EMG AMPLITUDE ESTIMATION: A REVIEW OF THE PAST AND A LOOK TOWARDS THE FUTURE

Edward A. Clancy
Liberty Mutual Research Center for Safety and Health
71 Frankland Road, Hopkinton, MA, USA, 01748 (MSmail5.ClancyE@ISOD.LMIG.com)

ABSTRACT AND INTRODUCTION

The amplitude of the surface EMG is frequently used as the control input to myoelectric prostheses, as a measure of muscular effort, and has also been investigated as an indicator of muscle force. This paper will review the methods which are used to estimate the EMG amplitude from recordings of the EMG waveform. (Note that this review does *not* include the related area of EMG-to-force processing.) Early investigators studied the type of non-linear detector which should be applied to the waveform. This work led to the routine use of analog rectify and smooth (low pass filter) processing and root-mean-square (RMS) processing of the EMG waveform to form an amplitude estimate. More recent investigation has shown the promise of whitening individual EMG waveform channels, combining multiple waveform channels into a single EMG amplitude estimate and adaptively tuning the smoothing window length. None of these recent techniques have been routinely incorporated into EMG amplitude estimators. Finally, a look towards what EMG processing might be in the future is described.

AMPLITUDE DETECTION

Early investigators treated the EMG waveform as a zero mean amplitude modulated signal. Inman *et al.* [11] suggested an amplitude estimator consisting of a full-wave rectifier (non-linear demodulator) followed by a simple resistor-capacitor low pass filter (smoother). They noted that a long filter time constant was desired to reduce noise in the estimate, while a short filter time constant reduces the time delay in tracking changes in the signal amplitude. This simple detector, with time constants from 0.1 to 1.0 second, has been applied extensively in the study of the surface electromyogram.

In an effort to improve the estimator of Inman *et al.* [11], Kreifeldt [13] compared the performance of three smoothers — the standard resistor-capacitor (RC) low pass filter, a third-order Butterworth filter, and a third-order approximation to a moving average filter. The performance of each amplitude estimator was evaluated from EMG data recorded during isometric, isotonic muscular contraction by computing a signal to noise ratio (SNR) from the output of each amplitude estimator. Because muscle contraction was constant, the mean value of an amplitude estimate was taken as the signal, and standard deviations about the mean were taken as noise. (This performance criterion has been widely adopted in surface EMG amplitude estimation.) Kreifeldt found that the SNR performance of the averaging filter was a 44% improvement over the RC filter, while the Butterworth filter provided an 11% improvement. Kreifeldt and Yao [14] experimentally investigated the performance of six non-linear demodulators. A second-power demodulator was found to be best for contraction levels of 10, 25 and 50% maximum voluntary contraction (MVC). A fourth-power demodulator was found to be best at 5% MVC. These power law demodulators improved the SNR performance of the full wave rectifier by 5–20%, depending on the force level.

Hogan and Mann [9,10] used a functional mathematical model of EMG to analytically predict that a second-power demodulator and an averaging filter, i.e. an RMS processor, would give the best maximum likelihood estimate of the EMG amplitude. Experimentally, they confirmed that an RMS processor is superior in SNR performance to a low pass filter by 26%. Hogan and Mann found no SNR performance difference between the RMS processor and a full wave rectifier. Clancy [1] consistently found full wave rectification to be a small improvement (2–8%) over RMS detection. Typical EMG amplitude estimators in use today utilize one of the above specified processors, with RMS processing being preferred.

WHITENING FILTERS

Several investigators have found that the inclusion of a whitening filter prior to demodulation and smoothing improves the performance of the amplitude estimate. A whitening filter is a filter whose output power spectrum is constant-valued when presented with the signal of interest as an input. Kaiser and Peterson [12] found that the shape of the whitening filter should change as a function of the contraction level. They suggested that measurement noise, present in differing relative degrees depending on the absolute signal (contraction) level, may be a major factor in determining the shape of the whitening filter. They designed an adaptive analog filter to achieve their desired whitening. Harba and Lynn [8] used auto-regressive modeling of the EMG power spectrum to form a whitening filter in an off-line algorithm. Their sixth-order model found only small changes in the shape of the whitening filter as a function of the contraction level. Whitening approximately doubled the probability of correctly differentiating between one of four discrete contraction levels. Their off-line results were confirmed with an analog on-line implementation. Hogan and Mann [9,10] found that whitening could be achieved by reducing the outer edge spacing of a pair of rectangular electrodes from 20mm to 10mm. An SNR performance improvement of 35% resulted. D'Alessio [4] and Filligoi and Mandarini [7] discussed whitening with respect to functional mathematical models of the EMG. Clancy and Hogan [2] systematically investigated the influence of various moving-average digital whitening filters for contractions over the range of 10–75% MVC. They found that fourth-order whitening filters, calibrated from a short segment (≤5s) of data, improved the SNR by 63%. These whitening filters, however, performed poorly for contractions less than 10% MVC. Additive background noise seemed to dominate the output of the whitening filters. As in the prior work of Kaiser and Peterson [12], Clancy [1] implemented an adaptive whitening filter which seemed to maintain the SNR performance improvement for contractions above 10% MVC, but reverted towards unwhitened processing for lower levels of contraction.

MULTIPLE SITE COMBINATION

Further improvements in EMG amplitude estimation have been achieved through the combination of multiple channels of the EMG waveform. Hogan and Mann [9,10] suggested that dispersing multiple electrodes about a single muscle would provide a broader, more complete, measure of the underlying electrophysiologic activity. They derived an optimal amplitude estimator assuming that separate EMG channels were spatially correlated but temporally uncorrelated. Using four electrodes, they achieved an SNR performance improvement of 91% compared to the single channel estimator of Inman *et al.* [11]. The combination of multiple channels and whitening via electrode geometry yielded an SNR performance improvement of 176% compared to the single channel estimator of Inman *et al.* [11]. The SNR performance of their algorithm was relatively insensitive to force levels over the range of 5–25% MVC. Hogan and Mann implemented their algorithm off-line on a digital computer and on-line with analog circuitry. Murray and Rolph [16] implemented this algorithm in real time on a digital microprocessor. Harba and Lynn [8] used four electrode pairs to improve the quality of an EMG processor which tried to differentiate between four discrete contraction levels. They were able to improve the probability of correctly differentiating between contraction levels by 40–70% (compared to using one electrode). Thesneyapan and Zahalak [18] reported a nine channel EMG amplitude estimator.

Clancy and Hogan [3] combined the techniques of waveform whitening and multiple channel combination. For contractions ranging from 10–75% MVC, a four channel, temporally whitened processor improved the SNR 187% compared to the estimator of Inman *et al.* [11]. Eight whitened combined channels provided an SNR improvement of 309% compared to the estimator of Inman *et al.* Calibration of the optimal processor was achieved with a single five second contraction trial at 50% MVC.

NON-STATIONARY PROCESSORS

In all of the EMG processors described above, selection of the smoothing window length (or time constant, as appropriate) is a trade-off between amplitude estimator variance (which is diminished via a *long* smoothing window) and error due to estimator bias (which is diminished via a *short* smoothing window). When EMG amplitude is varied dynamically during muscular contraction (i.e. the EMG waveform is non-stationary), higher fidelity EMG amplitude estimates can be achieved if the window length is tuned throughout the duration of the contraction.

D'Alessio [4,5] has argued theoretically that dynamic tuning of the window length should be a function of the EMG amplitude and its first two derivatives. However, since estimation of the second derivative proved too difficult, D'Alessio implemented a technique based on the EMG amplitude and only its first derivative. Recently, Meek and Fetherston [15] and Park and Meek [17] described adaptive techniques also based on the EMG amplitude and its first derivative. When contraction level was rapidly changing or slowly changing, the adaptive processors provided a marked improvement over fixed-duration smoothing window length processors.

As an alternative to the method described above, Evans *et al.* [6] proposed an amplitude estimation scheme based on a multiplicative (signal multiplied by noise) functional mathematical model of EMG. The authors proposed a logarithmic transformation of the myoelectric signal. This transformation yields an additive (signal plus noise) representation of the EMG. The authors then applied the theory of Kalman filters to estimate the amplitude of the transformed signal.

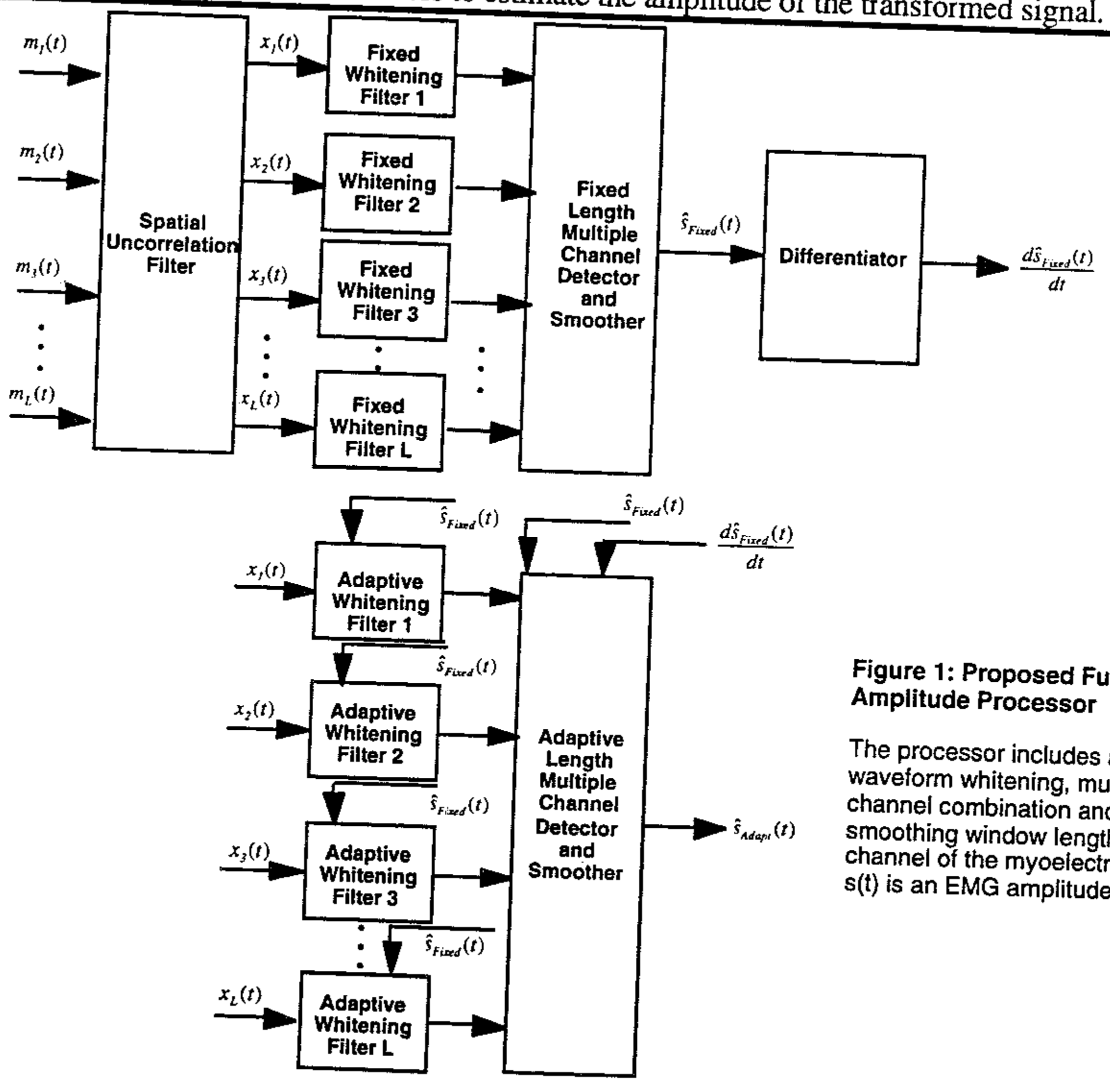

Figure 1: Proposed Future EMG Amplitude Processor

The processor includes adaptive waveform whitening, multiple channel combination and adaptive smoothing window length. $m_i(t)$ is a channel of the myoelectric waveform. s(t) is an EMG amplitude estimate.

THE FUTURE EMG AMPLITUDE PROCESSOR

The future of EMG amplitude estimation should incorporate all of the above performance improvements — adaptive waveform whitening, multiple channel combination and adaptive smoothing window length — into a robust, high-fidelity processor. Figure 1 shows a block diagram of a proposed EMG processor including all of these techniques. Multiple channels of the EMG waveform are acquired and spatially uncorrelated. The uncorrelated waveforms are then sent in parallel to two processing stages. The first processing stage exists *only* to guide the adaptation of the second stage. That is, the outputs of the first stage are used to adapt the whitening and smoothing window length used in the second processing stage. This first stage incorporates a fixed whitening filter and a fixed duration smoothing filter. The second stage performs adaptive whitening *and* adaptive smoothing window length detection. This parallel processing approach avoids the use of feedback, and thus assures that a stable processor results.

Several practical problems remain before such an EMG processor can be successfully implemented in full. First, robust whitening is not yet available, particular for the case of low contraction. Additional work similar to the adaptive whitening techniques proposed by Kaiser and Peterson [12] and Clancy [1] must be developed. Second, when multiple channels of EMG are recorded, the risk of failed recording channels (e.g. shorted electrodes, pick-up of large amounts of unwanted noise) grows with the number of electrodes. Automated methods for locating and managing failed channels may need to be developed. Third, the techniques for adaptive smoothing window length processors are relatively new, thus the relative merits of each proposed technique are not known. Therefore, selecting the appropriate technique for a given application — or perhaps identifying a globally "best" technique — has not been solved. And lastly, instrumentation utilizing all of these techniques must remain simple to use so that the user can reap the benefits of higher fidelity amplitude estimation without a time-consuming investment in equipment training and maintenance.

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