Electromyogram Whitening for Improved Classification Accuracy in Upper Limb 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 the coefficient of variation of time domain features (mean absolute value, average signal length and normalized zero crossing rate) was significantly reduced due to whitening. When using these features along with autoregressive power spectrum coefficients, whitening added approximately five percentage points to classification accuracy when small window lengths (< 100 ms) were considered.**

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

I. Introduction

APPROXIMATELY 1.5 million people in the U.S. are living with upper or lower limb loss, with 230 000 new cases occurring each year [1], [2]. 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 residual forearm flexors and extensors to control hand opening and closing. Additional degrees of freedom (e.g., wrist rotation) cannot currently be controlled simultaneously in commercial systems. Rather, prostheses apply EMG-based or mechanical mode switching, so that the same EMG sites sequentially control the additional function(s) [3], [4]. It is reported that control of more degrees of freedom is the greatest desired prosthetic improvement for below-elbow amputees [5]. 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 [3], [6]–[11]. Continuous control of multiple degrees of freedom is achieved by applying the pattern 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 classification.

Common time-domain features that are extracted include the EMG mean absolute value (MAV), signal length and zero crossing rate [6]. Frequency-domain features have also been used, e.g., the coefficients of autoregressive power spectral modeling of the EMG [10]. In both cases, features are extracted from an epoch/window of the EMG signal stream for 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 the EMG signal 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 areas of EMG amplitude estimation and EMG-force processing [12]–[15]. In these applications, signal whitening has been used to reduce the random error of the processed EMG, with substantial performance improvements resulting. Whitening temporally decorrelates the EMG signal, increasing the effective number of signal samples (a.k.a., statistical degrees of freedom) and reducing the variance in the amplitude estimate.

Whitening has not previously been applied to the EMG multifunction classification problem. In this paper, 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 high classification accuracy (often above 95%, for which little improvement is either available or needed). Shorter window durations are relevant, because they reduce the delay between user command

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and prosthesis actuation, permitting higher speed (bandwidth) movement and more realistic motion [16]. A preliminary report of this work appeared in [17].

II. Analytic Time-Domain Feature Performance

For purposes of classification analysis, the random variation of an EMG feature can be quantified as the standard deviation of the feature (σ) relative to its mean value (μ), i.e., the feature's coefficient of variation: CoV $= \sigma/\mu$. Lower CoVs should facilitate higher classification accuracy. An analysis of the CoV of common EMG time-domain classification features does not appear to have been previously reported. Thus, we do so here.

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 [13], [14], [18], where n is the sample index and $m[\cdot]$ is measured in millivolts. Without loss of generality, assume that successive model samples are independent [15], [18], [19]. In fact, these samples are correlated due to the limited bandwidth of the EMG signal. However, let window length N_{Eq} represent the equivalent number of independent samples within a window, given by [20]

$$N_{\mathrm{Eq}} = 2B_sT \tag{1}$$

where B_s is the statistical bandwidth of the EMG (Hz) and T is the window length (seconds). Since whitening increases N_{Eq} via an increase in statistical bandwidth [14], [15], the relevant analytic relationship is to determine the CoV versus N_{Eq} for each time-domain feature.

The MAV of an EMG window of N_{Eq} samples is defined as

$$\mathrm{MAV}_{N_{\mathrm{Eq}}} = \frac{1}{N_{\mathrm{Eq}}} \sum_{n=0}^{N_{\mathrm{Eq}}-1} |m\,[n]|. \tag{2}$$

Its CoV is the inverse of the signal-to-noise ratio (SNR), which has been previously analyzed [21]. Inverting the SNR result gives

$$\mathrm{CoV}_{\mathrm{MAV}}\,[N_{\mathrm{Eq}}] = \sqrt{\frac{\pi-2}{2N_{\mathrm{Eq}}}} \cong \frac{0.755}{\sqrt{N_{\mathrm{Eq}}}}. \tag{3}$$

The average signal length of N_{Eq} samples, in millivolts per second per sample, is defined as

$$\mathrm{SL}_{N_{\mathrm{Eq}}} = \frac{f_s}{N_{\mathrm{Eq}}-1} \sum_{n=1}^{N_{\mathrm{Eq}}-1} |m\,[n] - m\,[n-1]|. \tag{4}$$

The gain factor $f_s/N_{\mathrm{Eq}}-1$, not normally included in the definition of signal length, normalizes its values across sampling rates and window lengths. Since the $m[n]$ are zero-mean Gaussian, so is each difference term in the sum, but with a doubled variance. An analytic form for the sum was not readily apparent due to the correlation between adjacent differences, which share a common EMG sample. Hence, the CoV of average signal length was approximated numerically in MATLAB by creating 10^6 replicates of Gaussian vectors of size N_{Eq} and computing the sample mean and standard deviation of the average signal length, across these replica. Window length N_{Eq} was varied from 2–2000. The resulting CoV values versus N_{Eq} closely fit the model

$$\mathrm{CoV}_{\mathrm{SL}}\,[N_{\mathrm{Eq}}] \cong \frac{0.911}{\sqrt{N_{\mathrm{Eq}}}}. \tag{5}$$

The normalized zero crossing rate of N_{Eq} samples is defined as the number of adjacent samples with different polarity, normalized by the ratio between sampling rate and the number of samples

$$\mathrm{ZC}_{N_{\mathrm{Eq}}} = \frac{f_s}{(N_{\mathrm{Eq}}-1)} \sum_{n=1}^{N_{\mathrm{Eq}}-1} [1 - \mathrm{sgn}(m[n]\; m[n-1])]. \tag{6}$$

The gain factor $f_s/(N_{\mathrm{Eq}}-1)$ normalizes the zero crossing values across sampling rates and window lengths, so that its unit is Hertz, and

$$\mathrm{sgn}(t) = \begin{cases} 1, & t > 0 \\ 0, & t \le 0 \end{cases}$$

For independent identically distributed Gaussian samples, the probability of a sign change between a pair of samples is 0.5. Thus, the number of sign changes in N_{Eq} samples follows a Binomial distribution with $N_{\mathrm{Eq}}-1$ trials, and its coefficient of variation is [22]

$$\begin{aligned} \mathrm{CoV}_{ZC}\,[N_{\mathrm{Eq}}] &= \frac{\sigma_{ZC}}{\mu_{ZC}} = \frac{\frac{f_s}{N_{\mathrm{Eq}}-1} \cdot \sqrt{\frac{N_{\mathrm{Eq}}-1}{4}}}{\frac{f_s}{N_{\mathrm{Eq}}-1} \cdot \frac{N_{\mathrm{Eq}}-1}{2}} \\ &= \frac{1}{\sqrt{N_{\mathrm{Eq}}-1}} \cong \frac{1}{\sqrt{N_{\mathrm{Eq}}}}. \end{aligned} \tag{7}$$

We see that the CoV for each time-domain feature is (asymptotically) a univariate function of the number of equivalent independent samples, in the form of a constant divided by $\sqrt{N_{\mathrm{Eq}}}$, where N_{Eq} represents the equivalent number of independent samples. We expect that signal whitening will increase N_{Eq}, thereby reducing CoVs for any given window duration, with better classification accuracy hypothesized to result. An experimental trial evaluated this hypothesis.

III. Methods

A. Experimental Methods

Experimental data from two prior studies were analyzed. The Worcester Polytechnic Institute (WPI) Institutional Review Board (IRB) approved and supervised this analysis. Data from ten intact-limbed subjects, aged 19–32 years, had been collected at the University of New Brunswick [7]. Briefly, ten adhesive Duotrode electrodes (manufactured by 3 M) were applied about the circumference of the forearm of each intact subject. Twelve equally spaced locations were marked along the entire forearm circumference at 1/3 the distance from the elbow to the wrist, beginning at the palmar aspect (see [7] and Fig. 2).

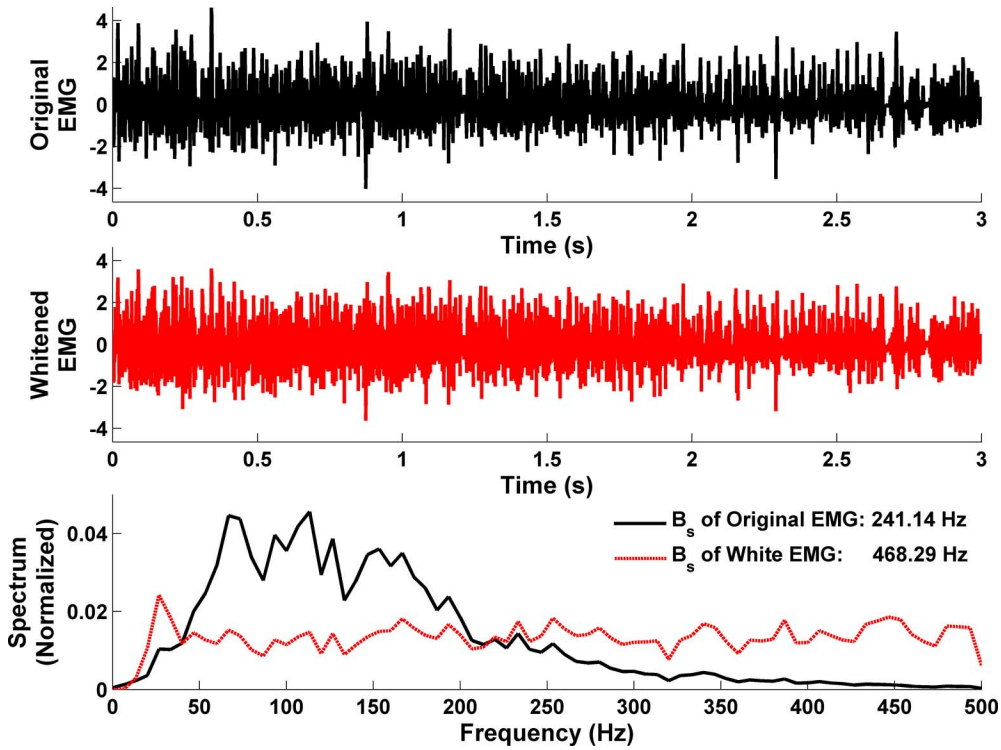

Fig. 1. Sample original EMG epoch (top), same epoch after whitening (middle) and the normalized spectrum of each (bottom). Statistical bandwidth, B_s, of each signal is listed. Data from healthy subject 6, channel 3, fine pinch grip motion, epoch 2.

The most medial and lateral locations were omitted(leaving ten locations). Bipolar electrodes had a contact diameter of 1.4 cm and a center-to-center distance of 2 cm. A subject began and ended each trial at rest (fixed posture with no motion attempted, muscle effort minimized) with their elbow supported on an armrest. Each trial consisted of two repetitions of the 11 motion classes: 1) and 2) wrist pronation/supination; 3) and 4) wrist flexion/extension; 5) hand open; 6) key grip; 7) chuck grip; 8) power grip; 9) fine pinch grip; 10) tool grip; and 11) no motion. Each motion class within a trial was maintained for 4 s, and the subject returned to the rest posture for a specified inter-motion delay period prior to producing the next motion class. 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 inactivity was given between each trial. A general familiarization session was provided prior to data collection, typically lasting approximately 15 minutes in duration. The EMG data were collected using a custom-built pre-amplification system (Liberating Technologies, Inc., Holliston, MA) with a frequency response from 30–350 Hz, and sampled at 1000 Hz using a 16-bit ADC.

The Rehabilitation Institute of Chicago collected EMG data from five subjects aged 28 to 77 years, who had received unilateral transradial amputation three months to 21 years prior [9]. Three subjects were myoelectric prosthesis 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 and center-to-center distance of 2 cm (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 [see [9] and Fig. 1(a)]. In this study, we used only the first ten electrodes, to most closely match the electrode placement of the intact-limbed subjects. Only data from the amputated side was used. The experiment protocol was the same as that of the intact subjects, including subject posture, the general familiarization session and the motion trials. Identical motion trial data were available for analysis. The EMG data were transduced using Liberating Technologies preamplifiers, bandpass filtered between 5–400 Hz and sampled at 1000 Hz using a 16-bit ADC.

B. *Methods of Analysis*

1) Feature Computation: The trials were segregated into training and testing data, as described in the following. The inter-trial delay segments were removed from data recordings, resulting in 22 4-s segments per electrode per trial (two repetitions of 11 motion classes). Each segment was zero-phase notch-filtered (0.4 Hz bandwidth) at the power-line frequency and its harmonics. When desired, each four-second segment was also whitened. To do so, each segment was highpass filtered at 15 Hz, then adaptively whitened using an algorithm that was tuned to the power spectrum of each EMG channel [12], [23]. Whitening filters were calibrated from a training trial by manually selecting, subject-by-subject for each electrode, the trial with the largest MAV. A no motion trial was also used to represent resting EMG in the whitening calibration. Prior to feature extraction, 0.5 s of data were truncated from the beginning and end of each segment to account for filter startup transients. Contiguous, nonoverlapping windows were formed from the remaining three-second epochs.

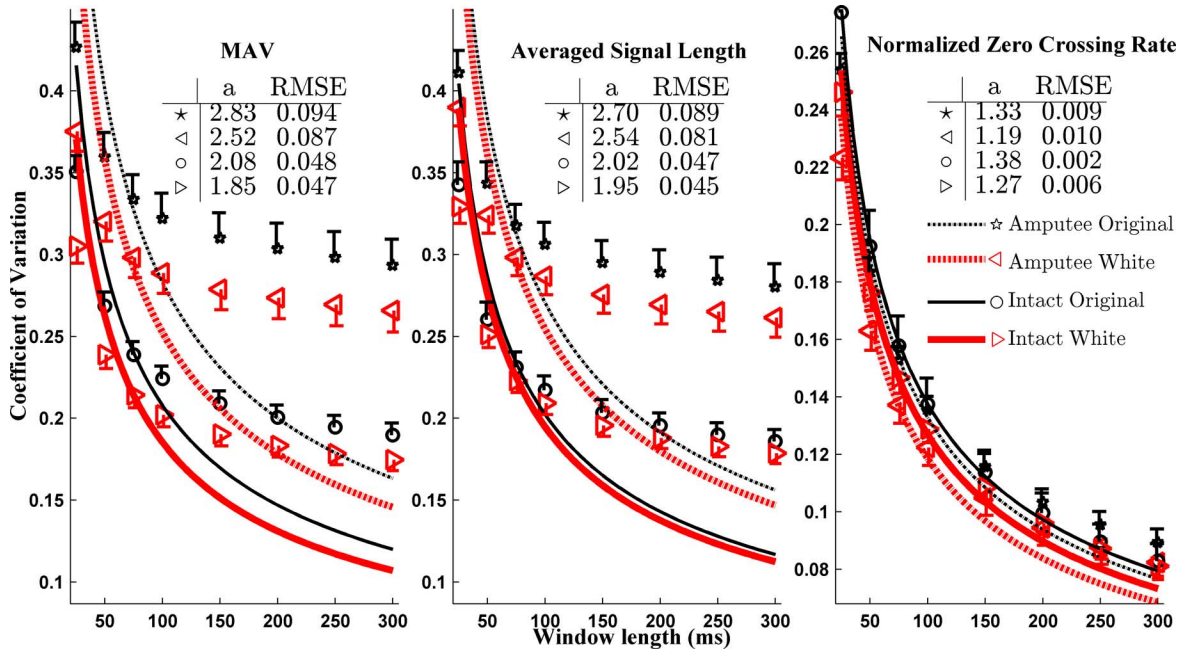

Fig. 2. Average coefficient of variation (plus or minus one standard error) for the time-domain features from ten intact and (separately) five amputee subjects. Two recordings per channel per subject with the largest MAV EMG were used for this analysis. Lines show fit to power decay model: $\mathrm{CoV}[N] = a/\sqrt{N}$. Inset tables show fit parameter "a" and fit rms error (RMSE). Scale of y-axis differs for normalized zero crossing rate. Sample size is 100 for intact subjects, 50 for amputee subjects.

Feature sets were extracted in each window within an epoch. The time-domain feature set consisted of the three featuresdescribed earlier: MAV, average signal length and normalized zero-crossing rate. Hysteresis as described in [6] was applied to normalized zero-crossing rate. Specifically, a zero-crossing was not counted if the absolute difference between the two adjacent samples did not exceed a fixed threshold value. The threshold value was set to approximately 1/6th the average RMS value of the no-motion class of all subjects and all electrodes. A frequency domain feature set consisted of the estimated AR coefficients of a seventh order AR model [10], [24]. A third (combined) feature set concatenated the seven AR coefficients and MAV. It has been shown that linear classification models give different weights to each feature, and the MAV feature alone tends to have a large amount of motion classification power.

2) Coefficient of Variation Analysis: CoV values were computed for each of the three time-domain EMG features. Because CoV is the ratio between standard deviation and the mean of a feature, EMG signals with a small mean value can lead to unstable CoV estimates (due to dividing two small numbers in the presence of noise). Thus CoV was calculated using only two training trials per channel by manually selecting, subject-by-subject for each channel, the two trials with the largest MAV. All motion classes were considered when searching for the maximum MAV. The sample standard deviation divided by the sample mean of the contiguous feature values from a 3-s epoch formed a CoV value. The average CoV from the two trials per channel served as the CoV estimate for that channel. Data from the intact subjects were studied separately from those of the amputee subjects. CoV values that compared unwhitened to whitened signals were computed for the following window durations: 25, 50, 75, 100, 150, 200, 250 and 300 ms. Once the CoV had been determined as a function of sample length N, we fit these results to the power decay model: $\mathrm{CoV}[N] = a/\sqrt{N}$.

We defined N as the number of samples corresponding to the window duration. The number of samples (N) is always greater than the equivalent number of independent samples (N_{Eq}) due to signal correlation. In practice, this correlation cannot be entirely eliminated via whitening. A more direct measure of whitening performance is to assess the statistical bandwidth of the EMG before and after whitening. The same 3-s epochs as previously mentioned were used to do so. The discrete-time power spectrum, $S_{mm}(k)$, of each epoch was estimated using Welch's method (window length of 150 ms, Hamming window, 50% overlap), where k is the frequency index. The statistical bandwidth was then estimated as [20]

$$B_s = \frac{\Delta f \cdot \left(\sum_{k=0}^{K-1} S_{mm}(k) \right)^2}{\sum_{k=0}^{K-1} S_{mm}^2(k)} \tag{8}$$

where K specifies the range of positive-valued frequencies and $\Delta f = 6.67$ Hz is the frequency increment. Values from the two trials per channel were averaged.

3) Classification Analysis: A linear discriminant classifier was employed. Trials 1–4 of the two repetitions were used to train the coefficients of the classifier and trials 5–8 to test classifier performance. The model was trained and tested for each individual subject using all features of a feature set, and only test results are reported. Eight window durations were used: 25, 50, 75, 100, 150, 200, 250 and 300 ms. We repeated the analysis after the EMG signal had been whitened.

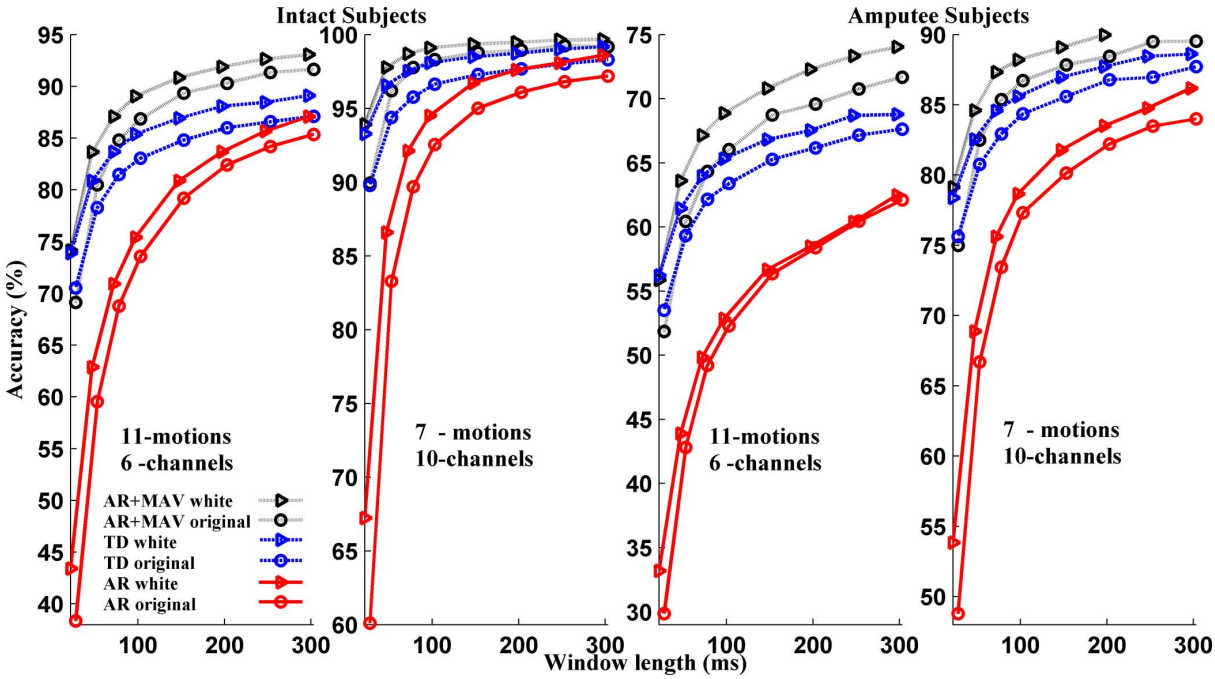

Fig. 3. Average classification accuracies from ten intact (left) and five amputee (right) subjects for each of the three feature sets, with and without whitening. Motion-channel combinations shown represent the lowest accuracies (fewest channels and most motion classes) and highest (most channels and fewest classes). Note the different y-axis scale for each plot.

Two global processing variants were also considered. First, the entire analysis was repeated using only seven preselected motion classes (the classes denoted above as numbers 1–5, 8 and 11), and again using only nine preselected motion classes (1–8 and 11), thereby giving three motion variations. Second, the entire analysis was repeated using a preselected set of six of the electrode channels (channels 1–6, spread around the arm circumference), giving two channel variations.

IV. Results

1) Coefficient of Variation Results: Fig. 1 shows a sample 3-s raw EMG epoch, the same epoch after whitening, and the spectrum of each of these two signals (normalized to the total power in each spectrum). The spectra show how whitening equalizes the contributions across frequency, increasing the statistical bandwidth of the signal. Fig. 2 shows all CoV results, averaged across subjects, for the three time-domain features, together with the standard errors. Lines within the figure show the best fit power decay model and the inset tables list the fit errors. The sample size for calculating the CoV and standard error was 100 for intact subjects (10 subjects $\times$ 10 EMG channels/subject) and 50 for amputees (5 subjects $\times$ 10 EMG channels/subject). The CoV for each feature improved (i.e., decreased) with window length and due to whitening, although the MAV and SL results were a poor fit to the power decay model. The normalized zero crossing rate exhibited substantially lower CoV values than the other two features and fit well to the power decay model. CoV values for intact subjects were consistently lower than those of amputee subjects. Paired sign tests were conducted between whitened and unwhitened features at each window duration and for each of the intact and amputee data sets. All comparisons were significant for MAV ($p < 10^{-4}$) and for average signal length ($p \leq 0.006$ for intact subjects, $p < 10^{-4}$ for amputees). For normalized zero crossing rate, whitened features only differed from unwhitened features in intact subjects when the window length was ≤ 50 ms ($p < 0.002$), and in amputees when the window length was ≤ 200 ms ($p < 0.008$).

TABLE I
Average $\pm$ Standard Deviation Statistical Bandwidths. Sample Size is 100 for Intact Subjects, 50 for Amputee Subjects

Subjects	Condition	
	Unwhitened	Whitened
Intact	238.0 ± 49.8 Hz	413.2 ± 73.0 Hz
Amputee	254.1 ± 53.4 Hz	423.1 ± 52.7 Hz

Table I shows the results of the statistical bandwidth computations. Whitening increased the statistical bandwidth by 65%–75%, on average. Statistically, the ten statistical bandwidth values per subject (one per electrode) were averaged. These values for unwhitened versus whitened processing were compared using a paired t-test. Results were significant for both the intact and amputee subjects ($p < 10^{-4}$).

2) Classifications Results: Complete classification results were produced for six classifier variants (11 or 9 or 7 motion classes versus ten or six electrodes). Higher accuracies were found when fewer motions and/or more electrode channels were included in the classifier. Hence, our presentation of results will be limited to the highest (7-motion, 10-channel) and lowest (11-motion, 6-channel) performing classifiers—all four remaining result variants fell between these two extremes. Fig. 3 shows the average test accuracies for intact and amputee subjects, for window lengths between 25 and 300 ms, for each feature set with and without whitening. The combined AR-MAV feature set gave the highest overall accuracy in each case, and the AR

features the lowest. For all feature sets, accuracy was generally improved by approximately 5% at shorter window durations (< 100 ms) due to whitening. The improvement was smaller as window duration increased further. Accuracy values for intact subject were consistently higher than those of amputee subjects. Because sample sizes were small (DoF $= 9$ for ten intact subjects, DoF $= 4$ for five amputees) paired t-tests compared unwhitened to whitened processors at each window duration. For the AR-MAV feature set and intact subjects, differences were significant for: the 7-motion, 10-channel case when the window length was ≤ 300 ms ($p < 0.009$), and the 11-motion, 6-channel case for all window lengths except 400 ms ($p < 0.005$). For the AR-MAV feature set and amputees, differences were significant for: the 7-motion, 10-channel case when the window length was ≤ 50 ms ($p < 0.006$), and the 11-motion, 6-channel case when the window length was ≤ 100 ms ($p < 0.008$). For the TD feature set, results were only significant for intact subjects with the 7-motion, 10-channel case when the window duration was ≤ 300 ms ($p < 0.01$) and in amputee subjects in the 11-motion, 6-channel case when the window duration was 25 ms ($p = 0.004$). For the AR feature set of amputees, unwhitened versus whitened result differences were significant in all cases when the window length was 25 ms ($p < 0.006$) and in intact subjects with the 7-motion, 10-channel case when the window duration was ≤ 400 ms ($p < 0.003$).

V. Discussion

We studied the use of EMG signal whitening in classification algorithms for prosthesis control. Signal whitening methods have existed for several years [12]–[15], having been shown in the laboratory to improve EMG amplitude estimation [12] as well as EMG-force estimation [25]. They had not previously been applied to the EMG multifunction classification problem. Whitening decorrelates the EMG signal in time—increasing its statistical bandwidth—resulting in a larger number of effective degrees of freedom in the data [20]. Essentially, whitening increases the effective sample size (N_{Eq}) of each individual data epoch, making each epoch more representative of the entire sequence.

Theoretically, the influence of epoch sample size on the MAV feature had been previously studied via the SNR (inverse of the CoV) [19]. The CoV decreases in a square root fashion with sample size. We extended this analysis to the other two time-domain features. The CoV of the average signal length and normalized zero crossing rate also each decrease in a square root relationship with sample size. Our theoretic model for normalized zero crossing rate did not include hysteresis. However, this effect is generally considered small when an appropriate (small) level of hysteresis is applied [6].

In practice, whitening increased statistical bandwidth by 65%–75% (Table I) and CoV was reduced for each of the three time-domain features (Fig. 2). However, the MAV and average signal length features produced CoV values that did not fit the power decay model. Further, our CoV values were consistently much higher than the model predictions, based on the statistical bandwidth. For example, for whitened data from intact subjects

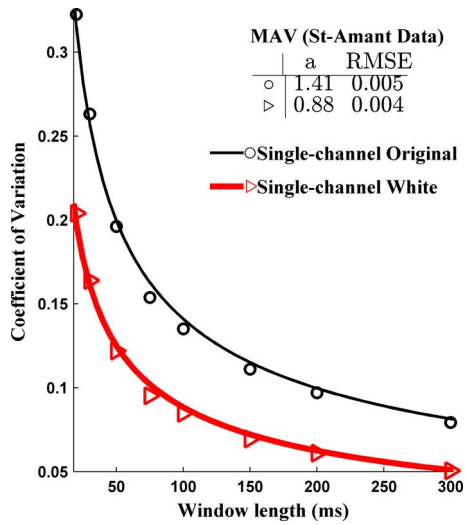

Fig. 4. Inverse of average SNR gives an estimate of average coefficient of variation, with and without whitening for MAV feature, from the data of St-Amant *et al.* [28]. Lines show fit to power decay model $\mathrm{CoV}[N] = a/\sqrt{N}$. Inset table shows fit parameter "a" and fit rms error (RMSE).

(average bandwidth of 413 Hz from Table I) using a 300 ms window, (1) and (2) can be used to compute an anticipated $\mathrm{CoV}_{\mathrm{MAV}}$ of 0.048. Our result of ~ 0.175 shown in Fig. 2 is well above this value. Visual inspection of the calibration data from both intact and amputee subjects found substantial modulations in EMG amplitude *within* each 3-s epoch. For the MAV and average signal length features, such modulations would greatly increase the standard deviation of the contiguous features extracted from an epoch, resulting in the observed CoV increase. Recall that intact subjects were not provided force feedback; amputee subjects cannot be provided such feedback. While such feedback could be provided to the intact subjects, it is generally considered best to train classifiers using the same conditions representative of their use—which would *exclude* feedback. Consistent with these observations, consider the SNR results of St-Amant *et al.* [26], which were produced by intact subjects utilizing force feedback. The inverse of their SNR calculation provides a CoV estimate. Fig. 4 plots the inverse of their average SNR measurements versus window length, as well as fits to our power decay model. The excellent model fits the result. Although the St-Amant *et al.* data are from different muscles using a smaller inter-electrode distance, they are supportive of the role of EMG amplitude modulation in artificially increasing estimated CoV values. Conversely, the zero crossing feature *did* follow a power decay model as a function of window length and had CoV values that followed theoretic expectations. So long as the crossing signal does not have a peak or trough near zero voltage, even a modest amount of amplitude modulation will not alter proper identification of the crossing. Hence, zero crossings would not be substantially affected by amplitude modulations, as observed in our results.

In any case, the experimental CoV for whitened features was consistently better (smaller) than that of unwhitened features for MAV and average signal length, and better at shorter epoch lengths for normalized zero crossing rate. Thus, the variability

of the time-domain features was generally reduced by preprocessing the signal with a whitening filter. Features with less variability would be expected to lead to more accurate classification. However, classification analysis does not solely rely on the CoV of the features. Individual features may be weighted differently in the linear classifier, giving a larger impact to some features than others; and small changes in the classification model space can have varied influence on classification accuracy.

The classification accuracy results consistently showed an improvement due to whitening, when the shorter epoch durations were considered. The shortest epoch durations of 25–100 ms generally experienced the greatest improvement—an approximate 4%–5% increase in accuracy. It is not surprising that the improvement diminishes with increased epoch length, since all accuracies are improving, but cannot exceed 100%. Larger sample sizes might be useful in demonstrating significant improvements due to whitening at these longer epoch lengths. Consistent with prior research [7], [9], our results also found that higher accuracies resulted when fewer motions and/or more electrode channels were included in the classifier.

Because the performance improvements due to whitening are modest, its inclusion in a prosthesis controller should be weighed versus its costs. Disadvantages/challenges of using whitening include its substantial added computation and memory requirements, the need to collect calibration data, and possible robustness issues in the presence of high frequency noise. Advantages include that whitening is implemented as a stand-alone preprocessing step whose output can be fed into all further EMG processing steps, accuracy improvements at the shorter epoch durations may facilitate the use of shorter epochs thereby reducing prosthesis response time, and that modern signal processing hardware is increasingly capable of the required processing demands. A logical next step to all of this work is to evaluate whitening within a myoelectric-controlled prosthesis.

We considered only simple feature vectors and classifiers in this analysis. Many more complex features/classifiers have appeared in the literature [7], [8], although their classification performance is not markedly distinct from those reported herein. Nonetheless, one would expect that EMG signal whitening would similarly improve the performance of those classifiers. Note that the data available to this research was collected from EMG electrodes with bandwidth out to 350–400 Hz. This bandwidth is common. However, whitened signals have been shown to take advantage of a wider bandwidth (out to nearly 2000 Hz in some cases [27], [28]), with additional performance improvement provided. Future work may wish to utilize a wider band EMG data acquisition system. In addition, we calibrated the whitening filters from available functional contractions that contained visible amplitude modulations. It may be better to collect dedicated calibration contractions at 0% and 50% MVC [12], [27].

In conclusion, we have shown that whitening the EMG signal leads to time-domain features with an increased statistical bandwidth and concomitantly smaller CoV, leading to a consistent increase in classification accuracy in both intact and amputee subjects in a laboratory evaluation. Whitening added approximately five percentage points to classification accuracy at the shortest epoch durations ($\sim 25 - 100$ ms). Improvement in classification accuracy at these shortest epoch durations is important, as it may allow prosthesis control systems to use shorter epochs, thereby improving response time.

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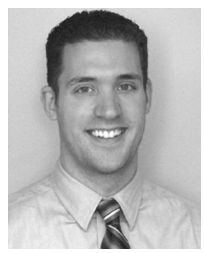

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