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Equalization filters for multiple-channel electromyogram arrays

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Abstract

Multiple channels of electromyogram activity are frequently transduced via electrodes, then combined electronically to form one electrophysiologic recording, e.g. bipolar, linear double difference and Laplacian montages. For high quality recordings, precise gain and frequency response matching of the individual electrode potentials is achieved in hardware (e.g., an instrumentation amplifier for bipolar recordings). This technique works well when the number of derived signals is small and the montages are pre-determined. However, for array electrodes employing a variety of montages, hardware channel matching can be expensive and tedious, and limits the number of derived signals monitored. This report describes a method for channel matching based on the concept of equalization filters. Monopolar potentials are recorded from each site without precise hardware matching. During a calibration phase, a time-varying linear chirp voltage is applied simultaneously to each site and recorded. Based on the calibration recording, each monopolar channel is digitally filtered to “correct” for (equalize) differences in the individual channels, and then any derived montages subsequently created. In a hardware demonstration system, the common mode rejection ratio (at 60 Hz) of bipolar montages improved from 35.2 ± 5.0 dB (prior to channel equalization) to 69.0 ± 5.0 dB (after equalization).

Keywords

Electrode array; Surface EMG; Equalization; Electromyography; EMG; Electrophysiology; Biomedical instrumentation

1. Introduction

For a number of years, the ability to investigate the electrical activity of distinct motor units (MUs) has been the domain of indwelling electrodes. These electrodes can be placed close to the origin of the electrical potential and selectively observe voltages in the area nearest to the electrodes. For many clinical and motor control studies, the recorded signals must be decomposed into constituent MUs (c.f., Kamen et al., 1995; LeFever and DeLuca 1982; LeFever et al., 1982; McGill et al., 1985; Stashuk and Paoli, 1998; Stashuk, 1999; Stashuk, 2001), taking

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advantage of the fact that these indwelling electrodes are highly spatially selective. A spatially selective signal decreases the number of superimposed action potentials (APs) and aids in reconstructing the firing times and shapes of specific MUAP trains. In healthy individuals, these techniques have allowed an evolving understanding of how the body controls the complex interplay of MUs, particularly with respect to MU firing rate and recruitment (DeLuca, 1979). As with any technique, however, there are limitations to the use of the standard indwelling electrode, chief among them that the high selectivity and sensitivity to movement of the electrode often limit investigation to constant-posture, slowly force-varying contractions of limited force. In addition, indwelling recording can be uncomfortable, is generally of short duration and cannot monitor the spread of electrical excitation along the muscle fiber membrane.

In recent years, surface electrode arrays that can monitor the activity of individual MUs have become increasingly prevalent. These systems have an inter-electrode distance of ≤ 8 mm and an electrode diameter ≤ 2 mm, with electrodes usually arranged in an equidistant linear or rectangular grid. Several early studies used these arrays to determine the locations of neuromuscular junctions (Masuda et al., 1985; Masuda and Sadoyama, 1988). Reucher et al. (1987a; 1987b) showed that weighted combinations of monopolar electrode recordings produce a myoelectric signal that is spatially selective. The simplest spatial filter is formed by a standard bipolar recording, which is a pair of electrodes with weighting coefficients (-1, +1). A longitudinal double differentiating (LDD) spatial filter is formed from three successive electrodes with weighting coefficients (+1, -2, +1), which has high spatial selectivity in one direction (Farina et al., 2000; Merletti et al., 2002; Rau and Disselhorst-Klug, 1997). To achieve two-dimensional spatial selectivity, two-dimensional electrode combinations are necessary, such as a normal double differentiating (NDD, a.k.a. Laplacian) filter (Disselhorst-Klug et al., 1997) that weights five electrodes, selected in the shape of a cross, with the weights (+1, +1, -4, +1, +1). The central electrode uses the -4 weight. With sufficiently small inter-electrode distances, the NDD filter permits observation of single MU activity for contractions up to 100% maximum voluntary contraction (MVC) (Disselhorst-Klug et al., 1999). Rau et al. (Rau and Disselhorst-Klug, 1997; Ramaekers et al., 1993) applied their noninvasive array to clinical applications, with initial studies of Duchenne muscular dystrophy and spinal muscular atrophy patients. Roeleveld et al. (1998), Disselhorst-Klug et al. (1999) and Sun et al. (1999) have used surface arrays to identify MU firing times and then provide spike-triggered averaging of individual array electrodes or additional surface electrodes—a non-invasive Macro-EMG. Roeleveld et al. studied patients with enlarged MU potentials due to prior poliomyelitis and Sun et al. studied patients with peripheral neuropathies (amyotrophic lateral sclerosis, progressive spinal muscular atrophy and polyneuropathies). Zwarts et al. (2000; Drost et al., 2006) reviewed the use of surface EMG for the diagnosis of neurological diseases.

To acquire surface EMG array data, an array of detection electrodes is applied to the skin and electronics used to amplify specific electrode combinations for further processing. The electronics produce specific weighted sums of the electrode voltages and then provide gain (to increase the signal level from the physiologic range of a few microvolts/millivolts to a level of a few volts), electrical isolation (to prevent injurious currents from flowing to/from the instrumentation), high pass filtering (to attenuate motion artifact) and low pass filtering (to provide anti-aliasing and attenuate noise in frequencies outside the band of the EMG signal). For bipolar weighting, a high-quality differential (instrumentation) amplifier typically performs the weighting, and the quality of the recording—in particular its ability to reject common mode interference (e.g., from the power line) as measured by the common mode rejection ratio (CMRR)—is related to the ability to tightly match the weights. For bipolar recording, modern electronics provide a CMRR of 80-120 dB at the power line frequency. With a hardware implementation, each different combination of detection sites requires a distinct hardware channel to apply the precise weights (c.f., Castrolforio et al., 2005).

Additional complexity is added in modern systems that combine more than two detection sites into one signal, e.g., the LDD and NDD configurations as well as other proposed optimal configurations that use many electrodes (Farina and Rainoldi, 1999; Quartararo and Clancy, 2007). Such montages provide spatial selectivity that can be crucial to the application (Disselhorst-Klug et al., 1997, 1999; Kleine et al., 2000; Merletti et al., 2004; Ramaekers et al., 1993; Rau and Disselhorst-Klug, 1997; Sun et al., 1999). In such systems, the number of possibly useful derived signals (i.e., the number of different combinations of bipolar, LDD and NDD signals) can be too large for practical precision implementation of all possibilities in hardware. One solution to this problem is to limit the number of derived signals that are acquired. Alternatively, some researchers acquire the monopolar voltage from each detection site and then compute the derived signals in software. This second technique generally produces inferior CMRR performance, since precise gain and frequency matching in hardware is very difficult (if not possible) to achieve. In addition to inferior CMRR performance, poor channel matching might degrade the spatial selectivity of the array by distorting the desired channel weights.

The challenges listed above are similar to those experienced by designers of other array sensor technology, such as phased-array radar and communication systems. A solution used in those systems is equalization filters (Haykin, 2000; Hero et al., 1998; Liu and Lin, 2004; Tugnait et al., 2000). In this report, the use of linear time-invariant equalization filters for EMG biopotential amplifiers is described. Such filters have not been previously investigated for use in EMG data acquisition systems. The general concept of the approach, one channel of which is shown in Fig. 1, is to initially instrument hardware *monopolar* channels using standard, inexpensive components (e.g., 1-5% tolerance resistors, 5-10% tolerance capacitors) and digitize each channel. Then, a distinct digital “equalization” filter (implemented off-line in software) is cascaded with each channel such that the resulting hardware-software cascade for each channel exhibits gain and frequency responses that are best matched to an ideal channel. The equalization filters are calibrated by simultaneously passing a broad-band calibration signal through all channels, determining the frequency response of each channel, then designing an equalization filter that seeks to eliminate the distortion in each channel with respect to an ideal channel. Our method for calibrating and designing these equalization filters is detailed in the following sections. We present the mathematical development of our equalization filters in section 2. Section 3 describes simulation methods and results that investigated certain filter design tradeoffs. Results from our bench tests with actual hardware are described in section 4. Preliminary results have been reported previously (Clancy et al., 2004a, 2004b; Xia, 2005).

2. Theory of Equalization Filter Design

Fig. 1 and Fig. 2 diagram the overall method for designing (a.k.a. calibrating) an equalization filter, either for actual hardware or in simulation. An order N linear, time-invariant finite impulse response (FIR) equalization filter was chosen for its simplicity in implementation and design. A common cosine linear chirp signal is used to excite each channel input (connected directly to each electrode) as this signal has an energy density spectrum that is flat over the frequency range of the chirp. For actual hardware, denote this common calibration signal as

$$x_{In}(t) = K \cos(2\pi a t^2 + 2\pi b t + \varphi), \quad (1)$$

where K (Volts) is the amplitude, a (Hz/s²) sets the sweep rate, b (Hz/s) is the initial frequency, φ is the initial phase (radians), and t (s) is the continuous-time variable. The signals arising from each channel and the calibration chirp signal are analog-to-digital converted and recorded. If we assume that each channel is a time-invariant linear system, then the output from each channel must also be a chirp with the same initial frequency and sweep rate, but the amplitude

and phase can be modified at each discrete-time sample (k). Thus, the i^{th} channel output can be written as:

$$x_{Out,i}(k) = A_i(k) \cos \left[2\pi a \left(\frac{k}{F_s} \right)^2 + 2\pi b \left(\frac{k}{F_s} \right) + \theta_i(k) \right] + n_i(k), \quad (2)$$

where $A_i(k)$ codes the amplitude variations, $\theta_i(k)$ codes the phase variations, $n_i(k)$ is measurement noise and F_s is the sampling rate. [Note that (k/F_s) , for $k = 0, 1, 2, \dots$, specifies the time instances (in seconds) at which the signal was sampled.]

Nominally, the channel outputs will be very similar, differing only due to component tolerances within each channel and noise. These component differences can cause both phase lags and phase *leads* relative to the ideal channel, which would result in the need to design non-causal and causal equalization filters, respectively. Non-causal filters require different discrete-time indexing than causal filters. However, it is not known *a priori* which channels require causal versus non-causal equalization. To avoid this problem entirely, the channel outputs $x_{Out,i}(k)$ are advanced relative to the calibration signal by $\left\lfloor \frac{N}{2} \right\rfloor$ samples (via a circular shift). Each channel then leads the ideal channel, coercing all equalization filter design to be causal. We will not explicitly write this shift mathematically; rather a compensating delay shift will be introduced when implementing an equalization filter.

Continuing to refer to Fig. 2, the reference chirp signal is additionally acquired directly during calibration (i.e., without passing through an analog input channel). This signal is digitally shaped with a filter that matches the desired “ideal” pass band of our hardware filters (described below). An order M FIR shaping filter was designed using the window method (Proakis and Manolakis, 1996), based on the ideal frequency response magnitude and phase of the hardware and a rectangular window. The shaped signal, $y(k)$, is transformed to the frequency domain using a DFT. The desired equalization filter $H_i(e^{j\omega})$ is specified in the frequency domain as:

$$H_i(e^{j\omega}) = \frac{Y(e^{j\omega})}{x_{Out,i}(e^{j\omega})}. \quad (3)$$

The low and high frequencies of this transfer function are corrupted due to the (head and tail) startup transients of the various filters, and because the hardware admits little power in these frequencies due to standard band pass filtering (for our hardware, over the range of 15-1800 Hz). Thus, transfer function values corresponding to frequencies below 25 Hz or above 1800 Hz were replaced with unity gain and a linear phase response. From this frequency-domain specification, the time-domain order N FIR filter is designed using the window method (Proakis and Manolakis, 1996), based on the transfer function magnitude and phase response and a Hamming window.

3. Simulation Investigation of Influence of Equalization Filter on the CMRR

3.1. Introduction and Purpose

There are two startup transients that corrupt the head of the calibration chirp recording during simulations (see Fig. 2)—the order M ideal channel simulator (FIR filter) through which all simulated data are shaped and the $\left\lfloor \frac{N}{2} \right\rfloor$ linear shift forward of each channel. Thus, the duration of the startup transient, in samples, equals:

$$\text{Startup}_{\text{Simulation}} = M + \left\lfloor \frac{N}{2} \right\rfloor. \quad (4)$$

This startup transient corrupts the lower frequencies in the equalization filter design (since the initial samples of the chirp correspond to low frequencies). For our EMG signal processing

bandwidth, we must limit this problem to frequencies out of the hardware pass band, or less than 15 Hz. These lower frequencies have their transfer function assigned (see above) so need not be included. With our sampling rate of 4096 Hz and a 100 s chirp input (0-2000 Hz), approximately 3000 samples are available for the startup transient. (Note that the transient occurring on the tail of the calibration chirp is not as restrictive, since the hardware pass band ends at 1800 Hz—well below the Nyquist frequency of 2048 Hz). These 3000 samples must be shared between M and N , according to equation (4). Thus, we studied the tradeoff in 60 Hz CMRR performance versus the allocation of the 3000 samples between the simulator filter order (M) and the equalization filter order (N).

3.2. Simulation Methods

All simulation and bench-test data used a sampling rate of 4096 Hz. All data processing was performed in MATLAB (The MathWorks, Natick, MA). Simulations began by creating a linear chirp (initial frequency of 0 Hz, initial phase of 0°, 3 V amplitude) spanning the frequency range from 0 Hz to 2000 Hz. This simulation work utilized the complete equalization process (see Fig. 2) with two simulated hardware channels and one simulated reference channel. For each hardware channel simulated, the simulation chirp signal was band pass filtered through a distinct filter that mimicked one realization of the frequency-domain magnitude and phase of our hardware high pass and low pass filters (described below). Resistor values were varied randomly (uniform distribution) over a 1% range about their nominal value and capacitor values were varied randomly (uniform distribution) over a 5% range about their nominal value. These ranges mimicked the 1% resistor and 5% capacitor tolerances of our hardware. These resistors and capacitors specified the frequency response of the filter realization. An order M FIR shaping filter (channel simulator) was designed for each channel using the window method (based on the distinct frequency response magnitude and phase of the simulated channel and a rectangular window). After band pass filtering, the signals were quantized to 16 bits, assuming a ± 5 V ADC range. White Gaussian noise (standard deviation of 30 mV, or 1% of the chirp amplitude) was then added to each signal (a different realization per signal) to represent measurement noise. The reference channel was created from the chirp plus an independent noise realization (30 mV standard deviation). This channel was shaped by the ideal channel simulator (as shown in Fig. 2). Equalization filters were formed using these resultant signals.

To evaluate performance of these equalization filters, a 3 V, 100 s duration, 60 Hz sine wave was created, passed through the pair of simulated hardware channels, and a distinct noise realization (white Gaussian noise, standard deviation of 30 mV, or 1% of the amplitude) was added to each simulated channel signal. Performance was then evaluated before (“no equalization” case) and after equalization by subtracting the signal pair (simulating a bipolar recording) and computing a CMRR. The simulated channels maintained the hardware characteristics assigned to them during the calibration stage. The CMRR (dB) was computed as:

$$\text{CMRR} = 20 \log\left(\frac{In}{Out}\right), \quad (5)$$

where Out is the amplitude of the difference sine wave and In is the average amplitude of the two input sine waves. The sine wave amplitudes were determined by notch filtering the difference waveform (50-70 Hz passband, 4th-order Butterworth, filtered forward then backward in time to achieve zero phase) and then fitting a 60 Hz sine wave with unknown amplitude and phase via non-linear least squares. One hundred simulations of channel pairs were conducted for each equalization filter order, with mean and standard deviation results reported. Equalization filter orders of $N = 200, 300, 500, 700, 900, 1200, 1500, 1800$ and 2100 were utilized, with the channel simulator filter order M selected in each case to give a total startup transient of 3000 samples, according to equation (4).

3.3. Simulation Results

The CMRR with *no* equalization did not vary much as a function of the simulator filter order (which changed as a function of the equalization filter order), having an overall average value of 37.1 ± 6.8 dB. As shown in Fig. 3, equalization provided a substantial performance improvement, on average, for all equalization filter orders. CMRR performance peaked at 69.1 ± 5.6 dB at an equalization filter order of $N = 900$, with poorer performance exhibited with filters of either higher or lower order.

4. Bench-Test Hardware Evaluation

4.1. Monopolar Array Hardware

To investigate the performance of the equalization filter technique in actual hardware, 28 analog monopolar channels were constructed. Each channel was comprised of a front-end electrode-amplifier in cascade with a separate signal conditioning circuit. Each electrode-amplifier incorporated a commercial instrumentation amplifier (AD620, Analog Devices, Norwood, MA, USA) arranged in a gain of 20 configuration. The second input of every instrumentation amplifier was connected to a common “isolated” reference electrode for monopolar use. Each signal conditioning circuit consisted of the cascade of a high pass filter stage (8th-order Butterworth, cutoff frequency at 15 Hz, with an embedded gain stage of 10), a selectable gain (available gains ranged from 1-128; a gain of 8 was utilized), a unity-gain optical isolation stage and a low pass filter stage (4th-order Butterworth, cutoff frequency at 1800 Hz) (Xia, 2005). The nominal overall channel gain in the pass band was $20 \times 10 \times 8 = 1600$. One percent tolerance resistors and 5% tolerance capacitors were used. All operational amplifiers were AD713KN (Analog Devices). Because each physical channel consists of distinct resistor, capacitor and operational amplifier components, their actual gain and filter responses varied.

4.2. Hardware Evaluation Methods

To calibrate equalization filters, a 100 s duration, linear chirp signal (2.94 mV peak amplitude) was simultaneously input to each electrode-amplifier (a Hewlett Packard 33120A signal generator produced a 0.61 V peak signal which was reduced in amplitude via a resistor divider network physically located adjacent to the electrode-amplifier inputs). The chirp signal ranged in frequency from 0-2000 Hz. The outputs of the 28 signal conditioning circuits along with the 0.61 V amplitude chirp from the signal generator (which served as the reference channel) were sampled at 4096 Hz using a ± 5 V input range, 16-bit analog-to-digital converter (ADC) (Manufacturing Computing model PCI-DAS6402/16, Mansfield, MA, USA) and processed off-line using MATLAB. Equalization filters were designed as described above.

To evaluate performance, a common 2.94 mV amplitude (again, originating from a larger signal that was reduced in amplitude via a resistor divider network), 100 s duration, 60 Hz sine wave was provided to the input of each of the 28 electrode-amplifiers. The 28 monopolar signals arising from the signal conditioning circuits were ADC converted and recorded. Fourteen bipolar configurations were assigned from adjacent pairs of the 28 monopolar channels. As with the simulations, the CMRR without equalization was evaluated by subtracting these monopolar pairs and computing the CMRR [see equation (5)]. The average magnitude of the two 60 Hz signals which comprised the bipolar pairs was taken as the amplitude of the input sine wave. The magnitude of the 60 Hz signal after subtraction was taken as the amplitude of the output sine wave. For these actual signals, estimation of the signal amplitude via least squares was not successful. Thus, amplitudes were estimated as the square root of two multiplied by the rms value of the signal. Next, each monopolar channel was equalized, the channel pairs subtracted and the CMRR again computed.

For hardware evaluation, the filter startup transient restrictions differ. As seen in Fig. 2, there is no channel simulation filter for the 28 monopolar channels. Instead, the startup transient due to the channel simulation filter applies only to the reference channel. But, this startup occurs in parallel with the linear shift forward of each monopolar channel. Thus, the overall startup (in samples) is:

$$\text{Startup}_{\text{Hardware}} = \max\left(M, \left\lfloor \frac{N}{2} \right\rfloor\right). \quad (6)$$

A wider range of filter orders was, therefore, permitted. Channel simulator filter orders of $M = 600, 800$ and 1000 were utilized with each combination of equalization filter order of $N = 200, 300, 500, 700, 900, 1200, 1500, 1800, 2100, 2300, 2500, 2800, 3100, 3600, 4000$ and 5000 .

4.3. Hardware Evaluation Results

Fourteen CMRR results were generated for each condition. The CMRR with no equalization (not a function of M or N) was 35.2 ± 5.0 dB. When equalization was applied, the CMRR showed little variation as a function of reference channel simulator filter order (M), thus results utilizing a simulator filter order of 600 samples are presented and analyzed in detail. Fig. 4 shows the CMRR performance results as a function of the equalization filter order. One-way analysis of variance confirmed that the results varied with equalization filter order ($p < 10^{-6}$). CMRR improved rapidly with N until an equalization filter order of 900, and then receded progressively. With an equalization filter order of $N = 900$, the CMRR was 69.0 ± 5.0 dB, an approximate 35 dB improvement compared to results without equalization. At this equalization filter order, the range of average CMRRs for the 14 channels was 62.0 to 77.4 dB.

5. Discussion and Conclusions

A rather substantial CMRR improvement (approximately 35 dB at 60 Hz) was realized with the use of equalization filters. Filters with an order of 900 (corresponding to a startup transient of 220 ms at a sampling rate of 4096 Hz) were necessary to produce this improvement. Thus, a cost for implementing these filters in recorded data epochs is either the loss of this startup transient from each data epoch or the addition of this time duration to the recorded epoch duration. Alternatively, these filters could be implemented in real-time within a data acquisition apparatus, thus eliminating the loss of any of the data epoch. Note that real-time implementation might also need alterations to the algorithm to account for the non-causal nature of our off-line implementation. In any case, these accommodations provide little or no interruption to most existing applications of array EMG data. Note that similar CMRR improvements would be expected at other frequencies, since the calibration process provided equalization across the complete pass band. Our calibration methods also incur a startup transient. For EMG acquisition systems, a modest startup transient is acceptable due to the typical high pass filter characteristic—set to 15 Hz in our equipment. Thus, the first 3000 samples from the chirp calibration waveform were not utilized.

In our hardware evaluation, the calibration chirp and 60 Hz test waveforms were recorded within a few minutes of each other in a laboratory environment (i.e., with relatively constant environmental temperature and humidity). Such controlled conditions would be common in research laboratories and many clinical settings. But, large changes in temperature and/or humidity might require the need to re-calibrate the equalization filters. Similarly, electronic components change their properties over time, again requiring re-calibration. In addition, many practical electrophysiologic monitoring systems incorporate selectable gain. Thus, calibration might be performed at each gain, or at the one gain setting used in an experimental/clinical test.

Without channel equalization, our monopolar hardware (1% tolerance resistors, 5% tolerance capacitors) provided a CMRR of approximately 35 dB (error of 1 part in 56), on average. If CMRR scales with the component tolerances, a CMRR of 80 dB (error of 1 part in 10,000) would require resistor and capacitor tolerances on the order of 0.01%. These component tolerances are prohibitive. Thus, adequate CMRR does not seem possible directly in monopolar hardware that includes our complete acquisition cascade (pre-amplifier, high-pass filter, selectable gain, signal isolation and low-pass filter).

5.1 Limitations and Future Work

While this work has demonstrated substantial gains in CMRR (average of nearly 35 dB, or a factor of 56 to 1), the overall achieved CMRR of approximately 70 dB is not a complete solution for most electrophysiologic signals, particularly when compared to hardware implementations. In general, 90-100 dB of CMRR is a minimum expected performance for bipolar electrodes (Clancy et al., 2002). Thus, further research is warranted, with the following suggestions. First, the overall goal of a high CMRR is generally instituted so as to reject common mode interference. An approach to doing so that augments this equalization technique is to reduce the interference prior to sensing it at the recording electrodes via a so-called “driven right leg” circuit (Winter and Webster, 1983a, 1983b). These circuits are particularly effective in reducing power line interference and can reduce large power line interference potentials by 20 dB or more. In addition, our technique only equalizes channel imbalances found in the hardware. In practice, another source of imbalances that lead to power-line contamination is channel-to-channel variations in electrode-skin impedance. Equalization of these differences might be achieved by applying the calibration signal to the skin surface rather than the electrode contact.

Second, development of de-noising techniques may prove useful in increasing the CMRR. We have made attempts to de-noise the recorded chirp waveforms with both linear (time-varying) and non-linear filters, but have yet to be able to produce a CMRR improvement. This lack of improvement may be related to the smoothing properties of the equalization filter design technique. The shape of the desired equalization filter was specified in the frequency domain by a very large number of points. For example, a 100 s chirp sampled at 4096 Hz results in 409,600 time-domain samples, and half this number of unique frequency-domain samples. When a 200-5000-order FIR equalization filter was designed to best match over 200,000 frequency locations, it would only have enough degrees of freedom to follow the general profile. Thus, the frequency-domain noise was inherently smoothed by the equalization filter design process. Perhaps this inherent de-noising obviates the improvement of simple de-noising techniques. Further investigation is needed to understand the limitations of de-noising on the resultant CMRR performance.

Third, our equalization technique provided the same level of performance across all frequencies. However, performance is most important at lower frequencies near the fundamental power-line frequency and its first few harmonics. It may prove better to merge calibrations from two frequency ranges: one long-duration, precision calibration for the low frequencies and a second (shorter-duration) calibration for the high frequencies. Thus, more calibration data (resulting in higher quality calibration) would be used in the predominant frequency ranges of the bioelectric signal and the power-line interference. Going one step further, Degen and Jackel (2006) adjusted a single gain factor (i.e., a zero-order FIR filter) based only on information at the power line frequency. Fourth, design of the time-domain equalization filter from its frequency-domain specification did not benefit from an optimized digital filter methodology (only the simple window technique was used). In addition, proper specification of the out-of-band frequencies (required for use of the window filter design technique) was not obvious. Thus, future work might apply a time-domain least squares optimal design methodology (c.f., (McCarthy, 2001)), which avoids this issue entirely. Fifth, anecdotal

evidence from our simulations and lab-bench tests suggest that the CMRR resulting after equalization is enhanced if the hardware components (resistors, capacitors, op amps, signal generator, etc.) are specified with tighter tolerances and if these components exhibit lower noise. For example, earlier versions of our hardware and simulator that utilized wider component tolerances seemed to exhibit overall lower CMRR results. The reasons for this observation are unclear. This effect can be more systematically investigated via simulation and lab-bench recordings.

Sixth, we utilized rather high-order analog filters in our hardware (eighth-order high pass, fourth-order low pass). Physical filter circuits inevitably introduce some level of non-linear distortion and this level grows with the filter order. Such non-linear effects might not be adequately counteracted using linear equalization techniques. These circuit effects are difficult to model mathematically, but might be studied by building hardware with minimum filter orders, for comparison. Seventh, there are several signal processing related details that might be approached differently, including selection of an FIR filter topology vs. an infinite impulse response approach, and selection of linear equalization filters vs. non-linear models. Eighth, extrapolation of this technique to other bioelectric signals (e.g., ECG or EEG) is hampered by the startup transient associated with the calibration task, which limits the ability to calibrate at low frequencies (recall that most EMG systems ignore—i.e., high pass filter—frequencies below 10-20 Hz, while many other bioelectric signals have usable pass bands down nearly to DC). A solution to this problem may be to alter the calibration chirp by arranging for the zero frequency portion to reside at the central time of the recording, as opposed to its present location at the beginning. The startup transient would then corrupt calibration of the very highest signal frequencies, which are not important to CMRR performance.

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Fig 1.

Diagram of one channel of an electrode array system with equalization. Signal $x_{In,i}(t)$ arises from a monopolar detection site, where t is the continuous-time variable and i is the channel number. The monopolar signal is conditioned by its own analog hardware channel (which provides high pass filtering, gain, isolation and low pass filtering) and then converted into a digital stream. A distinct digital equalization filter is then applied to each channel so that the response of each channel (i.e., the gain and frequency response of the complete channel cascade) is made as identical as possible to the ideal response. Signal $x_{Out,i}(k)$ is the input to the i^{th} equalization filter and $w_i(k)$ is its output, where k is the discrete-time index.

Fig 2.

Black box diagram of the equalization filter design (i.e., calibration) process. For simulation, a linear chirp signal with known initial frequency b , initial phase ϕ , and sweep rate parameter a is passed through a linear filter that simulates a hardware band pass filter. This filter output is quantized and then Gaussian noise is added to it. For experimental data, a linear chirp frequency is generated by a signal generator and input to the recording hardware. The input channel (simulated or experimental) is time advanced. A reference signal (simulated/experimental chirp that is *not* passed through a simulated/experimental signal channel) is digitally shaped to the pass band of an ideal channel. This same reference signal is used for comparison to each channel. These resultant signals are used to design an equalization filter.

Fig 3.

Simulation results of common mode rejection ratio (CMRR) at 60 Hz as a function of equalization filter order (N). Mean CMRR values (with one-sided standard deviation bars) are marked with an asterisk. The order of the FIR channel simulator filter (M) was selected such that the total startup transient in each case is 3000 samples. For comparison, the CMRR achieved with no equalization (open circle datum in the plot) was 37.1 ± 6.8 dB.

Fig 4.

Bench-test hardware evaluation common mode rejection ratio (CMRR) at 60 Hz as a function of equalization filter order (N). Mean CMRR values (with one-sided standard deviation bars) are marked with an asterisk for an ideal channel simulator FIR filter order of $M = 600$. For comparison, the CMRR achieved with no equalization (open circle datum in the plot) was 35.2 ± 5.0 dB.