34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Whitening of the Electromyogram for Improved Classification Accuracy in Prosthesis Control

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Abstract— **The electromyogram (EMG) signal has been used as the command input to myoelectric prostheses. A common control scheme is based on classifying the EMG signals from multiple electrodes into one of several distinct classes of user intent/function. In this work, we investigated the use of EMG whitening as a preprocessing step to EMG pattern recognition. Whitening is known to decorrelate the EMG signal, with improved performance shown in the related applications of EMG amplitude estimation and EMG-torque processing. We reanalyzed the EMG signals recorded from 10 electrodes placed circumferentially around the forearm of 10 intact subjects and 5 amputees. The coefficient of variation of two time-domain features—mean absolute value and signal length—was significantly reduced after whitening. Pre-whitened classification models using these features, along with autoregressive power spectrum coefficients, added approximately five percentage points to their classification accuracy. Improvement was best using smaller window durations (<100 ms).**

I. Introduction

Traditional myoelectric-controlled upper limb prostheses provide one degree of freedom of proportional control, often by subtracting the EMG amplitudes of an antagonist pair of muscles. The amputee uses manual mode switches to cycle between distinct functions (e.g., hand-wrist-elbow) in order to sequentially control different devices [1], [2]. More natural control of multiple degrees of freedom is greatly desired by below-elbow amputees [3]. One emerging method for such advanced control is based on EMG pattern recognition [1], [4]–[9]. A window ("epoch") of data from multiple electrodes is used to discriminate between a set of distinct hand/wrist/elbow actions. For continuous control, classification can be performed on the EMG signal stream at a periodic rate.

Pattern recognition consists of the sequential steps of EMG signal conditioning/ preprocessing, feature extraction, dimension reduction and pattern classification. Classification errors are due both to a systematic component (e.g., inability of the available features to distinguish all investigated motions) and a random component. In the related areas of EMG amplitude estimation and EMG-torque modeling, whitening has been shown to reduce the variation (i.e., random component) in the EMG signal and improve performance [10], [11]. Physiologically, whitening may counteract, in part, the lowpass filter effect imposed on the signal as it propagates from its origin along the muscle fiber membranes; through intervening muscle, fat and skin; before being recorded at the electrodes. From a stochastic processing standpoint, whitening temporally decorrelates the EMG signal, increasing the effective number of signal samples (a.k.a., statistical degrees of freedom), which reduces the variance in the amplitude estimate. Thus, we hypothesized that pre-whitening of the EMG signal would reduce the random variation of the EMG features used in classification, resulting in improved classification performance. This effect should be more evident at small window durations, since classification accuracy already approaches 100% when long epoch lengths are used. A preliminary report of this work appeared in [12].

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II. Methods

A. Experimental Methods

Data from two prior experiments with similar protocols were available for reanalysis. The reanalysis was approved and supervised by the WPI IRB. The original data collection was approved by the human studies boards of the respective institutions and written informed consent was received from each subject. Data from ten intact-limbed subjects were collected at the University of New Brunswick [5]. Data from five unilateral transradial amputees were collected at the Rehabilitation Institute of Chicago [6]. Distinct EMG acquisition systems were available at each site. In each case, ten disposable bipolar electrodes (3M Duotrode for intacts; Noraxon 1.25cm diameter Ag/AgCl for amputees) were secured about the circumference of the proximal forearm, oriented along the presumed direction of action potential conduction. EMG data were bandpass filtered (30–350 Hz for intacts; 5–400 Hz for amputees) and sampled at 1000 Hz.

Subjects completed two repetitions of eight trials. Each trial was initiated and terminated at rest with the subject's elbow supported on an armrest. Each trial was comprised of the sequential performance (or, for amputees, *attempted* performance) of 11 motion classes: 1, 2) 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; and 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. A minimum of two minutes rest was given between trials.

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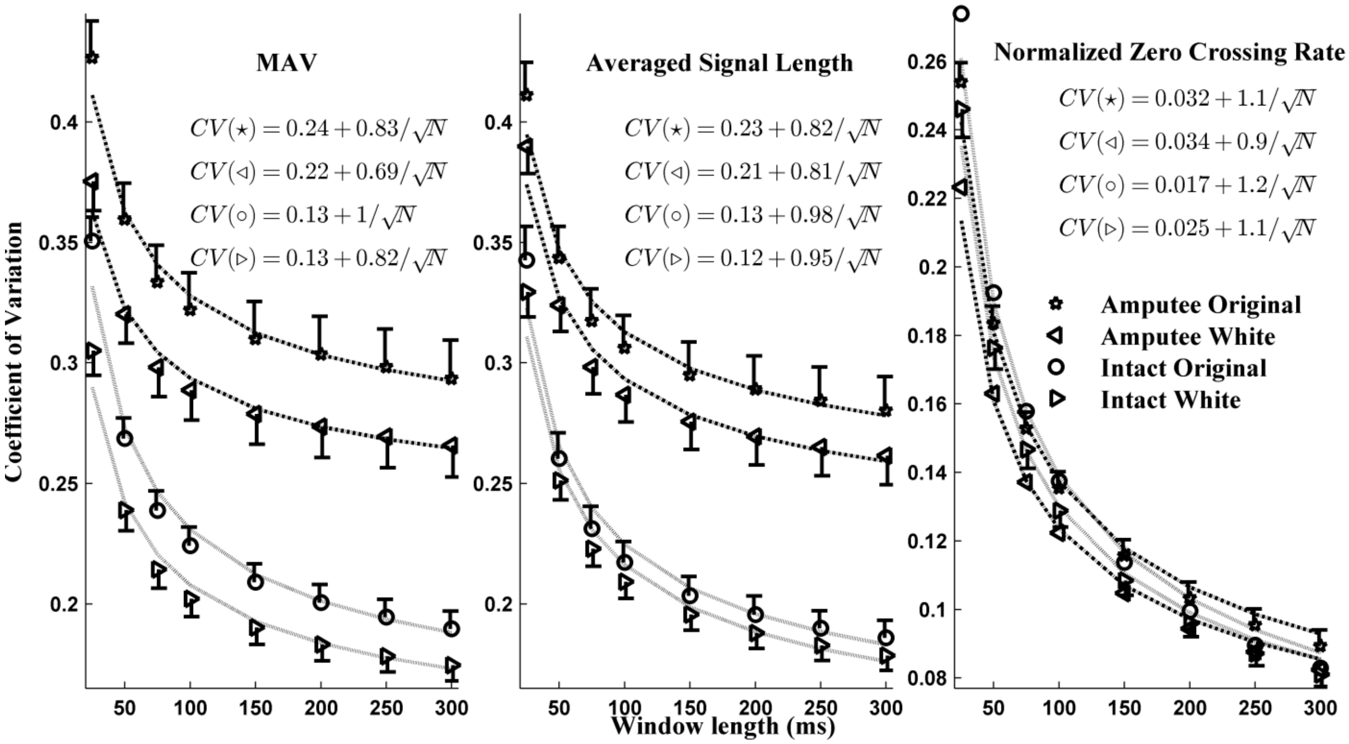

Fig. 1. Average coefficient of variation (plus or minus one standard error) for the time-domain features from ten intact and (separately) five amputee subjects, with and without whitening. Lines show fit to the model: $\mathrm{CoV}[N] = a + b/\sqrt{N}$. Scale of y-axis differs for normalized zero crossing rate. Sample size is 100 for intact subjects, 50 for amputee subjects.

B. Computation of EMG Features

The inter-motion delay portions of the data were removed, leaving epochs 4 s in duration. Each epoch was notch filtered at the power line frequency and each of its harmonics. When whitening was desired, each epoch was highpass filtered at 15 Hz, then adaptively whitened using the algorithm of [10], [13]. This algorithm initially whitens the complete signal (EMG signal plus noise) based on an estimate of the noise-free spectrum of the EMG signal. Unfortunately, this fixed filter also accentuates the high-frequency portion of the noise spectrum. Hence, an adaptive Weiner filter (optimal linear filter to attenuate additive noise) is cascaded after the fixed whitening filter. This filter adapts its shape based on the spectra of the background noise and the EMG signal. The EMG signal spectrum is amplitude modulated with muscle effort, while the background noise spectrum is fixed. In practice, the Weiner filter is lowpass in shape, with a higher cutoff location occurring when muscle effort is high. Adaptive whitening requires calibration to a rest and an active contraction, for each electrode. The “no motion” class was used as the rest contraction. One active class was manually selected per electrode per subject, corresponding to the class with the largest EMG amplitude. After this filtering, the first and last 0.5 seconds of the epoch were discarded, to account for filter start-up transients.

Features were then extracted from each trimmed (3 s) epoch by segregating the epoch into contiguous windows. The following window durations were investigated: N = 25, 50, 75, 100, 150, 200, 250 and 300 ms. The time-domain feature set consisted of the three features: mean absolute value (MAV), average signal length (SL) and normalized zero crossing rate (ZC) (see [4] for definitions). Our ZC feature used a noise threshold of approximately $1/6^{\text{th}}$ the average RMS value of the “no motion” class. The frequency-domain feature set consisted of the coefficients of a seventh-order autoregressive (AR) model [8], [14]. The “combined” feature set used the AR coefficients along with MAV.

C. Analysis of Coefficient of Variation of EMG Features

Since the mechanism of improvement due to signal whitening is hypothesized to be a reduction in the variation of feature values, we computed the coefficient of variation (CoV) of the features. We limited this analysis to the three time-domain features. For each electrode for each subject, we identified two classes with the largest EMG amplitudes. The CoV was computed for each epoch as the standard deviation of the features divided by their mean. Low amplitude recordings were avoided, since the CoV calculation is erratic when the mean feature value and its standard deviation are both small numbers. These CoV values were averaged across the two selected trials and across all subjects. Results were computed both with and without whitening, separately for intact-limbed subjects and amputees, and for each window duration N. Thereafter, a modified power decay model was fit to the mean values, using the model: $\mathrm{CoV}[N] = a + b/\sqrt{N}$. Lower CoV values denote less variability in the features.

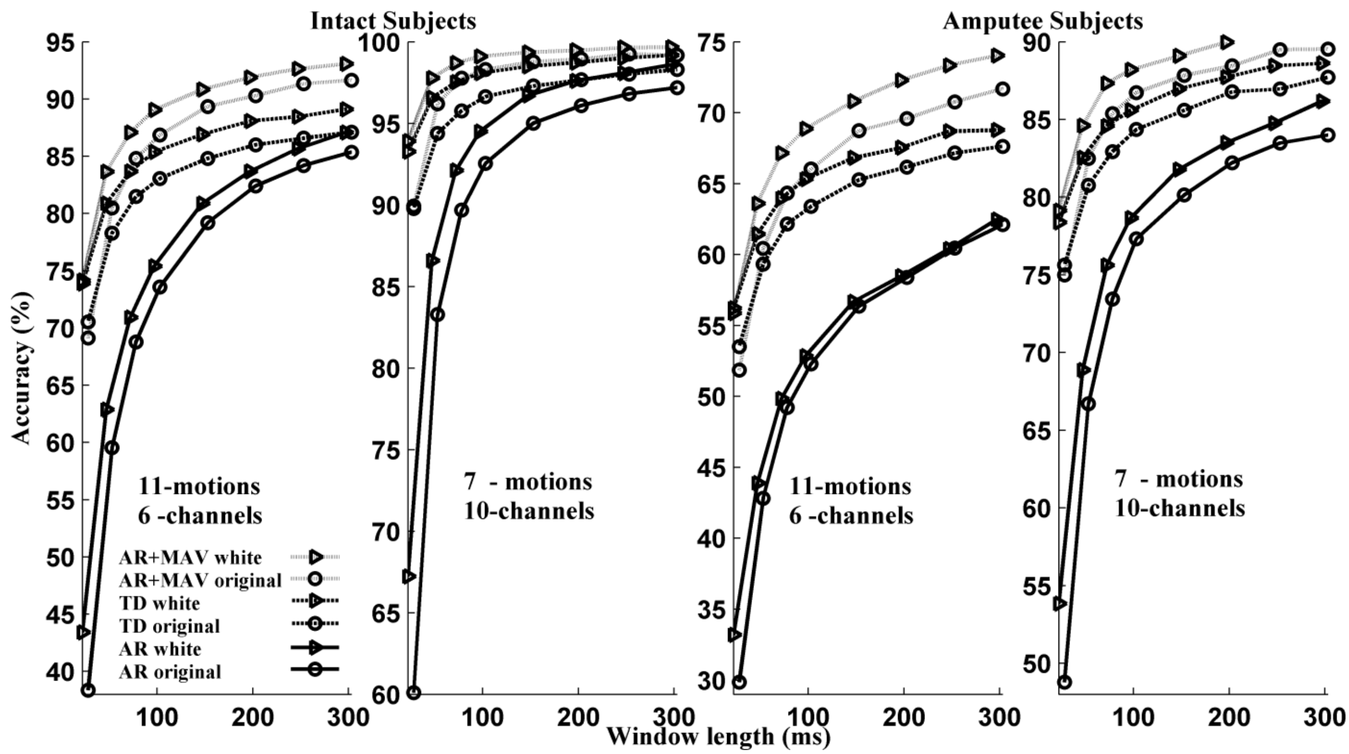

Fig. 2. Exhaustive selection average classification accuracies from ten intact (left) and five amputee (right) subjects for each of the three feature sets, with and without whitening. The motion-channel combinations shown represent the lowest accuracies (fewest channels and most motion classes) and highest (most channels and fewest classes). Window durations vary from 25 to 300 ms. Note the different y-axis scale for each plot.

D. Analysis of Classification Performance

Linear discriminant classification was used with an exhaustive search over all possible electrode combinations. For ten electrode channels, there were 1023 possible electrode combinations evaluated. Both repetitions of data trials 1–4 were used for training and both repetitions of data trials 5–8 were used for testing. The results from the best test result per subject are reported. The entire analysis was repeated using a preselected set of six electrodes spread evenly about the circumference of the forearm. For six electrode channels, there were 63 possible electrode combinations evaluated. The analysis was repeated again using only a preselected set of nine motion classes (classes 1–8 and 11); and again using a preselected set of seven motion classes (classes 1–5, 8 and 11). Results for intact-limbed subjects and amputees are reported separately for each of the window durations.

III. Results

Fig. 1 shows the average plus/minus standard error CoV results for the three time-domain features, with and without whitening, plotted separately for intact-limbed and amputee subjects. Whitening substantially reduced feature variation at all window durations for the MAV and SL features. There was rather limited affect due to whitening for the ZC feature. The CoV values were lower in the intact-limbed subjects. All plots fit well to the offset power law model.

Classification accuracy results were higher when the number of EMG channels was larger and when the number of motion classes was lower. Thus, results will only be presented for the best (10-channel, 7-motion) and worst (6-channel, 11-motion) combination. Fig. 2 shows the across-subject average classification accuracy for these channel-motion combinations, with and without whitening, for each of the three feature sets (time-domain, frequency-domain and combined), plotted separately for intact-limbed and amputee subjects. Whitening provided a consistent increase in performance. At low window durations, the performance increase is as much as five percent. The “combined” feature set (AR coefficients along with MAV) consistently provided the highest average classification accuracy. Accuracy was higher in the intact-limbed subjects than in the amputees.

IV. Discussion

Although signal whitening methods have been available for several years, they do not seem to have been applied to the EMG pattern recognition problem. When computing EMG MAV, the signal to noise ratio (SNR) of the amplitude estimate has been shown to increase with window duration in a square root fashion [15], with whitening improving the SNR. Since CoV is defined as the reciprocal of the SNR, it follows that the CoV of the MAV feature should decrease with window length as the reciprocal of a square root; thus our use of the power law model for fitting to the CoV values. Further, whitened MAV features should have lower CoV values than unwhitened MAV features. We found, however, that an offset term was needed in the power law model in order to achieve an acceptable fit (Fig. 1). Manual inspection of the epochs used to calculate the CoV showed that many subjects did not maintain a constant effort level across the 3 s used to form features. If the feature values are changing *within* a 3 s epoch, then a larger sample standard deviation will be found for that mean feature value. A larger CoV estimate will result. The inflated MAV CoV values fit better to a power law model that included an offset term than to the theoretically expected model that is absent an offset.

Although not described here, analytic and simulation analysis also predicted an inverse square root relationship with window duration for the SL and ZC features. Fig.1 shows that the SL feature also required substantial offset values in the power law fit, but the ZC feature did not. As effort varied *within* an epoch, the CoV of the SL feature would be expected to inflate, again due to the increased within-epoch variance. But, zero crossings are not substantially influenced by modulations in EMG amplitude within an epoch—so long as the EMG amplitude remains above the noise floor. Hence, the ZC features exhibited the lowest overall CoV values (and the lowest standard errors).

One would expect much lower CoV values for the MAV and SL features if the subject contractions were held more constant. However, acquisition of such data is only relevant to this intermediate evaluation of CoV. For training classifiers, it is better to collect data with the full range of within-epoch modulation that is representative of actual prosthesis control use. The classifier will then optimize for that realistic condition.

Regardless of this inter-epoch modulation concern, whitening decreased the CoV, making the features more repeatable. As shown in Fig. 2, an improvement in classification accuracy resulted. The improvement was most prominent at the shorter window durations. This result was expected, since classification performance increases towards 100% at the longer window durations. No further increase is possible.

V. Conclusion

We investigated whitening as a preprocessing step to EMG pattern recognition in intact-limb and amputee subjects. Whitening was shown to decrease the average CoV for MAV and SL features, with less influence on the ZC feature. Whitening was shown to consistently improve the average classification accuracy when distinguishing up to 11 distinct motion classes using up to 10 different electrodes. Improvement due to whitening was also found using fewer motion classes and fewer electrode channels.

Acknowledgment

The authors thank Guanglin Li and the Neural Engineering Center for Artificial Limbs, Rehabilitation Institute of Chicago, Chicago, IL 60611 USA, for providing the amputee data for this study.

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