Journal of Electromyography and Kinesiology 12 (2002) 1–16
www.elsevier.com/locate/jelekin

Sampling, noise-reduction and amplitude estimation issues in surface electromyography☆

E.A. Clancy [a,*], E.L. Morin [b], R. Merletti [c]

[a] Department of Electrical and Computer Engineering, and Department of Biomedical Engineering, Worcester Polytechnic Institute, 100 Institute Road, Worcester, MA 01609, USA
[b] Department of Electrical and Computer Engineering, and School of Physical and Health Education, Queen's University, Kingston, ON, Canada
[c] Centro di Bioingegneria, Politecnico di Torino, ASL1-Regione Piemonte, Torino, Italy

Received 25 July 2001; accepted 21 September 2001

Abstract

This paper reviews data acquisition and signal processing issues relative to producing an amplitude estimate of surface EMG. The paper covers two principle areas. First, methods for reducing noise, artefact and interference in recorded EMG are described. Wherever possible noise should be reduced at the source via appropriate skin preparation, and the use of well designed active electrodes and signal recording instrumentation. Despite these efforts, some noise will always accompany the desired signal, thus signal processing techniques for noise reduction (e.g. band-pass filtering, adaptive noise cancellation filters and filters based on the wavelet transform) are discussed. Second, methods for estimating the amplitude of the EMG are reviewed. Most advanced, high-fidelity methods consist of six sequential stages: noise rejection/filtering, whitening, multiple-channel combination, amplitude demodulation, smoothing and relinearization. Theoretical and experimental research related to each of the above topics is reviewed and the current recommended practices are described.

Keywords: Artefact rejection; Electromyography; EMG; EMG amplitude; Measurement noise; Noise; Surface EMG

1. Introduction

Electrical activity within a muscle arises due to transient ionic potentials in activated motor units, where the motor unit is the smallest functional grouping in muscle and is comprised of a single motor neuron and several associated muscle fibers. The EMG, which can be measured from within the muscle or from the skin surface overlying the muscle, is a spatial and temporal interference pattern of the electrical activity of the activated motor units located near the detection surfaces. Because of the nature of motor unit activation in muscle, the measured signal resembles a zero–mean random (stochastic) process whose standard deviation is proportional to the number of active motor units and the rate at which motor units are activated. (Additional details regarding motor unit activation can be found in [4].) This signal has been used to provide insight into musculoskeletal system function via estimation of muscle fiber conduction velocity, monitoring localized changes in the EMG during muscle fatigue, and analysis of muscle activation times and intervals, e.g. during the analysis of gait or motion trajectory studies. EMG has also been successfully employed as a control signal for powered upper limb prostheses [42,62]. For many applications, the *amplitude* of the EMG, estimated from bipolar recordings taken at the surface of the skin, has been used to monitor muscular activation level and duration, and to estimate the forces produced by the muscles. *EMG amplitude* may be defined as the time-varying standard deviation of the EMG.

☆ This paper by Clancy et al is the second paper published from a consensus conference held in Northern California in 1998 [Marconi Research Conference 1998—Estimating Muscle Load Using Surface EMG Amplitude, David Rempel, ed, Ergonomics Program, University of California, Richmond, CA]. The conference attendees addressed the question, "Under what circumstances can surface electromyography be used to estimate upper extremity and neck muscle load during the performance of precision tasks?" The purpose of the papers was to provide guidelines to the ergonomics community in the application of surface electromyography to evaluate tools and tasks.

* Corresponding author.
E-mail address: ted.clancy@alum.wpi.edu (E.A. Clancy).

1050-6411/02/$ - see front matter
PII: S1050-6411(01)00033-5

A general paradigm for EMG amplitude analysis can be logically segmented into three sequential stages: 1) electrode selection and placement; 2) processing of the acquired EMG to estimate EMG amplitude; and 3) interpretation and further modeling derived from the estimated EMG amplitude and, usually, other observed information. The study of changes in the frequency content of EMG is common for forceful (typically 50% or more of maximal force), short-duration tasks (e.g. for task durations ranging from 20–30 s to 2–4 min), however, its benefits have yet to be definitively shown for longer duration, precision and generally lower force tasks. Thus, this topic will not be discussed in this review. The purpose of this review is to describe the history and current state-of-the-art for stage two noted above. A discussion of the electrode characteristics and electrode site selection will be avoided, except where directly relevant to the EMG processing problem. In addition, interpretation and further modeling (e.g. EMG-force models) of the processed EMG signal will not be covered.

With the above limitations in mind, this paper covers two topics. The first concerns the sources of EMG measurement noise and techniques for diminishing its influence. For the analysis of low effort levels associated with many precision tasks, noise in the recorded EMG can have a significant influence on signal interpretation. A discussion of noise sources in EMG measurement and how to minimize the impact of these sources is presented. The second topic covers techniques for estimating the amplitude of the noise-reduced surface EMG. Most advanced, high-fidelity methods consist of the sequential steps of signal whitening, multiple-channel combination, amplitude demodulation, smoothing and relinearization. Each of these steps is described and a review of related research is presented. For more general issues concerning EMG detection, processing and applications, the reader is referred to [35].

2. Noise in the EMG and strategies for elimination/reduction

2.1. Electrode noise

The EMG can be detected using surface electrodes, which are affixed to the skin overlying the muscle of interest, or using indwelling electrodes (wire or needle), which are inserted into the muscle tissue. In either case, the basis by which the electrodes function is the formation of a layer of charge at the interface between the metal electrode and an electrolyte solution. The presence of a charge gradient at the electrode–electrolyte interface produces a voltage, or potential, called the half-cell potential. This potential is dependent on the electrode material and a considerable DC voltage difference (e.g. more than 1 V) can exist between electrodes of different metals and, to a much lesser extent, electrodes made of the same metal (see [31:317], for a table of half-cell potentials for various conditions). In EMG measurement, all recording electrodes should be made of the same material to minimize half-cell potential differences.

Aronson and Geddes [2] measured large fluctuations in the electrode potential when the charge layer was destabilized by the addition of a small amount of metal contaminant to two identical, electrolytically clean metal electrodes. Godin et al. [32], however, found that noise due to fluctuations of the charge layer was negligible over a frequency range of 8 to 1000 Hz for pairs of stainless steel electrodes which were well matched. It is known that the electrode–electrolyte interface of silver (Ag) electrodes is stabilized by coating the electrodes with a layer of silver chloride (AgCl) [31]. Ag–AgCl electrodes are very stable electrically and are widely used as surface recording electrodes.

In the case of surface EMG recording, the electrode–skin interface has a reactive impedance which has been modeled using passive circuit elements (e.g. [30,68]; see Geddes [31] for a review of several models). Electrode impedance depends on electrode size, the signal frequency and the current density at the electrodes. For low current densities, Godin et al. [32] measured electrode impedances as high as 3 MΩ, for a 2.5 mm diameter stainless steel electrode at a frequency of 10 Hz. Electrode impedance decreased with increasing size and signal frequency to well below 10 kΩ, for a 20 mm diameter electrode at 1000 Hz. A high electrode–skin impedance can lead to reduced signal amplitude, waveform distortion and power line interference in the recorded EMG. This problem can be reduced by minimizing the electrode–skin impedance and using a signal amplifier with an input impedance which is at least 100 times greater than the highest expected electrode impedance, i.e., an input impedance of 100 MΩ or greater. Paste-coupled electrodes generally exhibit a lower electrode–skin impedance than dry electrodes, because the high impedance of the epidermal layer of the skin is reduced with the use of a conductive gel or paste. Careful skin preparation, including cleansing with alcohol or lipid solvents (e.g. ether) and rubbing a conductive paste or gel into the skin will reduce the electrode–skin impedance to acceptable levels even with dry electrodes. The skin impedance under dry electrodes will also decrease with sweat production under the electrodes [68]. Indwelling electrodes generally have very small contact regions and thus very high impedances. It is extremely important to use a high input impedance amplifier with these electrodes.

2.2. Electrode motion artefact

There are two sources of motion artefact in surface electrodes: mechanical disturbance of the electrode charge layer and deformation of the skin under the electrodes. The first type of motion artefact occurs when there is relative movement between the electrode and the underlying skin. This type of artefact is greatly attenuated in recessed electrodes, in which the electrode–electrolyte interface is separated from the skin surface by a layer of conductive gel or paste. Any mechanical disturbances caused by relative motion between the electrode and the skin are damped by the intervening gel layer, and their effect on the signal is limited. The second type of motion artefact arises because a potential difference, the skin potential, exists across the layers of the skin, and the value of this potential changes when the skin is deformed or stretched. This type of motion artefact is not attenuated by the use of recessed electrodes, but can be reduced by reducing the skin impedance [72]. Tam and Webster [69] suggest reducing the skin impedance by removing the upper layers of the skin via abrasion and Burbank and Webster [9] found that skin impedance is lowered by puncturing the skin. However, both techniques have drawbacks including determining the proper level of abrasion or depth of puncture, the time required, and the possibility of skin irritation and infection. As mentioned above, cleansing the skin with solvents and rubbing a conductive paste into the skin is recommended for reducing skin impedance.

Motion artefact can also be reduced in EMG recordings through signal conditioning, both on-line and off-line. Since the power density of motion artefact is mostly below 20 Hz, a high pass filter is often incorporated into the measurement instrumentation. To avoid loss of myoelectric signal power, the corner frequency of the high pass filter is frequently set at 10 Hz and generally should be set no higher than 20 Hz. Cutoff frequencies much higher than 20 Hz begin to approach the median frequency of the signal (recall that real filters shape the signal at frequency locations adjacent to the cutoff frequency), particularly during fatigue, and thus can be problematic. Conforto et al. [20] compared four techniques for motion artefact removal from EMG: 1) filtering with an eighth order Chebyshev high pass filter with corner frequency at 20 Hz; 2) filtering with a moving average filter to estimate the motion artefact and subtracting the estimated artefact from the signal record; 3) filtering with a moving median filter to estimate the motion artefact and subtracting the estimated artefact from the signal record; and 4) filtering using an adaptive filter based on orthogonal Meyer wavelets. These techniques were tested on simulated bursts of EMG contaminated with low frequency artefacts and on real dynamic gait EMG contaminated with motion artefact. The wavelet filter gave superior performance in information preservation and time-detection of EMG bursts. Hamilton and Curley [33] have investigated an adaptive method, based on measuring the skin impedance, for removing motion artefact in ambulatory ECG recordings. Preliminary results indicated that motion artefact was reduced by as much as 12.5 dB using the adaptive system, but practical implementation was impeded by the high cost of the skin stretch sensors.

A different type of motion related artefact is generated by the relative movement between skin surface electrodes and the innervation zone(s) of the underlying motor units. A sharp decrement (up to 60–80%) of EMG amplitude results when an innervation zone slides under a differential pair of electrodes. There is no simple means to compensate for such an artefact since it is indistinguishable from a change in muscle activation level. In the future, linear electrode arrays will provide a means to detect the location of the innervation zone and avoid such artefact by placing electrode pairs away from it [57].

2.3. Cable motion artefact

The cables which connect the recording electrodes to the amplifier have an intrinsic capacitance. If unshielded cables are moved through an ambient magnetic or electric field, or are subjected to a time-varying magnetic or electric field, current is generated. The magnitude of the voltage induced in the cable is the product of the displacement current and the electrode–skin impedance plus the voltage induced by magnetic coupling (both affected by cable motion). This voltage can be comparable to the magnitude of the detected EMG. The artefact typically has a frequency range of 1 to 50 Hz.

Cable motion artefact can be reduced by reducing the electrode–skin impedance through careful skin preparation. It is also reduced by using shielded cables which provide a low impedance path to ground, external to the measurement system [30]. However, the shielded cables themselves can also be a source of cable motion artefact. When these cables are moved, friction and deformation of the cable insulation generates static charges which dissipate through the measurement system [49,72]. An excellent solution to cable motion artefact is the use of active electrodes, in which the electrode is mounted onto an operational amplifier (op amp) which has a high input impedance and a low output impedance and is configured as a unity gain buffer. The op amp acts as an impedance transformer, transforming a high impedance at the electrode side of the circuit to a low impedance at the cable side of the circuit. The displacement current now flows through this low impedance to ground and the cable motion artefact is greatly attenuated. As well, because the active electrode acts as an impedance transformer, extensive skin preparation to lower the electrode–skin impedance is not required. Several active electrode designs have been reported (e.g. [25,49,54,59]). Bourland et al. [8] incorporated an op amp into the clip of the lead which was attached to a dry electrode producing an “active cable”.

An active *bipolar* electrode (a.k.a. an electrode–amplifier) is formed by connecting *two* electrodes directly to the input of a differential amplifier circuit, with all of these components mounted into one miniature package. A differential gain (10–2000) is applied to the signal, which improves overall noise rejection by raising the signal strength above the noise floor found in subsequent electronics. In some cases (particularly field and clinical studies), disposable electrodes with short leads (a few centimeters) are connected to the miniature differential amplifier circuit. The disposable electrode option can be more sanitary and pre-gelled electrodes exist. However, maintaining a constant inter-electrode distance (both during application and throughout a contraction) is more difficult.

2.4. Alternating current power line interference

Ambient electromagnetic fields exist in the vicinity of AC 120 V (or 230 V) power lines and electric equipment. The frequency of these fields is at the frequency of the AC power supply (60 Hz in North America and 50 Hz in Europe) and its harmonics. The presence of such fields can result in a power line interference signal in the recorded EMG, which can be much larger than the EMG itself. The magnitude of the artefact can be reduced by shielding the EMG recording apparatus or moving it away from the interference source. However, these changes may not always be practical and it will be necessary to reduce the interference using other means.

The mode by which power line interference arises can be magnetic or electric [72]. In the first case, a closed loop is formed by the electrode leads, the subject and the signal amplifier. When a time-varying magnetic field passes through the loop, a current is induced in the leads. The magnitude of the current is proportional to the time derivative of the magnetic field and to the area enclosed by the loop. In the second case, the electrode leads and the subject are both capacitively coupled to the ambient electric field, which induces displacement currents in the leads and in the subject’s body. The current in the electrode leads flows through the electrode impedance, which is much smaller than the amplifier input impedance, resulting in an interference potential at the electrodes which is sensed by the amplifier. The displacement current in the subject flows through the skin impedance to ground at the ground electrode. This flow results in a common mode voltage which appears at the recording electrodes. With bipolar recording electrodes, the EMG is differentially amplified and, in the ideal case, any common mode signal would be removed by the differential amplifier. In a practical recording situation, however, some common mode signal is transformed into differential signal because the skin impedances at the two electrodes are not perfectly matched, the impedances at the amplifier inputs are not perfectly matched and the common mode rejection ratio is finite [74]. This transformed signal will appear as power line interference.

The magnetically induced power line interference can be reduced by keeping the electrode leads short and/or by twisting the leads together, such that the loop area enclosed by the electrode leads, subject and signal amplifier is minimized. Good skin preparation, to reduce the skin impedance and minimize the difference between the skin impedances at the recording electrode sites, is essential to reduce the magnitude of the artefact induced by displacement currents in the electrode leads and in the subject. This type of artefact can also be attenuated by shielding the electrode leads, with the shield grounded at the amplifier, and by using a well-designed differential amplifier with a common mode rejection ratio (CMRR = differential gain/common mode gain) of at least 100 dB at 50/60 Hz. Additionally, active grounding of the subject (i.e. active referencing to the power supply common) has been proposed for use in ECG recordings (this technique is also referred to as the driven right leg circuit) [58,74]. In this circuit, the common mode voltage on the body is negatively fed back (i.e. the phase is reversed) to a third electrode, through a feedback amplifier, driving the common mode voltage to a lower level and thereby reducing the power line interference.

For subject safety, the differential amplifiers used in EMG recording are generally optically or electrically isolated. An isolated amplifier consists of two sections with separate and isolated references (grounds), thereby providing a high impedance (called the isolation impedance) between the reference terminal of the input circuit and earth ground [60]. Some of the displacement current, induced in the subject by the ambient electric field from the power line, flows across the isolation impedance (capacitance) to ground, giving rise to an isolation mode voltage. The ability of the isolated amplifier to suppress this isolation mode voltage is measured as the isolation mode rejection ratio (IMRR). Metting van Rijn [52] suggested the addition of a pre-amplifier to an isolated amplifier to increase the circuit IMRR. Pallas-Areny [60] reported that there should be adequate sharing between the CMRR and IMRR for artefact suppression. Some of the isolation mode voltage will be converted to a differential voltage by differences in the electrode skin impedances. Thus good skin preparation is also necessary to reduce power line artefact from this source.

Even with good skin preparation at the recording electrode sites and using well designed instrumentation, it may not be possible to adequately attenuate power line interference in the EMG before signal acquisition, and off-line processing will be necessary to remove the recorded artefact. One possibility is to process the EMG through a narrow fixed notch filter centered at the fundamental frequency (50 or 60 Hz). This approach may be an acceptable compromise if only a rough EMG amplitude estimate is of interest (such as in simple biofeedback applications). However, notch filtering at 50 or 60 Hz will remove signal as well as power line components, altering the spectral content and rotating the phase of the recorded EMG, therefore altering the signal waveform. Ferdjallah and Barr [27] described three adaptive digital notch filters, which were designed to track and remove 60 Hz noise from biomedical signals. Although these adaptive filters have some advantages over fixed notch filters, signal as well as noise components would still be removed from recorded EMG. Baratta et al. [3] suggested a simple method for removing power line artefact from EMG in the time domain. The amplitude and phase of the fundamental frequency of the power line interference is estimated from a quiet segment of the EMG recording. A sinusoidal waveform with the same amplitude and phase as the interfering signal is then subtracted from the entire EMG record. This method assumes that the amplitude and phase of the power line artefact do not change over the duration of the EMG recording session, which is true only under restricted experimental conditions. Widrow et al. [73] decribed an adaptive interference cancellation method in which a reference input, which provides a signal correlated with the corrupting or interference signal, is adaptively filtered and subtracted from the corrupted signal, giving an estimate of the true signal. The basic element of the system is the LMS (least mean square) adaptive filter. This method can be applied for interference reduction wherever a reference “noise” signal can be obtained simultaneously with the corrupted signal. In their paper, Widrow et al. [73] demonstrated the ability of the adaptive cancellation method to reduce power line interference in ECG recordings. Ider and Koymen [40] described a similar algorithm for off-line removal of power line interference in ECG recording. This method involves monitoring a power line interference reference signal during signal recording and subtracting the interference signal, after appropriate scaling and phase shifting. The algorithm can be made adaptive to track changes in the interference signal over time. Both the algorithms described by Widrow et al. [73] and Ider and Koymen [40] would be appropriate for use in EMG recording to remove interference signals at the fundamental power line frequency and at its harmonics. Finally, note that algorithms that only remove signal at 50/60 Hz may have to be repeated in order to reject harmonics of the power line frequency. Often, these harmonics can contain more power than the fundamental frequency.

In field trials, electromagnetic interference at frequencies other than the power line frequency may be present. How such interference is removed from the EMG is determined by the frequency content of the interfering signal. High frequency interference can be adequately attenuated via analogue low pass filtering before EMG data acquisition and storage. If the frequency content of the interfering signal overlaps that of the EMG, more sophisticated methods to remove the interference, such as those discussed above for power line interference, are required. In these cases, it is important to understand the nature of the interfering signal and determine its frequency content.

2.5. Other noise sources

The noise and interference sources covered above are the major sources of contamination in EMG signal recording. There are other sources, however, and it is important to be aware of and to minimize the contamination from these sources as well.

The electronic instrumentation used to amplify and filter the EMG prior to signal recording or acquisition is a source of broad band noise. In well designed instrumentation, the amplitude of this noise signal is small, generally less than 1.5 μV RMS (referred to input and in the 10–500 Hz frequency band) with the bipolar recording electrodes shorted to the system reference. Relative to EMG amplitude, Clancy and Farry [14] found their RMS equipment noise to be 2.1±1.7% of the RMS EMG at 50% MVC (or, approximately 1% of the EMG amplitude corresponding to MVC). This level of noise is usually lower than the noise due to the electrode–skin interface plus any residual signal due to incomplete muscular relaxation and does not present a serious problem when EMG is recorded during moderate or high force contractions, because the signal-to-noise ratio (the ratio of EMG amplitude to noise magnitude) will be high. For example, Clancy and Farry [14] found the total background noise (due to the electronics, electrode–skin interface and any incomplete relaxation) to be broad band and have an RMS value equal to 6.3±6.1% of the RMS EMG at 50% MVC (or approximately 3% of the EMG amplitude corresponding to MVC). However, for low EMG signal levels, such as might be recorded during low force tasks, it is desirable to minimize the instrumentation and electrode–skin interface noise. This noise reduction may be accomplished by filtering the recorded signal through a low pass filter with a sharp roll-off characteristic and the corner frequency set at the upper frequency of the EMG signal. This filter will remove the high frequency components of the noise signal thereby reducing the overall noise signal power and improving the signal-to-noise ratio. The resultant “background” noise level should be measured for each subject during complete muscle relaxation, as it can vary considerably.

If the EMG signal is recorded on analogue tape before digitization, noise is introduced by the recorder [31]. This noise includes flutter due to oscillations in tape speed, wow due to a slight change in the tape speed, and tape noise. In most recent EMG recording situations, analogue recording is by-passed and the EMG is sampled directly for storage and off-line processing via an analogue-to-digital (A/D) converter. There are two issues to consider in signal sampling (or A/D conversion): sampling rate and sampling resolution. The sampling theorem states that a signal must be sampled at a rate which is at least twice the highest frequency in the signal in order to recover the complete information content. If there are components in the signal at frequencies higher than one-half the sampling rate, ambiguities will arise and information will be lost. This phenomenon is called aliasing. To prevent aliasing, it is essential to know the bandwidth of the sampled signal so that the minimum sampling rate can be determined. Most of the signal power in surface EMG is below 400–500 Hz. Also, it is recommended that the analogue signal be low pass filtered before sampling using a filter with a sharp roll-off and a corner frequency at or below one-half the sampling rate, taking care to preserve the bandwidth of the signal.

A/D conversion resolution is determined by the number of bits per sample, which defines the number of discrete levels into which the signal will be converted. Typically A/D converters provide 8-, 12-, or 16-bits. A 16-bit A/D converter divides the input voltage range into 65,536 discrete levels, a 12-bit A/D converter into 4096 discrete levels, and an 8-bit A/D converter into only 256 discrete levels. At each sampling instant, the signal is given the discrete value which is closest to the actual signal level. Because sampling divides the signal into a finite number of discrete levels, an error, called the quantization error, is introduced and quantization noise results. This noise is broad-band with an average magnitude of approximately one quarter of a bit (maximum magnitude of one half of a bit). A 12-bit A/D converter provides sufficient resolution for most EMG applications, provided the range of the converter is matched to the maximum peak-to-peak amplitude of the signal [46]. A 16-bit A/D converter may be preferable, since the added resolution may eliminate the need for manual gain selection of each EMG amplifier.

The EMG is occasionally contaminated by other biosignals. The most common of these is the ECG, which is frequently present when the EMG is recorded from electrode sites on the trunk and neck. Redfern [64] suggested a method for ECG removal from rectified, smoothed EMG recorded from the erector spinae muscles. EMG detected at the L3 spinal level was amplified, rectified and low-pass filtered using a time constant of 50 ms. The time occurrences of the ECG pulses in the data record were determined by cross-correlating with a representative ECG pulse. The ECG's were then removed by replacing the data points between the start and end point of the ECG by a straight line. The processed EMG provided a reasonable representation of the level of activity in the muscle. However, this method results in a loss of signal information and, depending on the application, the amplitude estimate may not be acceptable. Redfern et al. [65] were able to effectively remove ECG artefact from raw EMG recordings from the rectus abdominis, external oblique and erector spinae muscles by high pass filtering. A high pass corner frequency of 20–30 Hz was found to be best to remove ECG artefact with minimal impact on the total power of the EMG. Akkiraju and Reddy [1] used adaptive noise cancellation to remove ECG artefact from EMG recorded from intercostal muscles. The adaptive noise canceller was based on that of Widrow et al. [73] where the ECG was recorded separately and used as the reference input to the noise canceller. The ECG artefact was effectively removed from the EMG records by the adaptive noise cancellation.

3. EMG amplitude estimation

This section will review the methods which are used to estimate the EMG amplitude from recordings of the EMG. Historically, Inman et al. [41] are credited with the first continuous EMG amplitude estimator. They implemented a full-wave rectifier followed by a simple resistor–capacitor low pass filter. Early investigators studied the type of non-linear detector which should be applied to the waveform. This work led to the routine use of analogue rectify and smooth (low pass filter) processing, mean-absolute-value (MAV, a.k.a. mean-rectified-value) processing and root-mean-square (RMS) processing of the EMG signal to form an amplitude estimate. (These simple techniques still dominate most applied studies that incorporate EMG amplitude estimation.) Because amplitude estimation of a random signal shows a smaller variance when the samples are uncorrelated, ensuing investigation found that it is appropriate to decorrelate EMG samples. This process is referred to as whitening. Finally, combining multiple EMG channels into a single amplitude estimate has also been shown to reduce estimator variance.

Emerging from this work, a standard cascade of six sequential processing stages, as shown in Fig. 1, can be used to form a general processor for EMG amplitude estimation. The six stages are: (1) noise rejection/filtering; (2) whitening; (3) multiple-channel combination (including gain scaling); (4) demodulation; (5) smoothing; and (6) relinearization. Noise rejection and filtering have been described in detail above, and will not be repeated here (except for the influence of remaining additive noise on the whitening processes). The correlation between neighbouring EMG samples is a consequence of the limited signal bandwidth. The limited signal bandwidth reflects the actual biological generation of EMG and the low pass filtering effects of the

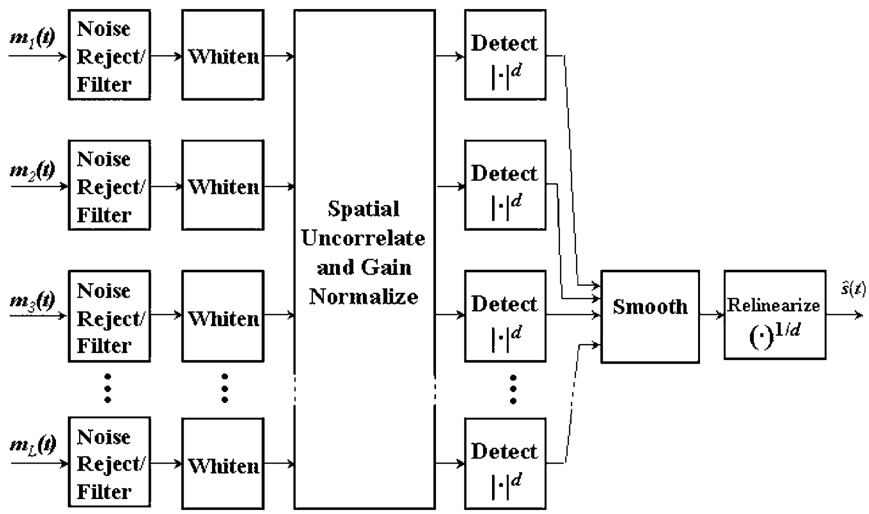

Fig. 1. Cascade of processing stages used to form an EMG amplitude estimate. The acquired EMG $m_1(t)$ through $m_L(t)$ are all assumed to be from bipolar electrodes placed over the same muscle. The EMG amplitude estimate is $\hat{s}(t)$. In the "Detect" and "Relinearize" stages, d=1 for MAV processing and d=2 for RMS processing.

tissues as the signal propagates from its source to the measurement apparatus. Decorrelation, that is whitening, makes the samples statistically uncorrelated, increases the "statistical bandwidth" (a measure of the number of statistical degrees of freedom in the data, defined in [5]) and reduces the variance of amplitude estimation. Multiple-channel combination is used to combine the information from several electrode recordings made over the same muscle. Demodulation rectifies the whitened EMG and then raises the result to a power (either 1 for MAV processing or 2 for RMS processing). Smoothing filters the signal, increasing the signal-to-noise-ratio, albeit at the expense of adding bias error to the estimate. Finally, relinearization inverts the power law applied during the demodulation stage, returning the signal to units of EMG amplitude. Measures for evaluating the performance of EMG amplitude estimates and techniques for implementing processing stages 2 through to 6 will be discussed in the following sections.

3.1. Measures of amplitude estimator performance

For objective assessment and comparison of EMG amplitude estimators, measures of amplitude estimator performance are required, a few of which are common in the literature. When contraction is constant-force, constant-posture and nonfatiguing, it is generally assumed that the EMG *amplitude* should be constant. (The EMG *signal*, of course, varies due to the random nature of the signal.) To quantify the "quality" of the amplitude estimate, it is common to define a dimensionless signal-to-noise-ratio (SNR) as the sample mean value of the amplitude estimate divided by its sample standard deviation, where "sample" refers to an estimate for one epoch. (This SNR should *not* be confused with SNR at the input of the amplifier chain.) This measure, which is the inverse of the coefficient of variation, is invariant with respect to the gain of the EMG channel and makes no assumption as to any relationship between EMG and muscle force. Because SNR is a measure of the random fluctuations of the EMG amplitude, better estimators yield higher SNR's. Note that some authors have used the square of this measure as a performance index.

When force or posture is changing, SNR is no longer a useful measure. In the case of computer generated signals (e.g. simulation models), the true EMG amplitude is known. In these cases, common measures of agreement (e.g. the RMS error between the true and estimated EMG amplitudes) are used. In physiologic situations, however, the true EMG amplitude is not known and alternative measures of performance must be used. One possibility is to display a real-time amplitude estimate to a subject as a form of bio-feedback. The experimenter generates a second target display for the subject to track. The target is moved over the range of desired EMG amplitudes, usually via computer control. The tracking error (e.g. RMS error between the target amplitude and the subject's response) serves as a performance measure, with better EMG amplitude estimators presumably providing lower error.

A common application of surface EMG is to estimate muscle force. Typically, an EMG amplitude estimate is formed from the EMG and then the amplitude is related to some measure of output force, e.g. joint torque. Again, better amplitude estimation is assumed to provide better EMG-force estimation. Common measures of agreement between the direct measurement of force (gold standard) and the indirect estimate are used to evaluate the difference between the two techniques. Note that the amplitude of EMG is affected by confounding factors other than force. Among these are the muscle fiber action potential amplitude and the distance between each active motor unit and the skin. Both factors may change from subject to subject, muscle to muscle, and even from time to time during the same contraction. As a consequence, EMG-based muscle force estimates must account for these (and other) confounds, and results must be appropriately limited and interpreted.

3.2. Whitening

As mentioned above, it has been shown that applying a whitening filter prior to demodulation and smoothing improves the amplitude estimate [10,14,16,18,21,23,28,34,37,38,45]. A whitening filter outputs a theoretically constant, or "whitened," power spectrum in response to an EMG input. If EMG is modeled as a discretely sampled Gaussian process, whitening orthogonalizes the data samples, making them independent. Zhang et al. [76] discuss the advantages of whitening based on a model of EMG as the superposition of simulated motor unit action potentials.

Whitening is typically implemented via software signal processing algorithms. A whitening filter is formed by first estimating the power spectral density (PSD) of the EMG. Then, the inverse of the square root of the PSD specifies the shape of the whitening filter. At least three general methods to achieve whitening have been described in the literature. First, for constant-force, constant-posture, nonfatiguing contractions, it is common to model the EMG as a wide-sense stationary (WSS), amplitude modulated, autoregressive (AR) process (software for doing so is readily available [50,63]). With this model, the PSD of EMG, denoted $S_{\mathrm{mm}}(e^{j\omega})$, can be written as

$$S_{\mathrm{mm}}(e^{j\omega})=\frac{a_0}{\left|1-\sum_{k=1}^{P}a_k e^{-kj\omega}\right|^2} \tag{1}$$

where the a_i are the AR coefficients, P is the model order, and ω is frequency in rad/s. These coefficients are fitted from a calibration contraction which is typically a few seconds in duration. Once these coefficients have been determined, whitening can be achieved on subsequent recordings with a discrete-time moving average filter, written as

$$y(n)=\frac{1}{\sqrt{a_0}}x(n)+\frac{-a_1}{\sqrt{a_0}}x(n-1)+\ldots+\frac{-a_P}{\sqrt{a_0}}x(n-P) \tag{2}$$

where $x(n)$ are the data input to the whitening filter, $y(n)$ are the whitened output data and n is the discrete-time sample index. Model orders of 4–6 have been found sufficient to model the PSD [16,34,71]. Fig. 2 shows an example of whitening using this method, and Fig. 3 graphically depicts this method for designing a whitening filter. For contractions at 10% MVC and higher, this technique has led to a 63% improvement in the SNR [16]. Note that although most of the signal power in surface EMG is below 400–500 Hz, whitening can recover important amplitude information at frequencies well above this range, improving the SNR (see [14,16] for details). Unfortunately, this whitening technique seems to fail at lower contraction levels due to the presence of additive background noise (a feature of recorded EMG which is generally not included in the EMG models described above).

A second method for whitening is similar to the first, but assumes that the PSD of the EMG can vary *in a general manner* (i.e. not just restricted to an amplitude modulated PSD), and thus the whitening filter must do so as well. In this case, the PSD model is continuously updated based on the most recent data input to the whitener [7,23,24]. For the AR model approach described in Eqs. (1) and (2), the AR coefficients would be written as time-dependent, i.e. $a_k(n)$.

A third whitening method solves the limitation of the first method for low contraction levels by modeling the fact that EMG is invariably acquired in the presence of an additive, broad-band measurement noise [10,14,16,45,62]. Thus, the whitening filter should be adapted, but the adaptation is not as general as that mentioned above. The adaptation specifically applies to an amplitude modulated "true" signal in the presence of additive measurement noise. The adaptation scheme can be determined in a calibration phase, based on the PSD of the additive noise and that from a reference contraction. For example, Clancy and Farry [14] have formed an adaptive whitener consisting of a non-adaptive whitening filter (similar to the whitener of method one above, except that an AR model is not used and the additive measurement noise is subtracted out of the power spectrum prior to determining the filter shape), followed by an adaptive Wiener filter. The Wiener filter adapts the overall filter shape based on the relative contribution of true signal to additive measurement noise. In experimental studies of this technique, subjects tracked a randomly-moving target on a computer screen with real-time EMG amplitude estimates. With a 0.25 Hz bandwidth target, adaptive whitening reduced the tracking error halfway to that of the error achieved using force feedback.

Compared to the adaptive whitening technique of Clancy and Farry [14], the general technique of D'Alessio et al. [23] is much less restrictive. It could provide better whitening if, or to the extent that, the true PSD shape changes with the EMG amplitude (or with localized muscle fatigue). However, since each PSD estimate is based on only a short segment of the most recent data, each PSD estimate (and, therefore, the resulting whitening filter) has a high variance. Hence, to the extent

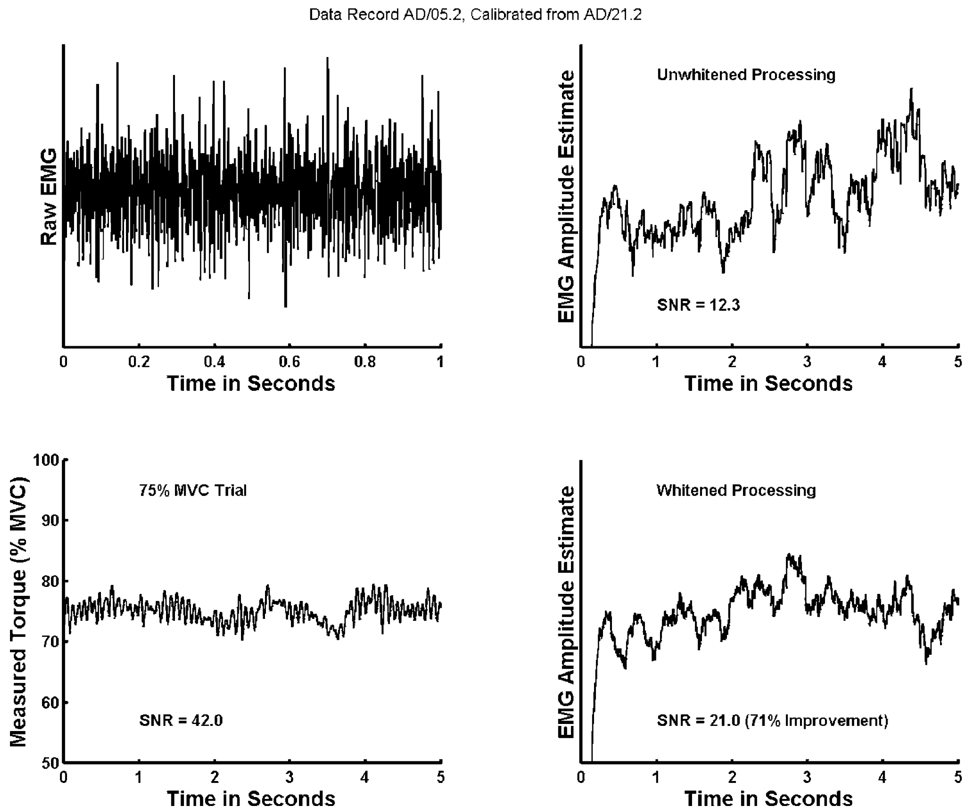

Fig. 2. Influence of whitening on the EMG amplitude estimate. Upper left is a 1 s portion of the EMG (total recording is 5 s). Lower left is the corresponding torque. Upper right is the moving average RMS (245 ms window) *unwhitened* EMG amplitude estimate. Lower right is the moving average RMS (245 ms window) *whitened* EMG amplitude estimate (4th-order AR model). Whitening improved the SNR (the sample mean value of the amplitude estimate divided by its sample standard deviation) by 71%. The *y*-axis of each EMG plot is independently normalized and all graph scales are linear. (Reprinted from [16] with permission, ©1994 IEEE.)

that the EMG PSD is truly amplitude modulated, the whitening method of Clancy and Farry is more stable and repeatable. Future research is needed to compare and contrast the strengths and weaknesses of these techniques.

Although these adaptive techniques are still emerging, the time is now appropriate to begin moving these methods into settings in which reduced EMG amplitude estimation variance is critical (e.g. instant-by-instant evaluation of motion patterns, EMG-force processing). For less demanding settings where reduced variance is not critical (e.g. evaluation of *average* EMG amplitude levels from long-duration recordings), whitening filters have significantly less to offer and may not be worth the added complexity.

3.3. Multiple-channel combination

Hogan and Mann [37,38] suggested that detecting EMG using multiple electrode pairs placed on a single muscle would provide a broader, more complete, measure of the underlying electrophysiologic activity, since a single differential electrode obtains most of its signal energy from a small portion of muscle underneath the electrode. To avoid observing correlated (redundant) information and to avoid the innervation zone, distinct bipolar electrodes are placed along a line perpendicular to the muscle fiber direction, away from the innervation zone. (The two electrodes from each bipolar pair are placed parallel to the muscle fiber direction.) Using four such electrodes, Hogan and Mann [37,38] achieved an SNR performance improvement of approximately 91% compared to the single site rectify and low-pass filter estimator of Inman et al. [41]. Other studies have also found an improvement using multiple channels [12,14,17,42,56,70].

Clancy and Hogan [17] combined the techniques of signal whitening and multiple channel combination. Sample results are shown in Fig. 4. 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. [41]. For this four channel processor, it was found that simple gain normalization of the four channels based on a single 5 s calibration contraction at 50% MVC performed as well as the complete spatial uncorrelation described by Hogan and Mann [37,38].

Some limitations of multiple channel processing

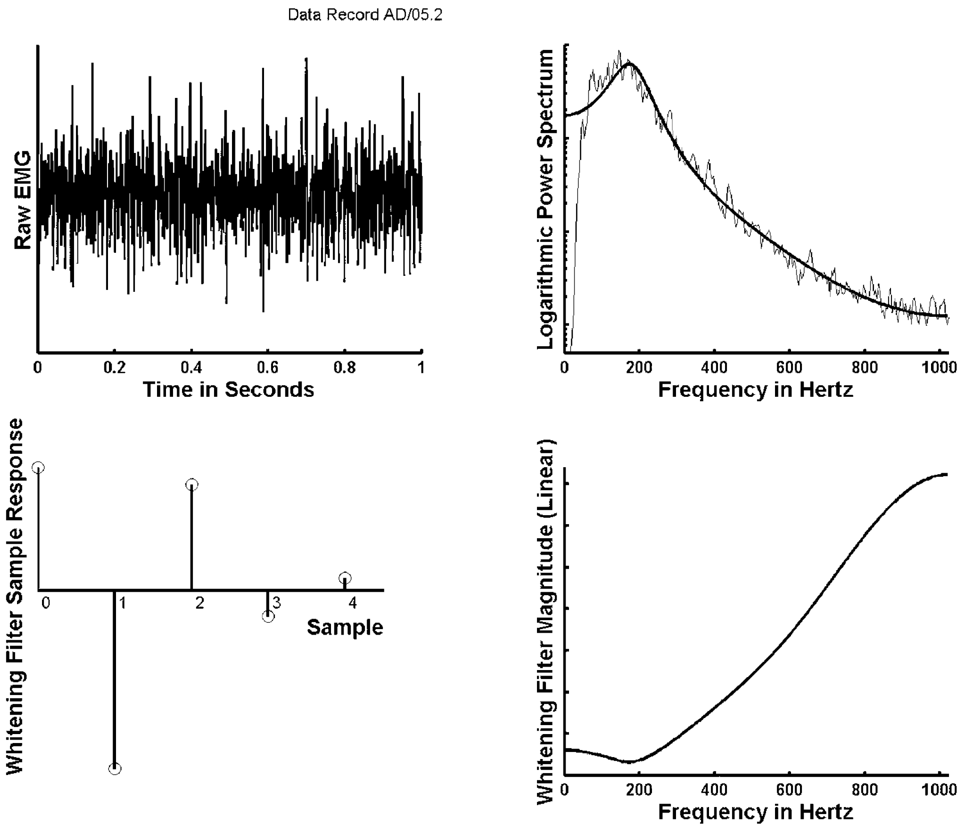

Fig. 3. Fixed whitening filter design. Upper left is a 1 s portion of the EMG signal (total recording is 5 s). Jagged plot at upper right is the discrete Fourier transform estimate of the EMG PSD. Smooth plot is the 4th-order AR estimate of the EMG PSD. Lower right is the magnitude response of the whitening filter formed from the AR PSD estimate and lower left is its sample response. (Reprinted from [16] with permission, ©1994 IEEE.)

should be mentioned. First, the fundamental assumption that multiple electrodes are recording different "views" of the same muscle may not always be appropriate. If different portions of a muscle exhibit independent control capability or if EMG crosstalk is present, for example, then it may be best to form amplitude estimates from each available electrode, perhaps combining their mutual information at some later stage in the analysis. Second, Clancy [11] noted that 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, etc) grows with the number of electrodes. Automated methods for locating and managing failed channels may need to be developed. Third, the added cost of the additional hardware must be weighed versus the benefits in amplitude estimate performance.

3.4. Demodulation and relinearization

Treating the EMG as a zero mean, amplitude modulated signal, Inman et al. [41] suggested demodulation with a full-wave rectifier, the analogue equivalent of the first-power (or absolute value) demodulator. Kreifeldt and Yao [48] experimentally investigated the performance of six non-linear demodulators. Hogan and Mann [37,38] used a functional mathematical model of EMG, based on a model of EMG as a *Gaussian* random process, to analytically predict that a second-power (or RMS) demodulator would give the best maximum likelihood estimate of the EMG amplitude for constant-force, constant-posture, nonfatiguing contractions. Theoretically, the SNR with this model is: $\mathrm{SNR} \cong \sqrt{2N}$, where N is the number of statistical degrees of freedom in the EMG [5]. Experimentally, they found no SNR performance difference between the RMS processor and a full wave rectifier. Similarly, Clancy [10] consistently found full wave rectification to be a small improvement (2–8%) over RMS detection. These experimental results are contrary to the predictions from Gaussian theory.

Surface EMG, particularly at higher contraction levels, has frequently been assumed to be Gaussian distributed, that is, having a probability density function written as

$$p_x(X)=\frac{1}{s\sqrt{2\pi}}e^{\frac{-x^2}{2s^2}},\ -\infty<X<\infty, \tag{3}$$

where the mean value is assumed to be zero, x is an

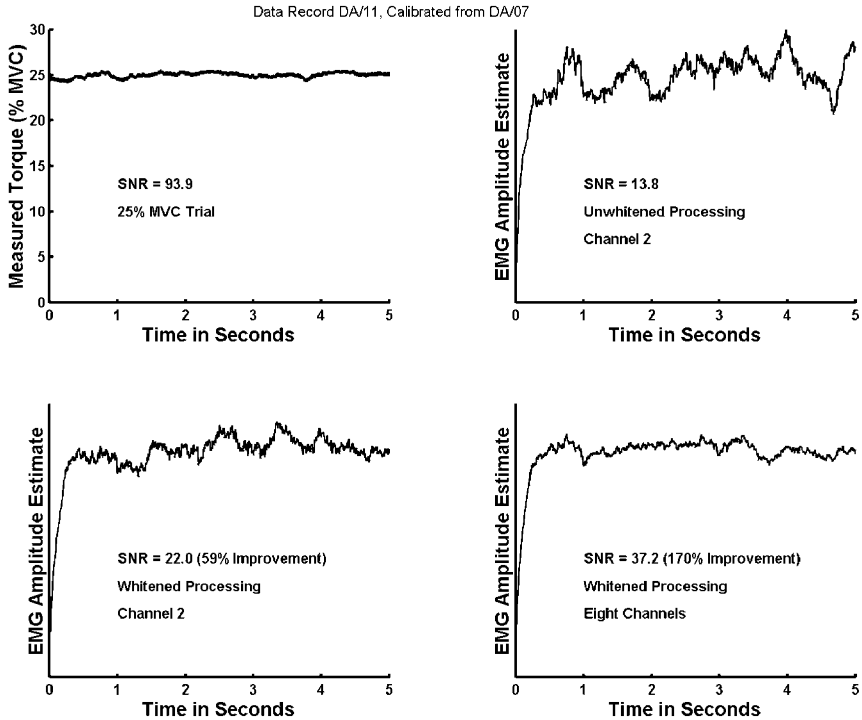

Fig. 4. Multiple-channel EMG amplitude estimation. Upper left is the torque measured from a constant-force, constant-posture, nonfatiguing 25% MVC. Upper right is the single-channel, *unwhitened* EMG amplitude estimate. Lower left is the single-channel, *whitened* EMG amplitude estimate. Lower right is the 8-channel, whitened EMG amplitude estimate. All estimates use a 245 ms moving average RMS window. SNR is defined as the sample mean value of the amplitude estimate divided by its sample standard deviation. The *y*-axis of each EMG plot is independently normalized and all graph scales are linear. (Reprinted from [15] with permission, ©1990 IEEE.)

EMG sample and s is the EMG amplitude. Some research studies have found evidence to support this assumption [16,66], while several others have found EMG to have a distribution which is more sharply peaked near zero than the Gaussian distribution [6,39,53]. Indeed, at low contraction levels, gaps between motor unit action potentials are clearly detectable and the distribution becomes sharper near zero. Similar changes occur when the muscle is fatigued. (See [6] and [19] for additional review of this topic.) Recently, Clancy and Hogan [19] proposed an alternative model for the EMG probability density, based on a *Laplacian* random process, written as

$$p_x(X)=\frac{\sqrt{2}}{2s}e^{\frac{-\sqrt{2}}{s}|X|},\ -\infty<X<\infty, \quad (4)$$

where the mean value is assumed to be zero and s is the EMG amplitude. The Laplacian density is more sharply peaked near zero than a Gaussian density. They showed that MAV processing (or first-order demodulation) gives the maximum likelihood estimate of the EMG amplitude in this case. Theoretically, the SNR with this model is: $\text{SNR}=\sqrt{N}$, performance that is approximately 32% inferior to that based on the Gaussian model. Thus, minor variations in the probability density of the EMG may result in large SNR decrements. Experimentally, it was found that the observed densities from constant-force, constant-posture, nonfatiguing contractions fell in between the theoretic Gaussian and Laplacian densities. On average, the Gaussian density was the better fit as shown in Fig. 5. For amplitude estimation, MAV processing had a higher SNR than RMS processing by 2.0–6.5%. Further simulation studies showed certain density shapes between Gaussian and Laplacian for which MAV processing was best. These simulation findings were consistent with the experimental results. Combined, these results suggest that forming EMG amplitude estimates via MAV processing may be at least as justified as RMS processing, both from theoretical and experimental perspectives. Thus, either detector can be used in practice, and there is little reason to debate between them.

3.5. Smoothing

For constant-force, constant-angle, non-fatiguing muscular contraction, the SNR of EMG amplitude estimates using root-mean-square detection has been shown theoretically (using a Gaussian model for the signal) by Hogan and Mann [38] to be related to the statistical bandwidth [5] of the EMG signal (B_s, in Hz), the number of EMG channels recorded on a muscle (L), and the length of the smoothing window (T, in seconds) applied

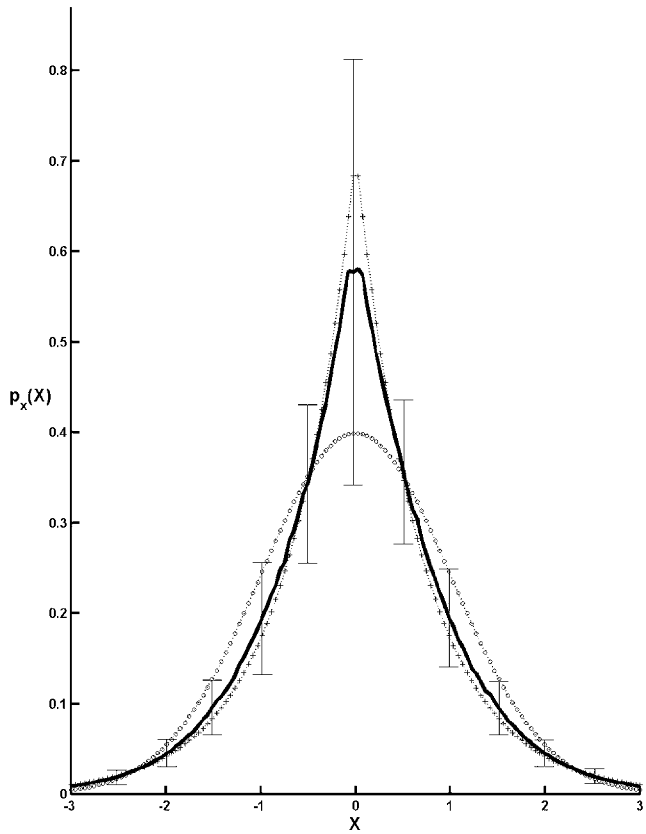

Fig. 5. Normalized probability density function estimate of EMG. Experimental density (solid line) is the average of 266 constant-force, constant-posture, nonfatiguing contractions at 50% MVC from triceps muscles. Error bars indicate one standard deviation above and below the average. Line with "+" indicates the Laplacian density, line with "o" the Gaussian density. (Modified and reprinted from [19] with permission, ©1999 IEEE.)

to the data (see also footnote 1 in [67]) as: $\mathrm{SNR} \cong \sqrt{2 \cdot 2B_s \cdot L \cdot T}$. This formula assumes that each EMG channel has the same statistical bandwidth. Note that for sampled data, $T=N_s/f$, where N_s is the number of samples in the smoothing window and f is the sampling frequency in Hz. Experimentally, a few studies in the literature provide evidence for an increasing SNR with window length [41,47,70]. St-Amant et al. [67] conducted a systematic, experimental study of the influence of smoothing window length on SNR for EMG recorded from biceps and triceps muscles during non-fatiguing, constant-force, constant-angle contractions. They found that both RMS and MAV processors increased the SNR in a square root fashion with window length. The shape of this relationship was consistent with theoretical predictions [19,37,38], however none of the processors achieved the absolute performance level predicted by the theory.

When either the exerted force, or muscle length, or both change during contraction, selection of an appropriate smoothing window length has been a topic of study [12,36,41,55,75]. In this case, variance (random) errors in the EMG amplitude estimate are diminished with a long smoothing window; however, bias (deterministic) errors in tracking the signal of interest are diminished with a short smoothing window. For fixed-length smoothers, an appropriate balance needs to be established. A model-based approach was taken by Miyano et al. [55] in developing a procedure to obtain the optimal time constant for a full-wave rectified detector. They showed that the optimal time constant could be determined by minimizing a nonlinear equation written as a function of the autocorrelation of EMG amplitude. Clancy [12, Appendix] derived a method for optimal selection of a fixed window length. Different results were derived for causal and noncausal (midpoint moving average) processing. For noncausal processing, the optimal window length was found to be:

$$\frac{N_{\mathrm{Noncausal}}}{f} = \left[\frac{72}{g}\right]^{\frac{1}{5}} \cdot \left[\frac{s^2_{\mathrm{Ave}}}{(\ddot{s}^2)_{\mathrm{Ave}}}\right]^{\frac{1}{5}} \tag{5}$$

where N is the window length (samples), f is the sampling frequency (Hz), s^2_{Ave} is the average value of the square of EMG amplitude, and $(\ddot{s}^2)_{\mathrm{Ave}}$ is the average value of the square of the second derivative of EMG amplitude. The quantities s^2_{Ave} and $(\ddot{s}^2)_{\mathrm{Ave}}$ take different values for different tasks. The constant g is a conglomeration of three other constants that specify the number of statistical degrees of freedom in the data and is determined by the statistical bandwidth of the EMG, the number of EMG channels and the detector type (see [12] for details). Using RMS processing and assuming the Gaussian model for EMG, then $g=2B_sL$ (B_s and L are defined above). This value is never fully achieved since neither whitening nor spatial uncorrelation perform perfectly, and the signal model is not exact. Therefore, Table 1 shows the value of g determined experimentally by St-Amant et al. [67] for eight different processors. For causal processing, the optimal window length was found to be:

$$\frac{N_{\mathrm{Causal}}}{f} = \frac{1}{g^{\frac{1}{3}}} \cdot \left[\frac{s^2_{\mathrm{Ave}}}{(\dot{s}^2)_{\mathrm{Ave}}}\right]^{\frac{1}{3}} \tag{6}$$

where $(\dot{s}^2)_{\mathrm{Ave}}$ is the average value of the square of the first derivative of EMG amplitude.

Rather than find one fixed-length window which is optimal for an entire application, several studies have attempted to improve the amplitude estimate by dynamically adapting the window length to the local characteristics of the EMG [12,21,22,29,42–44,51,61]. In direct comparison to the best *fixed-length* smoother, these *adaptive* smoothers have found little or no advantage for generic applications, with a few exceptions. Evans et al. [26] proposed a logarithmic transformation of the myoelectric signal, allowing use of the theory of Kalman filters to estimate the amplitude of the transformed signal.

In all of the above, selection of the window length

Table 1
Degrees of freedom constant g for several different EMG processors. This constant is determined by the statistical bandwidth of the EMG, the number of EMG channels and the detector type (see [12] for details)

EMG processor Detector	Whitened versus unwhitened	Number of EMG channels	Degrees of freedom constant g (Hz)
Mean-absolute-value (MAV)	Unwhitened	1	263
Mean-absolute-value (MAV)	Unwhitened	4	546.5
Mean-absolute-value (MAV)	Whitened	1	639
Mean-absolute-value (MAV)	Whitened	4	1427
Root-mean-square (RMS)	Unwhitened	1	234.5
Root-mean-square (RMS)	Unwhitened	4	463.5
Root-mean-square (RMS)	Whitened	1	617.5
Root-mean-square (RMS)	Whitened	4	1262

was discussed in view of optimizing the *amplitude* estimate only. For applications such as EMG-force estimation, the amplitude estimate is the input to an ensuing procedure (e.g. EMG amplitude to force model). In these cases, smoothing may be skipped entirely (leaving all of the smoothing to the ensuing application), or the smoothing parameters may be dictated by the requirements of the application.

Finally, it was previously noted that additive noise is invariably recorded along with the “true” EMG. Some researchers treat this noise after the smoothing stage by subtracting the noise level from the smoothed EMG amplitude estimate (either prior to or after relinearization). For several reasons, this straight-forward offset subtraction does not appear to provide the *best* treatment of the data. A few comments are in order. First, when the EMG amplitude is low, background noise must be attenuated in (or before) the whitening stage, else whitening will fail [18]. Thus, the noise must be treated earlier in the processing chain. Second, there do not appear to be any theoretical or experimental arguments for offset subtraction of background noise after demodulation. Clancy ([10, Appendix C]) showed that offset subtraction (in the power domain for an RMS processor) is best (in the maximum likelihood sense) *if both* the EMG and noise power spectra are white (and the signals are Gaussian distributed). However, clearly their spectra differ, with background noise being rather broadband, and EMG being band-limited. Accordingly, a few groups have developed noise attenuation methods that *adaptively* filter the signal to optimally remove the background noise [10,14,18,45,62]. Again, these methods attenuate the background noise prior to demodulation. Third, some authors have considered the case of *theoretical* distributions to argue that subtraction in the power domain (after demodulation) is appropriate. For RMS processors, they are noting that if two independent random variables are summed, the variance of the sum is the sum of the individual variances. Hence, the variance of one random variable (noise-free EMG) is equal to the variance of the sum (noise-free EMG plus noise) minus the variance of the other random variable (noise). While this argument is true for *theoretical* distributions in which the variance is *known*, it is not necessarily true for *estimations* based on a finite *sample* of a distribution. Finally, in spite of all the above discussion, the offset subtraction technique certainly provides *some* EMG amplitude estimate, even if it is sub-optimal. In cases where whitening is not desired, perhaps this estimator is sufficient. Theoretical and experimental study is needed to investigate this possibility.

4. Summary and conclusions

In this paper, techniques for reducing noise from EMG recordings and forming advanced amplitude estimates from the noise-attenuated signal have been reviewed. These techniques are important in low effort, high precision tasks and applications requiring a high-fidelity EMG amplitude estimate. Recent research into improving the amplitude estimate via EMG signal whitening and multiple channel combination has been highlighted. The discussions relative to the electrode apparatus and preparation were not meant to be comprehensive. Other issues, such as inter-electrode distance, electrode location on the muscle, etc. are also necessary to consider in recording situations, but have not been covered here. Nonetheless, the two most dominant issues in noise reduction are proper skin preparation prior to electrode placement and the use of active electrodes. Several unwanted signal sources (e.g. electrode–skin contact noise, motion artefact, cable motion artefact, power line interference) are attenuated by reducing the electrode–skin impedance through proper skin preparation. Active electrodes, which buffer the signal at the recording site, almost completely eliminate cable motion artefact and thus are recommended for applications in which there is appreciable subject motion during data recording. When these basic methods do not sufficiently reduce noise, artefacts and interference, then other approaches are appropriate, including: high pass filtering in the range of 10–20 Hz (to reject motion and ECG artefacts), adaptive interference cancellation based on a correlated reference signal (to reject motion artefact, power line interference and ECG artefacts), use of a "driven right leg circuit" (to cancel power line interference), and the use of various linear and non-linear power-line attenuation filters. Appropriate use of each would serve to increase the effective CMRR of the system.

Once the noise in the acquired EMG has been attenuated, five steps remain to produce an amplitude estimate: whitening, multiple-channel combination, demodulation, smoothing and relinearization. As detailed herein, both whitening and multiple-channel combination reduce the variance in the amplitude estimate without increasing its bias, while smoothing reduces variance at the expense of increased bias. The future of EMG amplitude estimation should combine all of the performance improvements described herein into a robust, high-fidelity processor. Lastly, instrumentation/software utilizing all of these techniques must remain simple so that users can easily incorporate the benefits of higher fidelity amplitude estimation into applied EMG projects and research investigations.

Acknowledgements

Portions reprinted with permission from [15, 16,19,67], ©IEEE 1990, 1994, 1999, 1998, and [13].

References

[1] Akkiraju P, Reddy DC. Adaptive cancellation technique in processing myoelectric activity of respiratory muscles. IEEE Trans Biomed Eng 1992;39:652–5.
[2] Aronson S, Geddes LA. Electrode potential stability. IEEE Trans Biomed Eng 1985;32:987–9.
[3] Baratta RV, Solomonow M, Zhou B-H, Zhu M. Methods to reduce the variability of EMG power spectrum estimates. J Electromyogr Kinesiol 1998;8:279–85.
[4] Basmajian JV, DeLuca CJ. Muscles alive: their functions revealed by electromyography. Baltimore: Williams and Wilkins, 1985.
[5] Bendat JS, Piersol AG. Random data: analysis and measurement procedures. New York: John Wiley and Sons Inc, 1971.
[6] Bilodeau M, Cincera M, Arsenault AB, Gravel D. Normality and stationarity of EMG signals of elbow flexor muscles during ramp and step isometric contractions. J Electromyogr Kinesiol 1997;7:87–96.
[7] Bonato P, D'Alessio T, Knaflitz M. A statistical method for the measurement of muscle activation intervals from surface myoelectric signal during gait. IEEE Trans Biomed Eng 1998;45:287–99.
[8] Bourland JD, Geddes LA, Sewell G, Baker R, Kruber J. Active cables for use with dry electrodes for electrocardiography. J Electrocardiol 1978;11:71–4.
[9] Burbank DP, Webster JG. Reducing skin potential motion artifact by skin abrasion. Med Bio Eng Comput 1978;16:31–8.
[10] Clancy EA. Stochastic modeling of the relationship between the surface electromyogram and muscle torque. PhD thesis, Dept Elect Eng Comp Sci, MIT, Cambridge, MA, 1991.
[11] Clancy EA. EMG amplitude estimation: a review of the past and a look towards the future. Presented at Institute of Biomedical Engineering "Issues in Upper Limb Prosthetics", University of New Brunswick, New Brunswick, CA, 1997.
[12] Clancy EA. Electromyogram amplitude estimation with adaptive smoothing window length. IEEE Trans Biomed Eng 1999;46:717–29.
[13] Clancy EA. EMG Amplitude estimation toolbox: user's guide. Alpha Version 0.02. May 1999.
[14] Clancy EA, Farry KA. Adaptive whitening of the electromyogram to improve amplitude estimation. IEEE Trans Biomed Eng 2000;47:709–19.
[15] Clancy EA, Hogan N. EMG amplitude estimation from temporally whitened, spatially uncorrelated multiple channel EMG. Ann Int Conf IEEE Eng Med Biol Soc 1990;12:0453–4.
[16] Clancy EA, Hogan N. Single site electromyograph amplitude estimation. IEEE Trans Biomed Eng 1994;41:159–67.
[17] Clancy EA, Hogan N. Multiple site electromyograph amplitude estimation. IEEE Trans Biomed Eng 1995;42:203–11.
[18] Clancy EA, Hogan N. Relating agonist-antagonist electromyograms to joint torque during isometric, quasi-isotonic, nonfatiguing contractions. IEEE Trans Biomed Eng 1997;44:1024–8.
[19] Clancy EA, Hogan N. Probability density of the surface electromyogram and its relation to amplitude detectors. IEEE Trans Biomed Eng 1999;46:730–9.
[20] Conforto S, D'Alessio TD, Pignatelli S. Optimal rejection of movement artefacts from myoelectric signals by means of a wavelet filtering procedure. J Electromyogr Kinesiol 1999;9:47–57.
[21] D'Alessio T. Some results on the optimization of a digital processor for surface EMG signals. Electromyo Clin Neurophysiol 1984;24:625–43.
[22] D'Alessio T. Analysis of a digital EMG signal processor in dynamic conditions. IEEE Trans Biomed Eng 1985;32:78–82.
[23] D'Alessio T, Accornero N, Berardelli A. Toward a real time adaptive processor for surface EMG signals. Ann Int Conf IEEE Eng Med Biol Soc 1987;9:323–4.
[24] D'Alessio T, Laurenti M, Turco B. On some algorithms for the tracking of spectral structure in non-stationary EMG signals. Proceedings of MIE '87, Rome, Italy, 1987.
[25] DeLuca CJ, LeFever RS, Stulen FB. Pasteless electrode for clinical use. Med Biol Eng Comput 1979;17:387–90.
[26] Evans HB, Pan Z, Parker PA, Scott RN. Signal processing for proportional myoelectric control. IEEE Trans Biomed Eng 1984;31:207–11.
[27] Ferdjallah M, Barr RE. Adaptive digital notch filter design on the unit circle for the removal of powerline noise from biomedical signals. IEEE Trans Biomed Eng 1994;41:529–36.
[28] Filligoi GC, Mandarini P. Some theoretic results on a digital EMG signal processor. IEEE Trans Biomed Eng 1984;31:333–41.
[29] Fullmer RR, Meek SG, Jacobsen SC. Optimization of an adaptive myoelectric filter. Ann Int Conf IEEE Eng in Med and Biol Soc 1984:586–591.
[30] Gatzke RD. The electrode: a measurement systems viewpoint. In: Miller HA, Harrison DC, editors. Biomedical electrode technology. New York: Academic Press, 1974:99–116.
[31] Geddes LA, Baker LE. Principles of applied biomedical instrumentation. New York: Wiley, 1989.
[32] Godin DT, Parker PA, Scott RN. Noise characteristics of stainless-steel surface electrodes. Med Biol Eng Comput 1991;29:585–90.

[33] Hamilton PS, Curley MG. Adaptive removal of motion artifact. Proc 19th IEEE/EMBS Int Conf, Chicago, IL 1997:297–299.

[34] Harba MIA, Lynn PA. Optimizing the acquisition and processing of surface electromyographic signals. J Biomed Eng 1981;3:100–6.

[35] Hermens H, Freriks B, Merletti R, Stegeman D, Block J, Rau G, Disselhorst-Klug C, Hagg G. SENIAM: European recommendations for surface electromyography. Roessingh Research and Development, Enschede, Holland, 1999 (ISBN 90-75452-15-2).

[36] Hershler C, Milner M. An optimality criterion for processing electromyographic (EMG) signals relating to human locomotion. IEEE Trans Biomed Eng 1978;25:413–20.

[37] Hogan N, Mann RW. Myoelectric signal processing: optimal estimation applied to electromyography — Part I: Derivation of the optimal myoprocessor. IEEE Trans Biomed Eng 1980;27:382–95.

[38] Hogan N, Mann RW. Myoelectric signal processing: optimal estimation applied to electromyography — Part II: Experimental demonstration of optimal myoprocessor performance. IEEE Trans Biomed Eng 1980;27:396–410.

[39] Hunter IW, Kearney RE, Jones LA. Estimation of the conduction velocity of muscle action potentials using phase and impulse response function techniques. Med Bio Eng Comput 1987;25:121–6.

[40] Ider YZ, Koymen H. A new technique for line interference monitoring and reduction in biopotential amplifiers. IEEE Trans Biomed Eng 1990;37:624–31.

[41] Inman VT, Ralston HJ, Saunders JBCM, Feinstein B, Wright EW Jr. Relation of human electomyogram to muscular tension. Electroenceph Clin Neurophys 1952;4:187–94.

[42] Jacobsen S, Knutti DF, Johnson RT, Sears HH. Development of the Utah artificial arm. IEEE Trans Biomed Eng 1982;29:249–69.

[43] Jacobsen SC, Meek SG, Fullmer RR. An adaptive myoelectric filter. Annu Int Conf IEEE Eng Med Biol Soc 1984:592–596.

[44] Jerard RB, Williams TW, Ohlenbusch CW. Practical design of an EMG controlled above elbow prosthesis. Proc 1974 Conf on Eng Devices in Rehabil, Boston MA 1974:73–77.

[45] Kaiser E, Petersén I. Adaptive filter for EMG control signals. In: Herberts P, Kadefors R, Magnusson R, Petersen I, editors. The control of upper-extremity prostheses and orthoses. Springfield, IL: Charles C. Thomas Publisher, 1974:54–7.

[46] Kamen G, Caldwell GE. Physiology and interpretation of the electromyogram. J Clin Neurophysiol 1996;13:366–84.

[47] Kreifeldt JG. Signal versus noise characteristics of filtered EMG used as a control source. IEEE Trans Biomed Eng 1971;18:16–22.

[48] Kreifeldt JG, Yao S. A signal-to-noise investigation of nonlinear electromyographic processors. IEEE Trans Biomed Eng 1974;21:298–308.

[49] Klijn JAJ, Kloprogge MJGM. Cable artefact suppressor for electrophysiological recording. Electromyogr Clin Neurophysiol 1973;13:87–92.

[50] MATLAB signal processing toolbox user's guide, version 4. Natick, MA: The MathWorks, Inc. pp. 6-210–6-213 (function "pmem"), 1996.

[51] Meek SG, Fetherston SJ. Comparison of signal-to-noise ratio of myoelectric filters for prosthesis control. J Rehabil Res Dev 1992;29:9–20.

[52] Metting van Rijn AC, Peper A, Grimbergen CA. The isolation mode rejection ratio in bioelectric amplifiers. IEEE Trans Biomed Eng 1991;38:1154–7.

[53] Milner-Brown HS, Stein RB. The relation between the surface electromyogram and muscular force. J Physiol 1975;246:549–69.

[54] Misener DL, Morin EL. A multichannel myoelectric amplifier using standard components. Proc 20th Canadian Medical and Biological Engng Conf 1994:98–9.

[55] Miyano H, Masuda T, Sadoyama T. A note on the time constant in low-pass filtering of rectified surface EMG. IEEE Trans Biomed Eng 1980;27:274–8.

[56] Murray WR, Rolph WD III. An optimal real-time digital processor for the electric activity of muscle. Med Inst 1985;19:77–82.

[57] Rainoldi A, Nazzaro M, Merletti R, Farina D, Caruso I, Gaudenti S. Geometric factors in surface EMG of the vastus medialis and lateralis muscles. J Electromyo Kinesiol 2000; 10:327–336.

[58] Neuman MR. Biopotential amplifiers. In: Webster JG, editor. Medical instrumentation: application and design, 3rd ed. New York: J. Wiley and Sons, 1998:233–86.

[59] Nishimura S, Tomita Y, Horiuchi T. Clinical application of an active electrode using an operational amplifier. IEEE Trans Biomed Eng 1992;39:1096–9.

[60] Pallas-Areny R. Interference–rejection characteristics of biopotential amplifiers: a comparative analysis. IEEE Trans Biomed Eng 1988;35:953–9.

[61] Park E, Meek SG. Adaptive filtering of the electromyographic signal for prosthetic control and force estimation. IEEE Trans Biomed Eng 1995;42:1048–52.

[62] Parker PA, Stuller JA, Scott RN. Signal processing for the multistate myoelectric channel. Proc IEEE 1977;65:662–74.

[63] Press WH, Vetterling WT, Teukolsky SA, Flannery BP. Numerical recipes in C: the art of scientific computing. 2nd ed Cambridge University Press, 1994:572–6.

[64] Redfern MS. Elimination of EKG contamination of torso electromyographic signals. In: Asfour SS, editor. Trends in ergonomics/human factors IV. North-Holland: Elsevier Science, 1987:725–9.

[65] Redfern MS, Hughes RE, Chaffin DB. High-pass filtering to remove electrocardiographic interference from torso EMG recordings. J Clin Biomech 1993;8:44–8.

[66] Roesler H. Statistical analysis and evaluation of myoelectric signals for proportional control. In: Herberts P, Kadefors R, Magnusson R, Petersen I, editors. The control of upper-extremity prostheses and orthoses. Springfield, IL: Charles C. Thomas Publisher, 1974:44–53.

[67] St-Amant Y, Rancourt D, Clancy EA. Influence of smoothing window length on electromyogram amplitude estimates. IEEE Trans Biomed Eng 1998;45:795–800.

[68] Swanson DK, Webster JG. A model for skin-electrode impedance. In: Miller HA, Harrison DC, editors. Biomedical electrode technology. New York: Academic Press, 1974:117–28.

[69] Tam HW, Webster JG. Minimizing electrode motion artifact by skin abrasion. IEEE Trans Biomed Eng 1977;24:134–9.

[70] Thusneyapan S, Zahalak GI. A practical electrode-array myoprocessor for surface electromyography. IEEE Trans Biomed Eng 1989;36:295–9.

[71] Triolo RJ, Nash DH, Moskowitz GD. The identification of time series models of lower extremity EMG for the control of prostheses using Box–Jenkins criteria. IEEE Trans Biomed Eng 1988;36:584–94.

[72] Webster JG. Reducing motion artifacts and interference in biopotential recordings. IEEE Trans Biomed Eng 1984;31:823–6.

[73] Widrow B, Glover JR, McCool JM, Kaunitz J, Williams CS, Hearn RH, Zeidler JR, Dong E, Goodlin RC. Adaptive noise cancelling: principles and applications. Proc IEEE 1975;63:1692–716.

[74] Winter BB, Webster JG. Reduction of interference due to common mode voltage in biopotential amplifiers. IEEE Trans Biomed Eng 1983;30:58–65.

[75] Xiong FQ, Shwedyk E. Some aspects of nonstationary myoelectric signal processing. IEEE Trans Biomed Eng 1987;34:166–72.

[76] Zhang YT, Parker PA, Scott RN. Study of the effects of motor unit recruitment and firing statistics on the signal-to-noise ratio

of a myoelectric control channel. Med Biol Eng Comp 1990;28:225–31.

Edward (Ted) A. Clancy received his BSc degree from Worcester Polytechnic Institute (WPI), and his SM and PhD degrees from Massachusetts Institute of Technology (MIT), all in Electrical Engineering. He has worked in industry for medical instrumentation and analysis companies interested in EMG, EEG, ECG and blood pressure, and the defence industry (aircraft instruments and radar). He is Assistant Professor of Electrical and Computer Engineering, and of Biomedical Engineering at WPI. He is a lecturer at MIT and Professor Associé at Laval University (Quebec, PQ, Canada). He is interested in signal processing, stochastic estimation and system identification, particularly as applied to problems in medical engineering and human rehabilitation.

Evelyn Morin received a BSc in Physiology from the University of Toronto in 1981 and an MScE and PhD in Electrical Engineering from the University of New Brunswick in 1984 and 1988 respectively. Since 1988, she has been at Queen's University, Kingston, Ontario, Canada, where she is currently an Associate Professor in the Department of Electrical and Computer Engineering and the School of Physical and Health Education. She is also a member of the Ergonomics Research Group at Queen's. Dr Morin's research interests are in the area of EMG signal acquisition and processing and human performance assessment, in particular during load carriage.

Roberto Merletti graduated in Electronics Engineering from Politecnico di Torino, Italy and obtained his MSc and PhD from The Ohio State University. He is Associate Professor of Biomedical Instrumentation at the Department of Electronics of Politecnico di Torino and Director of the Laboratory for Neuromuscular System Engineering in Torino, Italy. He has been Associate Professor at the Department of Biomedical Engineering and at the NeuroMusculat Research Center of Boston University. His research focuses on surface electromyography, myoelectric signal processing, electrical stimulation and neuromuscular control.