Short Time Fourier Analysis of the Electromyogram: Fast Movements and Constant Contraction

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Abstract—**We applied short-time Fourier analysis to surface electromyograms (EMG) recorded during rapid movements, and during isometric contractions at constant forces. We selected a portion of the data to be transformed by multiplying the signal by a Hamming window, then computed the discrete Fourier transform. Shifting the window along the data record, we computed a new spectrum each 10 ms. We displayed the transformed data in spectograms or "voiceprints." This short-time technique allowed us to see time-dependencies in the EMG that are normally averaged in the Fourier analysis of these signals. Spectra of EMG's during isometric contractions at constant force vary in the short (10–20 ms) term. Moments of the spectral distribution show this variability. Short-time spectra from EMG's recorded during rapid movements were much less variable. The windowing technique picked out the typical "three-burst pattern" in EMG's from both wrist and head movements. Spectra during the bursts were more consistent than those during isometric contractions. Furthermore, there was a consistent shift in spectral statistics in the course of the three bursts. Both the center frequency and the variance of the spectral energy distribution grew from the first burst to the second burst in the same muscle. We discuss this pattern with respect to the origin of the EMG bursts in rapid movement. We also extend the analogy between electromyograms and speech signals to argue for future applicability of short-time spectral analysis of EMG.**

I. Introduction

EMG's have been used historically as an indicator of the state of muscle contraction (Wacholder [33], DuBois-Raymond 1844, Licht [20]). The raw signal is easily detected, and rich in information. Most crudely, it is an indicator of muscle activity. The sum of many single motor unit action potentials, it grows in amplitude with fiber recruitment. This property has made it a candidate for a measure of muscle force, a measure otherwise difficult to obtain in intact subjects. The shapes and sizes of the individual potentials are clinically useful for diagnosis of myopathies. It is not surprising that the EMG has been processed in many ways in attempts to recover some of its components.

Signal Processing of EMG's

The zero-mean, apparently amplitude modulated character of the EMG signal has lead to efforts to compute an estimate of the envelope of this signal. Further processing has attempted to yield a signal proportional to muscle force.

Graupe and Cline [13] have used ARMA time series models to characterize the unrectified EMG. Through an identification and pattern recognition procedure, they were able to distinguish among several intended limb movements for prosthetic control. Yamada *et al.* used spectral features derived from bandpass filter outputs to identify intended hand activity which was then simulated on an animated display.

Spectral Analysis

The Fourier transform has been applied to the EMG to verify models of EMG generation (Gottlieb and Agarwal [12]), and for diagnosis of diseases affecting neuromuscular conduction (Inbar and Noujaim [17]).

Lindstrom and others ([21], [22]) have produced a general model of the EMG signal, including the filtering effects of volume conduction, summation of single MUAP's, jitter, and electrodes. They use the model to infer changes in physical parameters from changes in the EMG power spectrum (most notably, conduction velocity from the position of "dips," or zeros in the power spectrum).

Spectral analysis has been applied fruitfully in studies of fatigue. It has long been known that high frequencies in the EMG spectrum decline with muscle fatigue relative to low frequencies—the median frequency of the power spectrum falls (Lindstrom and Petersen [21] for bibliography). This effect has even been used to construct a "fatigue monitor" (Stulen and DeLuca [32]).

Very recent attempts to find the mechanism of this spectral shift have produced new resolution from surface EMG's. Kranz *et al.* [18] found the the rms amplitude of the surface EMG was relatively constant during the downward shift in median frequency brought on by 45 s maximum voluntary contractions of the biceps. They inferred a reduced motoneuron drive, and computed a generalized firing rate from the surface EMG. This calculated firing rate declined during fatigue, as measured directly by others (Bigland-Ritchie *et al.* [5]). Broman and DeLuca [7] measured spectral parameters during fatigue, and compared Lindstrom's predictions to measured conduction velocities. They found more change in the spectral parameters than in conduction velocity, and concluded that other mechanisms (e.g., firing statistics of individual motor

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neurons, correlation between firings) must also produce the spectral shift.

Features of the EMG spectrum have been explained by several derivations and models of the generation of EMG (Gottlieb and Agarwal [12], Lindstrom [21]). Because of the spacing of electrodes in the recording of the EMG from the skin surface, zeroes should be expected in the EMG spectrum at frequencies corresponding to an integral number of cycles in the interelectrode spacing (Lindstrom [21]). The frequencies of these zeros are

$$F_i = iv/d$$

where F_i is the frequency of the ith zero, v is the conduction velocity of the fiber, and d is the interelectrode distance. Thus, there is a strong dependence of the computed EMG spectrum on v, the conduction velocity of the fibers producing the EMG. This of course is also a function of electrode spacing. For a fixed d, as in the case of a data set taken from a single experiment, an observed shift in the spectrum may indicate recruitment of a different population of fibers. However, other mechanisms can shift the spectrum. For example, in the previously cited fatigue studies, the observed shift in frequency is thought to arise from changes in the electrochemical properties of the fiber with fatigue resulting in changed conduction velocity v.

Signal processing of EMG has been done on two very different time scales: on the order of milliseconds for needle EMG, on the order of seconds for surface EMG (including spectral analysis). The short time scale of needle EMG is appropriate to the short duration of single motor unit potentials. The long time scale of surface EMG is generally necessary to ensure convergence of the statistics of the spectrum. The previous spectral analysis studies have all used data sets containing from 0.5 to 45 s of EMG. The resulting spectrum is an average which characterizes the entire data set and suppresses the contribution of individual action potentials or bursts. Our interest is in rapid voluntary movement. The movements take place in 0.25–0.5 s with bursts of EMG that are on the order of 100 ms long. We therefore use an explicit windowing technique to analyze short segments of an ongoing signal.

Short Time Spectral Analysis

The classical use of short time Fourier analysis is for the analysis of speech [28], with the Vocoder, a device for real-time spectral analysis of speech (Dudley [10]) being perhaps the earliest.

An important tradeoff in short time spectral analysis is time versus frequency resolution. Thus, a spectrum computed from a relatively long time window will resolve detailed frequency features, but change little if the center time of the window is shifted by a small amount. Conversely, a narrow window will have good time resolution but show little detail in the computed spectrum. This tradeoff is of course the Heisenburg uncertainty principle.

$$\text{var}\,(X(j\omega)) * \text{var}\,(x(t)) >= c$$

where var ( ) denotes the variance, and c is a constant.

Fast Movement Control

Of particular interest are changes in spectral content of EMG among parts of the control signal used to generate fast movements. The fastest recorded movements in many human joint systems are accompanied by the so-called triphasic pattern of EMG activity. This consists of an initiating burst in the agonist, followed by a braking burst in the antagonist, and a final clamping burst in the agonist. These control pulses have been modeled and given the names *PA*, *PB*, and *PC* to suggest their functions: action, braking, and clamping (Hannaford and Stark [16]). Changes in spectra among the bursts could be an important clue to their origin and mode of control, an important question studied by many investigators (Ghez and Martin [11], Angel [3], Litvinsev and Seropayan [23]).

In search of information beyond the EMG envelope relevant to the control of fast movement, we have computed short time spectra as a function of time ("voiceprints") of EMG's taken during fast movements of the wrist and head. As a control, similar "voiceprints" have been computed for isometric and isotonic contraction at different force levels.

II. Methods

We recorded rapid movements of the head and of the wrist. Head movements were 40° in magnitude in the horizontal plane, and wrist movements were 30° flexions and extensions. In all cases, subjects were instructed to move as quickly as possible. Wrist movements were in response to a visual target. The subject held a lightweight handle instrumented to measure position, and viewed a CRT display of target and handle position. The subject practiced until consistent movements could be made, as judged by a display of the movement trajectory.

Disposable Ag/AgCl self-adhesive electrodes for neck muscle recordings were placed along the length of the left and right splenius capitus muscles after shaving where necessary and appropriate skin preparation. The muscles were located by palpitation of the neck as the subject cocontracted his neck muscles. The validity and lack of crosstalk of this method of recording (Hannaford *et al.* [15], [16]) is confirmed by needle electrode studies (Zangemeister *et al.* [40]), potential mapping of the back of the neck (Hannaford [15], [16]), by the observed reciprocal activation of the two muscles (lack of crosstalk between antagonists) and the geometry of the neck muscles (main synergist to the splenius is the *contralateral* sternocleido-mastoid).

Ag/AgCl surface electrodes were placed over the bellies of the flexor carpi radialis and the extensor carpi radialis, separated by 3.5 cm (Table I). A ground electrode was located on the subject's elbow. The relatively large electrodes (0.8 mm) and small muscles make crosstalk a possibility. Crosstalk from synergists (the flexor carpi ulnaris and the extensor carpi ulnaris) is likely to have occurred, but would not change the interpretation of our data because these muscles are known to produce burst patterns simultaneously with their radial counterparts during

TABLE I
EMG ELECTRODE PLACEMENT

Movement Type	Muscles	Electrode Spacing	Diameter
Wrist Flexion Extension	flexor carpi rad. extensor carpi rad.	3.5cm	8mm
Horiz. Head Rotation	left / right splenius capitus	4.7cm	1cm

rapid movements (e.g., Litvintsev and Seropyan [23]). The possibility of crosstalk from gripping muscles—palmaris longus, flexor digitorum sublimus, and profundus—was specifically checked and eliminated. We found no evidence of crosstalk from antagonists; our burst patterns showed reciprocal innervation in every case.

The signal was filtered to remove movement artifacts (half amplitude at 10 Hz) and to eliminate aliasing (half amplitude at 0.3 kHz).

In addition to fast movements, we also measured isometric contractions of wrist flexors and extensors. Force measurement was by a sensitive load cell (Sensotec model 31). Subjects maintained constant force (maximum observed force fluctuation: ± 5 percent) by keeping a force feedback display within a narrow target. Forces were 32, 64, and 128 N, or about 0.2, 0.4, and 0.8 maximum voluntary contractions. We repeated the measurements at $-60°$, $0°$, and $60°$ of wrist flexion.

Controls

Caution must be exercised in interpreting any observed spectral changes because of the possibility of changes in important state variables concomitant to but not dependent on the control of fast movement. For example, an observed change in the spectrum of *PC* with respect to *PA* may be caused by recruitment of a different population of motor units (a change in control strategy), or simply be due to the change in length of the agonist muscle (a concomitant effect). To identify and control for spectral effects due only to changes in position and force levels and not due to changes in recruitment, we have also analyzed data from isometric contractions at various joint positions and isotonic contractions at various force levels.

Movements

EMG data, digitized at either 1000 or 2000 Hz, were measured from surface electrodes placed on the skin above the muscles controlling the movements. Table I lists the muscles used and electrode parameters. EMG signals were amplified at gains between 2000 and 5000. Initial sampling was at 2000 Hz, but very little signal power occurred above 500 Hz. EMG's were recorded during two types of movements: maximally fast, so-called time optimal horizontal rotation of the head (Zangemeister *et al.* [40]) or flexion/extension of the wrist, and isometric and isotonic contractions of the wrist at different levels of voluntary contraction.

Mathematics of Short Time Spectral Analysis

We analyzed the electromyographic data using short-time Fourier analysis (Rabiner and Schafer [28]). The time dependent Fourier transform is defined by

$$X_n(e^{j\omega}) = \sum_m w(n - m)\, x(m) e^{-j\omega m} \qquad (1)$$

a function of discrete time n and continuous frequency w. The data to be transformed, $x(m)$, are weighted by a window sequence $w(n - m)$. As the time dependent Fourier transform takes on increasing values of n, the window $w(\cdot)$ slides along the data, selecting a portion for analysis.

For each fixed time n, (1) is the discrete Fourier transform of the product sequence $w(n - m)\, x(m)$. The Fourier transform of this product is the convolution of the separate Fourier transforms W of the window, and X of the data:

$$X_n e^{j\omega} = 1/(2\pi) \int W(-j\theta)\, e^{-j\theta n} X(j(\omega - \theta))\, d\theta. \qquad (2)$$

The windows we consider (rectangular and Hamming) are finite in duration, so they possess Fourier transforms. We can ensure that the EMG has a Fourier transform by defining it to be zero outside the window.

The convolution (2) exhibits the dependence of the time-dependent transform on the window. Windows $w(\cdot)$ with short time duration have broad transforms $W(\cdot)$ (the main lobe width is inversely proportional to window length), so short duration windows most accurately reflect $X(\cdot)$, the DFT of the signal. However, the spectrum of the signal changes in time, and short windows have proportionally lower frequency resolution, so a compromise is necessary. We chose window widths long enough to contain whole bursts of EMG.

Computations: Data in blocks of 512 or 1024 samples were multiplied by Hamming windows of various sizes and transformed by the FFT algorithm. To produce the "voiceprint" plot (Figs. 1 and 5), the computation was performed iteratively. Every 10 ms, a segment of EMG data was multiplied by a 75 ms Hamming window and Fourier transformed (Rabiner and Gold [27]). The FFT algorithm processes sequences of length 2^n so the remaining places were filled with zeros. Power spectra were computed at frequencies from 0 to 300 Hz at intervals (sampling rate/window width) of 8 Hz. Each spectrum was normalized by the total energy in the windowed data.

Spectra were plotted vertically at each 10 ms time increment. Energy is indicated by the width of the line. Readability of the voiceprints was improved by normalization, in which each spectrum is divided by the total energy, and thresholding, in which portions of the voiceprint below a certain power level are left blank. We set a threshold so that portions of each spectrum with energies below 7 percent of the maximum in that window are not plotted. The 7 percent threshold was selected to plot only spectral segments whose plotted energy would be greater than the plotting pen's width. To simplify the "voiceprints," we plotted spectra only for windowed samples of

the EMG with energy greater than 5 percent of the peak value of the windowed energy estimate over the entire movement (see below).

To provide the information removed by normalization, the windowed energy estimate

$$E = \sum_{w(t)\neq 0} (w(t)\, x(t))^2\, dt \tag{3}$$

(where $w(t)$ is the window function, and $x(t)$ is the EMG signal) is plotted above the spectrum. This quantity is analogous to the rectified, integrated EMG, but it is the output of a system whose impulse response is symmetrical in time or noncausal.

The center frequency and variance of the spectrum are plotted above the windowed EMG energy. Defining the nth moment of the power distribution as

$$M_n(X) = \sum \omega_i^n |X(\omega_i)| \tag{4}$$

the center frequency is the mean M_1/M_0 and the variance is

$$\text{variance} = \frac{M_2}{M_0} - \frac{(M_1)^2}{(M_0)^2}. \tag{5}$$

In the voiceprints, these are also thresholded (shown only if EMG energy is at least 5 percent of maximum) to improve readability.

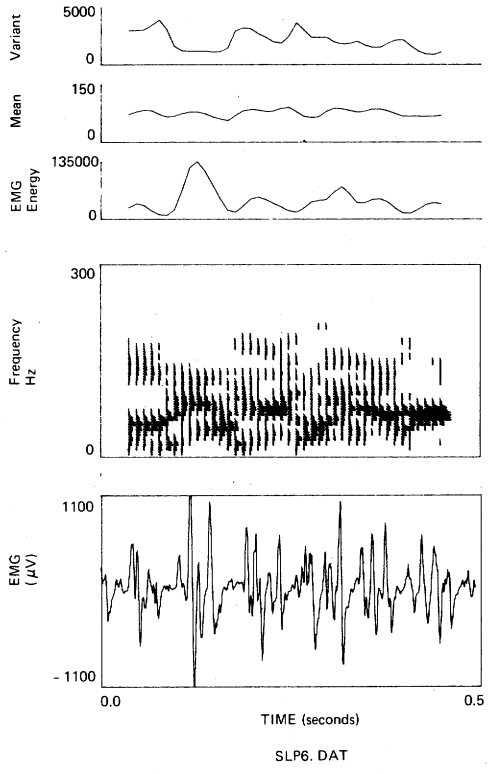
III. Results

Isometric Constant-Force Contractions

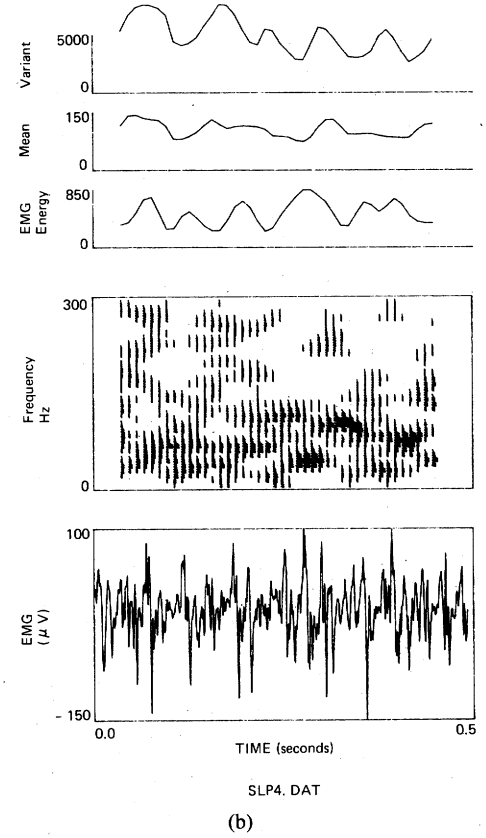
EMG data from wrist flexors and extensors were recorded during steady contractions at different force levels and joint positions. The variability of the spectrum of "constant" contraction is illustrated by the staggered dark bands in the time–frequency plot (Fig. 1). These bands appear to correspond to the frequency components of individual MUAP's. Amplitude variation is revealed by fluctuations in the windowed energy estimate. The spectral parameters, mean frequency, and variance showed changes as isometric force increased from 0.2 to 0.8 MVC. The variance decreased from 4000 to 2500 (Hz^2), and the mean frequency decreased from 102 to 80 Hz. The variance shift is consistent with the observations of Broman and DeLuca [7], but our mean frequency result is opposite.

To characterize the short time energy variations at different time scales, the computation was performed with window lengths of 16, 32, 50, 64, 75, and 128 ms. (Fig. 2).

A detailed spectrum was computed from the isometric data using a 500 ms Hamming window for comparison to traditional spectral analysis of EMG (Fig. 3). The resulting spectrum consists of spikes mostly below 250 Hz, with an additional distribution of energy between 250 and 375 Hz. This is in good agreement with earlier computations such as those of Gottlieb and Agarwal [12].



(a)



(b)

Fig. 1. EMG signal, spectogram, EMG energy estimate, mean frequency, and variance in frequency during isometric contractions at different forces [128 N (a), 32 N (b)]. Note short-time variability in the spectra, energy, and spectral statistics in both cases.

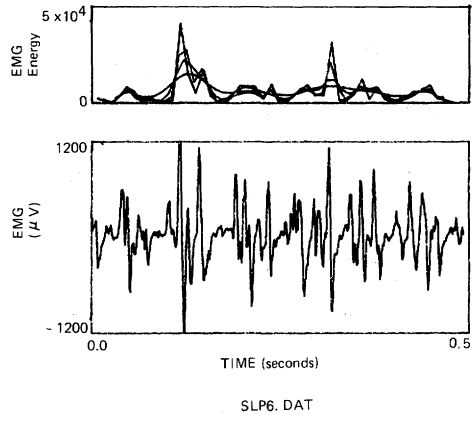


Fig. 2. The windowed energy estimate depends on the window width. Raw EMG signal from flexor carpi radialis during isometric contraction at constant force (128 N), and windowed energy estimates for Hamming windows of 16, 32, 64, and 128 ms duration.

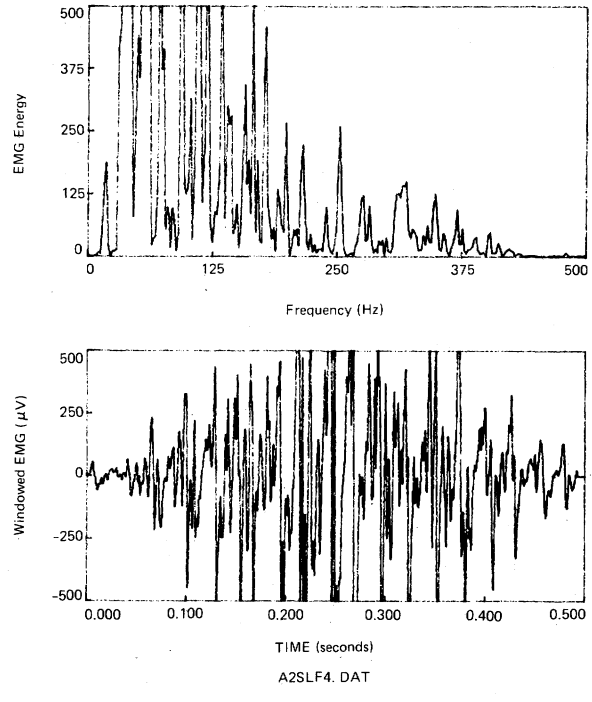


Fig. 3. EMG during isometric contraction, windowed by a 500 ms duration Hamming window, and Fourier transformed.

Fast Head Movements

Data from fast head movements consisted of records of position, velocity, and acceleration taken from horizontal head rotations, as well as EMG signals from neck muscles. EMG signals presented the commonly observed three-burst, or triphasic structure. The velocity and acceleration of these movements had peak values (590 °/s, and 10 700 °/s^2, respectively) characteristic of the fastest recorded voluntary horizontal head rotations (Zangemeister *et al.* [39], Hannaford *et al.* [15], [16]).

The windowed spectral analysis technique can be used to separate the individual control signal pulses for analysis (Fig. 4). The resulting spectra are distorted relatively little by the windowing because the pulsed EMG signals are near zero at the edges of the window. It should be kept in mind that these spectra are computed from a small set of data points with no assumption of stationarity. This means that the resulting spectra are not averages, but individual signatures which will vary as much as the individual time functions from which they are computed.

"Voiceprint" plots of fast movements were computed with a 75 ms Hamming window, whose center time was incremented by 10 ms intervals to produce each vertical line [Fig. 5(a)]. The windowed energy estimate indicates the location in time of the different pulses of activity in the agonist and antagonist muscles. The three-pulse control signal is usually clearly visible in the windowed energy estimate, although the energy in *PC* is usually small compared to that of *PA*.

Wrist Movements

"Voiceprints" of rapid wrist movements [Fig. 5(b)] were also computed with a 75 ms window, with the center time shifted in increments of 10 ms. Again, the windowed energy showed three clear-cut pulses. The second agonist pulse (*PC*) was even smaller, relative to *PA* (about 15 percent of its peak energy) and *PB* was also smaller (about 40 percent of the peak energy of *PA* in the same muscle). The EMG energy threshold gives a convenient measure of pulse width: *PA* ranged from 90 to 100 ms, *PB* ranged from 60 to 85 ms, and *PC* from 30 to 55 ms.

During EMG pulses, defined by above-threshold amplitudes of the energy estimate, the spectrum was very regular in all of the movements studied. This regularity is visible in the similarity among groups of 5–10 of the vertical lines. This implies stationarity of the spectrum of the pulses over periods of 50–100 ms.

Means and variances of the frequency distributions changed consistently in the fast head and wrist movements studied. The mean frequency usually declined slightly during *PA*, and rose to a higher value between *PA* and *PC*, again gradually declining thereafter. The measure of dispersion of energy in the frequency domain, showed a sharp jump between *PA* and *PC*. These changes were seen consistently in 20 movements in each direction in each of the two joint systems studied. The same regularities were found in pulses from wrist muscles as from neck muscles: center frequency and variance consistently rose from *PA* to *PC*. Both center frequency and variance fell during the wide (*PA* and *PB*) pulses.

IV. Discussion

Stationarity

Whenever a signal is subjected to Fourier analysis, the issue of stationarity becomes important. Stationarity is always assumed when a finite block of data is taken to be representative. In other words, if the spectrum computed from this block is said to represent the spectrum of the signal for all time, then an assumption of stationarity is being made. Short time spectral analysis avoids the question of stationarity by defining which time interval is used in the computation. The resulting spectrum represents

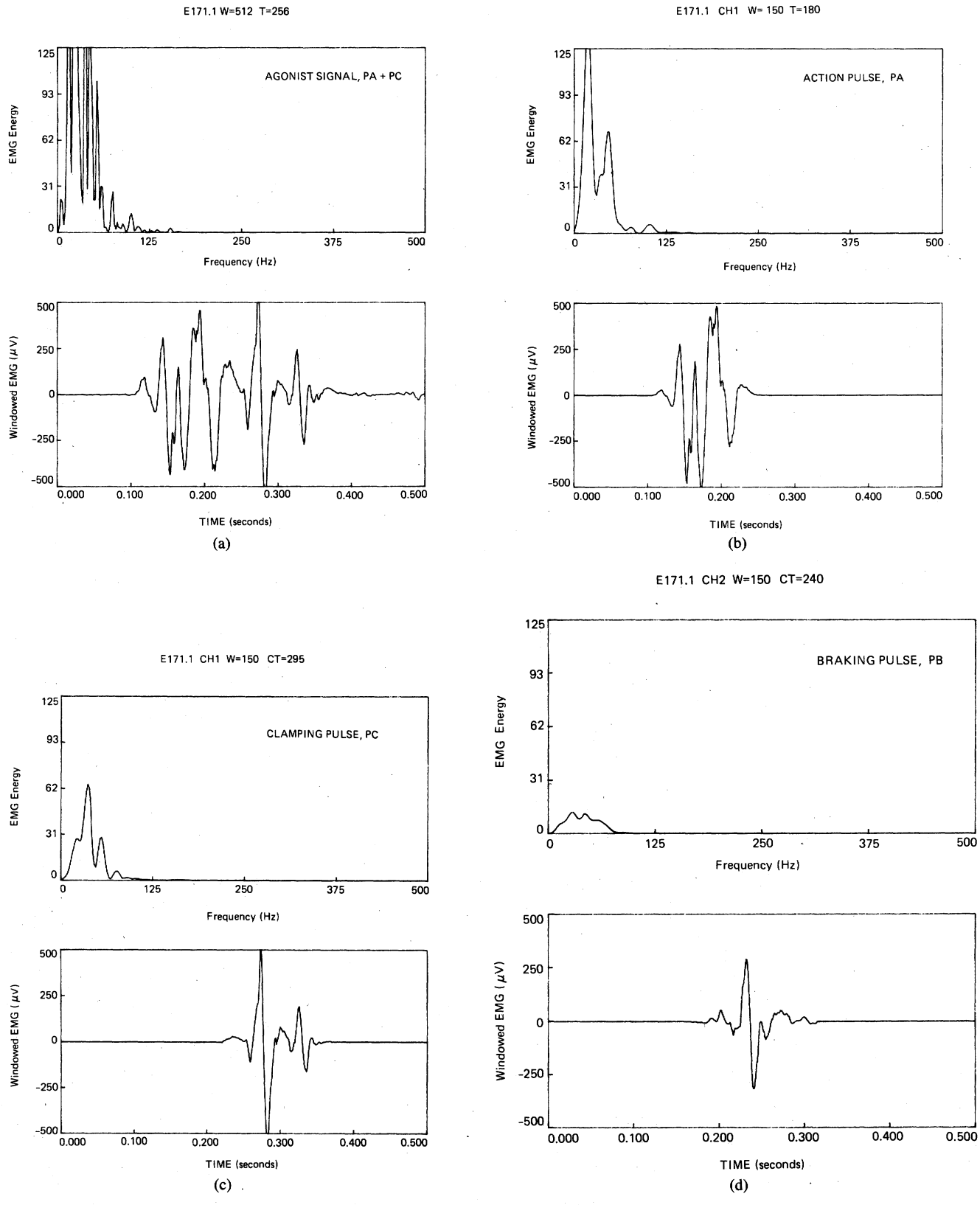


Fig. 4. EMG signal during a rapid head movement, windowed by a 500 ms duration Hamming window, and Fourier transformed. Windowed and transformed activity from agonist muscle (a) includes the first agonist burst *PA*, shown separately in (b), and the second agonist burst *PC*, windowed separately in (c). In the course of the movement, these bursts are separated by a pulse of EMG in the antagonist muscle *PB* shown in (d).

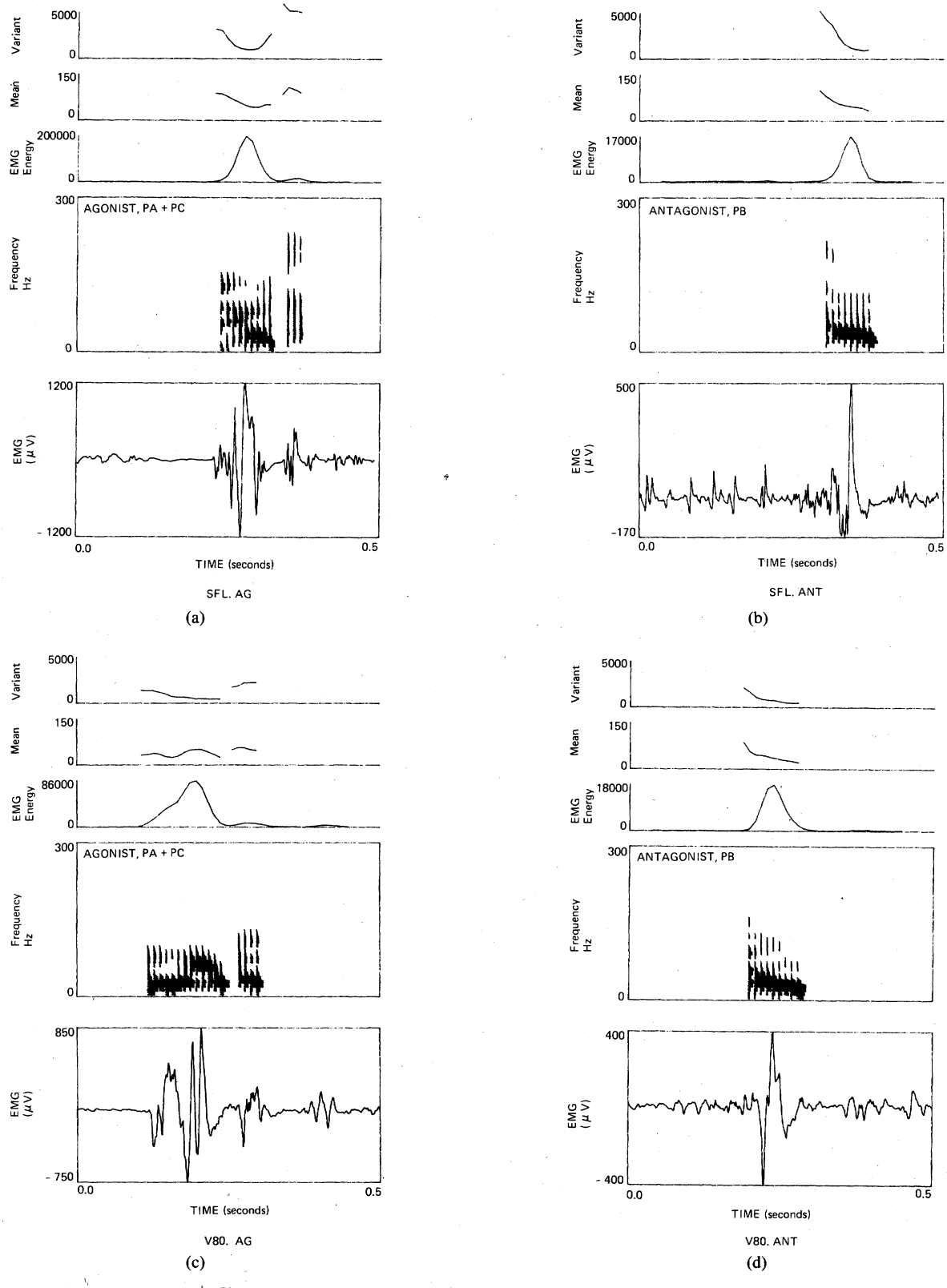


Fig. 5. Raw EMG, spectograms, windowed EMG energy, mean frequency, and variance in frequency for a rapid wrist movement [agonist (a), antagonist (b)] and a rapid head movement [agonist (c), antagonist (d)]. The spectra and statistics are shown only when EMG energy exceeds 5 percent of its maximum. The windowing technique picks out the three burst pattern. Shifts to higher mean frequencies and greater variance are visible in the "voiceprints" for both types of movement, and clearly displayed in the plots of spectral statistics.

only the data from that time interval (multiplied by the window function) and extrapolation of the short time spectrum to other times has no meaning.

We considered several possible explanations for the shift in spectral moments we measured from *PA* to *PC*. There may be recruitment of larger fibers, with faster conduction velocities. The spectra could depend on electrode placement over the muscle, so that the observed shift is a position effect. The small amplitude of the signal during the latter pulse might conceivably be so small as to shift the emphasis on background noise, whitening the signal.

We checked for a position dependency in the wrist movements by looking at spectra of isometric contractions at 0°, −60°, and +60°. We found no consistent effect of position. We did not perform the same test for neck muscles, but think a position effect less likely there, because the skin and electrode movement is less for the neck muscles than for the forearm.

A shift due to reduced signal to noise ratio is also unlikely. Although small compared to *PA*, the signal energy in *PC* was still at least 1000 times larger than background noise.

Recruitment of motor units with higher spectral moments is the most likely possibility. If larger, faster-conducting fibers were recruited, both mean frequency and variance would rise. Consider the simplest case, multiplication of all conduction velocities by some factor $a > 1$. The action potential amplitude $x(t)$ would compress in time to a signal $y(t) = x(at)$. The faster action potential would transform as

$$Y(j\omega) = F\{y(t)\} = F\{x(at)\} = (1/a)\, X(j\omega/a) \quad (6)$$

where $X(j\omega) = F(x(t))$. The moments of the frequency distribution would then scale.

$$M_n(Y) = \sum (\omega/a)^n\, X(j\omega/a) = a^{n+1} M_n(X) \qquad n = 0, 1, 2, \cdots \quad (7)$$

and likewise the mean (μ) and variance

$$\mu(Y) = M_1(Y)/M_0(Y) = a\mu(X)$$

$$\text{var}\,(Y) = a^2\, \text{var}\,(X). \quad (8)$$

The increased mean frequency in *PC* surprised us. Many believe the later bursts of EMG activity in rapid movement to arise from reflexes (Wadman *et al.* [34], Ghez and Martin [11]). It is also known that recruitment (in wrist flexors) follows the size principle, even during reflexes (Calancie and Bawa [8]). One might therefore suppose that *PC* would represent slower, smaller, lower frequency content fibers. Our evidence runs counter to this supposition. It seems to support a nonreflex origin of *PC*. Sanes and Jennings [30] did observe late bursts in muscles deafferented by ischemia. We may have a reversal of the normal recruitment order.

The "voiceprint" plot symbolizes an analogy between the myoelectric interpretation problem and that of speech recognition which we believe is a fruitful one. An example of the use of this analogy is the prosthetic control system resulting from the work of Graupe *et al.* [13], [14]. Their ARMA approach is analogous to linear predictive methods of speech processing.

The moments we computed of the short time spectrum of EMG's were roughly analogous to the primary formant frequency of the speech signal (M_1) and a measure of the unvoiced or fricative nature of a speech sound (M_2).

In speech analysis, representations such as the time-dependent Fourier transform are combined with models of speech production. Parameters of the model are varied so that the model output fits a measured speech waveform, and by this means the formant frequencies and glottal waveform of the speech are measured at once. An analogous treatment of the electromyogram to recover recruitment and MUAP waveform information is tempting.

The analogy between EMG processing and speech recognition can be carried further in that other speech recognition techniques should be evaluated for a role in sophisticated movement analysis applications such as identification of intended limb function from EMG activity in residual muscles of the amputee. As these techniques become more sophisticated through evolution of the current technologies, prosthetic devices may become capable of performing neurologically ballistic movements by recognition of an EMG pattern which triggers a preprogrammed sequence of control signals to the limb. This would be analogous to the case of word recognition for which a host of techniques have been developed to dynamically warp the speech signal to match stored templates. After isolated movement recognition systems are perfected, there will be a demand to be able to recognize a closely spaced sequence of such movements. In this case, the problem becomes analogous to the difficult one of continuous speech recognition.

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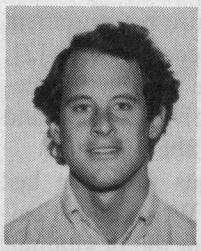

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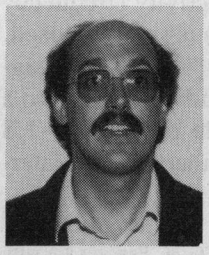

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