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Modeling Nonlinear Errors in Surface Electromyography Due To Baseline Noise: A New Methodology

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Abstract

The surface electromyographic (EMG) signal is often contaminated by some degree of baseline noise. It is customary for scientists to subtract baseline noise from the measured EMG signal prior to further analyses based on the assumption that baseline noise adds linearly to the observed EMG signal. The stochastic nature of both the baseline and EMG signal, however, may invalidate this assumption. Alternately, “true” EMG signals may be either minimally or nonlinearly affected by baseline noise. This information is particularly relevant at low contraction intensities when signal-to-noise ratios (SNR) may be lowest. Thus, the purpose of this simulation study was to investigate the influence of varying levels of baseline noise (approximately 2 – 40 % maximum EMG amplitude) on mean EMG burst amplitude and to assess the best means to account for signal noise. The simulations indicated baseline noise had minimal effects on mean EMG activity for maximum contractions, but increased nonlinearly with increasing noise levels and decreasing signal amplitudes. Thus, the simple baseline noise subtraction resulted in substantial error when estimating mean activity during low intensity EMG bursts. Conversely, correcting EMG signal as a nonlinear function of both baseline and measured signal amplitude provided highly accurate estimates of EMG amplitude. This novel nonlinear error modeling approach has potential implications for EMG signal processing, particularly when assessing co-activation of antagonist muscles or small amplitude contractions where the SNR can be low.

Keywords

EMG; Baseline; Error; Signal processing

Introduction

Surface electromyography (EMG) is extensively used to estimate muscle activation during muscle contractions (Dowling, 1997; Kellis, 1998; Kellis and Baltzopoulos, 1999; Kellis and Katis, 2008). The surface EMG signal is comprised of electrical signals from the

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contracting muscle and various noise components, such as thermal noise, electrochemical noise, power line noise, movement artifact, etc. (Clancy, et al., 2002; De Luca, et al., 2010; Huigen, et al., 2002). Thermal noise originates from the electronics of the amplification system, whereas the electrochemical noise is produced from fluctuations in electrical potential at the skin-electrode interface (Flasterstein, 1966; Godin, et al., 1991). Advances in technology have minimized the effects of extrinsic noise sources, such as power line and cable motion artifact, but thermal and electrochemical noise remain unaffected (De Luca, et al., 2010).

Baseline noise contamination can be particularly problematic when analyzing EMG signals with low signal-to-noise ratios (SNR) (Baratta, et al., 1998; Clancy, et al., 2002). For example, assessments of antagonist muscle co-activation can range from no activity (0% maximum) to moderate activation (over 50% maximum), despite an otherwise “clean” signal. Under the assumption that baseline noise adds linearly to the observed EMG signal, researchers often subtract the baseline signal from the measured EMG signal prior to further analyses (Hodges and Gandevia, 2000; Krishnan and Williams, 2009, 2010; Yao, et al., 2007). The validity of this approach, however, has not been fully verified through investigation. Because the amplitude of EMG is stochastic in nature, it is conceivable that the contribution of baseline noise to the measured EMG signal amplitude may either be minimal, or vary nonlinearly as a function of both the baseline and measured EMG signals. Therefore, the purpose of this study was to assess the influence of random baseline noise on EMG signals of varying intensities through simulation, and determine an optimal method to account for baseline artifact for use in mean amplitude assessments of discrete periods of EMG activity.

Materials & Methods

Signal Simulation

A single burst of quadriceps muscle activity obtained during a maximal knee extensor contraction (60 deg/sec, ~1.4 sec) as part of a separate investigation was isolated for the purpose of this study. All human data collection was approved by the local Institutional Review Board, with written informed consent obtained. The EMG signals were collected at 1000 Hz with a 20 – 450 Hz band-pass anti-aliasing filter (Delsys Bagnoli, Boston, MA), using custom LabVIEW software (v. 8.1, National Instruments Corp., Austin, TX, USA) and a 16-bit data acquisition card (National Instruments). A 10-second (1000 Hz) zero-baseline vector was added to the EMG signals using a custom program written in LabVIEW to simulate a “pure” zero baseline. The EMG signals were then halved three times and appended to create four EMG bursts of varying amplitude: 100%, 50%, 25% and 12.5% of maximum.

Random Gaussian white noise with a sampling frequency of 1000 Hz was created using the “simulate signal” subVI in LabVIEW, producing a signal with a mean of 0 and standard deviation of 1 (Clancy and Hogan, 1997; Clancy, et al., 2002). This noise vector was then band-pass filtered (20 – 450 Hz) and scaled to achieve random noise signals ranging from approximately 2% to 40% of the burst EMG maximum. A second experimentally-derived baseline signal, collected during a quiet EMG signal (Delsys, filtered 20-450 Hz), was scaled to similar magnitudes as the simulated noise and analyzed for comparison. The baseline noise signals were added to the simulated “true” EMG bursts to create multiple sets of EMG data with various levels of baseline noise (see Figure 1A).

Signal Analysis

The EMG data were rectified and low-pass filtered at 20Hz (linear envelope) with a digital recursive Butterworth filter (see Figure 1B). The root mean square (RMS) EMG activity during each of the four, 1.4 sec bursts were assessed at each simulated baseline level, including the zero baseline, and normalized to the maximum RMS activity (% max) using an automated, custom LabVIEW program. The resulting error was calculated by subtracting the measured normalized EMG activity for each burst from its corresponding “true” value with zero baseline noise (i.e., 100%, 50%, 25% and 12.5% max).

Error Assessment

Three techniques were compared to assess the effect of baseline noise on EMG burst amplitudes and how to best account for noise: 1) no correction; 2) simple linear baseline subtraction (prior to % max EMG standardization); and 3) a new, nonlinear error subtraction technique (following % max EMG standardization). The simple difference between final measured (uncorrected or corrected) EMG burst amplitude (% max) and “true” burst amplitude (% max) were compared. In addition, relative errors were calculated as these simple errors divided by the reference (true) EMG amplitude (% reference). SNRs were determined for each burst amplitude (A_s) and noise amplitude (A_n) combination in decibels (dB) as $20 \cdot \log(A_s/A_n)$, using the uncorrected signals. Thus, A_s was assessed as the measured signal rather than the “true” underlying signal, consistent with what is possible in practice.

To create the nonlinear error model for the third technique, the error data resulting from the no correction approach (measured – true EMG amplitude) were plotted (Figure 2) as a function of measured EMG (uncorrected) and baseline noise intensities. The resulting 3D surface was fit (Table Curve 3D, Systat, Inc., San Jose, CA) to over 3000 linear and nonlinear equations to determine one possible optimal error model, utilizing a minimum number of parameters (e.g. simplest model possible) while maximizing the model fit (R^2). The modeled errors were then subtracted from the measured values to calculate “nonlinearly corrected” EMG burst amplitudes.

Validation

To validate these findings, a 2nd set of scaled EMG bursts with varying levels of simulated and experimental noise were created, as previously described, using EMG bursts derived from an elbow flexor muscle. The signal was obtained from a different subject from an unrelated investigation. The EMG burst amplitudes were assessed using: no correction, correction via baseline subtraction, and nonlinear error correction (using modeled parameter values). The resulting errors (measured minus true amplitude) were calculated for all methods.

Results

Baseline noise had minimal effects on the amplitude of EMG activity when the discrete EMG burst signal-to-noise ratio (SNR) was at its maximum. However, errors increased nonlinearly with increasing noise levels and decreasing burst signal amplitude (Figures 1 and 2). Accordingly, noise artifact was most profound for low intensity EMG bursts, as might be expected during relatively quiet periods of muscle activity.

The uncorrected EMG burst amplitudes overestimated actual EMG values as the SNR decreased (see Table 1 & Figure 3). On the contrary, traditional baseline subtraction consistently underestimated the actual submaximal EMG amplitudes. The resulting errors

(uncorrected minus true EMG amplitudes) were well fit by a three parameter nonlinear equation:

$$\ln(\text{error}) = A + B(\text{measured EMG}) + C(\ln(\text{noise}))^2$$

This nonlinear error model explained 99.3% of the variation in the observed error (see Figure 2) with parameter values of: $A = -0.42251$, $B = -0.05668$, and $C = 0.44910$.

The associated errors for both the uncorrected and baseline subtraction methods were small for EMG amplitudes that were $\geq 50\%$ of maximum, irrespective of the noise. The lower intensity bursts, however, were highly affected by even moderate baseline noise. Using the nonlinear error model to correct EMG signal amplitude decreased errors to $\leq 3\%$ max even at low SNRs (Table 1), for both test and validation EMG tracings with simulated or experimental noise. Only the data obtained using the experimentally-derived baseline noise are provided in Table 1 for brevity.

Discussion

The purpose of this study was to assess the best correction technique for varying levels of baseline noise on measured EMG signal amplitudes. The findings of this study indicate that: 1) baseline noise adds nonlinearly to EMG signals as a function of both baseline and signal amplitude; 2) uncorrected baseline noise results in overestimation of mean amplitude of EMG activity, particularly for low SNRs; 3) the traditional method of baseline subtraction underestimates EMG amplitudes and is not better than uncorrected amplitudes for most SNRs; and 4) correcting baseline noise as a function of both baseline and measured signal amplitude (nonlinear error modeling) provides highly accurate estimates of EMG amplitude even at low SNRs. Accordingly, we recommend considering the nonlinear error modeling approach when accounting for baseline noise during discrete EMG burst periods, particularly when the SNR is low.

Several limitations of this study are worth noting. Modeling coefficients may be unique to each EMG analysis approach, requiring new coefficients for each unique EMG processing algorithm using simulated or experimental EMG and noise data. We have observed modeling coefficients to be interchangeable with different EMG processing approaches (i.e., low-pass filter vs. moving average, data not shown); however, it is not likely that this will be the case for all available methods of surface EMG processing. In addition, the simulated EMG signals were initially created using “real” EMG bursts, which inherently contained some level (albeit low) of baseline noise. The zero baseline was achieved artificially by placing the bursts within a vector of zero values, thus no “real” EMG signal is possible.

This technique does not work universally across a time signal, but only for discrete periods or bursts since it is a function of both EMG intensity and noise amplitude. Further it assumes a relatively constant level of baseline noise. If noise is elevated above initial baseline estimates during a burst, this additional noise would be misinterpreted as EMG signal. However, this limitation is also present for the traditional baseline subtraction method. Varying levels of baseline noise could be effectively corrected if new baseline noise estimates are determined between each task trial, during a period of quiet rest. Finally, true baseline noise may preferentially contain certain frequency content. Therefore the application of this error model when baseline noise is band limited or correlated may not be as accurate as predicted here. This is especially the case when the power spectrum of the background noise is dominated by other forms of noise, such as power line noise, movement artifact, etc. We recommend performing a power spectral analysis to confirm the Gaussian

nature of the background noise or use additional filtering techniques prior to the application of this nonlinear error modeling correction.

These results may be meaningful to scientists who routinely deal with baseline noise when performing signal processing in research related to inherently low-amplitude EMG signals, such as co-activation of the antagonist muscles when maximum activation can be clearly observed. We do not suggest this replaces the need for data rejection when peak SNRs are low, but rather may be useful for estimating discrete EMG amplitudes for periods of relatively low activity, such as co-contraction of antagonist muscles. This new error correction method provides a superior approach to accounting for baseline noise when assessing EMG burst amplitudes.

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References

1. Baratta RV, Solomonow M, Zhou BH, Zhu M. Methods to reduce the variability of EMG power spectrum estimates. *Journal of Electromyography & Kinesiology*. 1998; 8:279–285. [PubMed: 9785248]
2. Clancy EA, Hogan N. Relating agonist-antagonist electromyograms to joint torque during isometric, quasi-isotonic, nonfatiguing contractions. *IEEE Trans Biomed Eng*. 1997; 44:1024–1028. [PubMed: 9311171]
3. Clancy EA, Morin EL, Merletti R. Sampling, noise-reduction and amplitude estimation issues in surface electromyography. *J Electromyogr Kinesiol*. 2002; 12:1–16. [PubMed: 11804807]
4. De Luca CJ, Donald Gilmore L, Kuznetsov M, Roy SH. Filtering the surface EMG signal: Movement artifact and baseline noise contamination. *J Biomech*. 2010
5. Dowling JJ. The use of electromyography for the noninvasive prediction of muscle forces. *Current issues. Sports Med*. 1997; 24:82–96. [PubMed: 9291550]
6. Flasterstein AH. Voltage fluctuations of metal-electrolyte interfaces in electrophysiology. *Med Biol Eng*. 1966; 4:583–588. [PubMed: 5981591]
7. Godin DT, Parker PA, Scott RN. Noise characteristics of stainless-steel surface electrodes. *Med Biol Eng Comput*. 1991; 29:585–590. [PubMed: 1813753]
8. Hodges PW, Gandevia SC. Changes in intra-abdominal pressure during postural and respiratory activation of the human diaphragm. *J Appl Physiol*. 2000; 89:967–976. [PubMed: 10956340]
9. Huigen E, Peper A, Grimbergen CA. Investigation into the origin of the noise of surface electrodes. *Med Biol Eng Comput*. 2002; 40:332–338. [PubMed: 12195981]
10. Kellis E. Quantification of quadriceps and hamstring antagonist activity. *Sports Med*. 1998; 25:37–62. [PubMed: 9458526]
11. Kellis E, Baltzopoulos V. The effects of the antagonist muscle force on intersegmental loading during isokinetic efforts of the knee extensors. *J Biomech*. 1999; 32:19–25. [PubMed: 10050948]
12. Kellis E, Katis A. Hamstring antagonist moment estimation using clinically applicable models: Muscle dependency and synergy effects. *J Electromyogr Kinesiol*. 2008; 18:144–153. [PubMed: 17055745]
13. Krishnan C, Williams GN. Sex differences in quadriceps and hamstrings EMG-moment relationships. *Med Sci Sports Exerc*. 2009; 41:1652–1660. [PubMed: 19568193]
14. Krishnan C, Williams GN. Error associated with antagonist muscle activity in isometric knee strength testing. *Eur J Appl Physiol*. 2010; 109:527–536. [PubMed: 20174928]
15. Yao B, Salenius S, Yue GH, Brown RW, Liu JZ. Effects of surface EMG rectification on power and coherence analyses: an EEG and MEG study. *J Neurosci Methods*. 2007; 159:215–223. [PubMed: 16949676]

Figure 1. Simulated muscle EMG time series created by scaling a single maximum muscle EMG burst into a series of four bursts (100%, 50%, 25% and 12.5% maximum) with varying levels of random baseline noise added: A) raw simulated data; B) corresponding processed signals (rectified and low-pass filtered at 20 Hz using a recursive Butterworth filter). Note the noise influences low-intensity contractions greater than the high-intensity contractions.

Figure 2. Mean EMG burst amplitude error (uncorrected – true) plotted as a function of baseline noise (% maximum EMG) and measured (uncorrected) burst amplitude (% maximum EMG). The resulting nonlinear 3-dimensional surface fits the error data well, $R^2 = 0.993$.

Figure 3.

Relative EMG burst amplitude error (% of “true” EMG) is plotted as a function of apparent (uncorrected signal) signal-to-noise ratio (SNR, dB) for each simulated EMG burst (12.5 – 100% max) and baseline noise combination (2.3 – 41.0% max). Note that all three methods for determining EMG amplitude (uncorrected, baseline subtraction, and nonlinear subtraction) are equivalent for SNRs > 20 dB, but that the nonlinear subtraction method is superior for contractions with low SNRs.

Root Mean Square EMG burst amplitudes for validation EMG simulated signals (experimental baseline) using uncorrected and corrected methods, relative to reference (“true”) EMG amplitudes.

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