Simplified Whitening Filtering in the Processing of the Electromyogram

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Four different electromyogram (EMG) whitening implementations were studied with an optional noise correction stage. Most applications require a raw surface EMG to be processed to extract meaningful information about muscular activity [1, 2]. Many applications, including prosthesis control [3–5], estimation of joint torque [6–11] and mechanical impedance [12–17], require an estimate of the EMG standard deviation (EMGσ). The stages typically used to achieve an EMGσ estimate [18] are expressed in Figure 1. Whitening filters are included in EMG processing to temporally uncorrelate the samples. Previous research has shown that whitening preserves the average value of EMGσ while reducing its variability [19–21], which benefits applications that include this stage [6, 7, 22, 23]. In this study, the primary focus was to implement and compare performance of four distinct whitening methods with the goal of identifying a simpler method that maintains equal or comparable processing performance. Additionally, the influence of the noise correction stage was also considered. Noise correction was implemented as the square root of the noise estimate's variance subtracted from the square of the processed EMG, denoted root difference of squares (RDS) [24].

The first (and most complex) whitening filter is formed from the cascade of: 1) a fixed subject-specific whitening filter (i.e., calibrated to each specific subject), 2) an adaptive Weiner Filter for noise cancellation, 3) an adaptive gain stage and 4) a fixed whitening bandwidth limiting lowpass filter [19, 25]. This approach requires calibration data (active and rest EMG) for each individual subject. The second whitening filter was a universal whitening filter (i.e., same filter used for all subjects) created from the ensemble average of the magnitude responses of the whitening filters developed for each electrode of each subject. Once the ensemble filter shape was determined, a 2nd-order IIR universal whitening filter was produced using the novel differential evolution filter design method [26–28]. Both the subject-specific filters and universal whitening filter included the adaptive Weiner filter noise cancellation stage. The third whitening filter was a simple 1st-order Butterworth highpass filter with a cutoff frequency of 410 Hz, initially developed by Potvin and Brown [29]. We optimized this cutoff frequency selection to minimize EMG-force RMS error (see below). The low order of this filter coupled with its relatively high cutoff frequency yields a magnitude response similar to a whitening filter. This cutoff frequency must still be optimized to the application, but *not* to each subject. The fourth whitening method was the first difference [30, 31] of the EMG signal, which also has a magnitude response shape similar to that of a subject-specific whitening filter and does not require calibration.

To compare the performance of these four whitening filters, each was applied to processing of force-varying and constant-force contractions captured from 64 subjects (eight electrodes total per subject, four over the biceps and four over the triceps). WPI's IRB exempted these de-identified data from supervision (File 10-100). Force-varying contraction data were captured over 30 seconds as subjects tracked a random target spanning 50% extension to 50% flexion of the elbow. The target trajectory was uniform in its force

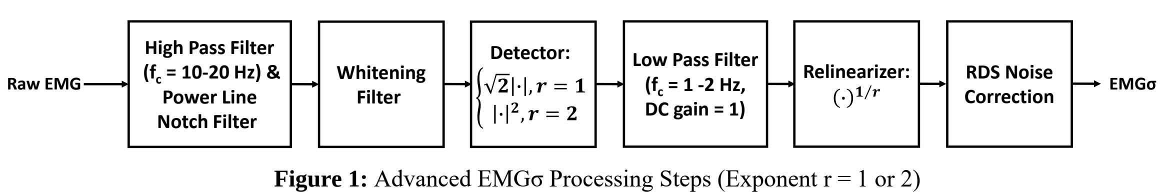

Figure 1: Advanced EMGσ Processing Steps (Exponent r = 1 or 2)

distribution, with a band-limited white power spectral density from 0-1 Hz. This broad range of forces is ideal for evaluating the different whitening filters. Unfortunately, the force-varying data do not offer insight into performance of the whitening filters for low effort levels, e.g. 0% maximum voluntary contraction (MVC) (rest). At lower effort levels, the influence of RDS noise correction is more dramatic because additive noise is greater in magnitude relative to EMGσ than at higher effort levels [32, 33]. To study whitening filters during rest, constant-force contraction data at 0% MVC and 50% MVC were used (5s duration per trial). A sampling rate of 4096 Hz was used for all data with a whitening band limit of 600 Hz. EMGσ was computed with and without RDS noise correction to compare its influence coupled with the whitening filters.

Table 1. Dynamic task mean ± std. dev. EMG-force errors (% MVC) vs. whitening method (*N*=64 subjects). Smaller error denotes better performance.

Whitening Method	RDS On	RDS Off
None	5.55 ± 2.4	—
Subject-Specific	4.86 ± 2.06	4.85 ± 2.04
IIR	4.95 ± 2.20	4.92 ± 2.17
Highpass	4.98 ± 2.15 (2047 Hz)	4.98 ± 2.15 (2047 Hz)
First Diff.	5.00 ± 2.16	4.99 ± 2.16

Table 2. Static task mean ± std. dev. ratios of 0% to 50% EMGσ vs, whitening method (*N*=64 subjects). Smaller ratios denote better performance.

Whitening Method	RDS On	RDS Off
Subject-Specific	0.048 ± 0.096	0.074 ± 0.076
IIR	0.066 ± 0.100	0.089 ± 0.082
Highpass	0.051 ± 0.096	0.098 ± 0.092
First Diff.	0.051 ± 0.095	0.096 ± 0.091

To compare performance of each whitening filter when applied to the force-varying data, EMGσ computed from one contraction trial was used to train an EMGσ-force model via regression [6]. The EMG-force model was a 15th-order quadratic FIR filter for each channel, fit using the Moore-Penrose pseudo-inverse. The RMSE between the force estimate and force measured on a separate trial was used as a metric of whitening performance. Because the other stages in the EMGσ processing are the same, any changes in the RMSE between the estimated and actual force are a result of the whitening filter. Table 1 summarizes RMSE mean and standard deviation error computed across the 64 subjects for each whitening filter with and without RDS processing.

For the constant force data, the average 0% MVC EMGσ was divided by the average 50% MVC EMGσ for each of eight electrodes per subject. Table 2 summarizes these ratio results with and without the RDS stage (across 64 subjects). A smaller magnitude ratio value represents better performance. Figure 2 displays the individual ratios for each subject and electrode.

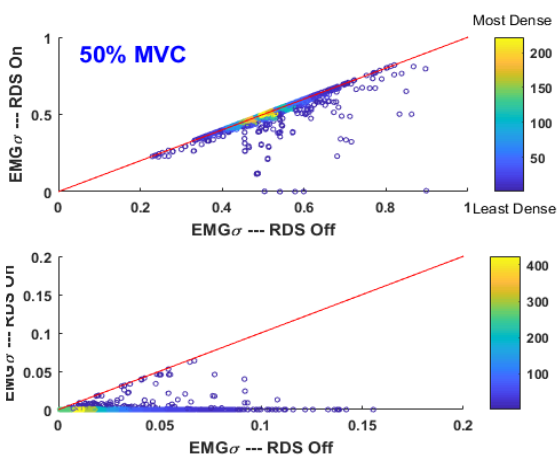

Figure 2: Heat scatter plot of the average 0% and 50% MVC with and without RDS enabled. RDS does not significantly alter the magnitude of the 50% MVC data as most points fall on the line of agreement. At 0% MVC, many of the ratios fall below the line of agreement. N = 64 subjects by 8 electrodes = 512 comparisons per test condition. Color scaled to number of comparisons. Note the axis scales are different between the two plots.

Because Shapiro-Wilk tests found the resulting data to be non-Gaussian, pair-wise statistical comparisons used the Wilcoxon signed-rank test (with Bonferroni-Holm adjustment) and tests between more than two groups used Friedman's test. For the dynamic data, no significant differences were found between the data with RDS on vs. off. For the constant force data, RDS on was significantly better than RDS off. Further statistical tests only considered data with RDS on. Friedman's test compared the four whitening filters. No significant differences were detected for the dynamic data, except that all performed better than data without whitening. For the constant-force ratios, subject-specific whitening performed better than the other whitening methods.

With the goal of developing a simpler whitening filter method, four different whitening implementations were studied and compared. Overall, all whitening methods performed better than no whitening. The best average EMG-force performance was demonstrated by the subject-specific whitener, then the universal IIR whitening filter, the 1st-order Butterworth highpass filter and the first difference. But statistical analysis of these dynamic data found no significant differences between them. Statistical analysis of the constant force data found RDS significantly reduced the influence of noise at lower effort contractions. Depending on the application and its requirements, one of the simpler whitening methods studied may be a suitable choice. In particular, the first difference filter performs well and requires no calibration or implementation decisions. Potvin and Brown's highpass filter requires the cutoff frequency of the filter to be optimized for a specific application, but once this cutoff is identified, the implementation is a simple 1st-order filter. The universal whitening method uses a higher order filter but relies on a set of known filter coefficients. Subject-specific whitening requires the most overhead to calibrate to each unique subject. Choice of whitening filter implementation should be made given the requirements of each application.

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