response in the adaptive filter. Further experiments with short time movements and position changes must be done to optimize the filter coefficients.

Cardiac artifact seems a feasible artifact to be reduced using this technique, but measurements in neonates are necessary to know the frequency characteristics of ventilation and artifacts in this population.

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Adaptive Filtering of the Electromyographic Signal for Prosthetic Control and Force Estimation

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Abstract—**An adaptive time constant filter is derived for electromyographic (EMG) signal processing in prosthetic control applications. The analysis indicates that the mean-squared estimation error can be reduced by varying the time constant of the filter as a function of the signal and its derivative. Results of several experiments indicated this filter provides faster response and smaller estimation error than several previously available filters.**

I. INTRODUCTION

The cutaneously measured EMG signal that arises as a byproduct of muscular contraction has been widely used for the control of prostheses [1]–[4]. Typically, three stages of processing must be performed in order to extract a usable proportional control signal [5]–[8]: 1) band-pass filtering to eliminate extraneous noises, 2) rectification to generate a nonzero mean signal, and 3) low-pass filtering to smooth the signals.

The EMG signal appears as a zero mean, amplitude modulated (AM) voltage, with the muscle force (or command) information modulating a higher frequency carrier-like random noise signal. Unlike a typical AM broadcast system where the spectra of the signal and carrier (noise) are widely separated, the noise spectrum of the rectified EMG overlaps that of the command signal and has a wider power spectrum. Furthermore, we cannot assign a stationary spectral model to the command signal. The muscle force can either be rapidly changing, or relatively constant. The typical bandwidth of force signal is under 3 Hz [5]. The overlapped spectra and the nonstationarity of the command signals pose difficulties with the processing of EMG signals. In order to provide sufficient noise rejection during slow motions as well as quick response to rapid commands, the filter must be able to adapt its bandwidth to the specific signal [5], [8]–[11].

Kreifeldt [2] found that a time averaging filter, for similar rise times, gave a 3–5-dB improvement in signal-to-noise ratio (SNR) over either a first-order filter or a third-order Butterworth filter. Meek *et al.* [12] compared the performance of linear, averaging, and the adaptive time constant filter which is explained later in this section, and reported that the SNR of the adaptive time constant filter was 20% higher than the ratio of a linear filter and 12% higher than that of an averaging filter with the same rise time. Kreidfeldt and Yao [13] evaluated several demodulators by simulation and concluded that root law processors, followed by power law processors, gave higher SNR outputs than conventional full wave rectification. These results are, however, valid in static conditions only [5], [8] and vary with the spectral composition of the EMG signal model. Kaiser *et al.* [14] determined that low frequency modulation of signals by noise could be minimized by distributing noise evenly over a spectrum via a prewhitening filter prior to demodulation. Fullmer [5] reported that the effect of prewhitening on the adaptive time constant filter is not

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pronounced, giving about a 0.5-dB improvement in the SNR. The effects of prewhitening are masked by the adaptive time constant filter's ability to provide a high SNR. Use of prewhitening should be based on practical considerations. It seems that spatial filters using multiple electrodes should significantly improve muscle force estimation from EMG signals [12]. Meek *et al.* [12] reported that the benefits of multiple sensors are marginal. The obvious disadvantage with this method is that a multiple electrode array is required.

Jacobsen *et al.* [1], [10], Fullmer [5], Meek [9], and Meek *et al.* [11] developed adaptive time constant filters that attempted to provide sufficient noise rejection, as well as fast response to rapidly changing command signals. The basic idea was to vary the time constant of the filter according to the rate of change of EMG signals. This adaptive time constant filter provides a proportional control signal with a high SNR and fast response. The adaptive time constant filter has been successfully used in the Utah Artificial Arm since 1982. The adaptation logic was empirically formulated and it is, therefore, difficult to choose the proper parameters used in the adaptation logic. Later, D'Alesio [8] also argued that the time constant of the smoothing filter cannot be fixed, as Miyano reported in [15], and must be locally adapted to EMG signals. He developed a procedure to calculate the averaging length of a moving-average smoothing filter that is adapted to local variability of muscle force.

During a sustained muscle contraction, the amplitude of the EMG signal increases and the spectrum of the EMG signal shifts toward lower frequencies. These muscular fatigue effects provide additional difficulties in EMG signal processing. In this paper, we assume that the EMG signal has been preprocessed so that the fatigue effects have been eliminated. One approach to fatigue compensation has been reported in [16] and [17].

In this paper, we will mathematically derive an algorithm for varying the time constant of a first-order low-pass filter without any assumption over the form of adaptation logic; hence, we will provide a mathematical background and possible improvement to the empirical approach. The adaptation logic should be practical and easy to implement in actual applications, like the Utah Artificial Arm. The algorithm will be derived based on the analysis of mean-squared estimation error (MSEE) of a time-invariant first-order low-pass filter.

II. Mathematical Derivation of Adaptation Logic

For the derivation, we will assume an amplitude modulated EMG signal model given by

$$W(t) = c(t) \cdot n(t) \tag{1}$$

where $W(t)$, $c(t)$, and $n(t)$ are the cutaneously measured EMG signal and the command signal representing force to be estimated and noise, respectively. Command signal $c(t)$ is generally time-varying and always positive. It is assumed to be deterministic, but *a priori* unknown. We will also assume that noise $n(t)$ belongs to an ergodic uncorrelated Gaussian process with zero-mean value. The first-order low-pass filter considered in this paper is described by the following input-output relationship:

$$\tau \frac{d\bar{c}(t)}{dt} + \bar{c}(t) = |W(t)| \tag{2}$$

where $\bar{c}(t)$ represents the estimated command signal, and τ is the time constant of the filter. The input to the first-order low-pass filter is the full-wave rectified EMG signal.

Let us define a constant b as

$$b = e^{-T/\tau} \tag{3}$$

where T represents the sampling time for the signal. It is well known that the differential equation in (2) can be discretized as

$$\bar{c}_k = b\bar{c}_{k-1} + (1-b)c_k q_k \tag{4}$$

where $|W_k|$, the kth sample of $|W(t)|$, has been replaced with $c_k q_k$, and c_k and q_k are the kth samples of $c(t)$ and $|n(t)|$, respectively. It is straightforward to show that the difference equation (4) can be written in the nonrecursive form [17]

$$\bar{c}_k = g_o c_k \sum_{i=0}^{N} (1-b)b^i \left(1 - \frac{z_k}{c_k} i\right) q_{k-i} \tag{5}$$

where z_k is the kth sample of $z(t)$, the derivative of command signal $c(t)$, and g_o is a constant such that the dc response of this filter is the same as that of the recursive filter in (4). When deriving (5), N was assumed to be an integer much larger than one such that $b^N \ll 1$, and the command signal varies with time very slowly with respect to the sampling rate (typically above 1 kHz) such that $c_{k-i} \approx c_k - z_k i$.

To expedite the analysis, q_k is assumed to be rectified noise with the known statistics of

$$E[q_k] = m, \tag{6}$$

$$E[q_k^2] = \sigma^2, \tag{7}$$

and

$$E[q_i q_j] = E[q_i] \cdot E[q_j] = m^2 \quad \text{when} \quad i \neq j. \tag{8}$$

Let's define the MSEE at the kth sample as

$$J_k^2 = E[(c_k - \bar{c}_k)^2]. \tag{9}$$

The MSEE can be written as

$$J_k^2 = u_k^2 + v_k^2 \tag{10}$$

where

$$u_k^2 = \{c_k - E[\bar{c}_k]\}^2 \tag{11}$$

and

$$v_k^2 = E[\bar{c}_k^2] - E^2[\bar{c}_k]. \tag{12}$$

In the above decomposition of the MSEE, the first term represents the squared value of bias and the second term the variance of the estimate. With the known statistics of (6)–(8) and (5), then (11) can be expressed as

$$u_k^2 = z_k^2 \frac{b^2}{(1-b)^2} \tag{13}$$

and the variance can also be expressed as [17]

$$v_k^2 = c_k^2 \left(\frac{\sigma^2}{m^2} - 1\right)\left[\frac{1-b}{1+b} - 2\frac{z_k}{c_k}\frac{b^2}{(1+b)^2} + \frac{z_k^2}{c_k^2}\frac{b^2(1+b^2)}{(1-b)(1+b)^3}\right]. \tag{14}$$

The above results indicate that the MSEE of the filter in (2) depends on the command signal as well as its derivative. Consequently, the optimal choice of parameter b depends on the command signal and its derivative. The optimization can be done by minimizing the MSEE in (9) with respect to b at each time. Assuming both c_k and z_k are slowly varying, the analysis done above for this fixed parameter case will also hold approximately for the time-varying case.

The optimal value for b at the kth sample can be obtained by differentiating the MSEE with respect to b, hence b can be calculated from the following:

$$\frac{dJ_k^2}{db} = 0. \tag{15}$$

The numerical solution of (15) in Fig. 1 represents the optimal time constant of the first-order low-pass filter which provides the minimum MSEE compromised between the errors caused by bias and variance.

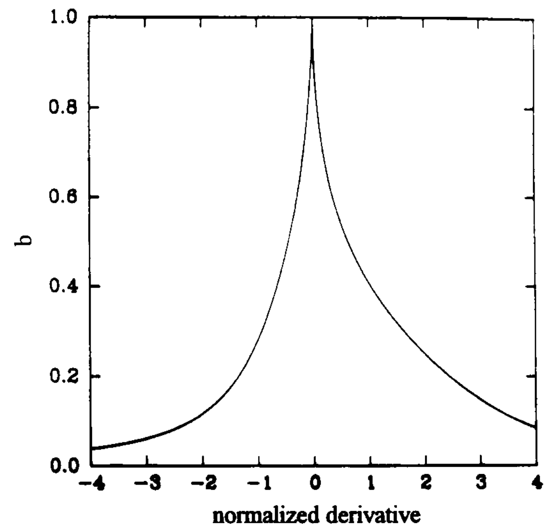

Fig. 1. Adaptation logic. The plot of the numerical solution of (15).

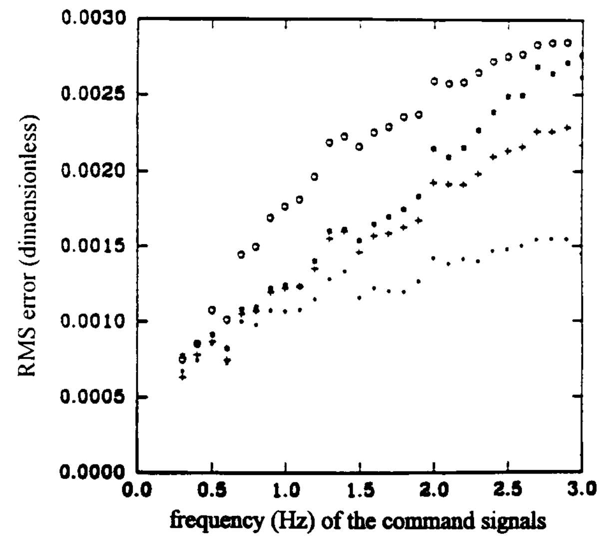

Fig. 2. Comparison of the root of the mean-square (rms) errors of several filters when the command signals vary sinusoidally: the current adaptive time constant filter (•), the previous adaptive time constant filter (+), the moving-average filter (∗), and the first-order linear filter (∘).

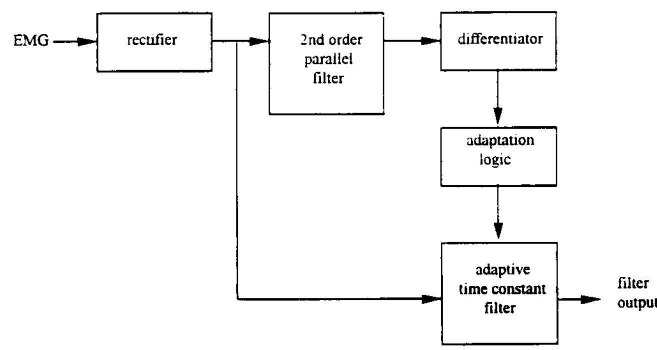

Fig. 3. Block diagram of the adaptive filter.

III. Simulation Results and Application to Actual EMG Signals

All the simulated EMG signals used in this section were generated using (1). The unrectified noise sequence belonged to a zero-mean and white pseudo-Gaussian process. The variance of the unrectified noise was determined so that the expected value of the rectified EMG signal is equal to the signal magnitude $c(t)$ in (1): $m = 1$ and $\sigma^2 = \sqrt{\pi/2}$ [5].

In the first experiment, the simulated EMG signals, when the command signals were sinusoidally varying, were processed by several filters. In Fig. 2, the root of the mean-squared (rms) errors of several filters *versus* the frequency of the command signals has been reported. The rms errors were averaged along the sequence $\{c_k\}$, and normalized to the mean-squared value of c_k. The following filters were used for comparison: the adaptive time constant filter with the current adaptation logic by numerically solving (15), the adaptive time constant filter with the previous adaptation logic reported in [5], the moving average filter with 100-ms averaging time, and the first-order linear filter with 100-ms time constant [5]. We can infer from the figure that all the filters estimate command signals with almost the same accuracy for the slowly changing command signals. However, the rms error grows markedly with frequency as the bias grows and becomes the main source of error as the command signal varies rapidly. From Fig. 2, we can clearly see that the adaptive time constant filter with the current adaptation logic gives more reduced estimation errors than the time-invariant filters and the empirically formulated adaptive filter over the wide range of the command signal frequency.

In the second experiment, the simulated EMG signal, when the command signal varied like a square wave, was processed according to the block diagram in Fig. 3. The EMG signal is rectified and low-pass filtered with the second-order low-pass filter. The output of this parallel filter is differentiated, the differentiator output is normalized by the output of the parallel filter, and this normalized derivative is fed to the adaptation logic. Next, the rectified EMG signal is low-pass filtered by the adaptive time constant filter. In order to approximately estimate the command signal and its derivative, we use the second-order low-pass filter parallel to the adaptive time constant filter [5]. This parallel filter should be at least the second order to remove noise amplification after differentiation. The optimal value for b was numerically calculated for every sample. Numerical optimization, however, is very difficult to implement in real time, especially in analog implementation of the filter. The functional relationship between the analog adaptive time constant and the normalized derivative, therefore, is found by least square fit

$$\tau(t) = \alpha \left| \frac{\dot{p}(t)}{p(t)} \right|^{-2/3} \tag{16}$$

where $p(t)$ is the output of the second-order parallel filter, and $\dot{p}(t)$ represents its derivative. The lower and upper limit of the adaptive time constant can be determined based on previous experience with EMG filtering. For the following experiments, α in (16) is set to 0.126 so that the adaptive time constant can vary within 50–500 ms [5] for the wide range of the normalized derivative values. Fig. 4 displays the outputs of the second-order parallel filter with a time constant of 100 ms, normalized derivative, and the output of the adaptive time constant filter. The response of the adaptive time constant filter is much faster than that of the second-order parallel filter. Also, the rise time stays the same while the command signal rises and falls. The adaptive time constant filter reduced the rms error about 20% when compared to the second-order parallel filter. During stationary periods, the output of the adaptive filter fluctuates more in the higher contraction level. This is due to the fact that the variance of estimation is greater in the higher contraction level, as expressed in (14).

To study the performance of the adaptive time constant filter for actual EMG signals, EMG signals were measured at the skin by two disk-differential preamplifiers with diameters of 13 mm and

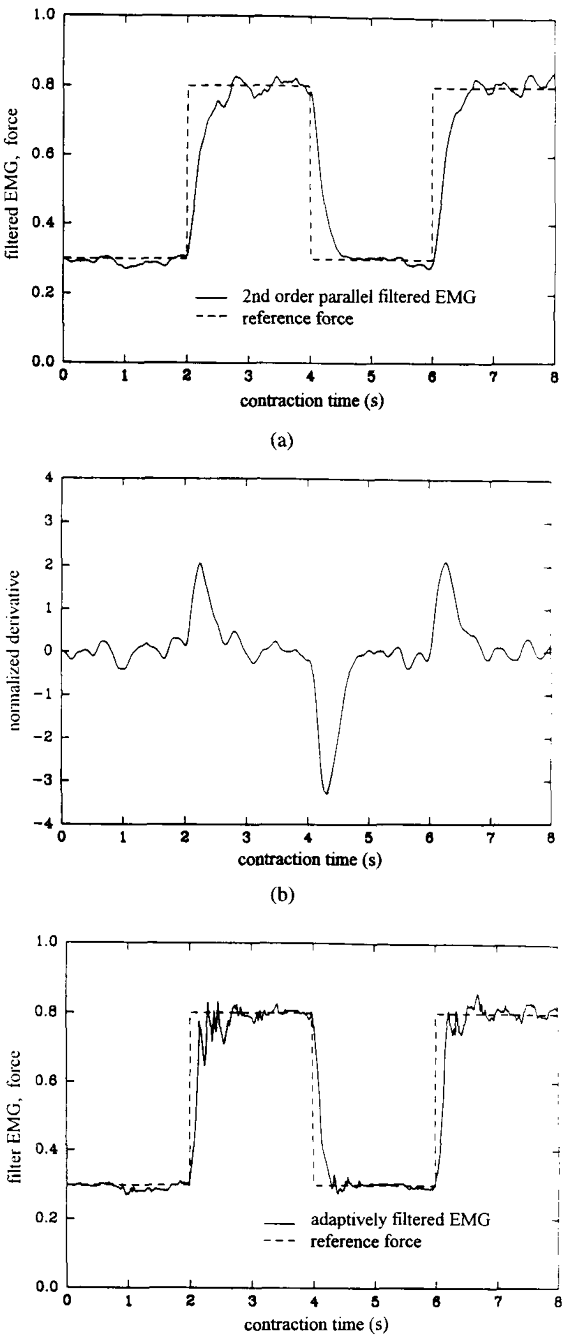

Fig. 4. (a) Parallel filter output when the command signal varies like a square wave. (b) Normalized derivative of the parallel filter output when the command signal varies like a square wave. (c) Adaptive time constant filter output when the command signal varies like a square wave.

a center separation of 35 mm. The common-mode rejection ratio of these preamplifiers is over 110 dB and the input impedance is on the order of $10^{11}\ \Omega$. The differential output was low-pass filtered with a 3-dB cut-off frequency at 500 Hz to prevent aliasing when sampled, and the output of the anti-aliasing filter is amplified and sampled at 1024 Hz. The EMG signals were measured at the skin over the flexor carpi radialis with the isometric constant and dynamic contraction conditions, and reference force signals were also measured simultaneously using a strain gauge instrumented load sensor. The ratios of mean-squared value and squared-mean value of the rectified EMG signals were calculated from the actual EMG

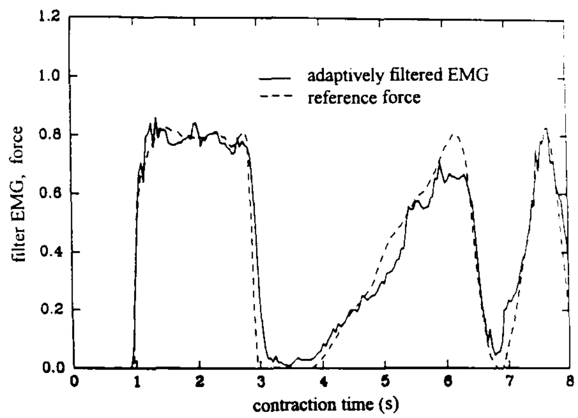

Fig. 5. Adaptive time constant filter output using the actual EMG signal with arbitrary varying contraction level in isometric dynamic condition.

signals measured on the several constant contraction conditions [15]. The average value of the ratio is about 1.8 with a variance of 0.21, hence the ratio is set to 2.0 for actual applications. Of importance for prosthesis control is how well the resulting control signal of the adaptive time constant filter can follow the varying contractions of the monitored muscle. This is best illustrated in Fig. 5.

IV. Conclusions

Based on the time-invariant and first-order low-pass filter approximation to a moving-average filter, we mathematically derived the adaptation logic which minimizes the mean-squared estimation error (MSEE), assuming the exact knowledge of a signal and its derivative. Using some appropriate approximations, the bias and variance of estimation were represented in closed forms. The analysis showed that the bias is the main source of the estimation error for a rapidly changing contraction, and the variance increases as a constant contraction level increases. The closed form representations of bias and variance, therefore, revealed that the adaptive time constant should be optimized as a function of the signal and its derivative. The adaptive time constant filter provides the minimum MSEE compromised between the error caused by the bias and the error caused by the variance.

The simulation results showed that the adaptive time constant filter performs better than a time-invariant filter as a contraction level is rapidly changing because of its ability to respond quickly. The adaptive time constant filter cannot be implemented for actual EMG signals, because the signal and its derivative are not available. Hence, the time-invariant second-order low-pass filter parallel to the adaptive time constant filter was used to provide the estimates of the signal and its derivative. The simulation results showed that this filter structure offers an improvement over the time-invariant filtering in that it can provide a fast response and a reduced rms error simultaneously.

The average values of the ratio of mean-squared value and squared-mean value of the rectified EMG signals were measured and the functional relationship between the analog adaptive time constant and the normalized derivative was presented for an analog implementation of the adaptive time constant filter.

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