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EMG Amplitude Estimation with Adaptive Smoothing Window Length

Edward A. Clancy (msmail5.clancye@tsod.lmig.com)
Liberty Mutual Research Center for Safety and Health, 71 Frankland Rd, Hopkinton, MA 01748

Abstract — Typical EMG amplitude estimators use a fixed window length for smoothing the amplitude estimate. When the EMG amplitude is dynamic, varying the smoothing length as a function of time can produce a higher quality amplitude estimate. This paper develops and investigates (in simulation and experimentally) a new technique for adaptive window length estimation. The simulations suggest that the "best" adaptive filter performed as well as the "best" fixed-length filter. Both filter types had to be tuned to the conditions of the simulation. Experimentally, it was found that multiple channel EMG amplitude estimators consistently performed better than single channel EMG amplitude estimators. Results with the adaptive processor were inconclusive. Perhaps due to task difficulty, no differences in adaptive vs. fixed-length processors were observed when subjects were asked to use real-time EMG amplitude estimates (presented on a video screen) to track a rapidly moving random target. When the target speed was slow, the experimental results were consistent with simulation predictions.

I. Introduction

Typical amplitude estimators use analog rectify and smooth processing or root-mean-square (RMS) processing of the EMG waveform. Research studies have demonstrated that this technique can be improved by three methods: whitening individual EMG waveform channels, combining multiple waveform channels into a single EMG amplitude estimate, and (when muscle contraction is dynamic) adaptively tuning the length of the smoothing window [1]–[4] (see also [5] for an alternative technique). This report describes a study of adaptive window length. First, a new adaptive window length processor is mathematically derived. Second, the new technique is studied using a stochastic simulation model of the EMG waveform. Third, a preliminary report of an experimental evaluation of the technique is provided.

II. Development of the Adaptive Estimator

Consider the composite mean square error (MSE) in the EMG amplitude estimate as comprised of two components: a variance component $\sigma^2(t)$ (due to random fluctuations in the EMG amplitude estimate about the true amplitude) and a bias component $b(t)$ (due to errors in tracking true changes in the amplitude) [4]:

$$MSE(t) = b^2(t) + \sigma^2(t)$$

In general, variance error is reduced with a large duration smoothing window and bias error is reduced with a small duration smoothing window. For improved amplitude estimation (i.e. minimum MSE), therefore, the smoothing window length should be dynamically tuned to the characteristics of the EMG amplitude each instant in time.

A. *Variance Component of the Error*

For the variance component, [6]–[8] have shown that the signal to noise ratio (SNR) of EMG amplitude estimates for constant-angle, isotonic, non-fatiguing contractions is

$$\text{SNR} = \sqrt{\frac{2 \cdot N \cdot g(B,L,D)}{f}} = \frac{s(t)}{\sigma(t)}$$

where N is the window length in samples, f is the sampling frequency (in Hertz), $s(t)$ is the EMG amplitude, $\sigma(t)$ is the EMG amplitude estimate standard deviation and g is a function of B, L and D. B is the statistical bandwidth of the EMG data (in Hertz). L is the number of EMG channels which are combined to form the amplitude estimate. D denotes the detector type—mean absolute value (MAV) or root mean square (RMS). Solving the above for $\sigma^2(t)$ gives

$$\sigma^2(t) = \frac{f \cdot s^2(t)}{2 \cdot N \cdot g(B,L,D)}$$

B. *Bias Component of the Error*

For the bias component, consider the error that would occur if no variance error existed, but the EMG amplitude was dynamically changing. Let the EMG amplitude in the neighborhood of sample t be modeled as the quadratic

$$s(t) = a_o + a_1 t + a_2 t^2$$

where a_o, a_1 and a_2 are constants. At sample $t-k$,

$$s(t-k) = s(t) - \frac{k\dot{s}(t)}{f} + \frac{k^2}{2f^2}\ddot{s}(t)$$

where $\dot{s}(t) = a_1 f + 2a_2 ft$ is the derivative of $s(t)$ with respect to t (expressed in units of EMG amplitude per second) and $\ddot{s}(t) = 2a_2 f^2$ is the second time derivative. If a causal MAV detector is used to form the amplitude estimate $\hat{s}$ at sample t from N EMG waveform samples, then

$$\hat{s}(t) = \frac{1}{N}\sum_{k=0}^{N-1} |m(t-k)|$$

where $m(t)$ are the EMG waveform samples. However, since this formulation of the bias error assumes that the variance error is nil, the magnitude of the waveform samples can be replaced by the true EMG amplitude $s(t)$, which is always non-negative. Substituting the relation for the amplitude at sample $t-k$ and simplifying gives

$$b(t) = \frac{(N-1)}{2f}\left[\frac{\ddot{s}(t)(2N-1)}{6f} - \dot{s}(t)\right]$$

where the bias error has been defined as $b(t) = \hat{s}(t) - s(t)$.

C. Minimum MSE: Causal Processing

If $MSE(t)$ is now written, the optimal window length can frequently be found by differentiating with respect to N, setting the derivative to zero, and then solving for N. Unfortunately, attempting to do so in this case leads to a complex non-linear equation. Hence, an exhaustive numerical search was used instead. To find an optimum N, $MSE(t)$ was computed for all possible window lengths corresponding to a duration ranging from 50–500ms, and the duration corresponding to the minimum error was selected.

D. Linear Model of EMG Amplitude Variation

Because the above development models the EMG amplitude in the neighborhood of sample t as a quadratic, a second derivative term results. In practice, limiting the solution to the first derivative may be beneficial. This solution can be formed using a linear model of EMG amplitude in the neighborhood of sample t by setting $\ddot{s}(t) = 0$ in the above development. For causal processing, this linear model gives a $\frac{dMSE(t)}{dN}$ of

$$\left.\frac{dMSE(t)}{dN}\right|_{Linear} = \frac{N\dot{s}^2(t)}{2f^2} - \frac{\dot{s}^2(t)}{2f^2} - \frac{f \cdot s^2(t)}{2 \cdot N^2 \cdot g(B,L,D)}$$

Setting this derivative to zero, solving for N and making the approximation $N^3 - N^2 \cong N^3$ leads to the optimal value for N of

$$N \cong \frac{f}{g^{1/3}(B,L,D)} \cdot \left[\frac{s^2(t)}{\dot{s}^2(t)}\right]^{1/3}$$

III. Simulation Study

Implementation of any of these adaptive processors presupposes the true value of the EMG amplitude and its derivatives. In practice, these values are not known and must be estimated from the EMG waveform. Hence, the adaptive algorithm was implemented in two passes. In the first pass, fixed-length processing stages were used to estimate the EMG amplitude and its derivatives. The window length N could then be selected for each sample time. In the second pass, the adaptive N was implemented to produce the adaptive amplitude estimate. Simulation was used to investigate the effectiveness of this two-pass method. The EMG waveform was simulated as an amplitude modulated, band-limited (256 Hz), Laplacian random noise process.

Initial investigation with the model quickly showed that estimation of the derivatives of the EMG amplitude could not be adequately obtained with simple differencing filters. Thus, polynomial derivative filters of degrees 1–6 were investigated. Filters were evaluated on the EMG model, with the simulated amplitude (denoted the target) changed as a band-limited random process with uniform density (ranging from simulated relaxation to simulated 50% maximum voluntary contraction (MVC)). Several target bandwidths were evaluated. It was found that a degree 1 polynomial was best for the first derivative and a degree 2 polynomial was best for the second derivative. However, the number of samples over which the polynomial should be fit varied with the target bandwidth. For example, first derivatives were best when using 875ms of data for a target bandwidth of 0.25 Hz, but were best using 375ms of data when the target bandwidth was 1 Hz.

Smoothing Window	**Tracking Bandwidth .25 Hz**	**.5 Hz**	**1 Hz**	**2 Hz**	**4 Hz**
Adaptive, Linear, Derivative Known	1.82	2.45	3.35	4.30	4.90
Adaptive, Quadratic, Derivative Known	1.82	2.42	3.12	3.63	4.35
Adaptive, Linear, Derivative Estimated	2.09		3.29		4.82
Adaptive, Quadratic, Derivative Estimated	2.01		4.46		5.69
Fixed, 50 ms	4.03	4.14	4.36	**4.21**	**4.56**
100 ms	2.85	3.10	**3.59**	4.41	5.20
150 ms	2.40	**2.85**	3.75	5.46	6.50
200 ms	2.19	2.91	4.23	6.68	7.60
250 ms	**2.11**	3.12	4.84	7.86	8.38
300 ms	2.13	3.40	5.50	8.92	8.89
350 ms	2.18	3.73	6.17	9.80	9.18
400 ms	2.27	4.10	6.83	10.50	9.36
450 ms	2.37	4.47	7.45	10.99	9.45
500 ms	2.50	4.86	8.03	11.32	9.53

Table I: Mean-square-error simulation results (in percent MVC) for causal processing.

Once these derivative estimators had been established, the simulation method was run to investigate the expected performance of the adaptive window length algorithm versus fixed length algorithms. Table I gives the results. Adaptive estimators were evaluated twice: first, with the derivatives known (to establish "ideal" technique performance) and second, with the derivatives estimated from the EMG waveform (as would be done with actual data). The preferred length polynomial differentiator was used for each target bandwidth. (Note that the adaptive window length processors were not sensitive to the method of estimating the first-pass EMG amplitude.) The results show that the first derivative algorithm performs equal to or better than the second derivative technique. For each target bandwidth, the adaptive algorithm (with estimated derivatives) performs about as well as the best fixed-length algorithm. The knowledge developed from these simulations was next used to guide an experimental evaluation of the causal adaptive estimator. Only a first derivative adaptive processor was considered since it gave superior results in the simulation.

IV. Experimental Study

A. Experimental Apparatus

For each of the biceps (flexor) and triceps (extensor) muscles, four commercial EMG electrode-amplifiers (Liberty Mutual MYO115) were located at the mid length of the

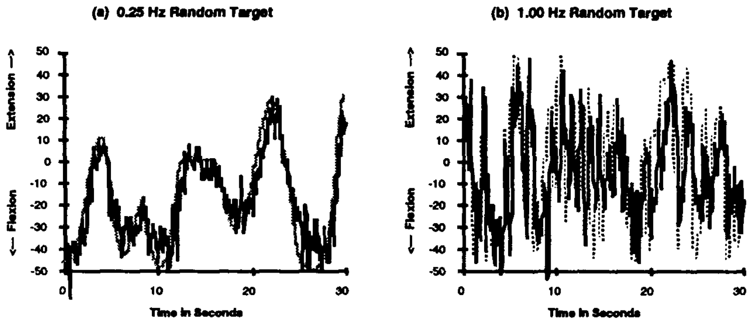

Fig. 1: Example data from tracking trials. Dotted lines are the target, solid lines are the subject pursuit profiles. Y-axis values give the EMG amplitude (scaled to percent MVC), with positive values denoting extension (i.e. triceps EMG greater than biceps EMG) and negative values denoting flexion. EMG processing was with the multiple channel adaptive processor in each case.

muscle, clustered about the muscle midline. The two contacts of each electrode-amplifier were oriented along the long axis of the arm. One ground electrode was applied. Electrode-amplifiers had a gain of 500 and a second-order 10–2000 Hz bandpass filter. The EMG signals were electrically isolated, amplified and low-pass filtered (2000 Hz).

The EMG signals were connected to a 16-bit A/D converter on an "EMG Workstation PC". The PC acquired the input data at 4096 Hz, formed a 4-point moving average, and decimated the data to 1024 Hz. The Workstation then computed EMG amplitude estimates in real time, formed the difference between the triceps and biceps amplitude, and sent the resulting differences out its serial port. Four EMG processors per muscle group (biceps/triceps) were produced:

1) Conventional single-channel MAV processing with a fixed smoothing window length of 250ms. Note that an electrode-amplifier most central on the muscle was used.
2,3) Conventional four-channel MAV processing with fixed smoothing window lengths of 100 and 250ms.
4) A four-channel adaptive (first-derivative), causal smoothing window length processor. *The duration of data contributing to the polynomial differentiator was 375ms (the best duration for a 1 Hz target).*

For each experimental trial, one processed triceps-biceps EMG amplitude difference was sent out the serial port (at a rate of 30 Hz) to a second "Target Tracking PC" which displayed the selected triceps-biceps processed EMG and a dynamic target to pursue. In Mode 1, the target moved horizontally along the screen as a band-limited (0.25 Hz) uniform random process. The range of the random process was scaled from 50% MVC flexion to 50% MVC extension. Mode 2 used a similar target, except that the statistical bandwidth of the target was 1 Hz. Additional tracking data were collected, but not used in this study.

B. Experimental Methods

Informed consent was received from each subject. Nineteen healthy subjects, 9 male and 10 female, ranging in age from 18 to 65 years, each participated in one experiment. A subject was seated in a Biodex exercise machine and secured to the seat back rest via three belts. The subject's right arm was oriented so that the upper arm and forearm were in the plane parallel to the floor, the forearm was oriented in the parasaggital plane, with the wrist in complete supination, and the angle between the upper arm and the forearm was 90°. The subject's right wrist was fit into a cuff which was rigidly attached to the Biodex. The arm position and orientation was fixed throughout the experiment.

Initially, subjects produced a series of contractions to calibrate their MVC and corresponding EMG amplitudes. Subjects then performed 30-second, constant-angle, anisotonic tracking task contractions. One triceps-biceps EMG processor and a dynamic target were simultaneously presented to the subject. The subject was blinded as to which EMG processor was selected. The subject was instructed to flex/extend about the elbow as necessary in order to produce an EMG difference signal which tracked the target as best as possible. (This technique mimics the use of an EMG-controlled upper-limb prosthesis.) A series of 3 sets of tracking contractions was conducted, each set randomly presenting all combinations of EMG processors and tracking modes. A rest period of two minutes was provided between trials.

C. Preliminary Experimental Results

Fig. 1 shows sample tracking data from each of the three tracking tasks. Preliminary analysis has consisted only of evaluating the MSE between the target and the achieved pursuit path. It was observed during the experiment that subjects were learning the tracking task during the first set of targets. This observation was confirmed statistically in that the tracking errors from the first tracking set were statistically different (larger) than those from the remaining two sets. For these reasons, data from the first tracking set were removed from further analysis. In addition, the tracking errors from one subject were more than three standard deviations greater than the mean error, thus the data from this subject were excluded. The remaining MSE results are presented in summary in Table II.

D. Discussion of Preliminary Experimental Results

All of the experimental errors listed in Table II are considerably larger than the simulation errors listed in Table

EMG Processor	Target Type	
	0.25 Hz Random	1.00 Hz Random
Single: Fixed, 250ms	8.67±2.34	21.51±3.07
Multiple: Fixed, 250ms	7.43±1.51	19.59±2.85
Multiple: Fixed, 100ms	9.43±2.14	19.69±2.85
Multiple: Adaptive	8.68±2.32	19.57±2.77

Table II: Mean±std. dev. tracking error results, in percent MVC, averaged across 18 subjects.

I. This result is expected for at least two reasons. First, the simulation errors do not account for the imprecise ability of subjects to track the target. This error grows with the difficulty (bandwidth) of the target being tracked. Second, the simulations evaluated estimation errors from a single EMG amplitude estimate, but the experiment evaluated errors which were formed from the difference of two EMG amplitude signals. The random error of this difference signal (assuming that the errors on the individual signals were uncorrelated) should be greater by a factor of $\sqrt{2}$.

Comparing the single vs. multiple channel fixed-window, 250ms detectors, Table II shows that the multiple channel detector performed better than the single channel detector for all target types ($p \leq 0.005$ for each target type using a t-test). This result continues to reinforce the advantage of multiple channel EMG amplitude estimation.

For the 1 Hz random target, none of the multiple channel algorithms performed differently ($p=0.95$ using a one-way ANOVA). The simulation results suggested that the 100ms fixed-window and adaptive processors should have performed equally well, but with 74% of the error of the 250ms fixed-window processor. Perhaps the lack of differences was due to the task difficulty. The errors may have been dominated by the imprecise ability of subjects to track the target at this high bandwidth, with smaller related to processor performance not easily detected.

For the 0.25 Hz random target, the 250ms fixed-window processor performed better than the 100ms fixed-window processor ($p<0.002$ using a t-test), as predicted by the simulations. No precise prediction was available for adaptive processing since the duration of data contributing to the polynomial derivative filter was not matched to this bandwidth (as it was in the case of the simulations). However, the experimental result fell between the two fixed-length detectors. It would be interesting to re-test tracking results using an adaptive processor with the appropriate derivative for the 0.25 Hz target. A higher quality derivative would be expected to lead to lower errors.

V. Summary/Conclusions

A new technique for adaptive window length estimation of the amplitude of the non-stationary EMG waveform was derived. This method includes consideration of the first and second derivative of the EMG amplitude. A simulation study investigated the ideal and practical performance of the technique in comparison to fixed-length processors. It was found that practical adaptive detectors, *with optimum selection of a polynomial derivative filter*, should work as well as the optimum fixed-length processor. Unfortunately, this results means that the burden of selecting the "best" window length (in the fixed-length processor case) is replaced by the burden of selecting the "best" derivative filter (in the adaptive-length case). Future research should be directed towards improved derivative filters which may correct this situation. Experimentally, it was confirmed that multiple channel processors performed better than the single channel processor. Results with the adaptive processor were inconclusive. Perhaps due to task difficulty, no differences in the multiple channel processors were observed at the 1 Hz target bandwidth. Results at the 0.25 bandwidth were consistent with simulation predictions.

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