the forearm flexors and extensors to control hand opening and closing. Additional degrees of freedom (e.g., wrist rotation) cannot currently be controlled simultaneously. Rather, prostheses apply EMG-based or mechanical mode switching, so that the same EMG sites sequentially control the additional function(s). It is reported that control of more degrees of freedom is the greatest desired prosthetic improvement for below-elbow amputees [10]. Accordingly, a pattern recognition approach has been emerging over the past several years in which EMG signals in the forearm are used to discern desired movements of the hand and wrist. Continuous control of multiple degrees of freedom is achieved by applying the recognition algorithm in a continuous manner along the EMG signal stream. The approach consists of four sequential steps: EMG signal conditioning and preprocessing, feature extraction, dimension reduction and pattern recognition/classification.

Common time-domain features that are extracted include the EMG mean absolute value (MAV), signal length and zero crossing rate [Hughes et al., IEEE Trans Biomed Eng 40:82–94, 1993]. Frequency-domain features can also be used, e.g., the coefficients of autoregressive power spectral modeling of the EMG. In any case, features are extracted from an epoch/window of the EMG signal stream for each classification. The extent to which these features—or their dimensionally reduced representations—distinguish the different motion classes directly relates to the accuracy of the classifier. Limitations in class separation in the feature space represent a systematic error (i.e., bias) in the classifier. Because EMG presents itself as a stochastic process, a distinct random error (i.e., variance) also exists. That is, even if amputees produce a repeatable force pattern in their residual limb, the EMG-derived features will vary trial-to-trial due to the inherent variations in the EMG signal.

Errors due to the stochastic component of the EMG signal are also problematic in the related topics of EMG amplitude estimation and EMG-force processing. In these applications, signal whitening has been used to reduce the random error of the processed EMG, with substantial performance improvements resulting [Clancy and Farru, Clancy, Morin and Merletti, Hogan and Mann a/d b]. Whitening temporally decorrelates the EMG signal, increasing the effective number of signal samples (a.k.a., statistical degrees of freedom), reducing the variance in the amplitude estimate [5].

In this report, we investigate the hypothesis that EMG signal whitening prior to feature extraction will similarly reduce the random error in EMG-based features and lead to improved classification accuracy. This effect should be most prominent at short window durations, since long window durations already experience a high classification accuracy (often above 95%, for which little improvement is either available or needed). Shorter window durations are relevant, since they reduce the delay between user command and prosthesis actuation, permitting higher speed (bandwidth) movement and more realistic motion. A preliminary report of this work appeared in [22].
II. Analytic Time-Domain Feature Performance

For purposes of classification analysis, the random variation of an EMG feature can be expressed as the standard deviation of the feature (σ) relative to its mean value (μ), i.e., the coefficient of variation: \( CV = \frac{\sigma}{\mu} \). Lower CoVs should facilitate higher classification accuracy. A common model of the EMG samples, \( m[n] \), from one window is that of a wide sense stationary, correlation-ergodic, zero-mean, Gaussian random process [xx], where \( n \) is the sample index. Without loss of generality, assume that successive model samples are independent. In fact, the sampled EMG samples are correlated. However, let window length \( N \) represent the equivalent number of independent samples [yy]. Since whitening increases the effective number of samples, \( N \), the relevant analytic relationship is to determine the CoV vs. \( N \) for each feature. We do so for the time-domain features used in this study, only.

The MAV of an EMG window of \( N \) samples is defined as:

\[
MAV_N = \frac{1}{N} \sum_{n=0}^{N-1} m[n].
\]

Its CoV has been shown to be equal to (see [Clancy and Hogan, 2000], where \( CV_{MAV} \) is the inverse of the signal to noise ratio):

\[
CV_{MAV}[N] = \sqrt{\frac{2}{N}} = \frac{\sqrt{2}}{\sqrt{N}}.
\]

The signal length of \( N \) samples is defined as:

\[
SL_N = \frac{1}{N} \sum_{n=0}^{N-1} |m[n] - m[0]|.
\]

Since the \( m[n] \) are zero-mean Gaussian, so each difference is within the sum (albeit with a variance that is doubled). However, an analytic form for the sum is not readily apparent due to the correlation that forms between adjacent difference terms (they share a common EMG sample). Hence, the CoV of signal length was approximated numerically in MATLAB at various values \( N \) by creating \( 1 \times 10^5 \) replicates of Gaussian vectors of length \( N \) and computing the sample mean and standard deviation across the replicates. The resulting CoV values vs. \( N \) closely fit the model:

\[
CV_{SL}[N] = \frac{\sqrt{2}}{\sqrt{N}}.
\]

The zero crossing rate of \( N \) samples is defined as the number of adjacent samples that change sign multiplied by the sampling rate and divided by the number of samples:

\[
ZCR_N = \frac{\sum_{n=0}^{N-1} (m[n] - m[n-1])}{N}.
\]

For independent samples drawn from a Gaussian distribution, the probability that adjacent samples will change sign is 0.5. Thus, the number of sign transitions in \( N \) samples follows a Bernoulli trial with \( (N-1) \) trials, giving a CVZCR of:

\[
CV_{ZCR}[N] = \sqrt{\frac{1}{2(N-1)}} = \frac{1}{\sqrt{2(N-1)}}.
\]

Note that the CoV for each feature is a function of the number of equivalent independent samples, \( N \), and varies as a constant divided by \( \sqrt{N} \). We expect that signal whitening will increase \( N \), thereby reducing CoV for a given window duration. Better classification accuracy is hypothesized to result. An experimental trial evaluated this hypothesis.

III. Methods

A. Experimental Methods

Experimental data from two prior studies were reanalyzed. The WPI IRB approved and supervised this reanalysis. Data from intact-limbed subjects were collected at the University of New Brunswick [1] and approved by their Research Ethics Board. Briefly, ten adhesive Duetrode™ electrodes (manufactured by 3M) were applied transversely about the entire circumference of the proximal forearm of each intact subject. A subject began and ended each trial at "rest" with their elbow supported on an armrest. Each trial consisted of two repetitions of the 11 sequential motion classes: 1) wrist pronation/supination; 3, 4) wrist flexion/extension; 5) hand open; 6) key grip; 7) chuck grip; 8) power grip; 9) fine pinch grip; 10) tool grip; 11) no motion. Each motion within a trial was maintained for 4 s, and the subject returned to the rest posture for a specified inter-motion delay period. Trials 1–4 used an inter-motion delay of 3, 2, 1 and 0 s respectively, and trials 5–8 used an inter-motion delay of 2 s. The eight trials were performed twice and a minimum of two minutes rest was given between each trial. The EMG data were collected using a custom-built pre-amplification system (Libering Technologies, Inc., Holliston, MA) with a frequency response from 30–350 Hz, and sampled at 1000 Hz using a 16-bit ADC.

The EMG data of five subjects aged 28 to 77 after three months to 21 years of unilateral transradial amputation were collected at the Rehabilitation Institute of Chicago [2] in an IRB approved experiment. Three subjects were myoelectric prosthetic users, one subject used a body-powered prosthesis and one subject had not yet received a prosthesis. A total of 12 self-adhesive Ag/AgCl snap bipolar electrodes with a 1.25-cm-diameter circular contact (Noraxon USA, Inc) were used. Eight of the 12 electrodes were placed around the proximal portion of the forearm over the apex of the muscle bulge and the other four on the distal end. In this study, we used only the first ten electrodes for amputee subjects. The experiment protocol was the same as intact subjects, except that amputees attempted hand/wrist motions in their affected side while mimicking these motions in the intact side.

B. Methods of Analysis

The inter-trial delay segments were removed from data recordings, resulting in 22 four-second segments per electrode per trial (two repetitions of 11 motion classes). Each segment was zero-phase notch-filtered (0.4Hz bandwidth) at the power-line frequency and its harmonics. When desired, each 4-second segment was also whitened, as described below. Prior to feature extraction, 0.5 seconds of data were truncated from the beginning and end of each segment. Contiguous,
non-overlapping windows were formed from the remaining 3-second epochs.

Feature sets were extracted in each window within an epoch. The time-domain feature set consisted of three features: MAV, signal length and zero-crossing rate. Hysteresis used in [3] was applied to zero-crossing rate. Specifically, the number of zero-crossings in a windowed segment remains unchanged if the absolute difference between two adjacent samples does not exceed a preselected threshold (0.01 ADC). A frequency domain feature set consisted of the estimated AR coefficients of a seventh order AR model [4]. A third ("combined") feature set concatenating the seven AR coefficients and MAV was also evaluated.

CoVs were computed directly from the EMG features. Because CoV is formed via division (standard deviation divided by the mean), averaging of CoV values across different conditions can produce illogical results. Thus, features with different global factors such as channel, motion variations, window lengths and different features were treated separately.

Next, classification analysis was performed. Trials 1–4 of both repetitions were used to train the coefficients of the classifier, and trials 5–8 of both repetitions were used to test classifier performance. The model was trained and tested for each individual subject using all features with a feature set. Only test results are reported.

Ten window durations were used: 25, 50, 75, 100, 150, 200, 250, 300, 400 and 500 ms. The analysis was then repeated after the EMG signal had been whitened. When doing so, each epoch was high-pass filtered at 15 Hz, then adaptively whitened using an algorithm that is tuned to the power spectrum of each EMG channel [5]. Two global variants were also considered. First, the entire analysis was repeated using only nine preselected motion classes (the classes denoted above as numbers 1–8 and 11), and again using only seven preselected motion classes (1–5, 8 and 11). Second, the entire analysis was repeated using a preselected set of six of the electrode channels (channels 1–6). A simple linear discriminant classifier was employed for the recognition task.

For each of the two channel variations, we performed exhaustive search for the channel combination that has highest testing accuracy. Specifically, $2^5$–1=63 combinations for the preselected six channels, and $2^{10}$–1=1023 combinations for all ten available channels are evaluated using training dataset for all motion variations and feature sets, and the channel sets with highest accuracies are then used for classification analysis. These are results: We found that typically, the accuracies of optimal channel combinations at small delays are about 30% higher than best achievable results from a single channel, and that eight out of ten channels and five out of six channels yield better performance by 1–2% higher than with all available channels used.

IV. RESULTS

Fig. 1 shows the fittings of features extracted EMG data as a function of window length $N$ to the denoted power decay model. Here the CoV curves for three time domain feature sets, and fitting results, are shown. The fitting coefficient pairs (original, white) are $[0.85, 0.70]$, $[0.89, 0.85]$ and $[1.14, 1.05]$ for the time-domain features in (1)–(3). The decreased factor $c$ of white signal and comparisons of CoV values are explanatory of improved classification accuracies due to whitening. Note also that the decrease in CoV and factor $c$ is more prominent in MAV than the other two time-domain features.

Figs. 2 and 3 show the averaged test accuracies for intact and amputee subjects, respectively, for window lengths varying between 25 ms and 300 ms. Motion-channel combinations with lowest (6-channel, 11-motion) and highest (10-channel, 7-motion) overall performance are shown in each plot. The combined AR-MAV feature set gives the highest overall accuracy in each plot, and the AR features the lowest. A consistent 5% increase of accuracy due to whitening is seen at shorter window durations (<100 ms) for all feature sets, although this improvement decreases with longer window duration.

Paired t-test at all ten window lengths suggests that powerline interference removal and whitening as a preprocessing stage significant improves classification performance with $p<0.05$.

V. DISCUSSION

We have shown that signal whitening prior to classification analysis of EMG system consistently improves the recognition accuracy, especially at short time delays. This modest improvement (about 5% for delays less than 100 ms) may help improve the accuracy of EMG-based artificial limb controllers. The fact that the most substantial improvement is seen with smaller window lengths and a diminishing return with longer delay is important, as it may allow a control system to use less data, and therefore decrease response time, or increase motion recognition accuracy for a certain response time.

We also used STFT for identifying and rejecting power line harmonics. The exhaustive channel selection is added to the offline training stage that selects optimal combination of electrodes, and further improves testing accuracy by 1–2%. Advanced feature selection methods [7] can be used to select features/channels and facilitate offline training, with expected accuracy improvement below 2%.

The coefficient of variation of time-domain features decreases due to signal whitening, especially for MAV. Fitting results of both simulation results and real EMG signal are consistent with analytical works based on prior research. This explains the improved classification accuracy, as decreased CoV implies increased SNR of feature distribution, thus enabling a linear discriminant classifier to achieve higher accuracy.

Future work may include applying presented work to other
Electromyogram Whitening for Improved Classification Accuracy in Prosthesis Control

EMG signal recognition techniques, such as universal principal components analysis [1] and more sophisticated classifiers. Motion onset detection [3] could also be added to our preprocessing stage.

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REFERENCES


Author Biographies Provided when requested.
Fig 1. Fitting of the coefficient of variation for time-domain features (signal length, zero-crossing rate and mean absolute value) of five amputee subjects, 10 motions, and channel number 6. Solid lines with circles are CoV of features from original data, with triangles are from whitened data, dashed lines are fitting curves. Fitting RMSEs are about 0.5%.

Fig 3. Averaged classification accuracies of testing dataset from ten intact subjects. Accuracies for three feature sets with and without whitening are shown in each plot, and two motion-channel variations apiece. The channel sets used for each trial are generated from exhaustive search method. Window durations vary from 25ms to 300 ms. Note the different y-axis scale for each plot.
Fig 4. Averaged classification accuracies for five amputee subjects.
APPENDIX A

Design and Construction of the Experimental Torque Chair Apparatus

Overview

The experimental torque chair was custom-built at WPI, based on a design developed by Francois Martel and Denis Rancourt (Sherbrooke University, Sherbrooke, Quebec, Canada). Apparatus construction was based around the use of the modular Series 50 mk Aluminum Framing System [mk North America, Inc., Bloomfield, CT, http://www.mknorthamerica.com/; Aluminum Framing, Series 50]. These modular aluminum profiles allow for easy cutting to a specified length and then manual assembly using various hardware accessories (angle brackets, screws, plates, leveling pads, etc.). Modular framing is a particularly strong choice when most/all of the structural pieces of the apparatus are attached at right angles. Attachments for the wrist/force sensor and a subject seat were then assembled to the framing. A side and front view of the completed experimental chair is shown below.
Fig. A1: Side view (left) and front view with subject seated (right) in the experimental torque chair.

Parts List
Some Notes on Assembling Modular Aluminum Framing Systems

- The primary method for securing parts together in a modular framing system involves screwing a bracket/plate/etc. (which is a part ordered with the framing system) to a nut that is placed within the embedded track of the protrusion framing part. The nut must be placed into the framing from an open end of the part—it cannot be inserted throughout the length of the part. If both ends of the part have already been obstructed (e.g., as the part is incorporated into the apparatus), then the nut cannot be inserted. Instead, the apparatus must be partially de-constructed to insert the nut. Therefore, it is advantageous to pre-place the nuts within the appropriate track for each such piece of the system. In
some cases, pre-placement of the nuts is not sufficient; rather, it is best to loosely secure one side of the attachment bracket/plate, etc.

- It is best to install end caps only after the complete apparatus is assembled. Once end caps are installed, nuts cannot be inserted using that end of the protrusion.

- It is best to only secure nuts to a modest torque until the entire apparatus is completed. Doing so may help the structure maintain its proper shape and is useful if portions of the structure need rework or access (e.g., to insert a nut).

- The apparatus is generally too wide to fit through a regular door. It may be best to perform assembly of the device directly within the room in which the completed device will reside.

Assembly of the Primary Frame

The primary frame consists of two side frame assemblies and four cross beams. The two side frame assemblies form mirror images of each other and are each comprised of two corner posts (part “A”), two rail structures (part “B”), one support column (part “C”) and two leveling pads (part “E”). The figure below labels these parts as assembled. The two side frames should be assembled initially.
For each side frame assembly, the five primary parts (parts A, A, B, B and C) are secured to each other using Angle 25s angles. Six angles are used per side frame assembly, as marked in the figure below. A gap of eight inches remains between the rear Corner Post and the Support Column.

Fig. A2: Side view of the experimental torque chair labeling parts A, B, C, D and E of the assembly.
Once the primary parts of the side frame are assembled, Leveling Pads (part E) are secured to the bottom of each Corner Post (part A). Screw taps (size M20) must be manually tapped into the ends of each Corner Post in order to attach the Leveling Pads. When appropriate, 50x100 End Caps are inserted into the top of each Corner Post (Part A).
The remainder of the primary frame is then assembled with the use of the four Cross Beams (part “D”). Two Cross Beams connect to the bottom of each Corner Post. Each of these Cross Beams is secured to the Corner Posts by an Angle B100 angle (one per post). As shown in the figure below, each angle is mounted to the top side of the Cross Beam. One other Cross Beam is secured at seat level between the two rear Corner Posts, such that the distance between the top of the rear Corner Post and the top of the Cross Beam is 9–10 inches. The beam is level with the floor. This Cross Beam forms the rear structural member of the seat. An Angle B100 angle is used to hold each Cross Beam to its respective Corner Post. These angles are mounted on the bottom side of the Cross Beam. The fourth Cross Beam is secured at seat level (same height as the other seat support Cross Beam) between the two Support Columns.) The beam is level with the floor. This Cross Beam forms the forward structural member of the seat. An Angle B100 angle is used to hold each Cross Beam to its respective Support Column. These angles are mounted on the bottom side of the Cross Beam.
A second, more close-up front view of the primary frame is shown below.

Fig. A4: Blue arrows show the locations of the four cross beams.
Assembly of the Elbow Torque Measuring Arm

An elbow torque measuring arm was designed to allow the elbow cuff to be oriented in three dimensions and also to be oriented over a range of elbow angles. Previous photographs of the torque chair show the overall arm, mounted to the top of the two Cross Beams (part “D”) that form the seat structure, situated to the subject’s right side. A closer view of the bottom portion of the measuring arm is shown below.
Fig. A6: Lower portion of the measurement arm.
Fig. A7: Rear view of lower portion of the measurement arm.
The base of the arm is comprised of two Arm Base profiles (part “F”) butted together as shown in the figure above. The overall dimension of the base becomes 50x200 mm. These profiles are held together at the end away from the subject (i.e., front of the chair) with any convenient bracket, secured to the underside of the base between the two Arm Base profiles. End caps were also used on the vertical face at this end. The Arm Base is secured to the seat Cross Beams using four Angle B100 angles. Two of these angles are visible in Fig. A6 (next to the subject seat). The other two were applied on the other side (i.e. outside) of the Arm Base. (In practice, it is likely that only the two inside angles are required, unless a subject is exceptionally strong.) During experiments, the Arm Base remains parallel to the two side frames. By loosening the four angles, the entire based can be moved front-to-back and side-to-side, providing two of the three degrees of freedom for cuff translation.

The Arm Column (part “G”) is placed upright near the rear of the Arm Base. Two Angle B100 angles are used to secure the Arm Column to the Arm Base. The angles are placed at the front and rear, at the mid-point of the long axis of the Arm Base. In this fashion, these angles also hold the two Arm Base
profiles together. The Arm Column is located as far to the rear of the Arm Base as possible, leaving just enough room to properly secure the rear angle bracket.

The Arm Extension (part “H”) is through-hole drilled prior to being secured to the torque chair. The through hole is 3/8 inch diameter (appropriate for the bolt used to secure the pivot arm, discussed subsequently). The hole is drilled top to bottom at the rear length of the profile. The whole is centered on the 100 mm width of the part, with its center located 5.5 inches from the rear. (See figures above.) The Arm Extension is then secured to the Arm Column so as to be parallel to the Arm Base. The through-hole is located closest to the Arm Column. The height of the Arm Extension above the base is adjustable, providing the third degree of freedom for cuff translation. The underside of the Arm Extension is secured to the Arm Column using a Cast Console 5 (see parts list). The top side of the Arm Extension is secured to the Arm Column using an Angle B100 angle.

The Pivot Arm (part “I”) is through-hole drilled prior to being secured to the torque chair. The through hole is 3/8 inch diameter (same size as the through-hole for the Arm Extension). The hole is drilled top to bottom at the rear length of the profile. The whole is centered on the 100 mm width of the part, with its center located 3 inches from the rear. (See figures above.) The Pivot Arm is bolted to the Arm Extension via a bolt passed top-to-bottom through the holes drilled in these parts. The Pivot Arm is rotated about the bolt center to provide one degree of freedom in cuff rotation. The bolt is secured tight, but does not provide sufficient attachment to prevent Pivot Arm rotation under load. Thus, once the Pivot Arm angle is selected, Angle B100 angles are used to secure the Pivot Arm to the Arm Extension. Depending on the desired rotation angle, the Angle B100 angles may need to be placed on the side closest to the subject or the side away from the subject. Angles not in use can remain attached to the Pivot Arm, but not secured to the Arm Extension.
Fig. A9: View of cuff assembly from perspective farthest away from subject.

Two through-holes have load cell mounting bolts inserted.

Plate 17

Cut PVC pipe (white)

Two bolts mount PVC “cuff” to the active end of the load cell

Fig. A10: View of cuff assembly from perspective closest to subject.
As shown in the two figures above, a Plate 17 is secured upright to the Pivot Arm. The plate is secured directly to the Pivot Arm on the side farthest away from the subject (two screw-nuts, applied to the lowest pair of holes in the Plate 17) and via an Angle B100 angle on the side closest to the subject. (It is unclear if the Angle B100 is necessary, as the direct attachment may be sufficient.) The location of the Plate 17 along the long axis of the Pivot Arm is adjustable to accommodate different length human arms. The Plate 17 is through-hole drilled in two locations before being attached to the Pivot Arm. The hole diameters and separation distance were dictated by the mounting location specifications of the load cell. The holes were drilled near one of the top end of the plate, as shown in Fig. A9. (Alternative load cells might require alternative mounting to the Plate 17.) The load cell (Vishay Tedea-Huntleigh Model 1042) was attached to the Plate 17 via the two custom through-holes, per the specifications of the load cell. This attachment served as the “mechanical ground” attachment for the load cell. The load cell output was transduced using an AC Powered Bridgesensor (Model DMD-465WB, Omega Engineering, Inc. Stamford, CT). A 3.25 inch length of PVC piping (5 inch diameter) was cut to form the wrist cuff. The chord length of the cut piping was 3 inches. The cuff was bolted to the active edge of the load cell via through-holes drilled in the cuff with size and spacing set according to the specifications of the load cell. Velcro (1.5 inch diameter) was glued to the rear of the cuff before it was attached to the load cell. In addition, the Velcro was compressed between the cuff and load cell, further strengthening the attachment. (Likely, the compression formed the primary attachment.) Lastly, a “safety” strap that was placed around the human arm (to mitigate injury in the event of a sudden failure of the cuff Velcro strap) was secured to the Pivot Arm via compression using one or more Clamp 1/30 clamps (or any other convenient method). A thin cushion was placed between the cuff and the subject during use. Fig. A11 shows an arm secured into the cuff (view from rear).
Assembly of the Subject Chair

The seat Cross Beams (described above) serve as the structure of the seat section of the subject chair. Two Seat Back Beams (part “J”) form the structure of the seat back. Fig. A5 shows the Seat Back Beams mounted to the rear of the chair. The Seat Back Beams are mounted upright, extending from the rear lower Cross Beam through the rear upper Cross Beam. The longitudinal centers of the two beams are located 12 inches and 20 inches from the rear Corner Post that is to the left of the subject. Angle B100 angles are used to secure the Seat Back Beams. Two angles (one per Seat Back Beam, shown in Fig. A5) connect the Seat Back Beams to the rear lower Cross Beam (mounted internally on the chair, at the top of the Cross Beam). Two angles (one per Seat Back Beam) connect the Seat Back Beams to the rear upper Cross Beam (mounted internally on the chair, at the underside of the Cross Beam).

An available 16 inch wide by 15.5 inch deep by 5/8 inch thick piece of wood (oak) is used as the subject seat. The wood piece is secured to the seat Cross Beams, arranged with an approximate 1.5 inch
gap between the Seat Back Beams and the rear edge of the wooden piece. Once arranged in this location, the location of the desired nuts was marked on the piece and a hole counter-bored into the piece (using hand tools). A screw was set in the counter-bored hole so that no part of the screw extended past the surface. The screw connects to a nut placed in the profile track of the Cross Beam to hold the piece in place. Four such screws were used, two in the rear Cross Beam and two in the front Cross Beam. An available 14 inch wide by 40 inch tall by 5/6 inch thick piece of wood (oak) forms the seat back. The long axis of this piece is centered at the mid-line of the long axis of the two Seat Back Beams, with a vertical gap of approximately 4.5 inches between the wood seat and the wood seat back. The wood seat back is secured to the Seat Back Beams using similar counter-bored screw holes, with nuts placed in the profile tracks of the Seat Back Beams. A seat pad and back pad is used to prevent subject discomfort.

Three seat belts [Lap Seat Belt, Chrome Lift Latch, 60 Inch Length, black (Code: 1800-60): SeatBeltsPlus.com] secured subjects to the chair at the lap and (two) across the shoulder. Belt sections were connected to the Seat Back Beams using Clamp 1/30 clamps, as shown below.
Fig. A12: Rear view looking down at the subject seat, showing the connection of two seat belts to the left, rear of the subject.
Fig. A13: View of subject seated in the chair and secured with the three seat belts (one lap belt and two crossing shoulder belts. The subject’s arm is secured into the wrist cuff and the safety strap is used.