Communications

Adaptive Whitening in Electromyogram Amplitude Estimation for Epoch-Based Applications

Punit Prakash, Christian A. Salini, John A. Tranquilli, Donald R. Brown, and Edward A. Clancy*

***Abstract*—Epoch-based electromyogram (EMG) amplitude estimates have not incorporated signal whitening, even though whitening has demonstrated significant improvements for stream-based estimates. This paper presents new epoch-based algorithms, for both single- and multiple-channel EMG, which include a whitening stage. The best multiple-channel whitening processor provided a 21.4%–22.5% improvement over single-channel unwhitened estimation in an EMG-to-torque application.**

***Index Terms*—Biomedical signal processing, electromyography, EMG amplitude estimation, functional electrical stimulation, myoelectric signal processing, whitening.**

I. Introduction

Estimates of the surface electromyogram (EMG) amplitude are used in a variety of applications, including: control inputs to myoelectric prostheses [1], assessments of muscular effort [2], [3], gait analysis and motion control studies [4], and control signals for functional electrical stimulation (FES) [5], [6]. Improved EMG amplitude estimation techniques should be of value to each of these applications. To this end, multiple-channel EMG measurements [7] and whitening of the EMG signal have been shown to improve amplitude estimation [7]–[10]. The uncorrelated information from multiple EMG channels located over one muscle add to the number of degrees of freedom in the EMG, thereby decreasing the variance of the amplitude estimate. Similarly, whitening orthogonalizes the EMG samples (in time), increasing the statistical bandwidth of the data to compensate for the inherently limited bandwidth of EMG. The whitened EMG again have more degrees of freedom, and therefore reduce the variance of the amplitude estimate. Recently, Clancy and Farry [8] implemented a digital adaptive whitening process that cascades a fixed whitening filter, an adaptive Wiener filter and an adaptive gain corrector. The adaptive filter/gain corrector attenuates the additive measurement noise, since noise has a disruptive effect on the overall whitener at low levels of EMG amplitude. A first-pass unwhitened amplitude estimate controls the shape of the adaptive filters, based on calibration measurements of the EMG and additive noise power spectra. This technique reduced the error in an EMG tracking task from 9.62% MVE (maximum voluntary EMG) to approximately 6.9% MVE [8].

While prior whitening algorithms were designed for use on continuous streams of EMG data, some applications (e.g., FES) segment data into independent (often noncontiguous) epochs with only one amplitude estimate made per epoch. For FES in particular, the epochs contain between 13 and 63 ms of data [5], [6]. Applying existing stream-based algorithms in these situations is not possible since the length of the digital filters' startup transients can exceed the duration of the epoch. Since the startup transient is discarded before analysis, little or no usable EMG data remain to form an amplitude estimate. St-Amant *et al.* [11] showed that using longer segments of EMG data improved the signal to noise ratio of the resulting amplitude estimates. Hence, new adaptive whitening algorithms are required to reduce the startup transient if whitening is to improve amplitude estimation in epoch-based applications.

This paper presents an epoch-based algorithm for whitening the EMG signal for use in single- and multiple-channel amplitude estimation. It specifically addresses the issues regarding filter startup transients mentioned above. A method for assessing the performance of EMG amplitude estimates using an EMG amplitude-to-torque (EMGamp-torque) model is presented. Finally, the performance of the algorithms is compared with existing techniques using experimental data.

II. Methodology

A. *Design of Epoch-Based EMG Amplitude Estimator*

The epoch-based EMG amplitude estimation algorithm followed the sequential six stage process of [12]: high-pass filtering, adaptive whitening, multiple-channel combination, detection, smoothing, and relinearization. Mathematical details of the noise rejection and adaptive whitening stages are provided in Fig. 1 and [8]. These stages are designed from two calibration contractions, one at 0% MVC and one at 50% MVC. The last four stages of the epoch-based algorithm are identical to those of the stream-based algorithm in [8], except that the window length is the entire epoch and only one amplitude estimate is produced per epoch.

In the stream-based algorithm [8], the shape of the adaptive Wiener filter, within the adaptive whitening stage, is updated each sample. For epoch-based implementations, this filter is only adapted once per epoch. Thus, all three filters in this stage and the initial noise rejection filter are linear time invariant within one epoch. They could therefore be combined for epoch-based analysis. This combined noise rejection/whitening filter was implemented as a finite impulse response filter.

The stream-based algorithm's adaptive whitening filter in [8] was not computed using an optimal filter-design technique (the filter order was set to 60, since performance did not appreciably increase past this order) and was not intended for use with short epochs of data. In general, higher order filters better fit the desired frequency response. For stream-based whitening, this relationship translates to improved whitening of the signal as filter order increases, which in turn yields improved amplitude estimates.However, longer filters are associated with longer startup transients, thereby reducing the amount of usable

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Digital Object Identifier 10.1109/TBME.2004.840498

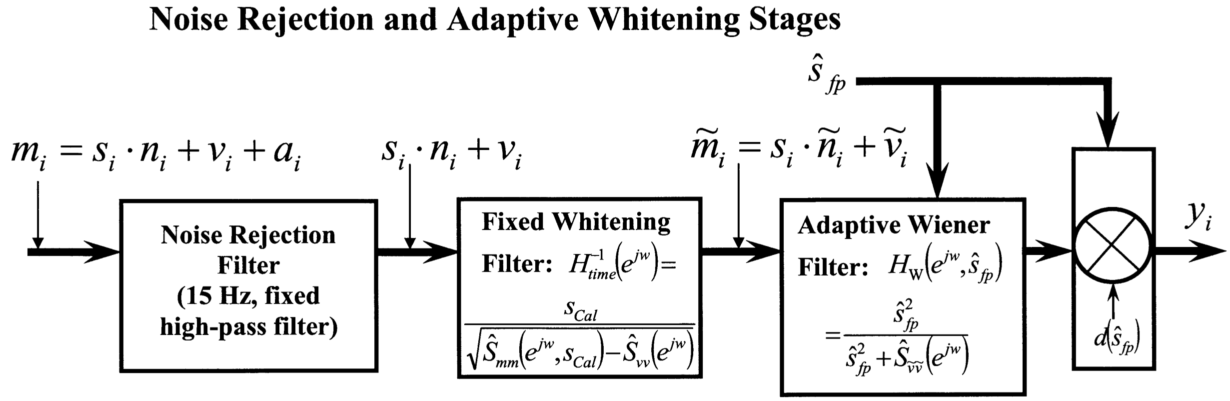

Fig. 1. Noise rejection and adaptive whitening stages. Surface EMG m_i (i is the discrete-time index) is modeled as the EMG amplitude s_i multiplied by a unit-variance random process n_i, plus an additive random measurement noise v_i, plus cable and motion artifact a_i. The random noise and process are zero-mean, band limited, wide sense stationary, correlation-ergodic and mutually independent. The high-pass filter stage removes the cable and motion artifact. The fixed whitening filter $H^{-1}_{\rm time}(e^{j\omega})$ produces a whitened EMG signal $s_i\hat{n}_i$, plus an altered additive noise $\hat{v}_i \cdot \hat{S}_{vv}(e^{j\omega})$ is the power spectral density (PSD) estimate of the additive noise (computed from a 0% MVC calibration contraction), $\hat{S}_{\rm mm}(e^{j\omega}, s_{\rm cal})$ is the PSD estimate of the surface EMG (computed from a 50% MVC calibration contraction), and $s_{\rm Cal}$ is a scaling coefficient typically normalized to 0.5 (corresponding to the 50% MVC calibration contraction). The adaptive Wiener filter $H_W(e^{j\omega}, \hat{s}_{\rm fp})$ then makes the optimum linear least squares estimate of the noise/artifact free whitened EMG based on first-pass unwhitened amplitude estimate $\hat{s}_{\rm fp}$. $\hat{S}_{\tilde{v}\tilde{v}}(e^{j\omega})$ is the PSD estimate of the additive noise after it passes through $H^{-1}_{\rm time}(e^{j\omega})$. Lastly, the adaptive gain correction $d(\hat{s}_{\rm fp})$ scales the signal to maintain, on average, the variance of the signal through the system. Gain factor $d(\hat{s}_{\rm fp})$ is also a function of $\hat{s}_{\rm fp}$ and the calibration contractions, as given in [8].

EMG data for epoch-based algorithms. With short epochs, these two competing factors form a tradeoff between shape of the filter and length of the usable data segment. The epoch-based algorithms presented in this paper use a least-squares filter design method (see [13] and MATLAB function "firls") to optimize the filter coefficients so that the optimal filter order is reduced. Coefficients are selected to minimize the mean squared error between the desired and achieved filter magnitude response. For many filter shapes, this technique characteristically produces a filter that more closely follows the desired magnitude response with fewer filter coefficients than the window filter design method. If more of the epoch is usable for amplitude estimation, more accurate estimates should result. For completeness, epoch-based adaptive whitening algorithms implemented using the window filter design method [13], which was used in the stream-based adaptive whitening algorithms [8], were also studied (see [14] for a full description). Since these algorithms produced poorer results overall, no quantitative results from this method will be presented.

B. Experimental Data

The data used for this project were collected previously from fifteen subjects. Full experimental details are available in [8]. Briefly, four channels of EMG were measured from both the biceps and triceps muscles. In addition, the torque about the elbow joint was measured using a dynamometer. Subjects produced constant-posture, nonfatiguing contractions about the elbow while tracking a random target between 50% maximum voluntary contraction (MVC) extension and 50% MVC flexion. The tests were divided into two groups, the first of which limited the tracking target's bandwidth to 1 Hz, while the second limited the bandwidth to 0.25 Hz. Data were recorded at a sampling frequency of 4096 Hz and 20 seconds of each dataset were used in analysis. For each subject there were three sets of data recordings, each consisting of five recordings per tracking speed. Calibration contractions at 0% and 50% MVC were also recorded.

C. Experimental Methods

For each EMG recording, one amplitude estimate per epoch was computed for every combination of the following testing parameters: EMG amplitude estimation technique (single-channel unwhitened, single-channel whitened, multiple-channel unwhitened, multiple-channel whitened), combined noise rejection/whitening filter order (6–60 in multiples of 6), and epoch duration (33, 42, and 80 ms, corresponding to FES stimulation rates of 30, 24, and 12.5 Hz, respectively). Multiple-channel processing used all four EMG channel recordings per muscle group. The multiple channels on one muscle were sufficiently uncorrelated spatially, that they only needed to be gain normalized prior to multiple-channel combination (c.f., [12]). One centrally-located EMG channel recording per muscle group was selected for use in single-channel processing. For all recordings, a blanking interval of 20 ms was removed to simulate the effects of stimulation artifacts [5], [6], and all data within an epoch rendered invalid due to filter startup transients were discarded prior to the smoothing stage of EMG amplitude estimation.

To evaluate the performance of the epoch-based EMG amplitude estimation algorithm, an EMGamp-torque relationship was fit to a training recording and then used to predict torque from a separate test recording. This method assumed that a more accurate EMG amplitude estimate results in a more precise torque estimate. For each epoch, the torque was averaged to obtain a single value. To train the EMGamp-torque relationship, a linear least squares solution to the linear dynamic system equation: $\mathrm{T}(i) = e_0E(i) + e_1E(i-1) + \cdots + e_NE(i-N) + f_0F(i) + f_1F(i-1) + \cdots + f_NF(i-N)$ was found [2], [3]. This equation relates torque (T) at sample i, to the present and N past samples of the EMG amplitude estimates of extensor (E) and flexor (F) muscles using the fit coefficients $e_0, e_1, \ldots, e_N$ and $f_0, f_1, \ldots, f_N$. This least squares solution was then used to estimate torque and compare against the measured torque in the test recording (RMS error was measured in percent flexion MVC, averaged across all epochs in a trial). A dynamic linear model was selected because it has been shown to capture a great deal of the EMGamp-torque relationship, and is commonly employed in the literature (c.f., [2]). Hence, comparison of the reduction of torque estimation error due to different EMG amplitude estimates can be related to other studies found in the literature. The order, N, of the EMGamp-torque model was varied from one to sixty to determine the model order's effect on torque estimation error. We used each of the five recordings, in each of the three data sets, as training data for the EMGamp-torque model and tested the remaining four recordings of that set with the model. This arrangement resulted in 60 training-test combinations per tracking speed for each subject, under each test condition. All computation was performed in MATLAB (The MathWorks, Inc., Natick, MA).

TABLE I

RMS TORQUE ESTIMATION ERRORS, COMPUTED ACROSS ALL TRAIN-TEST COMBINATIONS FOR ALL SUBJECTS, IN PERCENT FLEXION MVC. EACH CELL LISTS MEAN ± STANDARD DEVIATION. ERRORS ASSESSED AT THE OPTIMUM NOISE REJECTION/WHITENING FILTER ORDER (FOR WHITENED PROCESSORS)

	Slow Tracking				Fast Tracking			
Epoch Duration	Single-Channel Unwhitened	Single-Channel Whitened	Multiple-Channel Unwhitened	Multiple-Channel Whitened	Single-Channel Unwhitened	Single-Channel Whitened	Multiple-Channel Unwhitened	Multiple-Channel Whitened
80 ms	11.90±8.83%	10.49±7.05%	10.20±8.76%	9.22±6.68%	10.09±7.99%	9.15±6.83%	8.75±6.94%	7.93±5.94%
42 ms	11.98±8.87%	10.50±6.81%	10.36±9.16%	9.30±6.69%	10.16±7.93%	9.24±6.70%	8.67±6.54%	7.92±5.50%
33 ms	12.23±9.36%	10.70±6.90%	10.71±10.08%	9.48±6.86%	10.51±8.39%	9.44±6.78%	9.00±7.03%	8.14±5.48%

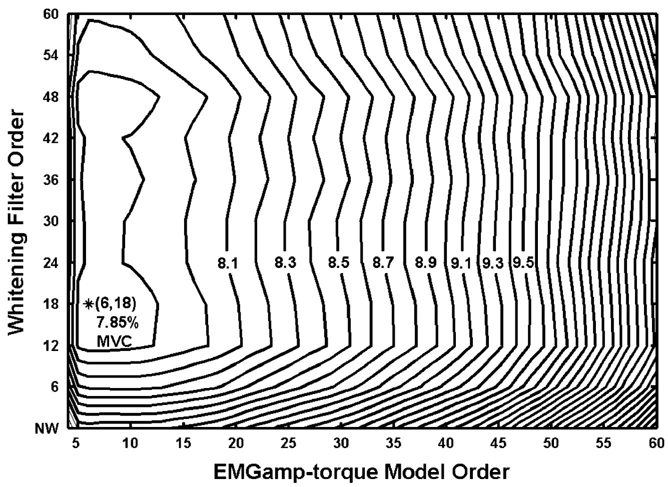

Fig. 2. Contour plot of EMG to torque estimation errors (averaged over all trials and subjects) as a function of EMGamp-torque model order and whitening filter order. NW corresponds to the error level without whitening. Test conditions: Multiple-channel, 80-ms epochs, fast-tracking task, least-squares filter design method. Asterisk shows location and error value of minimum. All errors are expressed in percent flexion MVC.

TABLE II

PERCENTAGE REDUCTION IN AVERAGE RMS TORQUE ESTIMATION ERRORS COMPARED TO RESULTS WHEN USING SINGLE-CHANNEL UNWHITENED AMPLITUDE ESTIMATES. ERRORS ASSESSED AT THE OPTIMUM NOISE REJECTION/WHITENING FILTER ORDER

	Slow Tracking			Fast Tracking		
Epoch Duration	Single-Channel Whitened	Multiple-Channel Unwhitened	Multiple-Channel Whitened	Single-Channel Whitened	Multiple-Channel Unwhitened	Multiple-Channel Whitened
80 ms	11.8%	14.3%	22.5%	9.3%	13.3%	21.4%
42 ms	12.4%	13.5%	22.4%	9.1%	11.5%	22.0%
33 ms	12.5%	12.4%	22.5%	10.2%	14.4%	22.5%

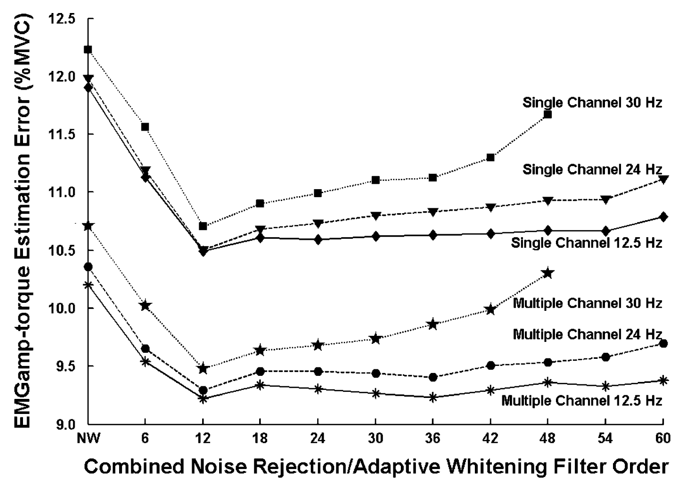

Fig. 3. Comparison of multiple- and single-channel results using varying epoch lengths for the slow tracking speed. Each plot shows the EMGamp-torque estimation error (in percent flexion MVC) versus the order of the combined noise rejection/adaptive whitening filter. NW corresponds to the error level without whitening. Top three plots are for single-channel EMG amplitude estimates, bottom three plots are for multiple-channel EMG amplitude estimates. Lines are an aid to the eye only.

III. RESULTS

The contour plot in Fig. 2 illustrates an example of the change in torque estimation error as the system identification and noise rejection/whitening filter orders were varied. For each test condition, the system identification model order at which the error in the contour plot was minimized was used for all subsequent analysis. Table I lists the RMS errors, averaged across all train-test combinations for all subjects, at the optimum noise rejection/whitening filter order. Table II lists the percentage improvement of each EMG processor, as compared to single-channel unwhitened estimates. Whitening single-channel EMG data provided a 9.1%–12.5% improvement over unwhitened single-channel estimates. Using multiple channels of EMG data without whitening yielded an 11.5%–14.4% improvement over unwhitened single-channel estimates. By subtracting the multiple-channel unwhitened percentages from the multiple-channel whitened percentages in the table, it is evident that whitening multiple-channel EMG data provided an additional 8.1%–10.5% improvement over unwhitened multiple-channel estimates.

Fig. 3 shows the influence of noise rejection/whitening filter order on EMGamp-torque estimation error for the slow tracking speed. The shorter epoch durations exhibited a more pronounced minimum error, while the longer epoch durations had a flat region after the minimum. For all conditions evaluated (including the fast tracking speed results), the lowest error occurred at a model order of either 12 or 18 (corresponding to a startup transient of 2.9 or 4.4 ms, respectively). This order is well below the filter order of 60 used in the stream-based adaptive whitening algorithm [8], leaving far more of the epoch available for amplitude estimation. Conversely, when the window filter design method was used, the best filter order was typically more than twice as long, varied considerably with the testing condition, and resulted in larger EMGamp-torque errors. Higher filter orders result in there being fewer samples with which to compute each amplitude estimate. Since estimation accuracy decreases as epoch duration decreases, shorter epochs result in higher average torque estimation error. This effect occurs for both single- and multiple-channels and can also be seen in Fig. 3.

Our results also found that whitened estimates gave lower torque errors than unwhitened estimates in a higher percentage of comparisons at the optimal filter order. For each of the 15 subjects, paired t-tests were performed on the differences in RMS estimation error (averaged over all epochs in a trail) between each filter order and unwhitened estimates (from the 60 train-test combinations for a set of testing parameters). At the optimal filter order (12 or 18), whitening yielded a statistically significant performance improvement for a total of 9–13 of the subjects (tests were computed to a significance level of 0.05), depending on the testing parameters.

IV. Summary and Conclusion

The results presented in this paper suggest that whitening can be used to improve EMG amplitude estimation for FES (and other systems that require epoch-based estimates). The improvement, evaluated via EMGamp-torque estimation errors, when going from single-channel unwhitened to multiple-channel whitened estimates was approximately 22%. Generally, half of this improvement was due to whitening, while the other half was attributed to the use of multiple-channel EMG. Furthermore, computing whitened single-channel estimates yielded roughly the same results as multiple-channel estimates without whitening. This result is consistent with the work presented in [8]. It is important to note that torque estimation was used as a proxy for EMG amplitude estimation, and a one-to-one relationship between them does not exist. For instance, even if the processing techniques provided perfect estimates of EMG amplitude, the resulting torque estimation error would not be 0% due to model inaccuracies and measurement errors. Thus, the percentage reductions in torque errors due to whitening and multiple channels likely underestimate the improvement in EMG amplitude estimator performance.

For the combined noise rejection/adaptive whitening filter, orders between 12 and 18 yielded both the lowest average error in estimated torque and the highest percentage of whitened estimates being an improvement over unwhitened estimates. The optimal order for the whitening filter also stays between 12 and 18 at each of the three epoch durations. The epoch-based algorithms presented in this paper were an improvement over the stream-based algorithms in terms of average error, optimal filter length, and filter length consistency. Filter design via the least-squares design technique might also be useful in stream-based algorithms when lower filter orders are beneficial (e.g., to reduce computational load in real-time applications). In summary, our best epoch-based, multiple-channel, adaptive whitening algorithm produced 21.4%–22.5% less error than the unwhitened single-channel technique in an EMGamp-torque estimation task.

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Analytical Model of Extracellular Potentials in a Tissue Slab With a Finite Bath

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***Abstract*—Extracellular potentials are often used to assess the activation and repolarization of transmembrane action potentials in cardiac tissue under a variety of experimental conditions. An analytical model of the extracellular potentials arising from a planar wavefront propagating in a three-dimensional slab of cardiac tissue with a variably thick adjacent volume conductor or bath is presented. Starting with the transmembrane potential, the model yields the extracellular potentials at various points in the bath and inside tissue. The results show that the analytical model produces signal timecourses with trivial computational costs that are similar to those computed from a full reaction-diffusion bidomain model with different bath thicknesses for tissue with uniform properties and for tissue with an abrupt ionic inhomogeneity.**

***Index Terms*—Bidomain, cardiac electrophysiology, extracellular potentials.**

I. Introduction

Extracellular potentials (ϕ_e) are often used to determine the time of cellular activation during propagation and, thus, provide spatial maps of the activation wavefront. In some situations, the signals are also used to access local and spatial changes in refractoriness, possibly revealing an arrhythmogenic substrate. Because the extracellular potential is the result of current sources throughout the tissue, it depends on many factors, including the timecourse of the transmembrane potential, the relative locations of the sensing and reference electrodes, the electrical conductivities of the intracellular and interstitial spaces and the size of the adjacent volume conductor. Numerically solving the full reaction-diffusion bidomain equations that govern cardiac current flow in three dimensions can require considerable computational resources.

Manuscript received January 25, 2004; revised July 2, 2004. This work was supported in part by National Science Foundation (NSF) under Grant DBI-9974533. *Asterisk indicates corresponding author.*

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Digital Object Identifier 10.1109/TBME.2004.840467