Electromyogram Bandwidth Requirements When the Signal is Whitened

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***Abstract*—Whitening the surface electromyogram (EMG) improves EMG amplitude ($\mathrm{EMG}\sigma$) and EMG-torque estimation. Laboratory studies utilizing contraction levels up to maximum voluntary contraction (MVC) show that whitening is useful over a frequency band extending to 1000–2000 Hz. However, EMG electrode systems with such wide bandwidth are uncommon, particularly in real-time applications; and these contraction levels are also not common. Thus, we studied the influence of the frequency band over which whitening was performed versus the resulting performance. Low-level, torque-varying contractions (average torque level of 18.5% flexion MVC) of the elbow were contrasted with medium-level 50% MVC constant-torque contractions. For each, the maximum whitening bandwidth was varied between 30–2000 Hz. The low-level contractions (which incorporate the contraction range of most daily tasks) showed that performance utilizing frequencies out to 400–500 Hz was not statistically different ($p < 0.01$) than results out to the full available frequency (2000 Hz). For the medium-level (50% MVC) contractions, frequencies out to 800–900 Hz were statistically equivalent to the full bandwidth. These results suggest that conventional electrodes with a typical passband of $\sim$500 Hz are appropriate when whitening data from contraction levels typically experienced in many applications. Wider bandwidths may be advantageous for strenuous activities.**

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

I. Introduction

WHITENING of the electromyogram (EMG) signal has been performed for several decades, dating back at least to the work of Kaiser and Petersen in 1974 [1]. Whitening temporally decorrelates EMG samples, reducing the variance of parameters that are extracted from it [2]–[11]. These parameters are used in various applications, including: myoelectric prosthesis control [12], ergonomic assessment [13], [14], clinical biomechanics [15], [16], motor control research [17], control of powered exoskeletons [18]–[22], and the actuation of powered rehabilitation devices [23]–[25]. In laboratory studies, whitened EMG processors have been shown to improve the signal-to-noise ratio (SNR) by 32%–65% in the assessment of constant-torque EMG [2], [3], [8], [9], reduce classification errors by 25%–50% in myoelectric multifunction selection [4], [11] and reduce EMG-torque estimation errors by 12%–26% [3], [26]–[30].

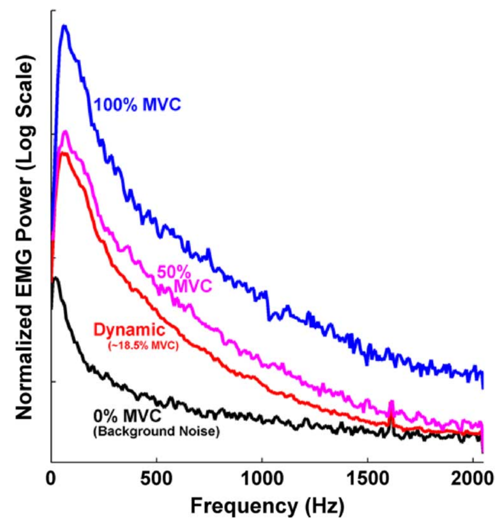

Fig. 1. Power spectra of EMG demonstrating amplitude modulated behavior. All spectra are from constant-posture contractions (see Section II). Top two plots show EMG power spectra at different MVC levels (100% and 50%) during constant-torque contractions. Plot labeled "Dynamic" is from force-varying contractions that averaged 18.5% MVC. Bottom plot is EMG during rest, representing the background noise level. All spectra computed using Welch's method. Subject LB09.

Referring to Fig. 1, the EMG spectrum peaks (mode frequency) at $\sim$100–150 Hz, then decays as the frequency increases. Accordingly, whitening filters exhibit their minimum gain in the frequency range of 100–150 Hz, with an increase in gain as the frequency increases [8]. At different effort levels, the EMG spectrum maintains the same general shape, but is amplitude modulated [3]. In contrast, EMG background noise is considered constant in spectral shape and amplitude. Hence, Fig. 1 depicts that the relative SNR as a function of frequency varies with the effort level; higher effort levels maintain a higher SNR. Whitening should be limited to those frequencies at which there is significantly more signal power than noise power. At high effort levels, there exists significantly more signal than noise out to higher frequencies. At low effort levels, there exists significantly more signal than noise out to a much lower frequency.

To resolve these contrasting whitening bandwidth needs, Kaiser and Peterson [1] implemented whitening with an adaptive analog filter. Their filter was comprised of a broadband fixed whitening filter, cascaded with an adaptive lowpass filter.

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At high effort levels, frequencies out to at least 1000 Hz were whitened; while at low effort levels, whitening was only applied at frequencies out to the EMG mode frequency. Filter shapes were a function of the analog components. A similar adaptive concept has since been implemented in discrete-time [31], [32]. This system cascades a fixed broadband digital whitening filter with an adaptive Wiener filter/noise canceller. The Wiener filter assumes a lowpass characteristic. These filters are tuned to the spectrum of each subject via two calibration contractions—one at rest (to estimate the noise spectrum) and another at a modest contraction effort, typically 50% maximum voluntary contraction (MVC). At 100% MVC, these filters whiten out to 2048 Hz (the Nyquist frequency).

In each of the above adaptive filtering methods, the EMG acquisition system incorporated a passband from just above dc out to 1000–2000 Hz. Such a wide passband is not characteristic of many commercially-available electrode systems (particularly when also considering the real-time computational requirements of some applications) and, thus, were custom-built by the respective investigators. Many commercial passbands for surface EMG systems only extend to $\sim$500–600 Hz, limited either by the analog electrodes or by sampling rates/processor computation power (e.g., the standard Delsys Inc., Bagnoli Desktop EMG Systems are limited by their acquisition system to a maximum frequency of 450 Hz). This bandwidth limit is consistent with the frequency band containing most of the EMG signal power (see Fig. 1 and [3]). While the wider passbands appear useful when whitening at high effort contractions, the vast majority of contraction levels in most EMG applications are relatively low (e.g., [33], [34]). Thus, the benefit of the custom passband and increased computation/throughput is unclear in these applications, particularly weighed versus their cost. In fact, the need for custom wide bandwidth electrode systems can be an impediment to adoption of whitening into these applications.

Thus, this project investigated the role of whitening bandwidth, contrasting low- and medium-intensity contractions from the same data set. The low-intensity contractions consisted of constant-posture, torque-varying contractions of the elbow, limited in effort over the range from 50% MVC extension to 50% MVC flexion. The $\mu \pm \sigma$ instantaneous contraction level was 18.5 $\pm$ 11.1% MVC flexion $(\mathrm{MVC_F})$. EMG was related to joint torque, with the rms error between actual torque and EMG-estimated torque serving as our performance measure. Medium-intensity contractions consisted of constant-posture, constant-torque contractions at 50% MVC. In this case, the more customary SNR was used as the performance measure. In each case, we characterized performance as a function of the whitening bandwidth. Preliminary results of this work appeared in [35].

II. Methods

A. Experimental Data and Experimental Methods

Experimental data from 54 subjects (30 male, 24 female; aged 37.6 $\pm$ 16.5 years) from three prior experimental studies were analyzed. This study was approved and supervised by the WPI IRB. All subjects had previously provided written informed consent. The three studies had nearly identical experimental apparatus and protocols (fully described in [31], [36]). Subjects were seated and secured with their shoulder abducted 90°, forearm oriented in a parasaggital plane, wrist fully supinated and elbow flexed 90°. Their right wrist was tightly cuffed to a load cell (Biodex dynamometer; or Vishay Tedea-Huntleigh Model 1042, 75 kg capacity) at the styloid process. The skin surface above the muscles under investigation was scrubbed with an alcohol wipe. In one study, a small bead of electrode gel was massaged into the skin. Four bipolar electrode-amplifiers were placed transversely across each of the biceps and triceps muscles, midway between the elbow and the midpoint of the upper arm, centered on the muscle midline. Each electrode-amplifier had a pair of 4-mm (or 8-mm) diameter, stainless steel, hemispherical contacts separated by 10 mm edge-to-edge, oriented along the muscle's long axis. The distance between adjacent electrode-amplifiers was $\sim$1.75 cm. A single ground electrode was gelled and secured above the acromion process or on the upper arm. Custom electronics amplified each EMG signal (CMRR of approximately 90 dB at 60 Hz) followed by bandpass filtering (either a second-order, 10–2000 Hz bandpass filter; or eighth-order highpass at 15 Hz followed by a fourth-order lowpass at 1800 Hz). All signals were sampled at 4096 Hz with 16-bit resolution.

After a warm-up period, MVC torque was measured in both elbow extension and flexion. Two repetitions of 5-s duration, constant-posture constant-torque contractions at 50% MVC extension, 50% MVC flexion and rest were recorded. A real-time feedback signal consisting of either the load cell voltage or a four-channel whitened $\mathrm{EMG}\sigma$ processor (formed by subtracting the extensor $\mathrm{EMG}\sigma$ from the flexor $\mathrm{EMG}\sigma$ [36]) was provided on a computer screen. Thirty-second duration, constant-posture torque-varying contraction trials were then recorded. The subjects used the feedback signal to track a computer-generated target that moved across the screen as a band-limited (1 Hz) uniform random process, spanning 50% MVC extension to 50% MVC flexion. Three trials were collected. At least 3 min of rest were provided between contractions to prevent cumulative fatigue.

B. Methods of Analysis

All analysis was performed offline in MATLAB. For all EMG-torque analyses, a four-channel, whitened (but bandwidth limited) EMG amplitude ($\mathrm{EMG}\sigma$—the time-varying standard deviation of the EMG signal) processor was used, one processor for the biceps muscles and separately one for the triceps muscles. For a processor, each of the four EMG channels was highpass filtered (15 Hz cutoff, causal, fifth-order, Butterworth filter) and notch filtered at the power-line and each harmonic frequency (second-order IIR filter, notch bandwidth $\leq$ 1.5 Hz). Each channel was then adaptively whitened across all frequencies (causal algorithm of Clancy *et al.* [31], [32], [37]). Whitening filters were calibrated from one of the constant-torque contraction sets, comprised of a 50% MVC extension, 50% MVC flexion, and a rest recording. To restrict bandwidth, the (full-band) whitened signal was lowpass filtered using a causal, ninth-order, Chebyshev Type I filter whose cutoff frequency was selectable. The cutoff frequencies investigated were: 30–200 Hz in increments of 10 Hz and 300–2000 Hz in increments of 100 Hz. After bandwidth restriction, each channel was first-order demodulated (i.e., absolute value) and the four channels were ensemble averaged.

The torque-varying contractions served as the low-intensity data set. For these data, each $\mathrm{EMG}\sigma$ signal was formed by decimating the ensemble average by a factor of 100 (effective lowpass filter prior to downsampling of 16.4 Hz, causal, ninth-order, Chebyshev Type I) to a sampling rate of 40.96 Hz. The torque signal was similarly decimated to 40.96 Hz, yielding $\mathrm{EMG}\sigma$ (input) data with bandwidth approximately ten times that of the (output) torque signal [38]. Extension and flexion $\mathrm{EMG}\sigma$s were related to joint torque via the parametric model [29]

$$T[m]=\sum_{d=1}^{D}\sum_{q=0}^{Q} e_{q,d}\sigma_E^d[m-q]+\sum_{d=1}^{D}\sum_{q=0}^{Q} f_{q,d}\sigma_F^d[m-q] \quad (1)$$

where T is the decimated torque signal at samples m, σ_E is the extension $\mathrm{EMG}\sigma$, σ_F is the flexion $\mathrm{EMG}\sigma$, $e_{q,d}$ are extension fit coefficients and $f_{q,d}$ are flexion fit coefficients. Integer Q sets the number of signal lags. When integer $D = 1$, the model is linear. When integer $D = 2$, a nonlinear dynamic model is facilitated. Model parameters were fit using the pseudo-inverse technique to regularize a least squares minimization [29], [39]. The tolerance (Tol) for removal of singular values was the ratio of the largest singular value to each other singular value in the design matrix. Based on a prior model optimization study utilizing non-causal processing [29], two optimal model forms (30th-order linear, $Tol = 0.0056$; 15th-order nonlinear, $Tol = 0.01$) were implemented. Models were calibrated (trained) from two of the torque-varying trials [29] and tested on the third trial per subject. This set of three trials utilized the same real-time feedback signal. The rms error between the measured torque from the load cell and the EMG-estimated torque on the test trial from each subject was expressed as a fraction of twice the torque at 50% MVC flexion $(\mathrm{MVC_F})$ of each subject. The first 2 s of signal were omitted from the rms error computation to account for filter startup transients. Error was evaluated as a function of the whitening cutoff frequency, with full bandwidth results (2000 Hz) serving as the reference.

The second set of 50% MVCs served as the medium-intensity data set. Extension electrodes from extension contractions and flexion electrodes from flexion contractions were analyzed separately. Initial EMG processing for each *individual* channel, through the demodulation stage, was the same as above. After demodulation, $\mathrm{EMG}\sigma$ was formed for each individual channel by performing a moving average, using a 125 ms smoothing window. For constant-torque contractions, it is customary to compare performance via the EMG SNR [40]. Thus, the SNR of each $\mathrm{EMG}\sigma$ was computed as the sample mean divided by the sample standard deviation. The first 250 ms of the signal was ignored, to account for filter startup transients. The SNR values from the four channels on one muscle were averaged and this value reported. SNR was evaluated as a function of the whitening cutoff frequency. All statistical comparisons were between pairs of data values and were computed using the paired sign test [41].

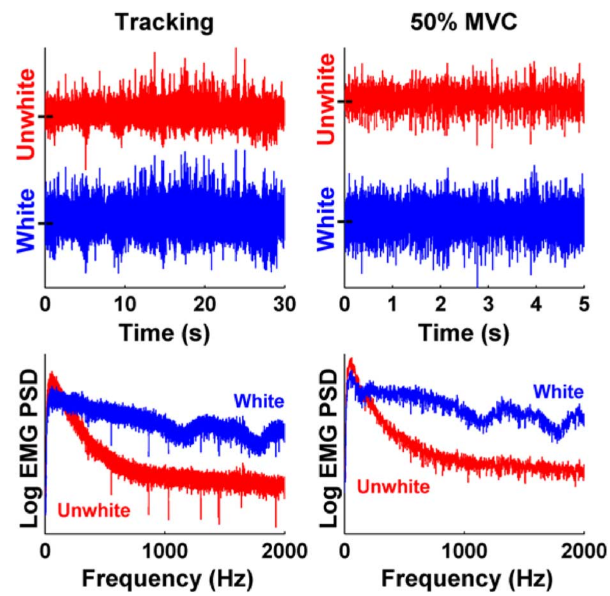

Fig. 2. EMG signals and their spectra, contrasting unwhitened versus whitened processing. Top left shows unwhite and corresponding whitened EMG signal during a 30 s tracking trial, superimposed on the same axis. Bottom left shows their spectra, each normalized to their respective total signal power. Plots at right show equivalent data from a 5-s duration 50% MVC trial. All spectra computed using Welch's method. Single-channel biceps EMG data from subject LA05.

III. Results

Fig. 2 shows sample EMG waveforms and their power spectral density estimates from both the low-intensity tracking trials and the medium-intensity 50% MVC trials, contrasting unwhitened versus whitened processing. While the effects of whitening can be subtle to visualize in the time domain (top plots) at this time-scale, the spectra (bottom plots) of the whitened signals are clearly flatter, as desired. Note that the spectra of the tracking trial exhibit noticeable downward spikes due to power-line notch filtering. Fig. 3 shows typical processed time-series plots—torque estimates for a low-intensity tracking trial and $\mathrm{EMG}\sigma$ estimates for a medium-intensity 50% MVC trial. The plots contrast full whitening bandwidth (cutoff frequency of 2000 Hz) versus greatly restricted whitening bandwidth (cutoff frequency of 100 Hz). As would be expected, poorer performance was found at the greatly restricted whitening bandwidth.

Fig. 4 shows $\mu \pm \sigma$ error results from 54 subjects versus the whitening cutoff frequency for the two parametric models (linear and nonlinear), corresponding to the low-intensity contractions. Lower errors correspond to superior performance. For both models, the error remained essentially flat for cutoff frequencies extending from 2000 Hz down to ~400–500 Hz. The error rose slowly thereafter as the cutoff frequency was reduced towards zero, until a rapid rise occurred for frequencies below approximately 50 Hz. For the linear model, the minimum error of $6.05 \pm 2.24\%$ $\mathrm{MVC_F}$ occurred at a cutoff frequency of 700 Hz, but this error did not differ significantly from the error at the maximum cutoff frequency of 2000 Hz $(p = 0.77)$. More importantly, however, was to test when error results first significantly departed from the minimum error at the 700 Hz cutoff frequency. Thus, we applied a *backward progressive* paired

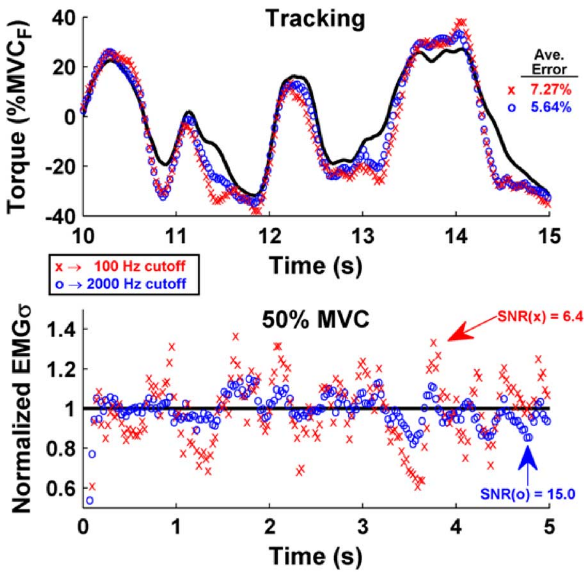

Fig. 3. Typical (low-intensity) torque tracking and (medium-intensity) $\mathrm{EMG}\sigma$ estimates at full bandwidth (2000 Hz cutoff) and restricted bandwidth (100 Hz cutoff). Top shows 10-s portion of the torque estimates from one trial, along with the actual torque (solid line). Trial errors in $\%\mathrm{MVC}_\mathrm{F}$ are listed. Bottom shows normalized $\mathrm{EMG}\sigma$ estimates, along with the ideal $\mathrm{EMG}\sigma$ (solid line). SNRs are listed. Note the $\mathrm{EMG}\sigma$ startup transient during the first 250 ms. Subject wx11 (single-channel biceps data used for 50% MVCs).

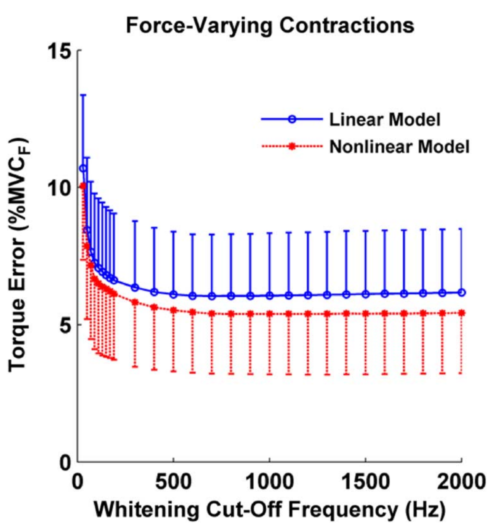

Fig. 4. Low-intensity torque-varying contraction results. Average plus (or minus) one standard deviation error (expressed in percent maximum voluntary flexion contraction—$\%\mathrm{MVC}_\mathrm{F}$) from 54 subjects versus the whitening cutoff frequency for the linear and nonlinear models, each using four EMG channels. Lower error corresponds to better performance.

sign test. Our backward progressive technique began with a paired sign test using data from the cutoff frequency of the error minimum and one backward frequency increment (i.e., 700 Hz and 600 Hz). If this result was nonsignificant $(p > 0.01)$, we widened the frequency span backward to 700 Hz and 500 Hz and recomputed the paired sign test. The frequency span was progressively increased until a significant difference $(p < 0.01)$ was achieved. That corresponding cutoff frequency indicated when the increasing error became statistically significant. This statistically significant change occurred at 400 Hz. For the nonlinear model, the minimum error of 5.39 ± 2.20% MVC_F

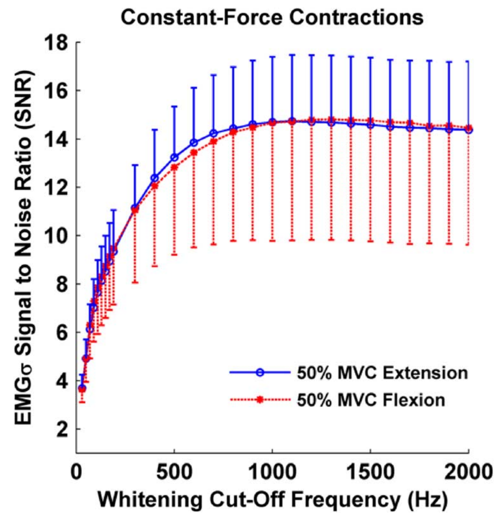

Fig. 5. Medium-intensity contraction results. Average plus (or minus) one standard deviation signal to noise ratio (SNR) from 54 subjects versus the whitening cutoff frequency for the extension and flexion 50% maximum voluntary contractions. All results are single-channel EMG. Higher SNR corresponds to better performance.

occurred at a cutoff frequency of 900 Hz, but this error did not differ significantly from the error at the maximum cutoff frequency of 2000 Hz $(p = 0.93)$. A backward progressive paired sign test found that the error first significantly deviated from the location of the minimum error (900 Hz) at a cutoff frequency of 500 Hz. Lastly, we contrasted the linear versus nonlinear model performances, pairing data from the minimum error location of each, respectively. The nonlinear model had a statistically significant lower error $(p < 10^{-4})$. Note that these lowest average error values, as well as the relative errors found when contrasting the linear to nonlinear models, are consistent with past analysis of a subset of these data [29].

Fig. 5 shows $\mu \pm \sigma$ SNR results from 54 subjects versus the whitening cutoff frequency for the 50% MVC constant-torque contractions, corresponding to the medium-intensity contractions. Higher SNRs correspond to superior performance. For both models, the error remained somewhat flat for cutoff frequencies extending from 2000 Hz down to ∼800–900 Hz. The SNR decayed progressively thereafter as the cutoff frequency was reduced towards zero. For extension contractions, the maximum SNR of 14.74 ± 2.75 occurred at a cutoff frequency of 1100 Hz, but this error did not differ significantly from the error at 2000 Hz $(p = 0.25)$. A backward progressive paired sign test found that the error first significantly deviated from the location of the maximum SNR (1100 Hz) at a cutoff frequency of 800 Hz. For flexion contractions, the maximum SNR of 14.81 ± 4.98 occurred at a cutoff frequency of 1300 Hz, but this error did not differ significantly from the error at 2000 Hz $(p = 0.34)$. A backward progressive paired sign test found that the error first significantly deviated from the location of the maximum SNR (1300 Hz) at a cutoff frequency of 900 Hz. Lastly, we contrasted the extension versus flexion performances, pairing data from the maximum SNR location of each, respectively. The results did not differ $(p = 0.55)$. Note that these highest average SNR results are consistent with past results in the literature [8].

IV. Discussion

Signal whitening has been used in *laboratory settings* to reduce the variability of parameters extracted from the EMG signal since at least the work of Kaiser and Petersen in 1974 [1]. Their work implemented a form of adaptive whitening (based on effort level) in an analog filter. Harba and Lynn [4] implemented whitening offline in software; continuing advances have been reported in the literature over the intervening years (see [40] and [42] for reviews). Unfortunately, few of these advances seem to have transitioned far outside of those research groups who have developed the techniques, and none have seemed to transition to commercial devices. One issue has been the historically limited amount of computation performed on microprocessor-controlled commercial devices in prosthetics, orthotics, and related areas [43], [44], although manufacturer experience and increases in microprocessor performance over time are likely mitigating this issue. Another issue is the complexity of whitening algorithms, particularly time-adaptive processing to attenuate noise [31]. To combat the challenge in algorithm complexity, Potvin and Brown [27] implemented whitening with a fixed, low-order FIR highpass filter. Of interest, their system sampled EMG at 1024 Hz, hence whitening only occurred out to a frequency of 512 Hz (the Nyquist frequency). Their implementation was inherently bandwidth limited.

The issue investigated in this paper was that of the bandwidth (maximum frequency) required when whitening. Wide bandwidths, out to 1000–2000 Hz have been successfully implemented in the laboratory [1], [31]. But, these wide bandwidths can require the development of custom wideband electrodes and necessitate more powerful microprocessors–factors which can impede the transition of whitening into real-time commercial devices. The literature suggested that the primary advantage of the wider bandwidths is at high contraction levels; such levels have been commonly tested in laboratory studies. However, most routine tasks and most applications of EMG processing primarily utilize the low range of muscle contraction force.

Our results in this study from the low-level contractions (Fig. 4) suggest that conventional electrodes with passbands out to 400–500 Hz and an inter-electrode spacing of 10 mm edge-to-edge capture *all* of the relevant EMG-torque information in our data, at least if $\mathrm{EMG}\sigma$ is the parameter of interest. This electrode passband and spacing is consistent with many common commercial electrode systems. Joint torque estimation is a common usage of $\mathrm{EMG}/\mathrm{EMG}\sigma$. We found that a cutoff frequency as low as 400–500 Hz was the first to exhibit torque estimation errors that were significantly different from that of the full-band signal (at least as defined using a significance level of $p < 0.01$). Although we termed our torque-varying contractions as "low-level," they span 50% MVC extension to 50% MVC flexion, with approximately equal use of each contraction level in between (uniform distribution). The average instantaneous contraction level was 18.5% $\mathrm{MVC_F}$. Hence, these contractions are representative of a wide class of daily muscle usages and, thus, EMG applications.

To contrast these results, we compared to medium-level, static 50% MVC contractions (Fig. 5). Since these contractions were constant-torque and non-fatiguing, SNR was used as the performance measure. This measure assumes that $\mathrm{EMG}\sigma$ is unchanging during the trial, but takes advantage of not having to assume/estimate a relationship between $\mathrm{EMG}\sigma$ and joint torque. At this higher contraction level, somewhat wider bandwidth proved advantageous, out to approximately 800–900 Hz. SNRs at cutoff frequencies of 800–900 Hz were first to differ statistically from the highest SNRs. This result is consistent with the data shown in Fig. 1 in which recorded EMG is closely represented as the sum of an amplitude modulated "true" EMG (i.e., noise-free) and background noise. As the EMG signal strength is increased, the frequency region over which there exists more signal than noise also increases. These regions can be successfully whitened. Many commercial electrode systems may not facilitate this full bandwidth, thus reducing (but not eliminating) the improvement due to whitening. Of course, when the EMG signal is *not* whitened, this wider bandwidth is not necessary.

Hence, the required bandwidth for whitening seems largely related to the noise power relative to the true EMG power, as a function of frequency. Logically, increased bandwidth could be utilized if noise power can be reduced. However, noise power due to the acquisition electronics is typically only a few μVs rms [45] or about 1% of the rms level at MVC [31]. Additional noise sources, including electrode–skin interface noise, only increase the total rms noise to approximately 3% of the rms level at MVC [31]. Hence, large reductions in noise are unlikely, at least for conventional surface EMG with standard skin site preparation.

Our inter-electrode spacing of 10 mm edge-to-edge is typical of many commercial electrodes. However, smaller electrode spacing leads to increased statistical bandwidth of the acquired EMG signal [3], which might then permit whitening out to higher frequencies. Additionally, other factors can influence the bandwidth of the EMG signal. For example, localized muscle fatigue tends to compress the spectrum towards lower frequencies [46]. The resulting reduced bandwidth would likely reduce the range over which whitening should be applied. Finally, other contraction profiles/dynamics might also influence the average contraction level or the EMG spectrum [47]—each of which influences the whitening bandwidth.

Although we contrasted results from two different contraction levels, the actual comparison measure varied (EMG-torque error and SNR). However, each measure is applicable to the contraction type studied. For constant-torque contractions, use of the SNR avoids the need for a model relating $\mathrm{EMG}\sigma$ to torque. Since torque was largely held constant during these contractions (no dynamics or even any change in torque level occurred), a model serves little purpose other than to set a system gain. SNR is gain invariant, thereby avoiding the issue altogether. For dynamic (torque-varying) trials, a dynamic $\mathrm{EMG}\sigma$-torque model is required. In either case, we studied *relative* changes in performance, which should be more robust to variations in the performance measure. Other factors that might influence the interpretation of these results include the use of alternative electrode shapes and inter-electrode distances, and the extraction of other features from the EMG signal (e.g., zero crossing rate and average signal length). In particular, whitening has been shown to reduce classification errors by 25%–50% in myoelectric multifunction selection when utilizing $\mathrm{EMG}\sigma$, zero crossing rate and average signal length [4], [11], but the role of whitening bandwidth was not investigated. Since most EMG-based multifunction classification utilizes lower-effort contractions, we would hypothesize that the bandwidth requirement of 400–500 Hz provided by our lower-level contractions would be applicable. However, direct evaluation of this hypothesis in the future seems appropriate.

In this offline study, we limited whitening bandwidth via the use of a lowpass filter inserted after EMG had been whitened to the full Nyquist frequency (2048 Hz). This method was convenient for off-line study of performance versus whitening bandwidth, but would clearly be inefficient in a real-time system. In practice, anti-aliasing lowpass filters would be applied at the desired whitening cutoff frequency and the signal appropriately sampled at a rate that is a least twice this frequency. Presumably, this rate is well below the rate of 4096 Hz used in this study. Whitening would then be performed in its normal manner, over the full Nyquist frequency, without further bandwidth restriction.

Another advantage of reduced-bandwidth whitening is related to power line interference. At high frequencies (e.g., above 500 Hz), power line interference can easily be larger in magnitude than the EMG signal power. Since whitening accentuates the higher frequency range via high gains, our own whitening algorithms now apply notch filters at the power line frequency and each of its harmonics. For offline analysis utilizing double precision floating-point arithmetic, very sharp filters are readily achieved. However, many real-time applications are limited to fixed-point arithmetic, in which such narrow notch filters present a challenge. Reduced-bandwidth whitening may eliminate this problem altogether by simply avoiding these troublesome frequency bands.

In summary, we conclude that the torque-varying contractions studied in these experiments only require a frequency bandwidth of 400–500 Hz when whitening is applied, at least when $\mathrm{EMG}\sigma$-torque is studied. These contractions uniformly occupied the torque range from 50% MVC extension to 50% MVC flexion (average instantaneous contraction level of 18.5% $\mathrm{MVC_F}$)—thus they include contraction levels at or above typical muscular exertions. Medium-level contractions (e.g., constant-torque 50% MVC contractions) benefit from a bandwidth out to approximately 800–900 Hz. Contractions at even higher levels would presumably benefit from an even wider frequency band.

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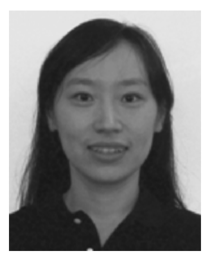

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