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Comparison of signal-to-noise ratio of myoelectric filters for prosthesis control

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Abstract—A comparison of signal-to-noise ratios and rise times was performed on several myoelectric filters used for muscle-force estimation and prosthesis control. Linear, averaging, and adaptive filters were compared using single as well as multiple electrode pairs (spatial filtering). The filters were matched for having the same rise time (0–95%) and the signal-to-noise ratios were measured off-line using the same myoelectric signal recording. The linear filter was a low-pass filter with a time constant of 80 ms. The averaging filter had an averaging time of 250 ms. The adaptive filter was the same as is used in the Utah Artificial Arm. The adaptive filter varied its time constant according to the rate of change of the signal mean. If the rate was high, the time constant was set low. If the rate was low, the time constant was set high. Spatial filtering is where the myoelectric signals from four cutaneous sites over the same muscle were summed, that is, spatially filtered, and the resultant signal was smoothed by the linear, averaging, or adaptive filter. Significant improvement in the signal-to-noise ratio has been shown over conventional linear or averaging filters when using spatial and adaptive filtering, both when used separately and when used together.

Key words: *myoelectric filters, prosthesis control, signal-to-noise ratios, upper-limb prosthetics.*

INTRODUCTION

Electromyographic (EMG) signals have been used for many years to estimate muscle forces during various activities as well as to control prosthetic limbs. Prosthetic control systems utilize either a simple on-off control, as in the Otto Bock Hand system, or proportional control, as in the Utah Arm system (1). For proportional control of a prosthesis with a high-speed response, a fast-responding signal with a high signal-to-noise ratio is required.

The EMG signal, when used for proportional control, is usually treated as an amplitude modulated signal. The mean amplitude of the rectified cutaneous myoelectric signal is used as the control signal and is the desired output from the myoelectric processor. The cutaneous myoelectric signal at some contraction level, the frequencies of which are between 10 Hz and 1,000 Hz, functions as the "carrier" (2). However, the use of myoelectric signals as control signals poses a fundamental problem: the EMG spectrum of frequencies overlaps the frequencies of desired control. This makes the separation of the desired control signal (amplitude) from the noise (EMG carrier) difficult. Jacobsen (3) observed a fundamental filtering paradox whereby, with a stationary (fixed time-constant) filter, it is possible to have either a fast response or a high signal-to-noise ratio, but not both. Several methods of myoelectric filtering have been investigated (4,5), including simple, first-order linear filters, averaging filters, and adaptive filters. The latter has been shown to have the highest signal-to-noise ratio as well as the fastest response of any present-day filtering system (6). The processed EMG signal is usually compared to the measured muscle force or

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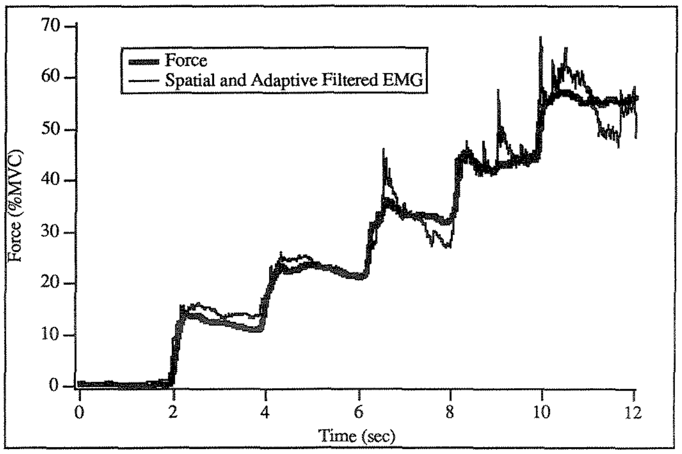

Figure 1.
Control signal (measured force) and spatially adaptive filtered EMG demonstrating that EMG "noise" scales with the control signal amplitude.

joint torque in evaluating the signal-to-noise ratio, as prosthesis controllability is subjective and qualitative (7).

Another method that has been shown to improve the signal-to-noise ratio of myoelectric signals is spatial filtering, in which multiple sensors are used to detect the myoelectric signal of one muscle (8). Herein, we will present the results of an investigation of a combined adaptive and spatial filter system, comparing the rise times and signal-to-noise ratios of the spatial-adaptive filter with averaging and linear filters. A brief description of myoelectric processing in general is given, followed by a description of adaptive filtering and spatial filtering.

METHODS

Myoelectric processing

For prosthesis control, the EMG signal is detected from the surface of the skin through the use of stainless steel electrodes without any skin preparation. This requires very high performance preamplifiers* with high common-mode rejection and high input impedance for the signal detection near the site of the electrodes.

We desire a usable proportional control signal from the unprocessed EMG and therefore make some assumptions about the character of the "raw" EMG signal. We treat the EMG signal as an amplitude modulated "carrier" with multiplicative noise. Logically, the assumption of multiplicative noise is satisfying because as muscle-force level increases, so does the firing and the recruitment of motor units near the sensors. **Figure 1** shows a "stair-step" control signal (measured load-cell output or isometric muscle force) and the corresponding processed EMG signal demonstrating the increase in "noise" with EMG signal amplitude increase. The raw EMG is processed much like AM radio demodulation. First, bandpass filtering removes unrelated signals and prevents aliasing if a digital filtering system is used. Second, rectification produces a non-zero-mean signal. Last, the signal is smoothed with a low-pass filter (4,9). **Figure 2** shows the general flow of the signal. The nature of the low-pass filter has been extensively researched, and many definitions of the optimal filter for myoelectric processing have been proposed (8,9,10,11,12,13,14).

Many researchers have designed filters based upon static (isometric, constant force) contractions of the muscles (8). Some have investigated dynamic (isometric, varying force level) contractions (5,12). When only static contractions are considered, variational calculus techniques can be employed to find an optimal filter. The result of the assumption leads to an averaging filter as the optimal filter. The output of an averaging filter is the arithmetic mean of a fixed time history of the signal. The resulting filter is not optimal for dynamic conditions, however. A better approach is to use a variable time-constant filter in which the time constant changes with the signal, that is, an adaptive filter (3,10,11,15,16).

Several researchers have investigated the use of multiple detectors on a single muscle to improve the signal-to-noise ratio (6,8,13,14). Multiple detectors (spatial filters) require additional hardware and are complex to implement in clinical prosthetic devices. Therefore, methods to simplify spatial filters in the clinical setting are needed if those filters are to be used clinically.

Adaptive filtering

The basic idea behind overcoming the EMG filter paradox is to vary the time constant of the

* In the work presented in this paper, we used preamplifiers manufactured by IOMED, Inc., of Salt Lake City, Utah. The common-mode rejection ratio is over 110 dB and the input impedance is on the order of 10^{11} ohms.

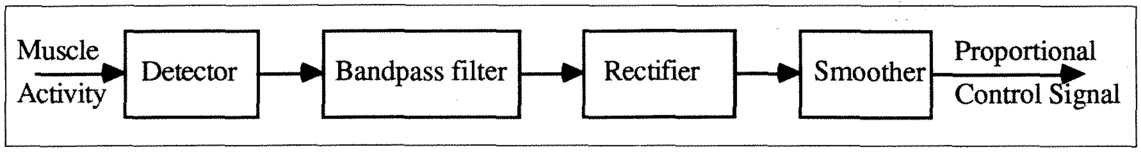

Figure 2. General proportional myoelectric processing flow.

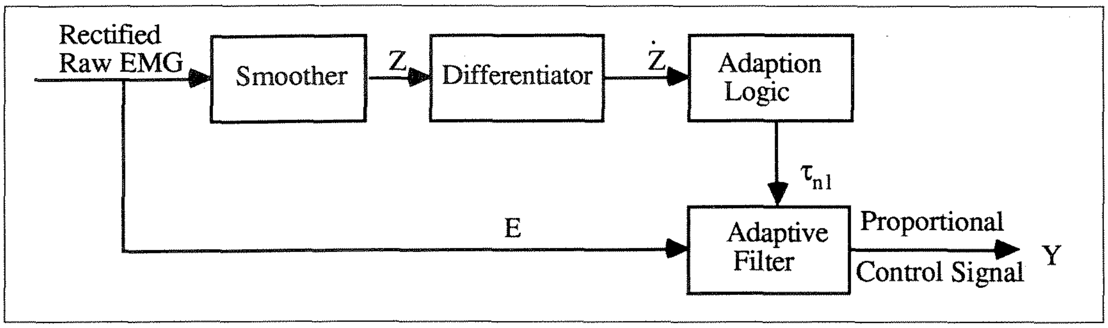

Figure 3. Adaptive filter signal flow.

filter according to the rate-of-change of the EMG signal. The rate-of-change of the EMG signal relates to the rate-of-change of the muscle contraction. The rate-of-change of the signal is determined by the derivative of the smoothed signal. When the signal is changing rapidly (high amplitude of the derivative) during rapid motions, the time constant is low, allowing fast response but with more noise. When the signal is steady (derivative amplitude is low) during slow, precise motions, the time constant is high, allowing a high signal-to-noise ratio, but slow response. **Figure 3** shows the signal flow of the adaptive filter. The assumption is that an amputee can tolerate noise when moving the prosthesis rapidly, but will not tolerate delays in control; and when holding the prosthesis steady, the amputee will tolerate slow response as long as there is low noise. In this way, the adaptive filter can overcome the EMG filter paradox of the fixed time-constant filter. The response time and the signal-to-noise ratio depend, then, not upon the time constant but rather upon the adaption logic. The adaption logic is defined by Equation [1] and is shown graphically in **Figure 4**.

The adaptive filter system is basically two filters in parallel. The derivative of the output of one filter with a time constant τ_z (Equation [3]) is used to control the time constant, τ_{nl} of the other filter (Equation [2]). Several parameters can be adjusted to control the response of the filter: the time constant, τ_z, of the parallel filter; the maximum and minimum time constants of the adaptive filter, τ_l and τ_s, respectively; and the gain, a, of the adaption logic. The relationships between the parameters for the adaption logic and the rise time, signal-to-noise ratio, and squared error can be defined and are shown in **Figure 5** (11,16).

$$\tau_{nl} = \frac{\tau_l - \tau_s}{a\dot{Z}^2 + 1} + \tau_s \qquad [1]$$

$$E = \tau_{nl}\,\dot{Y} + Y \qquad [2]$$

$$E = \tau_z\dot{Z} + Z \qquad [3]$$

where: τ_{nl} is the adaptive time constant in seconds
τ_l is the maximum time constant of the adaptive filter
τ_s is the minimum time constant of the adaptive filter
Z, $\dot{Z}$ are the smoothed EMG signal and its derivative
E is the rectified unsmoothed EMG signal
Y, $\dot{Y}$ are the output (control) signal and its derivative
a is a gain factor for the adaption logic
τ_z is the time constant of the parallel filter.

Spatial filtering

Spatial filtering is the use of multiple sensors (differential electrode pairs) to "pre-whiten" the EMG spectrum. Pre-whitening increases the randomness of the signal, thus making the signal

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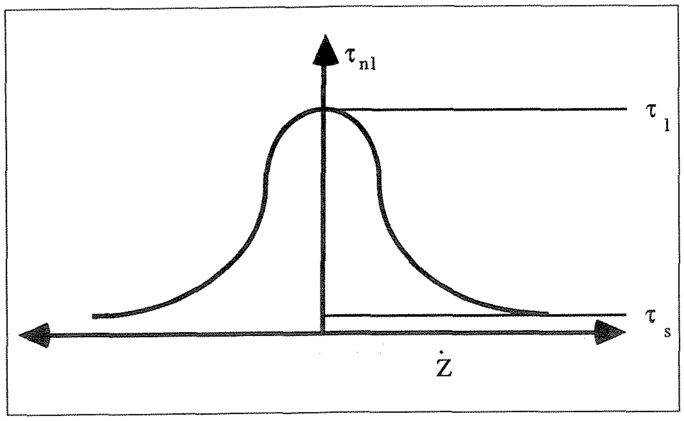

Figure 4. Time-constant function.

spectrum "whiter." It is postulated that limited spatial sampling (not enough active muscle motor units being detected) produces a low-frequency artifact (from the low-frequency firing and relaxation of motor units near the sensor), and that by combining the signals of several sensors, more of the total muscle is monitored and the low-frequency artifact disappears. The process is basically a weighted least-squares estimate filter (17). Hogan (8) has shown that multiple sensor systems have higher signal-to-noise ratios than single sensor systems, yet both have the same rise time.

Each sensor channel is weighted by a constant, and all the channels are summed, forming one signal which is then smoothed by a low-pass filter. The weighting of each channel is defined by the eigenvalues and the eigenvectors determined from a time series of EMG data by the following procedure: 1) time series of four channels of EMG data are collected for a constant isometric contraction of a muscle; 2) the eigenvalues and eigenvectors for each channel are computed for these data; 3) the eigenvectors "transform" each channel to create four "new" channels, which are linear combinations of the original channels, to maximize independence; and, 4) each of the "new" channels is weighted according to the eigenvalues and summed, producing a single signal that is then smoothed. In other

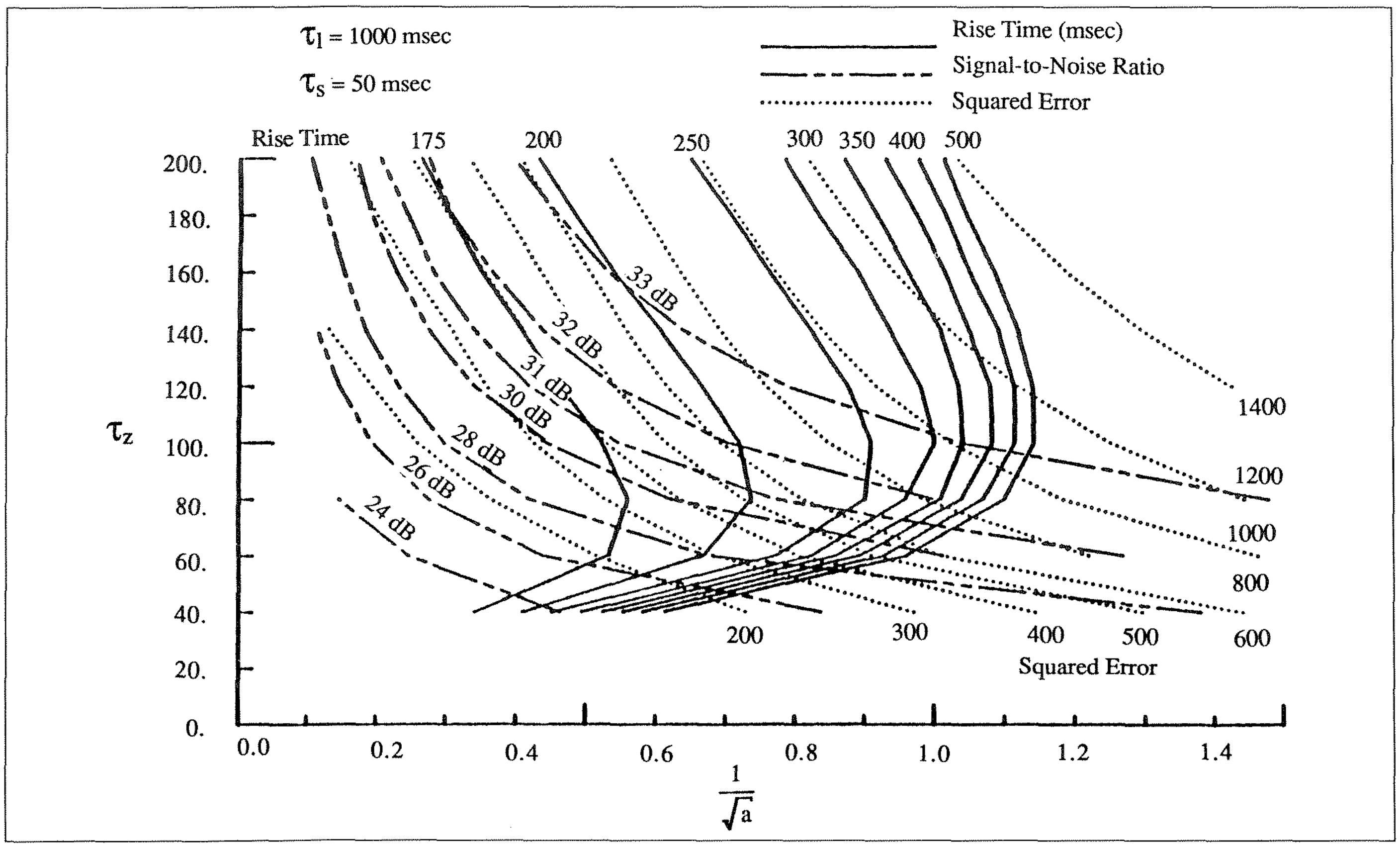

Figure 5. Signal-to-noise ratio and rise time as functions of adaption parameters.

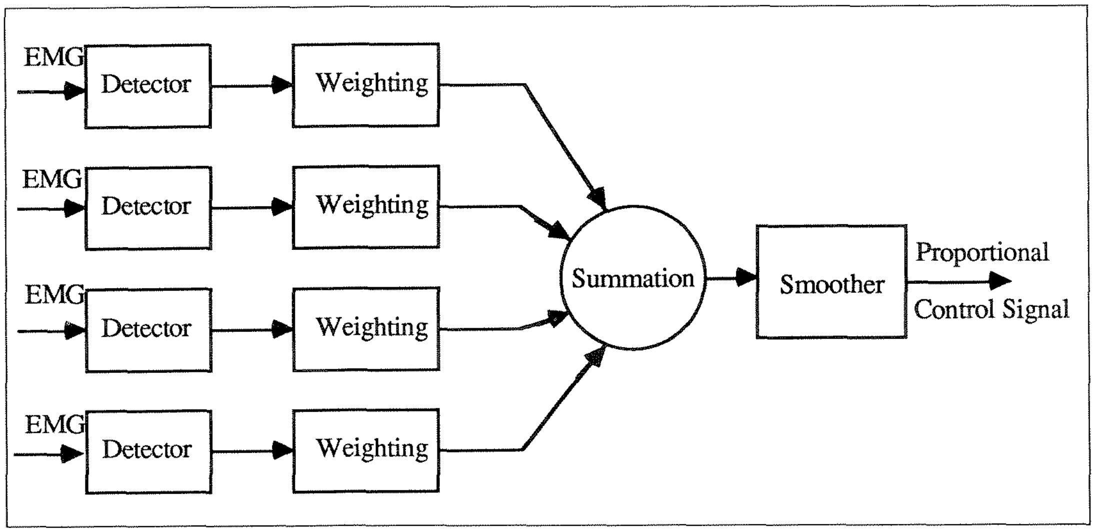

Figure 6.
Spatial filter signal flow.

words, each channel contributes to the summation according to its eigenvalue. A channel with no difference in eigenvalues (no additional information) is essentially ignored. This procedure maximizes the independence of each channel, increasing the randomness of the final signal. This is known as pre-whitening the signal. The final result of this procedure is the generation of a weighting coefficient for each EMG channel when the channels are summed. The spatial filter is defined by Equation [4]. Hogan (8) used an averaging filter to smooth the combined signal. A schematic of this is shown in **Figure 6**.

$$E = \lambda^T \mathbf{T}^T \mathbf{M} \qquad [4]$$

Where: E is the summed EMG signal (scalar)
λ is the vector of eigenvalues
T is a matrix whose columns are the eigenvectors
M is the vector of the EMG channels.

One difficulty with this approach is the requirement to find the weights for each measured muscle of each individual. Additionally, the eigenvalues change with electrode placement and with recruitment patterns of the muscle for different contraction actions such as flexion/extension and abduction/adduction (18). This would require calculating these weightings for every subject and for every electrode configuration and would make the system impractical for prosthetic use because it would require every prosthetist to have a data collection system and computer to calculate the weighting coefficients during the fitting procedure.

In this paper, we call the eigenvalue/eigenvector weights the optimal weightings. We have explored unity weighting in addition to the optimal weights. Unity weighting would set all of the EMG weight coefficients equally so that the spatial filter would be a simple summation amplifier. The removal of the necessity to determine the optimal weighting (recording of a time series of EMG signals and calculation of the eigenvalues and eigenvectors) would simplify the use of multiple sensors and also simplify the fitting and circuitry of a prosthesis so long as the signal-to-noise ratio is not degraded significantly.

The spatial-adaptive filter

Since the adaptive filter has an overall higher signal-to-noise ratio than the averaging filter, an improved signal-to-noise ratio should result from using an adaptive filter rather than an averaging filter for the final stage after a spatial filter. In order to test this idea, a multichannel, adaptive filter was designed, built, and tested.

Signal and filter comparison

Since muscle contractions are time varying and difficult to duplicate, comparisons cannot be made between different filtering systems if different EMG signal traces (recordings) are used with each of the filters. Therefore, the same EMG recording is processed by all of the systems and comparisons can then be made between the filtering systems.

It is also important that actual myoelectric signals be used to compare the systems rather than

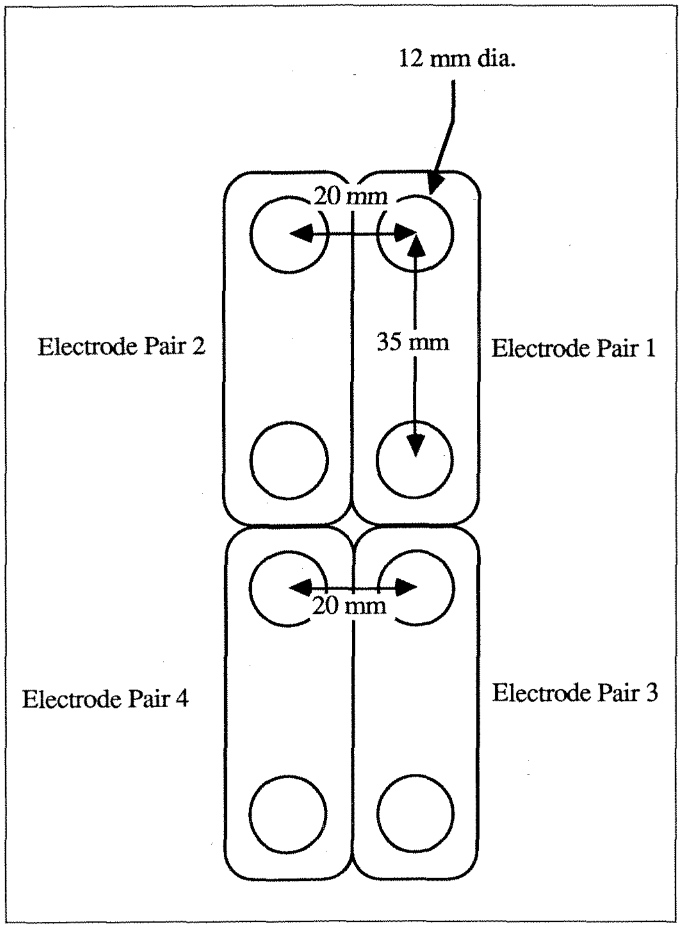

Figure 7.
The electrode array for spatial EMG filtering.

myoelectric models. However, when using actual EMG signals, the definition of the actual or original signal to be used in the calculation of the signal-to-noise is difficult. One must determine what part of the output is the desired, volitional control signal and what part is noise. It has been well-established (2,8) that the amplitude of the EMG signal relates to the isometric muscle force. Although force or torque control is not always used for prosthesis control, isometric muscle force is typically the signal used to calculate signal-to-noise of EMG signal processors. However, the muscle force is not directly accessible in an intact human arm so that the moment about a joint is usually monitored. Several muscles are recruited to apply a torque about a joint. Unless all of the muscles that act on the joint in question are monitored, how a particular muscle's myoelectric signal relates to the overall measured torque cannot be assumed with complete assurance. In the evaluation experiments described below, the EMG signals of one muscle were used for the filter comparisons. Other muscles were monitored to ensure their minimal activity.

Experimental procedure

Three nondisabled, healthy males were used as subjects in this study. The third digit of the subject's right hand was isometrically flexed. The force at the finger tip and the cutaneous myoelectric signals were simultaneously recorded by a computer.

The flexor carpi radialis and flexor digit superficialis muscles were monitored. Four pairs of stainless steel electrodes attached to EMG preamplifiers were placed on the skin directly over the muscles with no skin preparation. **Figure 7** shows the electrode array. A square array was used, as it was the only configuration that could be fit on the muscle belly without a modification of the electrodes or the preamplifiers. Hogan (8) used other configurations. Ours was an attempt to see what could be done with "off-the-shelf" electrodes and preamplifiers that a prosthetist could use. Each electrode of a pair was separated by 35 mm. Each electrode pair was separated from the adjacent pair by 20 mm. The EMG signal was rectified and anti-alias filtered at 250 Hz, then digitized to 12-bit resolution, and finally recorded by the computer.

The force at the finger tip was monitored by a strain gauge load cell. The arm and wrist were laid on a rest to prevent unwanted movements and muscle activity. The subject watched a monitor and was presented a target on the monitor. The subject pulled on the load cell and the applied force was displayed on the same monitor as was the target. The subject simply tried to keep the two points on the display together.

In the experimental data collection set-up, the subject pulled against a load cell as fast as he could to a specified force level. The load cell was stiff so that movement of the finger was constrained. The force and the unprocessed EMG signals from each of the four preamplifiers were recorded by a computer at a sample rate of 500 samples/s for 10 s. The force was applied between 5 and 6 s, and the signal-to-noise ratio was calculated using the EMG and force data between 8 and 9 s (**Figure 8**). A force of 50 percent of maximum voluntary contraction (MVC) was used in all cases. Tests were conducted with a minimum of 10 min between each data

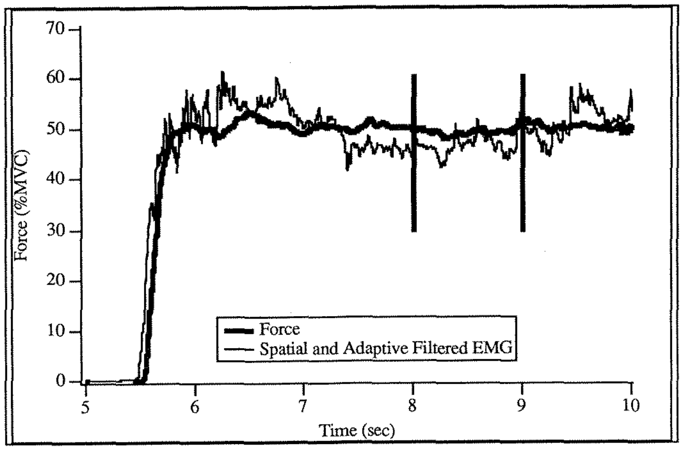

Figure 8.
Example of the data used to calculate the signal-to-noise ratio in the interval from 8 to 9 seconds.

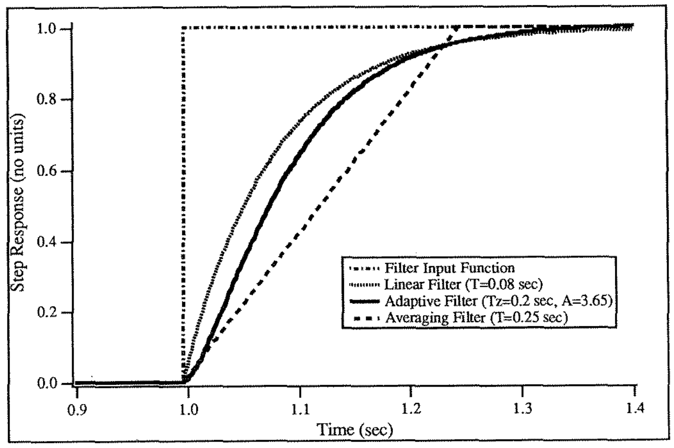

Figure 9.
Step response of the linear, averaging, and adaptive filters given a 0–95-percent rise time of 0.24 seconds.

collection period to minimize fatigue effects. The recorded data were then processed by all of the filtering techniques off-line.

Both rise time and signal-to-noise ratio are of interest for comparisons between the different filter systems. In order to simplify the comparisons, the signal-to-noise ratios were compared for the different systems adjusted to have the same rise time (0 percent–95 percent) of 240 ms as shown in **Figure 9**.

The signal-to-noise ratios and rise times were calculated using Equation [5] for each of the filter types: linear, averaging, and adaptive low-pass filters using single sensors and multiple sensors weighted by the optimal (eigenvalues and eigenvectors) values as well as unity weighting. The signal-to-noise ratio was calculated over 1 s.

$$\frac{\text{Signal}}{\text{Noise}} = \frac{\Sigma\ (\text{Force})^2}{\Sigma\ (\text{Force} - \text{EMG})^2} \qquad [5]$$

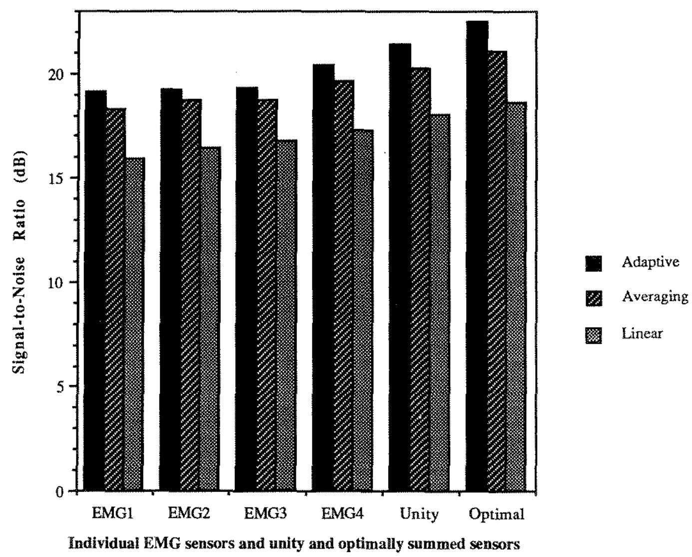

Figure 10.
Mean signal-to-noise ratios (in decibels) of all tests showing the relative performance of the adaptive, averaging, and linear filters.

RESULTS

The average signal-to-noise ratios for 11 different constant-force muscle recordings are given in **Table 1**, **Table 2**, and **Table 3**. A summary of the signal-to-noise ratios of each of the low-pass filters and for each EMG channel, unity-weighted, and optimal-weighted spatial filters is given in **Table 4**. **Figure 10** shows a graphical summary of **Table 4**.

Of importance for prosthesis control is how well the resulting control signal from each system can follow the varying contractions of the monitored muscle, not just a step function input. This is best illustrated visually in **Figures 11–17**, in which the output of each processing system is shown as well as the measured muscle force. The same data were used in all cases. The data are from Subject 2, who was not following any specified trajectory, but kept the force levels at 60 percent MVC or below. These data were not used in the signal-to-noise ratio calculations of **Tables 1, 2,** and **3**.

Table 1.
Signal-to-noise ratio (in dB) of the adaptive filter parameters: $\tau_1 = 1.0$ s, $\tau_s = 0.05$ s, $\tau_z = 0.2$ s, a $= 3.65$ s^2/V^2.

	Individual EMG Channels				4 Channel Spatial Filter Weightings	
Data File	**EMG1**	**EMG2**	**EMG3**	**EMG4**	**Unity**	**Optimal**
Subject 1	16.159	15.556	19.616	17.860	21.258	18.348
Subject 1	16.602	17.740	15.372	18.262	17.846	21.367
Subject 1	14.333	14.230	16.230	17.461	16.100	17.068
Subject 1	26.175	19.002	18.345	18.386	22.584	24.049
Subject 2	17.163	18.504	17.101	20.681	20.933	16.639
Subject 2	13.460	17.734	20.470	21.906	20.089	20.477
Subject 2	21.065	22.196	23.107	23.405	25.534	27.352
Subject 2	20.014	20.248	22.148	21.885	23.594	25.650
Subject 3	21.042	22.443	20.135	20.792	22.171	27.397
Subject 3	21.290	20.667	17.574	20.307	20.548	23.778
Subject 3	22.812	23.464	21.927	23.800	24.912	25.089
Mean	19.101	19.253	19.275	20.431	21.415	22.474
Stand. Dev.	3.696	2.758	2.435	2.110	2.690	3.749

Figures 11, 12, and **13** show the outputs of single-channel linear, averaging, and adaptive filters, respectively. A visual comparison shows that the adaptive filter has the least noise of the three. **Figures 14, 15,** and **16** show the outputs of the optimal spatial filter with linear, averaging, and adaptive smoothing filters, respectively. In the particular example shown, the averaging filter performed better than the adaptive. Generally, however, the adaptive filter performs better than the averaging filter as indicated in **Tables 1, 2,** and **3**. This particular data set is interesting in that the uniformly weighted spatial filter performs better using a visual comparison than the optimally weighted filter, as indicated by **Figure 17**, showing the output of a unity-weighted spatial filter and an adaptive smoothing filter. The same force and EMG data were used for **Figures 11–17**.

An analysis of variance (ANOVA) was performed on the signal-to-noise ratio results of **Tables 1, 2,** and **3** to test for significance of any differences between the variables, that is, the different filter types and the different spatial weighting techniques. Additionally, a Tukey analysis (19) was computed for differences found significant by the ANOVA to find which variables caused the significance (i.e., which filter was significantly different from the

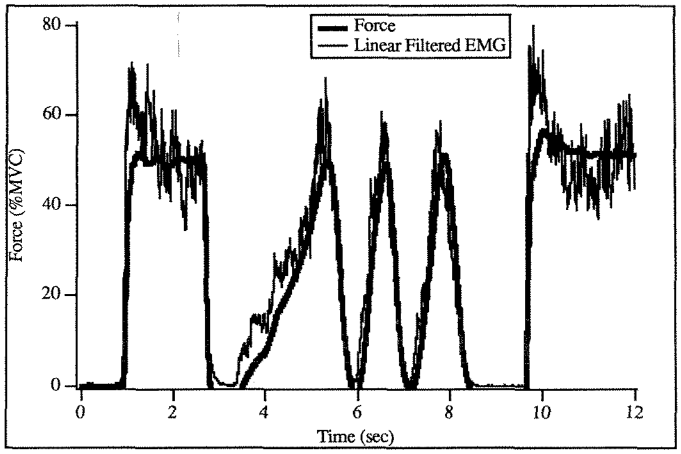

Figure 11.
Force and single-channel, linear-filtered (τ = 0.08 s) EMG.

Table 2.
Signal-to-noise ratio (in dB) of the averaging filter (Averaging time = 250 ms).

	Individual EMG Channels				4 Channel Spatial Filter Weightings	
Data File	**EMG1**	**EMG2**	**EMG3**	**EMG4**	**Unity**	**Optimal**
Subject 1	15.455	14.592	19.273	18.796	19.235	17.274
Subject 1	16.078	17.963	15.859	17.209	17.569	20.514
Subject 1	14.470	14.130	16.069	17.676	15.850	16.841
Subject 1	23.605	18.409	17.806	17.702	21.196	22.417
Subject 2	17.236	18.573	17.283	19.396	19.841	17.135
Subject 2	13.481	17.635	19.160	20.600	18.824	19.316
Subject 2	21.547	22.010	22.293	22.730	24.305	25.165
Subject 2	19.380	19.605	21.886	21.531	23.400	24.160
Subject 3	20.721	21.135	18.192	18.792	19.736	24.199
Subject 3	19.986	20.226	17.149	20.173	19.885	22.372
Subject 3	19.774	21.672	20.593	21.761	22.386	22.304
Mean	18.339	18.722	18.687	19.669	20.202	21.063
Stand. Dev.	3.056	2.493	2.081	1.753	2.373	2.896

others). The results of the Tukey analysis for significance of the low-pass filters are shown in **Table 5**. The Tukey honestly significant difference (HSD) level was 0.5148. Each low-pass filter was found to be significantly different. The significances of each individual EMG channel, the unity-weighted spatial filter, and the optimally weighted spatial filter are shown in **Table 6**. The Tukey HSD level was 1.179. Both spatial filters are significantly different than the individual channels, but the unity-weighted spatial filter is not significantly different from the optimally weighted spatial filter.

The results of the statistical analysis can be summarized as follows:

1. The use of multiple sensors (spatial filtering) significantly improved the signal-to-noise ratio.
2. There was no statistically significant difference between optimally weighted (using eigenvalues and eigenvectors) and uniformly weighted spatial filters.
3. Adaptive filtering was significantly better than averaging filtering, which was significantly better than linear filtering.

Table 3.
Signal-to-noise ratio (in dB) of the linear filter (time constant = 80 ms).

	Individual EMG Channels				4 Channel Spatial Filter Weightings	
Data File	**EMG1**	**EMG2**	**EMG3**	**EMG4**	**Unity**	**Optimal**
Subject 1	13.976	13.362	17.917	16.869	17.621	15.895
Subject 1	15.017	16.219	15.391	16.451	17.007	19.940
Subject 1	13.557	12.904	15.354	15.986	14.973	16.062
Subject 1	19.578	17.599	16.083	15.705	19.588	20.664
Subject 2	13.862	15.800	15.320	16.722	16.928	13.786
Subject 2	12.629	15.582	17.165	17.646	16.917	17.477
Subject 2	17.910	17.963	18.061	18.325	19.573	19.576
Subject 2	16.967	17.375	18.780	18.725	20.206	20.380
Subject 3	17.553	18.133	16.069	16.646	17.607	21.487
Subject 3	17.489	17.266	15.395	17.212	17.460	19.842
Subject 3	17.018	18.664	18.980	19.712	20.318	20.268
Mean	15.959	16.442	16.774	17.272	18.018	18.670
Stand. Dev.	2.132	1.814	1.379	1.166	1.603	2.354

CONCLUSIONS

Comparisons were made of the signal-to-noise ratios of three types of EMG filters with and without multiple sensor arrays. These filters have been used to estimate muscle forces from EMG signals and to proportionately control prosthetic limbs. The purpose of the investigation was to quantify the ability of each filter to provide high signal-to-noise ratios as well as fast response (short

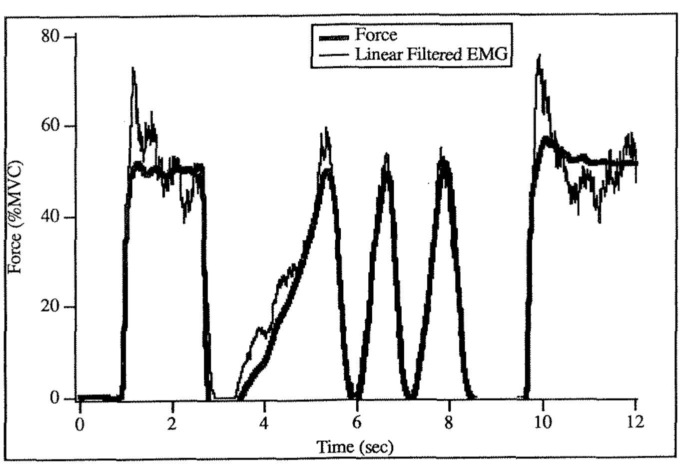

Figure 12.
Force and single-channel, averaging-filtered EMG (averaging time = 0.25 s).

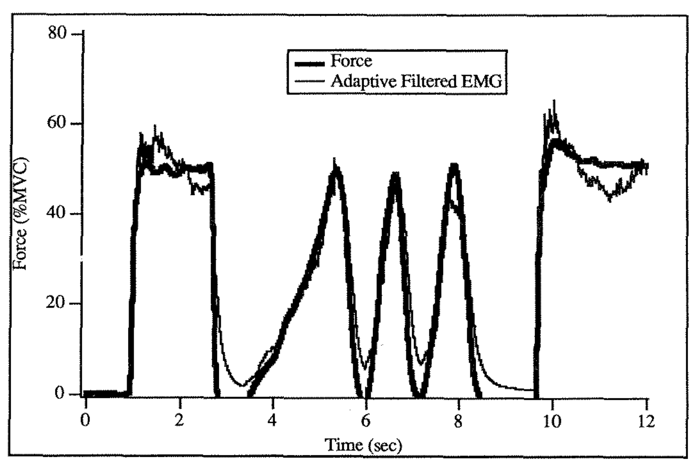

Figure 13.
Force and adaptive-filtered EMG (τ_l = 1.0 s, τ_s = 0.05 s, τ_z = 0.2 s, a = 3.65).

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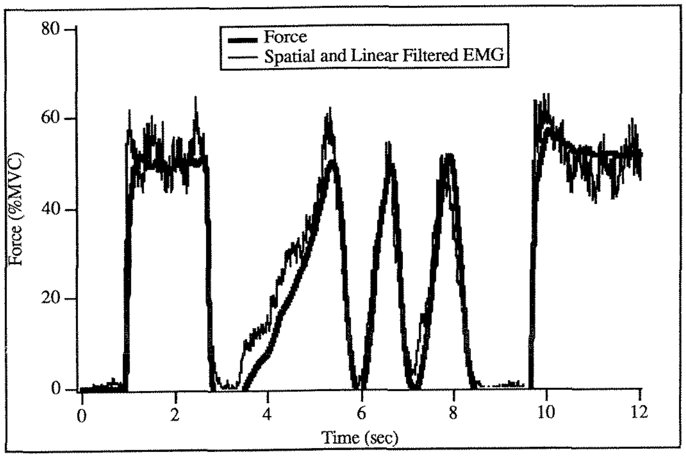

Figure 14.
Force and optimal-spatial, linear-filtered EMG (τ = 0.08 s).

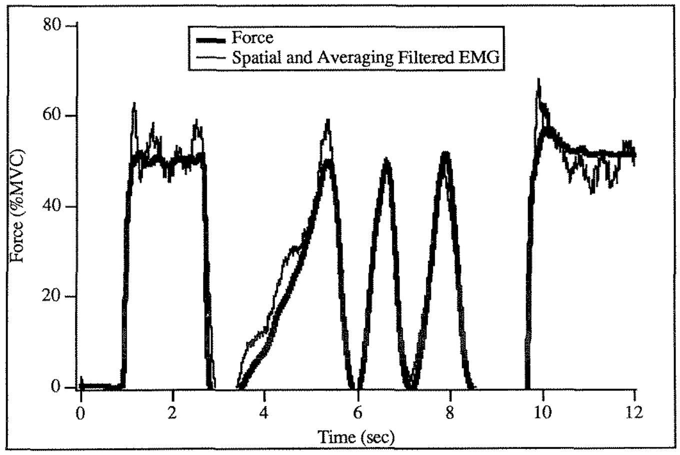

Figure 15.
Force and optimal-spatial, averaging-filtered EMG (averaging time = 0.25 s).

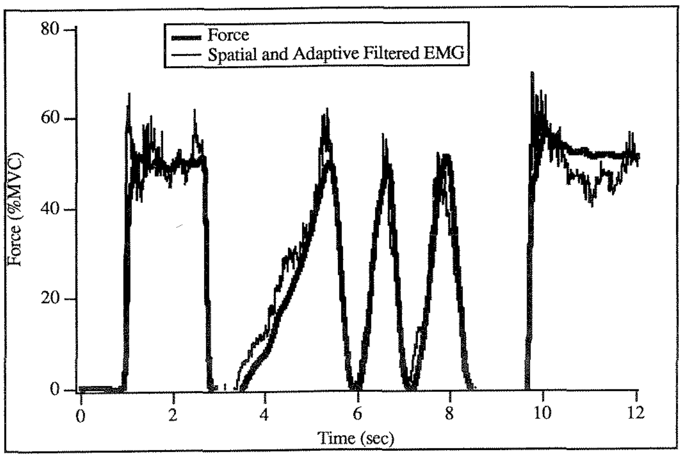

Figure 16.
Force and optimal-spatial, adaptive-filtered EMG (τ_l = 1.0 s, τ_s = 0.05 s, τ_z = 0.2 s, a = 3.65).

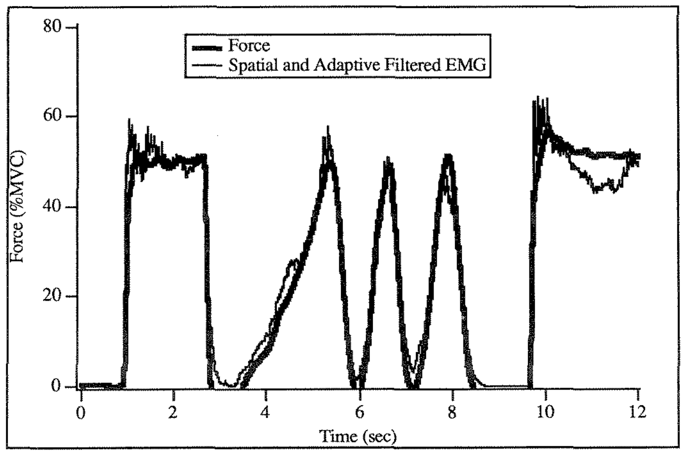

Figure 17.
Force and uniform-spatial, adaptive-filtered EMG (τ_l = 1.0 s, τ_s = 0.05 s, τ_z = 0.2 s, a = 3.65).

rise time) with regard to prosthetic limb control and force estimation applications. In order to simplify the comparisons, the rise time of each filter was matched so that only signal-to-noise ratios needed to be compared. We postulate that the inverse comparison is valid—that matching signal-to-noise ratios and measuring rise time would yield the same results.

It was found that the signal-to-noise ratio of the adaptive filter described in the paper was 20 percent higher than the ratio of a linear filter with the same rise time, with each filter using a single EMG sensor over the muscle. Also, the adaptive filter had a 12 percent higher signal-to-noise ratio than that of an averaging filter. Using an array of four EMG sensors further increased the ratio of the adaptive filter by 7 percent without affecting the rise time.

The choice of what technique to use for a particular purpose depends upon the weighing of several factors. Among these are: How important is the improvement of the signal-to-noise ratio? What is the cost of the filter? How easy is the filter to implement? Both the adaptive filter and the averaging filter (approximated by a third-order Paynter filter) cost little more than and are almost as easy to implement as the linear filter (8). In fact, the adaptive filter has been successfully used in the Utah Artificial Arm since 1982 (1,20). The question

Table 4.
Summary of mean signal-to-noise ratios (in dB) of all filters.

	Individual EMG Channels				4 Channel Spatial Filter Weightings	
Data File	**EMG1**	**EMG2**	**EMG3**	**EMG4**	**Unity**	**Optimal**
Adaptive	19.101	19.253	19.275	20.431	21.415	22.474
Averaging	18.339	18.722	18.687	19.669	20.202	21.063
Linear	15.959	16.442	16.774	17.272	18.018	18.670

Table 5.
Tukey analysis of low pass filters (ANOVA significance >1%).

(Mean)	Adaptive (20.32)	Averaging (19.45)	Linear (17.18)
Adaptive	—	3.145*	.879*
Averaging		—	2.267*
Linear			—

*greater than d_t = .5148.

remains, How important is the use of multiple sensors? The EMG sensors are the highest cost components of the EMG system. The improvement in signal-to-noise ratio using multiple sensors is minor (7 percent). Furthermore, if multiple sensors are used, it does not seem necessary to find sensor gains through the calculation of the eigenvectors and eigenvalues as has been proposed by Hogan (8). No significant difference was found in the signal-to-noise ratio using unity-weighted sensor gains versus eigenvalue/eigenvector-weighted sensor gains.

It would seem that multiple sensors should significantly improve muscle force estimation from EMG signals. However, our study has shown that the benefits of multiple sensors are marginal. For both prosthetics and muscle-force estimation uses, adaptive filtering is easily implemented and provides superior results. Unless a radically new signal-processing technique is developed, further attempts at improving the signal-to-noise ratio of EMG signal processors are probably not warranted for practical applications. The authors are currently investigating improvements in fatigue measurements and fatigue compensation of EMG/force estimation. Fatigue causes large errors between the EMG and muscle-force estimates. If a reliable, real-time fatigue estimator were developed, it could be used to compensate the EMG/force estimation, removing the error caused by the fatigue.

Table 6.
Tukey analysis of spatial filters (ANOVA significance >1%).

	Individual EMG Channel				Spatial (4 channel)	
(mean)	1 (17.178)	2 (18.139)	3 (18.254)	4 (19.124)	Unity (19.876)	Optimal (20.762)
1	—	.361	.476	1.345*	2.097*	2.964*
2		—	.115	.985	1.736*	2.603*
3			—	.869	1.621*	2.488*
4					.752	1.618*
Unity					—	.867
Optimal						—

*greater than d_t = 1.179.

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