

MODELING NONLINEAR ERRORS IN SURFACE ELECTROMYOGRAPHY DUE TO BASELINE NOISE: A NEW METHODOLOGY

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INTRODUCTION

Surface electromyography (EMG) is extensively used to estimate muscle activation and force [1, 2]. Standard practice includes subtracting the baseline signal from the measured EMG signal prior to further analyses [2, 3]. However, to our knowledge this premise has not been verified experimentally. In particular, due to low signal-to-noise ratio for low-amplitude muscle contractions, such as antagonist muscle co-activation, baseline noise may be a potentially significant error source. Therefore, the purpose of this study was to model the influence of varying levels of random baseline noise on EMG signals of varying intensities, and determine an optimal method to account for baseline signal.

METHODS

A single burst of quadriceps muscle activity obtained during a maximal knee extensor contraction (60 deg/sec, ~1.4 sec) was isolated for the purpose of this study. The EMG signals were collected (Delsys Bagnoli, Boston, MA) at 1000 Hz with a 20 – 450 Hz band-pass anti-aliasing filter using custom Labview software (National Instruments) and a 16-bit data acquisition card (National Instruments). A 10-second zero-baseline vector was added to the EMG signals using a custom program written in Matlab (Mathworks, Natick, MA). 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 noise was created using the “randn” command in Matlab, producing a signal with a mean of 0 and standard deviation of 1. This noise vector was then scaled to achieve random noise signals ranging from 5% to 50% of the burst EMG maximum. The noise signals were added to the simulated EMG bursts to create multiple trials

of EMG data with varying levels of baseline noise (Figure 1A). The EMG data were rectified and low-pass filtered with a 200 ms moving average window (Figure 1B). The mean EMG activity was determined for each of the 4 bursts for each simulated baseline trial. The resulting error was calculated by subtracting the measured (corrected or uncorrected) mean EMG activity for each burst from its corresponding true value (i.e., 100%, 50%, 25% and 12.5% max).

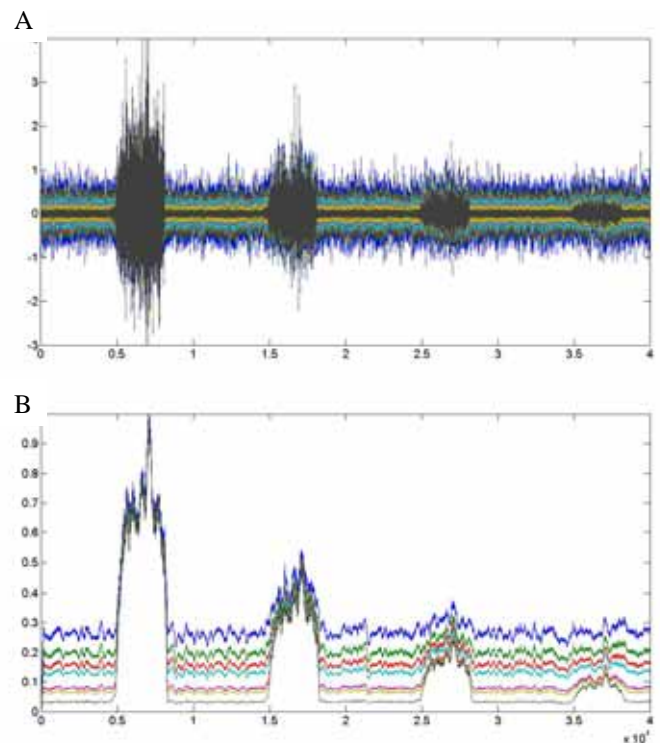


Figure 1: A) Raw and B) processed EMG bursts (100%, 50%, 25%, 12.5% maximum amplitude) with varying levels of added noise.

These error data were plotted (Figure 2) as a function of measured EMG and baseline noise. The resulting 3D surface was best fit (Table Curve 3D) to a three parameter equation:

$\ln(\text{error}) = A + B(\text{measured EMG}) + C(\ln(\text{noise}))^2$
 The modeled errors were then removed from the measured values to calculate “corrected” EMG burst amplitudes. To validate this approach, a 2nd set of scaled EMG bursts with varying levels of simulated noise were created using EMG derived from a shoulder abductor muscle in a different subject. Corrected EMG burst amplitudes were assessed using both the constant baseline and the nonlinear modeled error (using prior a, b, and c values) subtraction methods. The resulting errors (measured relative to expected amplitude) were calculated for both methods.

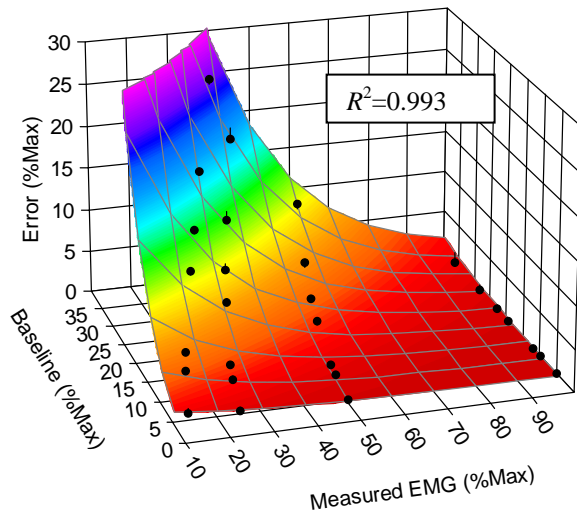


Figure 2: Model surface fit of errors (Measured – Actual) for mean EMG amplitude as a function of baseline noise and measured activation intensity.

RESULTS AND DISCUSSION

Baseline noise had minimal effects at max EMG amplitude, but increased nonlinearly (see Figures 1 and 2) with increasing baseline noise and decreasing signal amplitude. The nonlinear error model explained 99.3% of the variation in the measured error (Figure 2). The uncorrected EMG burst amplitudes overestimated actual EMG values as the signal to noise ratio decreased. Traditional

baseline subtraction reversed this finding, consistently underestimating actual EMG amplitude (see Table 1) for low intensity bursts. The associated errors were relatively small for EMG amplitudes that were >50% of maximum, but on average resulted in errors approaching 100% of actual values for the lowest intensity bursts (either uncorrected or baseline subtraction methods). Using the nonlinear error model to correct EMG decreased errors to <1% max, in both test and validation EMG tracings (see Table 1 for validation EMG results).

CONCLUSIONS

Our results indicate that correcting baseline noise as a function of both baseline and measured signal amplitude (“true” + noise) produces highly accurate estimates of EMG amplitude when assessing mean activity during burst periods. Therefore, we recommend considering this approach when accounting for baseline noise during signal processing, particularly when the signal-to-noise ratio is low. It is to be noted the modeling coefficients are not universal, but would need to be estimated for each unique EMG processing algorithm using simulated EMG and noise data.

REFERENCES

1. Dowling JJ. *Sports Med.* **24**, 82-96, 1997.
2. Krishnan C, Williams GN. *Med Sci Sports Exerc.* **41**, 1652-60, 2010.
3. Hodges PW, Gandevia SC. *J Appl Physiol.* **89**, 967-76, 2000.

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Table 1: Mean corrected EMG activation assessments and the associated error following correction.

Baseline Noise (% max)	Constant Baseline Subtraction: mean EMG (% max)				Nonlinear Error Subtraction: mean EMG (% max)			
	100%	50%	25%	12.5%	100%	50%	25%	12.5%
47.8	100.0	34.5	11.0	1.0	97.2	51.3	27.5	14.8
34.3	100.0	36.9	12.0	2.4	98.9	50.7	25.1	12.6
26.5	100.0	39.2	13.5	3.2	99.5	50.7	25.0	12.6
18.1	100.0	42.0	15.8	4.7	99.8	50.4	25.2	12.9
9.2	100.0	45.5	19.4	7.1	99.9	49.9	25.0	12.6
Ave Error	0.0	-10.4	-10.7	-8.8	0.9	0.6	0.6	0.6