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

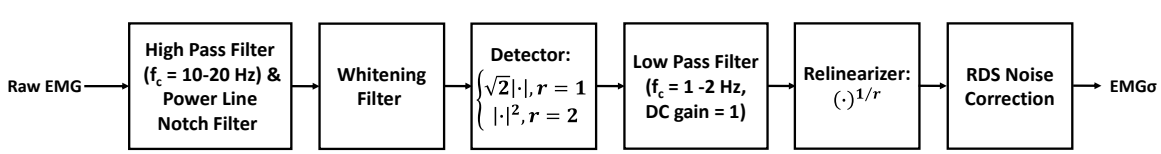

Figure 1: Advanced EMGσ Processing Steps (Exponent r = 1 or 2)

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.

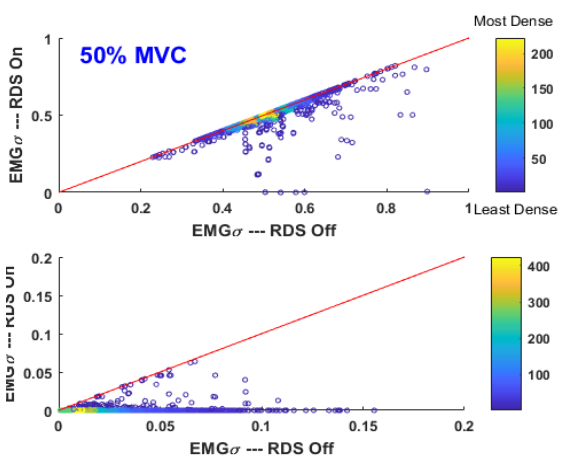

Figure 2: Heat scatter plot of the average 0% and 50% MVC with and without RDS enabled. RDS does not significantly alter the magnitude of the 50% MVC data as most points fall on the line of agreement. At 0% MVC, many of the ratios fall below the line of agreement. N = 64 subjects by 8 electrodes = 512 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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Simplified Whitening Filtering in the Processing of the Electromyogram

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Abstract

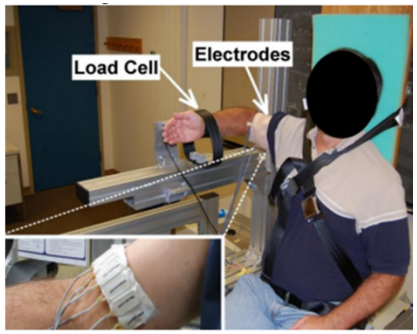
- An electromyogram (EMG) is the measurement of the electrical activity of muscles. In most applications, the raw EMG measured on the surface of the skin requires additional signal processing to extract information about the muscle's activity.
- The standard deviation of the EMG signal (EMGσ) is often computed as a metric of neural input to the muscle. Inclusion of the optional whitening filter in the computation of EMGσ reduces variability of EMGσ which, in turn, increases the signal-to-noise ratio.

High Pass Filter (f_c = 10-20Hz) & Power line notch filtering
↓
Whitening Filter
↓
Detector (Absolute value or square)
↓
Low Pass Filter (fc = 1-2 Hz)
↓
Relinearize (only required if square detector is used)
↓
Noise Correction

- To simplify the whitening stage, four whitening methods of varying complexity were implemented, and their performance compared.

Capturing the EMG Data

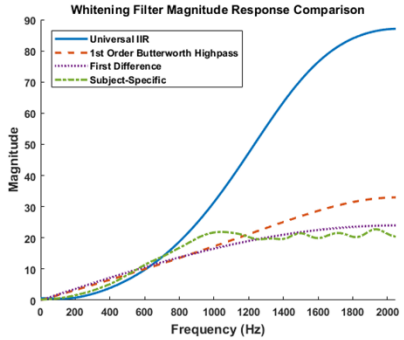
- The experimental data used for this analysis were captured from 64 able-bodied subjects. Subjects were seated and secured as shown in the photo below:



- Eight bipolar electrodes were placed on each subject (plus a reference electrode). Four electrodes were placed above the biceps, and four above the triceps.
- Force-varying data in the range of 50% MVC extension to 50% MVC flexion of the elbow were captured over 30 s as subjects tracked a random target (1 Hz bandwidth) displayed on a computer.
- Constant-force data were captured over a 5 s interval at 0% MVC (rest) and 50% MVC.
- All data were sampled at 4096 Hz with a whitening band limit of 600 Hz.

Whitening Filter Developments

1. The first and most complex filter to implement is a subject-specific whitening filter. This filter is custom designed to each subject, so calibration data are required to create each filter.
2. The second filter is the universal IIR whitening filter. This filter was developed using the ensemble average of the subject-specific whitening filters from all 64 subjects. Once the desired filter shape was known, a universal IIR filter was developed with a similar magnitude response via the novel differential evolution filter design method.
3. The third filter considered was a simple 1st order Butterworth highpass filter. The optimum cutoff frequency of this filter for our analysis was 410 Hz. This cutoff frequency was selected to minimize the RMS error computed when modelling EMG to force.
4. The final whitening method is the first difference filter. This is the simplest filter as no implementation decisions are required and calibration data are not required.



Noise Correction

- When EMG is measured, noise from the environment (electromagnetic interference, noise related to the measurement device(s), noise at the electrode-skin interface, influence from other electrical signals on the body) is present in the measurement.
- The optimal noise correction is the square root of the difference of the squared EMGσ and the noise variance.

$$\hat{s}_{MAV} = \sqrt{\max(0, (\sqrt{2}MAV)^2 - q^2)},$$

where MAV is the EMG data, q^2 is the variance of the noise and $\hat{s}_{MAV}$ is the noise corrected processed EMG

- At rest, the influence of additive noise is greatest. Noise correction is beneficial across efforts levels but shows the greatest impact for rest contractions.
- To study the influence of the noise correction stage with the 4 different whitening filters, constant-force contractions at 0%MVC (rest) and 50%MVC were used in this study.

Testing the Whitening Filters

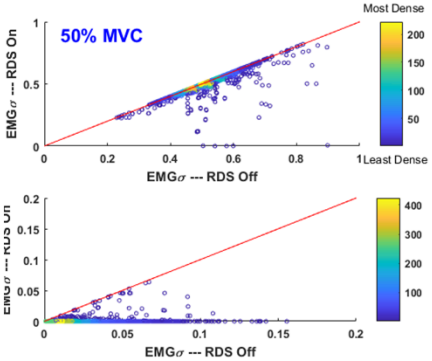
- Each of the four filters was applied to the force-varying data as well as the constant-force contractions (0%MVC and 50%MVC) with and without the RDS noise correction included.
- To compare the performance of the whitening filters when applied to the force-varying data, the processed EMG was used to model force about the elbow. The EMG-force model was a 15th order quadratic FIR filter for each channel and was fit using the Moore-Penrose Pseudo-inverse. The RMS error between the actual force measurement and estimated force acts as a performance metric. Because all other processing stages remain unchanged, any variation in the RMSE is a result of the whitening filter. The table below shows the mean and standard deviation of the EMG-force errors for the force-varying data.

Whitening Method	RDS Enabled (%MVC)	RDS Disabled (%MVC)
Subject-specific	4.86 ± 2.06	4.85 ± 2.04
Universal IIR	4.95 ± 2.20	4.92 ± 2.17
Highpass (2047 Hz)	4.98 ± 2.15	4.98 ± 2.15
First Difference	5.00 ± 2.16	4.99 ± 2.16

- For the constant-force data, the average value for each channel for each subject was computed. The average value of the 0% MVC was compared to the 50% MVC as a ratio. A summary of the average ratio computed across all channels for all subjects is shown in the table below:

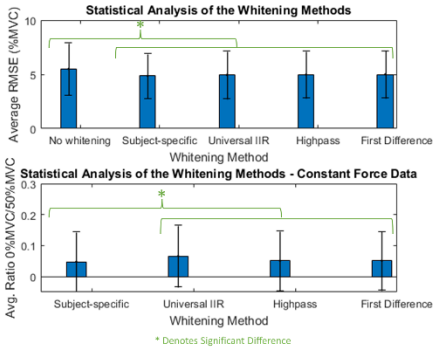
Whitening Method	RDS Enabled	RDS Disabled
Subject-specific	0.048 ± 0.096	0.074 ± 0.076
Universal IIR	0.066 ± 0.100	0.089 ± 0.082
Highpass	0.051 ± 0.096	0.098 ± 0.092
First Difference	0.051 ± 0.095	0.096 ± 0.091

- To capture the influence of RDS on lower effort level contractions, the heat scatter plot below shows the average 0% MVC and 50% MVC with and without RDS enabled. Each point represents the average value for each of the 8 electrodes per each subject (64 subjects) for each filter tested.



Statistical Results

- Shapiro-Wilk testing showed that the result data were non-Gaussian. Wilcoxon signed-rank test with Bonferroni adjustment was used for pair-wise statistical comparisons. If more than two groups were tested, Friedman's test was used.
- When looking at the force-varying data, no significant differences were found between the data with and without RDS enabled. For the constant-force data, significant differences were detected between the data with and without RDS enabled.
- To compare the whitening filters, only data with RDS enabled were considered.



- Overall, each whitening method performed better compared to data without whitening but did not differ from each other. Depending on the application and its requirements, one of the simpler whitening methods may be suitable.
- It is recommended to always include root difference of squares processing for noise correction. This stage is not difficult to implement and can significantly reduce additive noise at low effort level contractions.

Summary

- All whitening filter methods performed better than not whitening. No statistical differences were detected between the four methods studied.
- The subject-specific whitening filter requires calibration data to develop the filter custom to each subject.
- The universal filter relies on a set of known filter coefficients and does not require any implementation decisions to be made.
- The 1st-order highpass filter requires the cutoff frequency to be optimized for each application, but the filter implementation is simple.
- The simplest method, the first difference had the highest average error of the whitened techniques, but was not statistically different. This method offers comparable performance with a significantly simpler implementation that the other methods.