ELECTROMYOGRAPHY

ANATOMY AND PHYSIOLOGY

Muscles convert chemical energy into mechanical energy. Since they can pull but not push, at least two muscles are needed for each joint connecting two body segments: the agonist and the antagonist. Cocontraction of both muscles causes

carefully controlled movements and stiffening of the joint. Skeletal muscles are *striated,* whereas muscles of internal organs (stomach and intestines, vessels, uterus) are *smooth.*

Muscles consist of long thin cells (fibers) whose membranes are excitable. The membrane presents a resting voltage of about −70 mV between the inside and the outside. If the membrane voltage is disturbed to the point that a threshold is reached, a phenomenon called *action potential,* similar to the firing of a monostable multivibrator (one shot), is triggered. This voltage transient evolves in time for 2–5 ms and propagates in space from the point of trigger to the two ends of the fiber with a velocity of 3–6 m/s. The traveling action potential generates a field of current flowing into the surrounding conductive medium (volume conductor) and producing voltages detectable between any two points in the surrounding medium as well as on the skin surface.

Motor neurons establish a connection between the spinal cord and the muscles. When it reaches the muscle, each motor neuron branches into a number of terminals, each of which makes an electrochemical connection, called the end-plate or neuromuscular junction (NMJ), with a single muscle fiber. Each fiber has only one NMJ and belongs to only one motor neuron. A motor neuron and the muscle fibers it innervates form a motor unit (MU) whose fibers are activated synchronously and may range in number from approximately 10 to 2000. A muscle may contain 50 to 1500 MUs whose fibers are scattered in overlapping territories. Fibers differ in size (diameter may range from 10 μm to 100 μm, length may range from a few millimeters to 300 mm), metabolism, and electrical and mechanical behavior. Two main types can be identified: Type I fibers are smaller, are more fatigue-resistant, produce lower forces, and have lower contraction speed and lower conduction velocity. Type II are usually larger, are less fatigue-resistant, produce higher forces, and have higher contraction speed and conduction velocity. The two fiber types have different metabolism, and their distribution is affected by genetic factors as well as training (1).

Each action potential transmitted along a motor neuron is called a *firing* and triggers a mechanical contraction (single twitch) of the MU. As the firing frequency increases from a few pulses per second to 15 to 20 pulses per second the MU has no time to relax between pulses and remains contracted, generating a tetanic contraction. The brain controls and smoothly adjusts the level of muscle force by controlling the number and the firing frequencies of the activated MUs.

ELECTROPHYSIOLOGY OF MUSCLES AND EMG DETECTION

The summation of the single-fiber action potentials generated by a MU is the MU action potential (MUAP). A sequence of firings generates a MUAP train. The electromyographic (EMG) or myoelectric signal is the voltage detected with two (or more) electrodes within the volume conductor (needle or wire detection) or on the surface of the skin (surface detection). Figures 1(a) and 1(b) show the depolarization zone of a cell, its schematic representation as a current tripole, and its contribution to the surface and needle potentials for two depths. The deeper the source, the smaller and more diffused is its two-dimensional potential distribution on the surface. As this distribution travels on the surface and in the direction of the fiber, it generates a time-varying potential at the detection point(s).

Figure 1(c) shows a schematic for a three-fiber MU, the traveling action potentials of one fiber, and the needle and surface detection technique. Figure 2 shows examples of needles used for EMG detection. The detection volume of an electrode system is the volume from which signal contributions are above noise level. This volume depends on the interelectrode distance; it is a hemisphere of about 0.5–1 mm diameter in the case of needles and a few centimeters in the case of surface detection. At the present state of the art, surface detection provides information about superficial muscles only. Surface signals have amplitudes ranging from the noise level to a few millivolts, with most of the power comprised between 10 Hz and 300 to 400 Hz.

Needle detection allows the monitoring of potentials generated by fibers that may belong to a few different MUs, and it provides local information with good morphological details that allow identification and separation of the contributions due to different MUs as well as the recognition of MUAP shapes that reflect pathologies. Needle-detected signals have amplitudes ranging from the noise level to a few millivolts, with most of the power ranging from 10 Hz to 1 kHz.

Surface detection provides global information with poor morphological details. Distant but large muscle portions may provide signal contribution comparable to those of smaller and closer portions. When these contributions come from muscles different from the one in or on which the electrodes are placed, they are referred to as *crosstalk.*

When many MUs firing asynchronously contribute to the detected signal, algebraic summation takes place; the signal appears random and is referred to as the *interference pattern.* This is the signal observable during voluntary muscle contractions. If the motor neurons (or their terminal branches) are activated synchronously by an external electrical stimulator, the different MUAPs are synchronized and add to form the compound action potential or motor wave (CAP or M-wave).

APPLICATIONS OF EMG

Today the main clinical application of the EMG techniques is based on the use of needles for diagnosing neuromuscular diseases that modify the morphology of MUAPs. However, surface techniques are becoming more popular because they are noninvasive and inexpensive and provide global information. The most important applications of surface techniques are listed below.

Estimation of Nerve Fiber Conduction Velocity. A peripheral nerve is electrically stimulated and the muscle response (M-wave) is detected. Measurement of the distance between the stimulation and detection sites, along with appropriate measurement of the stimulus–response delay, allows estimation of the nerve fibers conduction velocity (2).

Myoelectric Manifestations of Muscle Fatigue. As a voluntary or electrically elicited muscle contraction is sustained in time under isometric conditions, the EMG signal becomes progressively slower. This change precedes the inability to sustain the required effort (mechanical fatigue), is referred to as *myoelectric manifestations of muscle fatigue,* and depends on the fiber type constituency of the muscle. It is likely that current

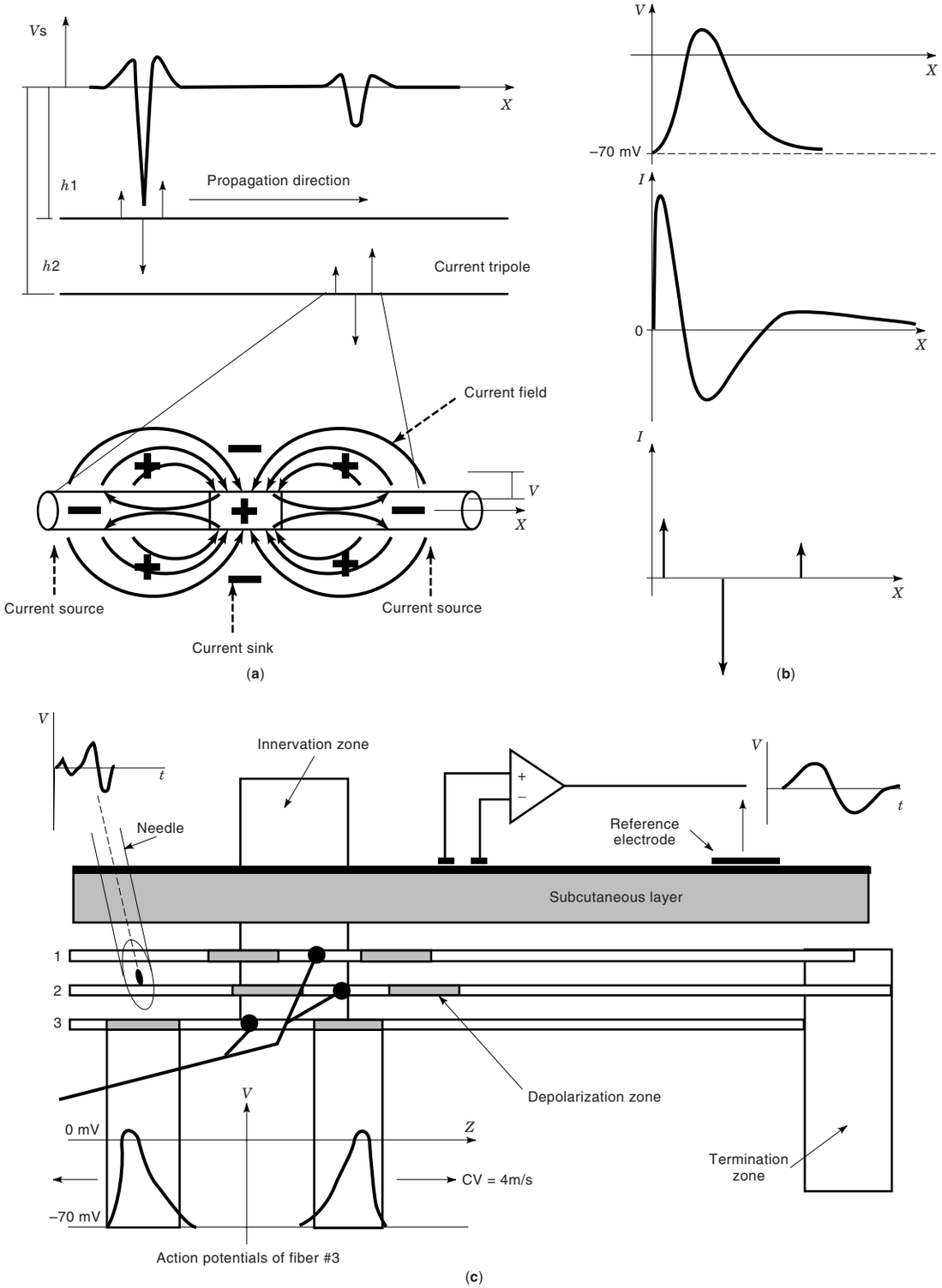


Figure 1. (a) Depolarization zone of a muscle fiber, description of the membrane current, and monopolar surface potentials V_s generated on the skin by two depolarized zones at two depths h_1 and h_2. (b) Muscle fiber transmembrane voltage, current, and tripole model of the transmembrane current. (c) Schematic representation of a motor unit (example with three fibers only) and of the signal detected by a differential amplifier (surface electrodes) or by a coaxial needle. Physical dimensions are not in correct proportions.

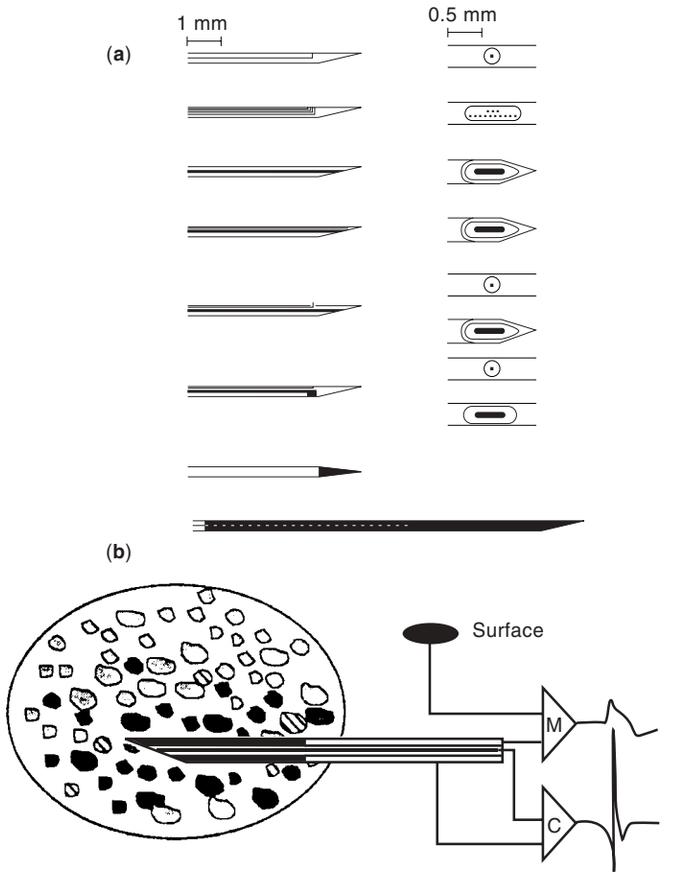


Figure 2. (a) Examples of EMG needles. A, single-fiber needle with one recording surface; B, single fiber needle with multiple recording surfaces; C, concentric needle; D–F, dual electrodes; G, monopolar needle (insulated, only tip exposed); H, macro-EMG electrode. (b) Macro-EMG detection and macro-EMG electrodes [from Jabre in Desmedt (12)].

research will lead to a noninvasive estimation of the percentage of Type I and Type II fibers thereby reducing the need for muscle biopsies (3–5).

Myoelectric manifestations of muscle fatigue are also observable in intermittent isometric contractions, isokinetic contractions, and, in general, in dynamic contractions. Particularly important fields of interest concern respiratory muscle fatigue and back muscle fatigue in occupational medicine (6).

Gait Analysis and Muscle Activation Intervals. During movements, such as gait, sport activities, or rehabilitation exercises, it is important to detect the time and the level of individual muscle activations. Surface EMG is the appropriate tool for this purpose. Crosstalk and relative movement between muscle and electrodes still represent important confounding factors (7,8).

Control of Myoelectric Prosthesis. The motors of artificial limbs (mostly hands, wrists, and elbows) may be controlled by surface EMG signals detected from muscles above the level of amputation. Many systems of this kind are commercially available (9).

Biofeedback. Providing a patient with real-time information about the level of activity of a particular muscle (or muscle group) helps him/her in learning strategies to increase the voluntary control or decrease the involuntary activity of the muscle and recover whatever degree of voluntary control is possible after a lesion (10).

Occupational Medicine and Ergonomics. EMG is used in ergonomic studies to evaluate how workplace factors such as tasks, posture, tool design, layout, and so on, influence the activity of a set of muscles (11).

FINE WIRE AND NEEDLE EMG; DECOMPOSITION INTO THE CONSTITUENT MUAP TRAINS

The EMG signal may be detected invasively with fine wires or needle electrodes, or noninvasively with surface electrodes. Fine wire electrodes are made of a spiral or multitread insulated stainless steel wire, with diameter 25 μm or 50 μm, with a bared hook-shaped terminal portion about 1 to 2 mm long. The wire is positioned inside the muscle by a hypodermic needle which is then withdrawn leaving the wire in position. This technique is applied for kinesiological studies and gait analysis. Technical details about fine wire electrodes can be found in Ref. (10).

Concentric (coaxial) needle electrodes are more selective than wires and allow the detection of the interfering contributions of up to 10 to 15 MUs. The separation of the constituent MUAP trains provides information on the firing rate of the individual MUs and on the change of this rate during increasing or decreasing contraction level. This task becomes progressively more difficult as the contraction level increases and the resolution of partially overlapping MUAP (superpositions) becomes more important. At the present state of the art it is possible to separate 10 to 12 MUAP trains during voluntary contractions of level up to the maximum. Figure 3 is a diagram of the system which has been provided by Basmajan and De Luca (10) and used by Guiheneuc, Haas and Meyer, McGill and Dorfman, Jabre, Kamen, and De Luca, whose work is collected in Ref. 12. The algorithms used for decompo-

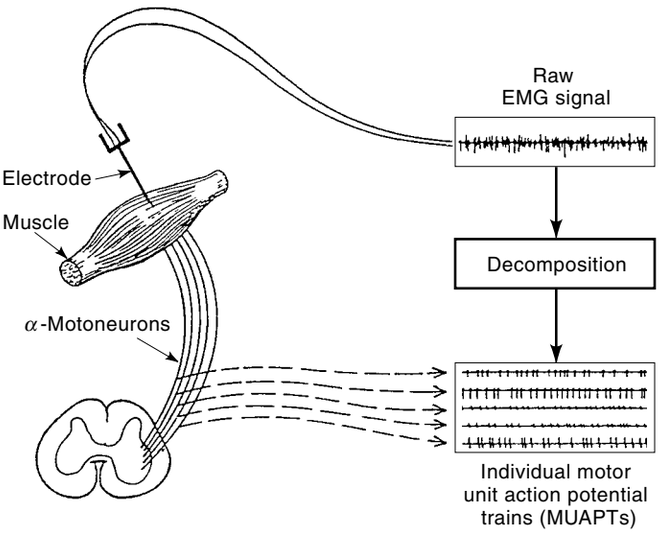


Figure 3. A schematic representation of the decomposition of the needle EMG signal into its constituent motor unit action potential trains [from Basmajan and De Luca (10)].

sition are based on (a) MUAP shape information and (b) MUAP firing statistics. An interesting observation made possible by precision decomposition is that the firing rates of different motor units often fluctuate together as if they were entrained by *a common drive* mechanism. This phenomenon was first studied in detail by Basmajan and De Luca (10) and was reported, among others, by Kamen and De Luca in Ref. 12.

Special needle electrodes (Fig. 2) allow the detection of single-fiber extracellular potentials (single-fiber EMG). *Macro EMG* is a technique that uses single-fiber firing information to trigger the acquisition of the signal detected between the needle cannula and a skin reference electrode. By averaging the signal detected between the cannula and the reference, using the single-fiber signal as a trigger (the technique is similar to that used for EEG evoked potentials), the contribution of the MU to which the single fiber belongs can be separated from signals of other MUs. By slow withdrawal of the Macro-EMG needle and search for stable single-fiber signals, one can scan a large portion of the muscle and study many MUs. This technique is called *scanning Macro EMG* (described by Jabre in Ref. 12).

A technique that has been extensively used to provide a quantitative evaluation of needle (as well as surface) EMG is the turn and amplitude (T&A) analysis. The term *turn* or *count* is defined as the occurrence of a peak separated by the preceding and following ones by at least a ΔV (usually 100 μV) and at least a Δt (usually 0.3 ms). The distribution, mean, and variance of the interturn amplitude and time intervals provide indices of signal complexity that may be related to pathological situations (as reported by Gilai in Ref. 12). The frequency of crossings of a 100 μV band centered on zero (zero crossings) is also used in clinical practice. This frequency is related to the second-order moment of the power spectral density of the EMG signal. Other descriptions of "complexity" are based on chaos and fractal approaches.

SURFACE EMG DETECTION, SPATIAL FILTERS, AND LINEAR ARRAYS

Detection of surface EMG is performed with small bar (1 mm diameter, 5 to 10 mm long, 5 to 10 mm apart) or disk electrodes (3 to 10 mm diameter). Detection is said to be monopolar when the voltage is measured between one point above the muscle and one reference, electrically unrelated, location. In this case the detection volume is large, and thus crosstalk and power line interference may be serious problems. This configuration is the most sensitive to nontraveling potentials generated at the innervation and termination zones (far-field potentials). Detection is said to be bipolar (or single differential) when a differential amplifier is used to detect signals present between two points on the same muscle, usually in the direction of the fibers. This system, which samples the voltage in two spatial locations and computes their difference, is the simplest form of spatial filter. As shown in Fig. 4(a), neither a common mode voltage (spatial dc component) nor any sinusoidal distribution of potential in space with half wavelength $\lambda/2 = e/2n$, for any integer n, will be detected. On the other hand, sinusoidal distributions with $\lambda/2 = e/(2n + 1)$ will generate differential signals with amplitude equal to the peak-to-peak amplitude of the monopolar distribution. In general a spatial potential distribution will have many sinusoidal components (spatial Fourier series or transform) for which the detection system will present different sensitivities (hence the name of spatial filter). If $e \ll \lambda_{\min}$ the single differential system approaches the one-dimensional spatial differentiation. This detection modality is the most appropriate to outline the innervation zone [see Fig. 5(a)]. Another commonly used detection method is the double differential filter depicted in Fig. 4(b) whose dual version is often used for muscle fiber conduction velocity estimation (13) because it is the least sensitive to nontraveling signal components [see Figs. 5(a) and 14]. Two-dimensional filters can be used as well to improve selectivity. The two-dimensional double differentiator (Laplacian) is depicted in Fig. 4(c). More sophisticated detection techniques are being developed for high-resolution EMG (see also Fig. 10) (14).

Linear surface electrode arrays provide useful geometric information about individual MUs. Figure 5(a) shows an example of monopolar, single differential and double differential detection of surface EMG with a linear array. Figure 5(b) depicts an example of single differential recording showing three MUs with different features. It can be observed that the technique for recognition and classification of motor units is in this case very different from the one used with needle detection. While morphological information about the MUAP is lost because of tissue filtering, additional information about innervation zone location, fiber length, and conduction velocity is gained from the array and may be used for recognition, classification, and clustering.

The surface of the detection electrodes affects the contact noise (the smaller the electrode the higher the noise), and has a smoothing effect on the signal because of the averaging of the potential underneath the contact area (the larger the electrode the greater the smoothing effect).

MYOELECTRIC MANIFESTATIONS OF MUSCLE FATIGUE DURING VOLUNTARY AND ELECTRICALLY ELICITED ISOMETRIC CONTRACTIONS

Voluntary and electrically elicited contractions provide two ways of studying the same system. Figures 6(a) and 6(b) show the model of generation of EMG during these two conditions. In the first case the detected signal is stochastic, while in the second it is deterministic because the contributions of the active motor units are synchronized. It is well known that during a sustained contraction the surface myoelectric signal becomes progressively "slower," and this slowing reflects physiological changes of the muscle fiber membranes. During electrically elicited contractions, this "slowing" appears to be a combination of scaling (stretching in time and in amplitude) and change of shape of the M-wave. During voluntary contractions, the "slowing" is more difficult to quantify since the signal is random. A quantitative evaluation of this "slowing" during stimulation may be obtained by "stretching" the initial M-wave until it matches (in the mean square sense) the subsequent and progressively wider ones. The scaling coefficient would indicate how "slowing" evolves in time. This approach is not suitable for voluntary signals since they never repeat and there is no reference signal to "stretch." It is therefore preferred to apply the "stretching and matching" procedure in the frequency domain to the power spectral density of the signal, considering that, for any signal, scaling in time by a

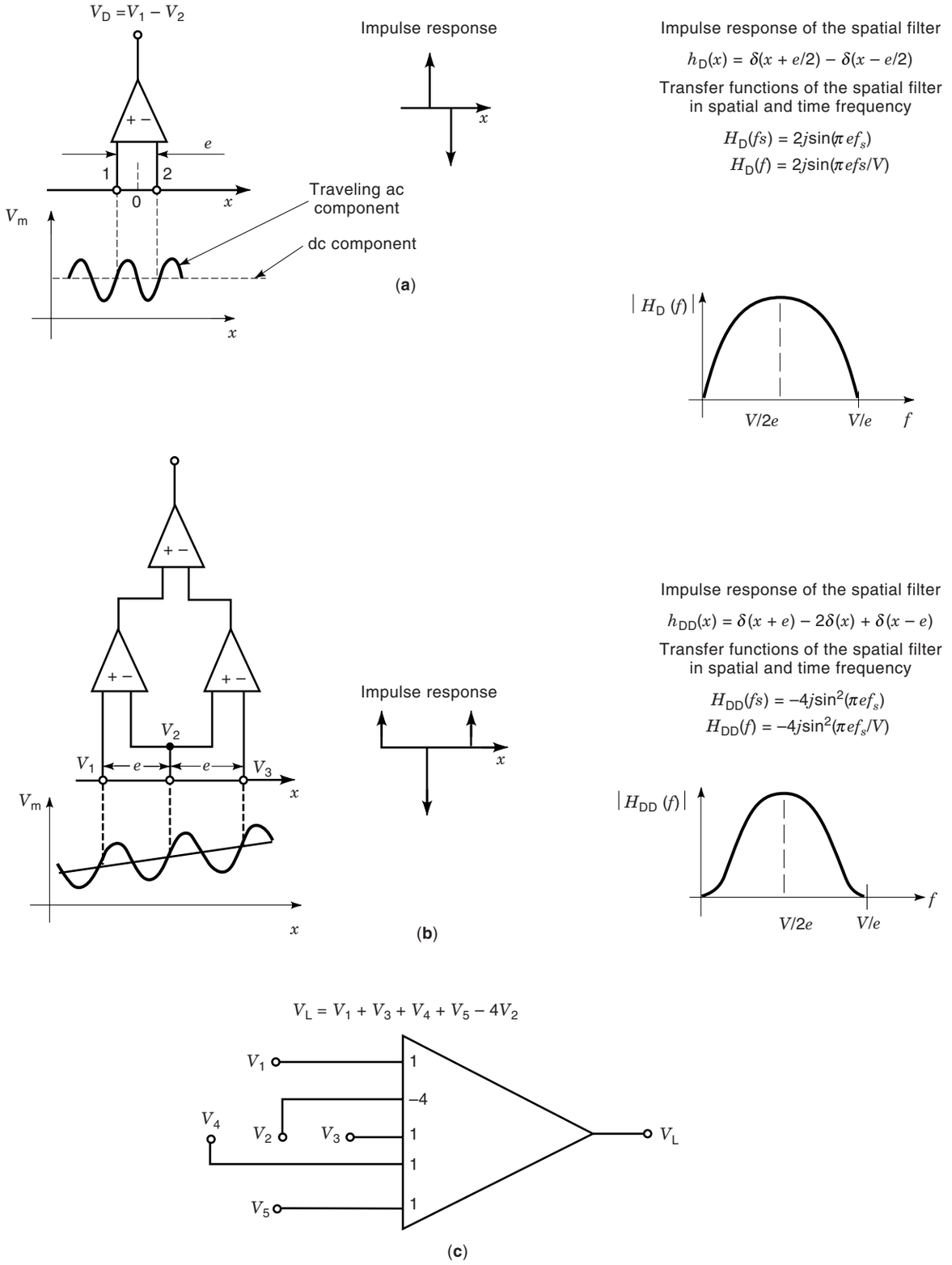


Figure 4. Detection techniques and spatial filtering effects. v = conduction velocity, V_m = monopolar voltage. (a) Single differential (or bipolar) detection. Impulse response and transfer function of the spatial filter. (b) Double differential detection. Impulse response and transfer function of the spatial filter. (c) A Laplacian spatial filter performing a discrete two-dimensional differentiation.

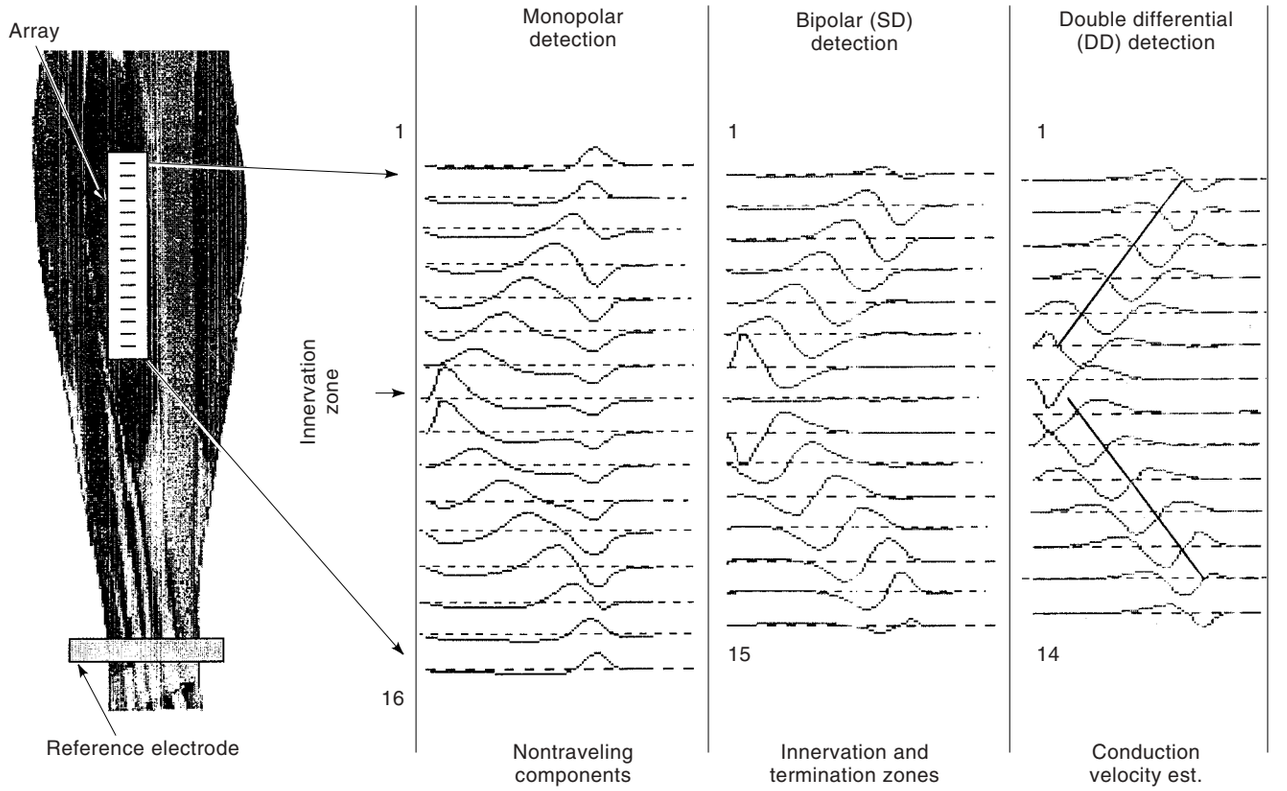


Figure 5. (a) Linear array detection of a single motor unit action potential. A nontraveling potential is seen in the monopolar detection and is due to the extinction of the depolarized zones at the tendon endings. Innervation and termination zones can be clearly seen in the single differential recording. Conduction velocity may be well estimated using the double differential signals. Signals are simulated using the model depicted in Fig. 14. (b) Example of array detection of three motor units, with different properties, from the biceps brachii of a healthy subject. Interelectrode distance is 5 mm. Straight lines have been added to outline the bi-directional propagation and the different innervation zones [from Merletti and Lo Conte (15)].

factor k implies a scaling in frequency by a factor $1/k$. This approach in the frequency domain is applicable to both situations and is widely used. Its operation is described in the following.

Consider the experimental EMG signals $x_1(t)$ and $x_2(t) = x_1(kt)$, taken during time epochs 1 and 2 (e.g., two 0.5 s epochs) during a sustained contraction, with power spectral densities $P_1(f) = |X_1(f)|^2$, and $P_2(f) = P_1(f/k)/k^2$. The mean frequency (MNF, also called centroid or first moment) and median frequency (MDF) of a general $P(f)$ are defined as

$$f_{\text{mean}} = \int_0^\infty fP(f)\,df \Big/ \int_0^\infty P(f)\,df$$

and

$$\int_0^{f_{\text{med}}} P(f)\,df = \int_{f_{\text{med}}}^\infty P(f)\,df = 0.5\int_0^\infty P(f)\,df \tag{1}$$

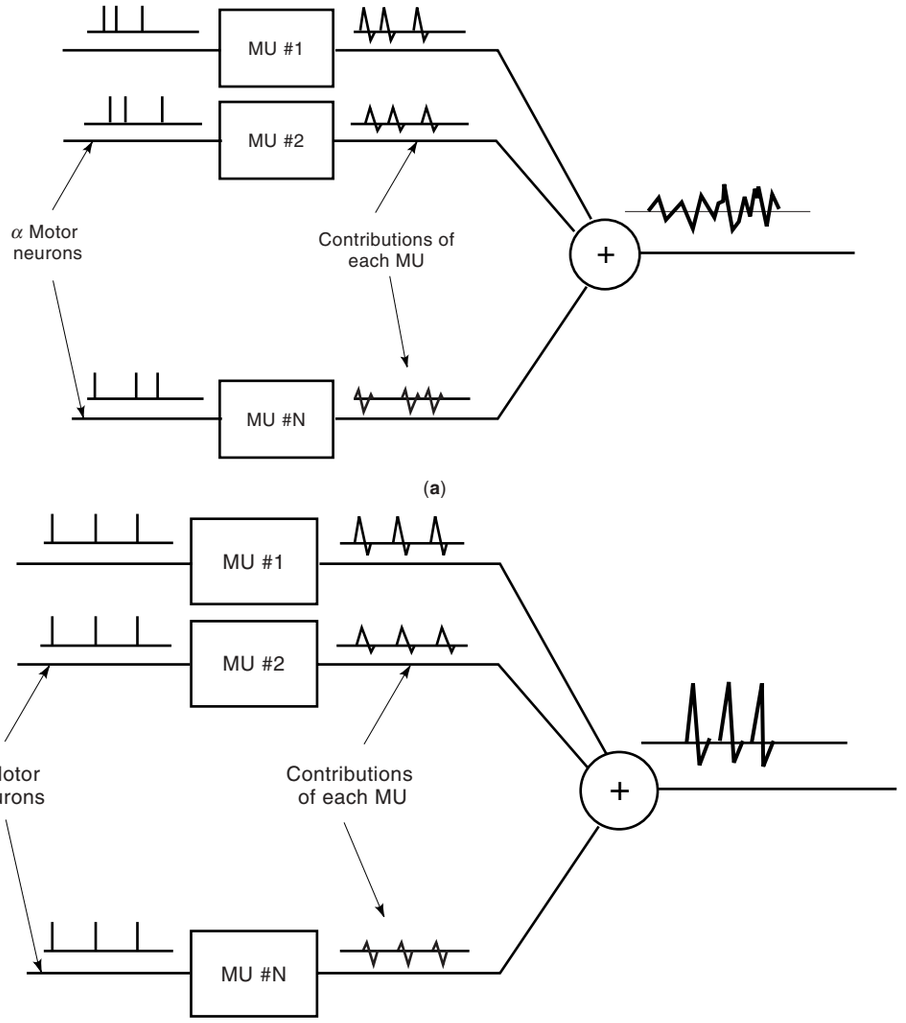

MU #1
MU #2
MU #N
α Motor neurons
Contributions of each MU
+
(a)
MU #1
MU #2
MU #N
α Motor neurons
Contributions of each MU
+
(b)
Initial values: MNF = 131 Hz
RMS = 0.342 mV CV = 5.49 m/s
Torque = 60% MVC
RMS
Torque
MNF
CV
Percent of initial value
Time (s)
Fatigue plot (MNF, RMS, CV, Torque) at 60% MVC
EMG signal
EMG PSD
MNF = 129 Hz
MNF = 100 Hz
MNF = 81 Hz
MNF = 68 Hz
Time (ms)
Frequency (Hz)
(c)

Figure 6

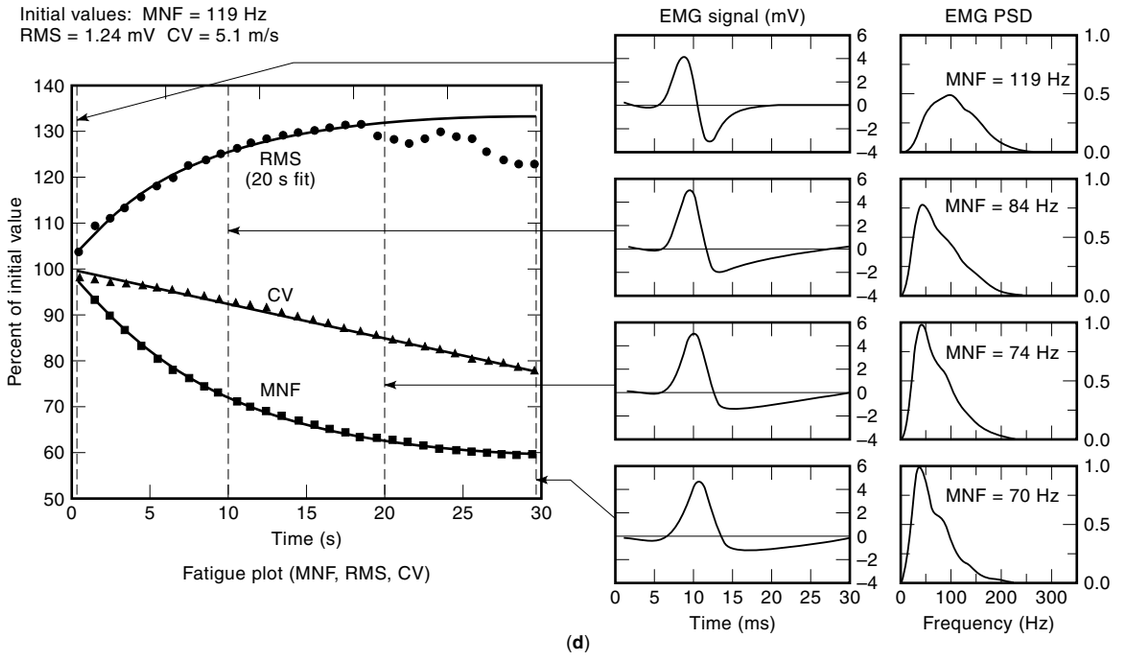


Figure 6 (*Continued*) (a) Schematic diagram of generation of voluntary EMG. (b) Schematic diagram of generation of electrically elicited EMG. (c) Experimental data from a voluntary contraction of a tibialis anterior muscle. All variables are normalized to their initial value to obtain the fatigue plot. Notice that voluntary torque could be maintained at 60% MVC (maximal voluntary contraction) for 60 s; but myoelectric variables started to change from the beginning of the contraction, showing myoelectric manifestations of muscle fatigue. EMG signal detected bipolarly with 10 mm interelectrode distance. PSD, power spectral density function; RMS, root mean square value; MNF, mean frequency; CV, conduction velocity [from Merletti and Lo Conte (11)]. (d) Experimental data from an electrically elicited contraction of a vastus medialis muscle. Notice the change of shape of the M-wave. Detection as in c; f = 30 pulses per second [from Merletti and Lo Conte (15)].

It can be shown that $f_{\text{mean2}} = kf_{\text{mean1}}$ and $f_{\text{med2}} = kf_{\text{med1}}$. In general the two signals (and the relative spectra) will not be exactly scaled and the ratios $f_{\text{mean2}}/f_{\text{mean1}}$ and $f_{\text{med2}}/f_{\text{med1}}$ will not be identical but can provide an estimate of k and quantify the scaling phenomenon. If we define A as the average rectified value (ARV) and R as the root mean square value (RMS), then it is $A_2 = A_1/k$ and $R_2 = R_1/\sqrt{k}$. The normalized plots of MNF, MDF, ARV, RMS, and CV (see next section for a discussion of CV estimation) versus time describe signal changes and are often referred to as the *fatigue plot* (15).

Figures 6(c) and 6(d) show an example of fatigue plots and signals in both experimental situations. It has been demonstrated from animal experiments that the rate of decay of MNF or MDF in each muscle—that is, the estimated scaling factor k—is related to the percentage of Type I and Type II fibers in the muscle (5). This finding suggests the possibility of noninvasive fiber type estimation and, if confirmed by human biopsies, is expected to be very relevant in future research concerning rehabilitation and sport medicine. More advanced approaches are being developed to separate the contribution of scaling from that of spectral shape change and to relate them to different underlying physiological phenomena.

Applications concern rehabilitation, sports and occupational medicine. An important clinical application of myoelectric manifestations of muscle fatigue concerns the analysis of back muscle impairment for the investigation of back problems and low back pain (6,16). Issue 4 of volume 34 of the *Journal of Rehabilitation Research and Development* (1997) is devoted to this topic. In particular, the works of Roy et al. (17) and Oddson et al. (18) focus on the classification of muscle impairments and on the development of clinical protocols.

The spectral approach requires the signal to be "quasi-stationary," that is, its statistical properties must not change during each time epoch. This requirement is not satisfied during dynamic contractions when the EMG is often generated in short bursts. More sophisticated methods, based on "time-frequency representations" and "wavelet expansions," are being investigated for the quantification of myoelectric manifestations of muscle fatigue in dynamic conditions.

MEASUREMENT OF MUSCLE FIBER CONDUCTION VELOCITY

The velocity at which a muscle fiber conducts an action potential along its length is an indication of its functional state. Thus the measurement of conduction velocity (CV) is used to study muscles in both clinical and research applications. The measurements can be made with voluntary or evoked potentials and with invasive or noninvasive methods. The range of values for CV in muscle is 3 to 6 m/s, with an average value near 4 m/s (19–23).

As in the case of any propagating signal, the conduction velocity value, v, is typically determined (see Fig. 7) from the measurement of propagation time delay, Δ, over some known distance, d; that is, $v = d/\Delta$. The time delay can be measured from observation of the signals $S_1(t)$ and $S_2(t)$, or some function of the signals, at two electrode sites spaced a distance d along the axis of the fiber, where $S_2(t) = S_1(t - \Delta)$. This latter condition can be difficult to achieve in practical EMG work because of the physical dimension of the electrodes and of possible misalignment between fibers and electrodes in either the vertical or horizontal planes. These issues result in measurement errors.

Voluntary EMG

The CVs of single muscle fibers are usually measured with two intramuscular needle electrodes (19,20), in which case the delay is measured from the time displacement of identical points on the two waveforms. In the event that two or more fibers are detected by the electrodes, they can be individually identified, using decomposition techniques, and their respective CVs measured. In this manner and with different electrode positions, a measure of the fiber CV distribution can be obtained.

The CV of a single motor unit must be defined because the motor unit action potential (MUAP) is the spatial and temporal sum of signals from the constituent fibers, each of which can have a slightly different CV. With $M_1(t)$ and $M_2(t)$ being the MUAPs seen at the two electrodes, we have

$$M_1(t) = \sum_{i=1}^{N} S_i(t) \quad \text{and} \quad M_2(t) = \sum_{i=1}^{N} S_i'(t - \Delta_i) \qquad (2)$$

where $\Delta_i = d/v_i$, N is the number of fibers in the unit, and $S_i(t)$ and $S_i'(t)$ are the ith fiber's signals at electrodes 1 and 2, respectively. Now it is clear that $M_2(t) = M_1(t - \Delta)$ only if $\Delta_i = \Delta$, and $S_i'(t) = S_i(t)$ for all i; otherwise $M_2(t)$ is different from $M_1(t)$ and delay is not well-defined. Indeed there is a range of delays, and if we proceed to measure delay from two similar points at the onsets of $M_1(t)$ and $M_2(t)$, we will have the delay corresponding approximately to maximum velocity and, from the tails, approximately the minimum velocity. If some midpoints, say the signal peaks, are chosen for the "delay" measurement, then some "average" velocity is obtained. However, the precise nature of this "average" is impossible to define without information regarding the probability distributions for the fiber delays and waveforms.

In the case of EMG signals involving more than a few motor units, particularly when obtained with surface electrodes, the possibility of determining conduction delay and hence velocity from instantaneous values as above is problematic. This is because variables such as fiber depths, end-plate positions, and so on, which affect the spatial and temporal sum output, cause the signals from the two electrodes to be significantly different. It is common in such cases to measure CV from the cross-correlation function (21) or from a linear system impulse response identification approach (22). Both of these approaches give what amounts to a weighted-average CV where the average is across fibers and the weighting depends primarily on the contribution of a fiber to the total EMG power. The conduction delay is obtained from the cross-correlation function by observation of the time shift of the function peak from zero lag (see Fig. 8). This approach has the attractive feature that the cross-correlation between signals of different motor units goes to zero (assuming uncorrelated unit innerva-

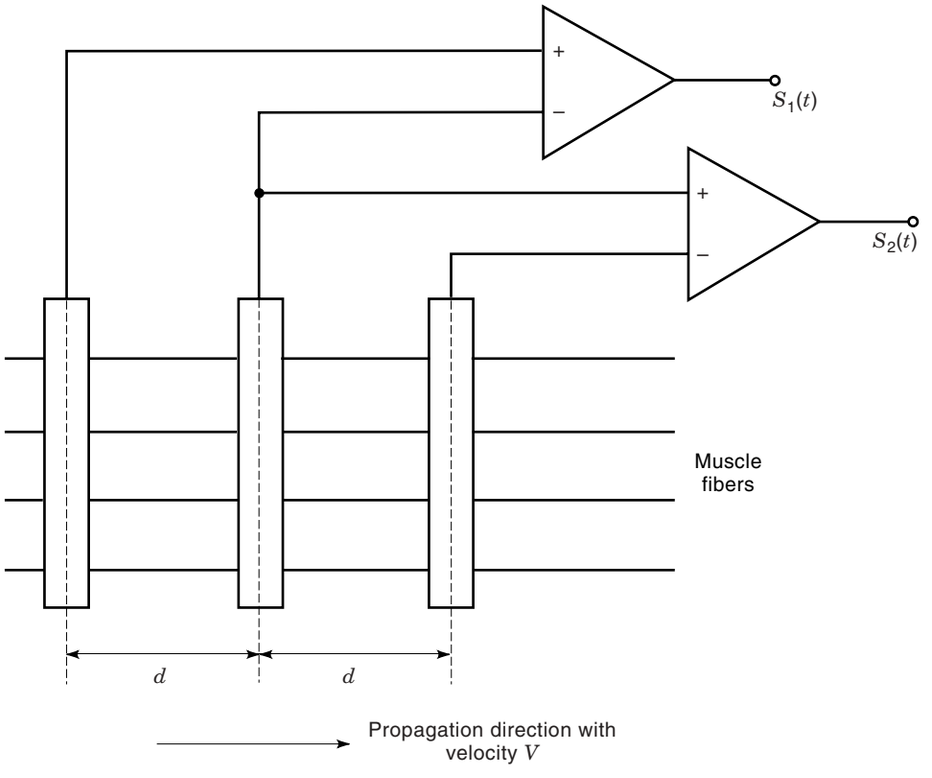


Figure 7. A three-bar electrode configuration with interelectrode spacing d for the measurement of muscle fiber conduction velocity.

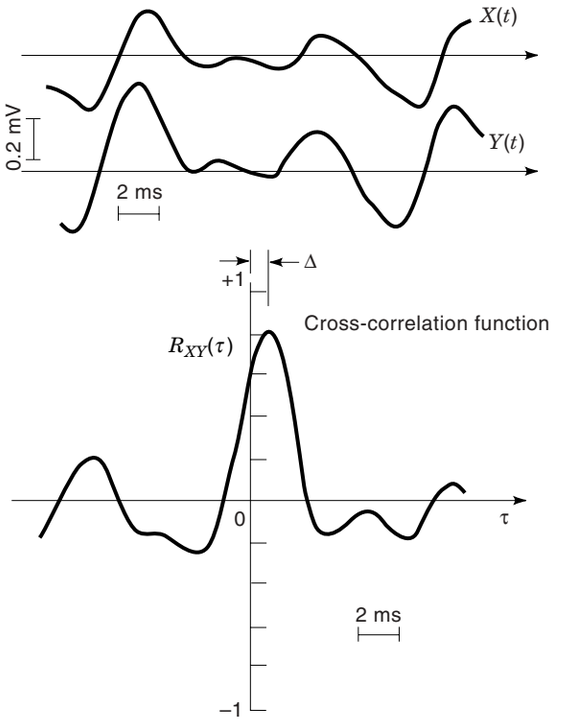


Figure 8. Cross-correlation function between two EMG signal channels recorded from human biceps showing propagation delay as a shift in peak of the function [from Li and Sakamoto (26)]. Interelectrode distance: 5 mm.

tion processes), thus eliminating erroneous delay measured from firings of different units. In addition, the peak value of the cross-correlation function, normalized with respect to the signal powers, provides the cross-correlation coefficient, which is an index of similarity between the signals and quality of the estimate of CV.

A confounding factor which is of particular concern with the cross-correlation and impulse response identification approaches is the presence of coherent nondelayed EMG components in the two electrode signals. These nondelayed components appear due to, among other things, the termination of the fibers at the tendon [see Fig. 5(a)] (13). This effect, which is to give a positive bias to the CV estimate, can be greatly reduced by using the double differential electrode configuration [see Fig. 4(b) and Fig. 5(a)].

Other techniques which have been developed but which are not widely used include the spectrum dip, zero-crossing, and polarity correlation. For a review of these various approaches and their application, see the work of Arendt-Nielsen and Zwarts (23).

Evoked EMG

The CV can also be measured, invasively or noninvasively, from the EMGs or M-waves acquired at two sites in response to an electrical stimulation of the fibers. In the case of invasive needle measurements, direct muscle fiber stimulation may be obtained near a tendon and end-plate variation across the fibers is not a problem (20). With surface stimulation, axonal branches are excited, many units can be involved and end-plate variation will introduce a bias in the estimate. In both invasive and noninvasive evoked measurements the signal quality is higher than for the voluntary case as the random innervation of the central nervous system is replaced with a deterministic stimulus (see Fig. 6). However, the repeatability is not necessarily better.

CV Distribution Estimation

The muscle fiber CVs are distributed over a range, and the measurement techniques described above give only a number related to that distribution. Noninvasive techniques for CV distribution estimation based on surface EMG give significantly more information about the muscle state, and they would be useful for both clinical and research purposes.

Two recent approaches are based on measurements of the cross and auto power spectra ratio of the EMGs from the two sites (22,24). From Eq. (2) with $S_i(t)$ defined as the ith motor unit train and assuming uncorrelated units with identical firing statistics, the ratio, $\Phi(f)$, of the cross to auto power spectra is given by

$$\Phi(f) = \sum_{i=1}^{N} P_{ii}(f) \exp(-j2\pi f \Delta_i) \Big/ \sum_{i=1}^{N} P_{ii}(f) \tag{3}$$

where $P_{ii}(f)$ is the autospectra for the ith unit, and N is the number of units. Note that only autospectra terms appear in Eq. (3) because of the assumption of uncorrelated units, in which case all the cross-spectra terms are zero. Now assuming identical MUAPs (a strong limitation) across the units, the $P_{ii}(f)$ are identical and Eq. (3) becomes

$$\Phi(f) = N^{-1} \sum_{i=1}^{N} \exp(-j2\pi f \Delta_i) \tag{4}$$

For large N, Eq. (4) is approximately equivalent to the statistical expectation operator over Δi, in which

$$\Phi(f) \cong \int_0^\infty f_\Delta(\Delta) \exp(-j2\pi f \Delta)\, d\Delta = F_\Delta(f) \tag{5}$$

where $f_\Delta(\Delta)$ and $F_\Delta(f)$ are the probability density function for Δ and its Fourier transform.

Thus the inverse Fourier transform of the measured $\Phi(f)$ is an estimate of the probability density function (PDF) for the fiber conduction delays.

Figure 9 shows a measurement of the PDF of CV for the biceps brachii muscle with the impulse response method proposed by Hunter et al. (22). Although still in the development stage and with considerable improvement required, the techniques show promise and are worthy of further research effort.

The latter two techniques obtain the CV distribution from surface EMG, with many units contributing to an interference signal. An alternative approach is to separate the contributing unit signals and obtain the CV for each component unit and thus determine the distribution. This approach is based on the use of spatial filters constructed from two-dimensional electrode arrays which can be designed to spatially focus on specific regions of muscle and hence separate the component units and their velocities (14,25). Figure 10 gives an example of the detection of motor units from surface EMG obtained

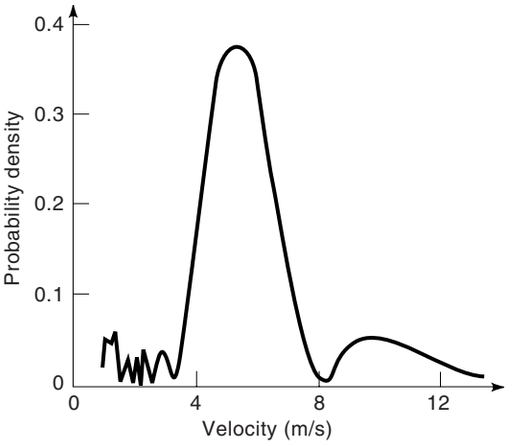


Figure 9. Results from the measurement of conduction velocity probability density function for biceps using the impulse response function method [from Hunter et al. (22)].

with an electrode array. This approach is very promising and deserves considerable attention.

Sources of Error in CV Estimation

The most obvious source of error in CV estimation is misalignment of the electrode pair principal axis with the muscle fibers. Misalignment produces a bias error which depends on (a) the degree of misalignment and (b) the electrical properties of the medium. A second important source of error is electrode pair placement with respect to the muscle innervation and termination zones. If the electrode pair is positioned so that it is near the innervation zone, a positive bias in the CV estimation will result. Electrode pairs too close to the tendon can also introduce nondelayed components in the EMGs, thus, again, giving a positive bias to the CV measurement. These errors can be reduced using different or multiple pairs of a linear electrode array placed along the muscle fiber and by use of the double differential electrode configuration (13). Figure 5(b) shows that electrodes located in between two innervation zones (e.g., electrode pairs 5, 6, 7, 8) detect potentials propagating in opposite directions. They are suitable for CV estimation only if individual motor unit action potentials are identified. Electrical noise will introduce additional errors in the determination of parameter values such as the peak position of the cross-correction function, corresponding points on the two waveform, etc. For a discussion of noise-induced errors, see Rababy et al. (27).

CROSSTALK AND MUSCLE MOVEMENT ARTIFACTS

Crosstalk is the component of EMG signal that is detected above a specific muscle but is generated by another. This component may be a serious confounding factor in dynamic EMG when the time and intensity of activation of a muscle are of interest. One way to study it is to selectively stimulate a specific muscle and observe the signals present on the neighboring muscles (28,29). This technique, however, is appropriate for investigating the problem but not for solving it in a clinical setting. A clinically satisfactory solution is not yet

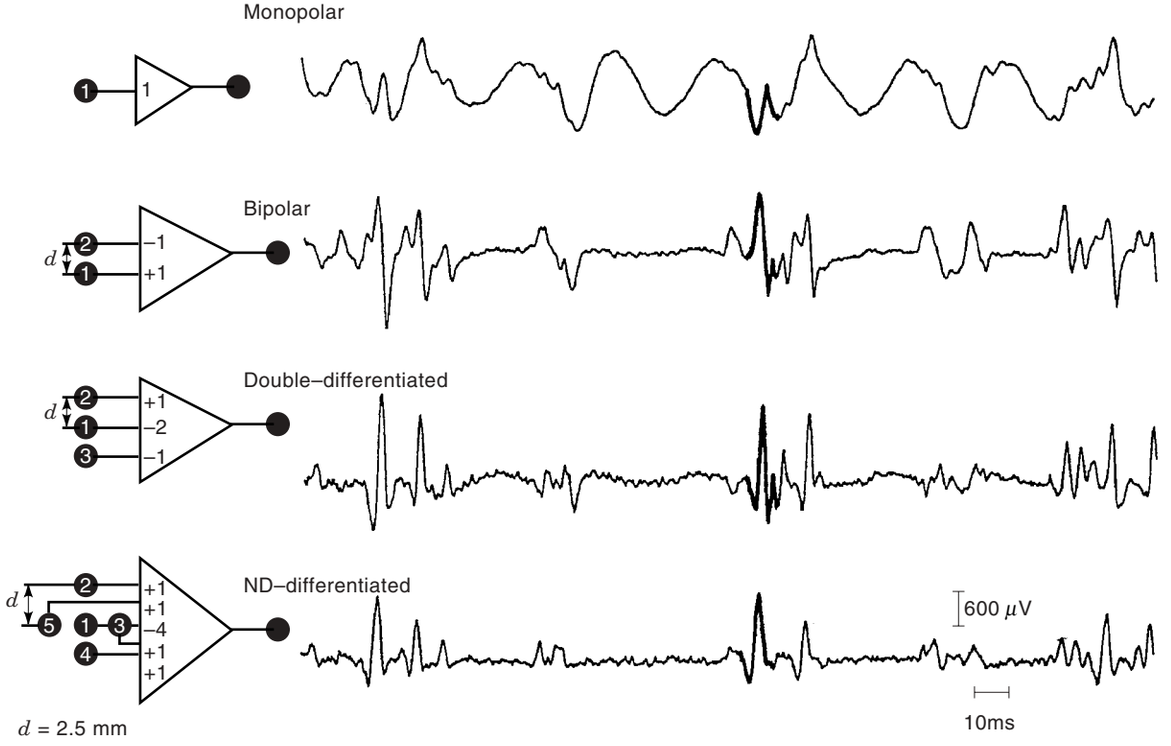


Figure 10. Surface EMG acquired with different electrode configurations showing single motor unit signals [from Rau and Disselhorst-Klug (14)].

available. The crosstalk phenomenon is strictly related to the biophysics of volume conduction through a layered medium (anisotropic muscle, isotropic subcutaneous fat, isotropic skin). Particular situations (e.g., a rather conducting skin on top of an insulating layer of fat) may strongly enhance it (30).

During dynamic contractions the muscle moves under the skin, and the geometry of the electrode-muscle system changes. In particular, a sliding of the innervation zone near or below a bipolar electrode set may cause a marked change of signal amplitude that might be mistakenly interpreted as a change of muscle activation. This possibility may be seen in Fig. 5(a) and Fig. 5(b) for a single motor unit but may be easily generalized for many motor units innervated in the same location. For example, the innervation zone of the first two motor units in Fig. 5(b) is between electrode pairs 8 and 9. A sliding of 5 to 10 mm would bring the zone under electrode pairs 7 or 8 with marked decrement of the EMG amplitude detected by such electrodes and an increment of the signal detected by pair 9. This sliding may happen cyclically during a repetitive movement, and its effect may be misinterpreted as a change of muscle activation level.

Other artifacts are due to a relative movement between electrodes and skin or to large changes of electrode contact impedance. Automatic detection and correction of these confounding factors is an engineering challenge. Signal filtering is usually not sufficient, and adaptive techniques are being investigated.

MOVEMENT AND GAIT ANALYSIS

During movements of the human body the muscles involved in moving the joints are activated by the brain according to specific patterns. In particular, the pattern of activation of back muscles during lifting or leg muscles during gait has great relevance in clinical evaluation (6,8,31,32). A simple model of dynamic EMG assumes the signals to be Gaussian zero-mean noise modulated by a function representing the intensity of activation. Such a function may be estimated by amplitude demodulation of the EMG, that is, by rectification and smoothing, a process often referred to as linear envelope detection. The choice of the smoothing filter is critical: on-line analog filtering with equivalent time constants ranging from 25 ms to 130 ms have been used as well as digital noncausal FIR filters with symmetric coefficients and zero phase shift, producing very different results. Indeed the analog filter's time constant or the impulse response length of the digital filter should automatically adapt to the local properties of the signal in order to track equally well fast and slow variations without introducing significant delays (32,33). Figure 11 shows an example of dynamic EMG recording from a group of muscles during normal gait. Signals are detected with bipolar surface electrodes. It is evident that the identification of the on/off timing of the muscles and of their intensity of activation is not an easy task. It should also be considered that many additional confounding factors, besides the level of muscle activation, affect the EMG amplitude. Among these are crosstalk, the thickness of the subcutaneous layers, the location of the electrodes, and the amount of muscle shortening and sliding under the electrodes. It is evident that these factors mask the relationship between level of muscle activation or contraction force on one hand and the EMG amplitude on the other. Cyclical activities (such as gait) allow averaging of repeating patterns and the attenuation of those factors that are not synchronized with the pattern (8).

The analysis of nonrepetitive movements is more complex. For example, it is known that improper shoulder–neck muscle load in the workplace is a major factor for developing musculoskeletal disorders. Surface EMG techniques have been used to evaluate muscle involvement during occupational work. Such evaluation, as well as gait analysis, requires some form of normalization and standardization. The problem is discussed in detail in the recent review by Mathiassen et al. (34).

EMG CONTROL FOR POWERED LIMB PROSTHESES

Motor information from the CNS is present in the electrical signals from nerves (ENG) and residual muscle fibers (EMG) of both traumatic and congenital amputees, and it can be acquired and used for the control of powered limb prostheses. A major challenge in this application is the extraction of the control information from the available EMG. The CNS can vary (a) the number of motor units and their respective firing rates and (b) the combination or pattern of activated muscles. These variables give the surface EMG certain characteristics (power, spectral content, etc.) and an EMG processor must, with appropriate algorithms, measure these characteristics and in turn decide which prosthesis function to select in order to satisfy the intent of the CNS.

The number of units and their firing rates, along with the pattern of muscle activity above the level of amputation, are reflected in the average rectified value (ARV) and the local waveform or spectral content, respectively, of the EMG. The type and characteristics of the EMG processor used for prosthesis control depend, in part, on whether EMG ARV, waveform, or both form the basis of control. A block diagram showing the relationship of the EMG control system to the normal system is given in Fig. 12. EMG prosthesis controllers can, from the point of view of their EMG processors, be classified as either multistate or pattern based. Extensive reviews of EMG control systems for powered limb prostheses are given in Refs. 35 and 36.

Multistate EMG Controllers

The multistate controller subdivides the EMG amplitude or ARV range into a number of levels or states and assigns a particular prosthesis function to each state—a form of amplitude modulation. To select a function the operator generates EMG with the appropriate ARV. The processor estimates this ARV and, on the basis of the estimate, decides which function to operate. The ARV estimator typically consists of a full-wave rectifier followed by a first-order low-pass filter. The ARV estimation error will, with a predictable probability, cause some decision errors in function operation. The decision error can be reduced by increasing the time constant of the filter, but only at the expense of prosthesis dynamic response.

Commercial systems are now available and for the most part the number of states is two or three. The two-state controller is used to switch on/off a given degree-of-freedom, and the three-state controller is used to select one of two directions of a given degree-of-freedom. In order to provide more functionality for the user (i.e., more prosthesis degree-of-free-

doms) it is necessary with current systems to either have parallel two- or three-state controllers (one for each degree-of-freedom) or have a single controller with as many states as required. Unfortunately, it has been found that multistate systems with more than three states have unacceptable error performance due to excessive demand put on the operator's ability to reliably generate the appropriate EMG, and hence are neither practical nor commercially available.

EMG Pattern Controllers

In order to increase the number of prosthesis functions without putting excessive demand on the operator, control strate-

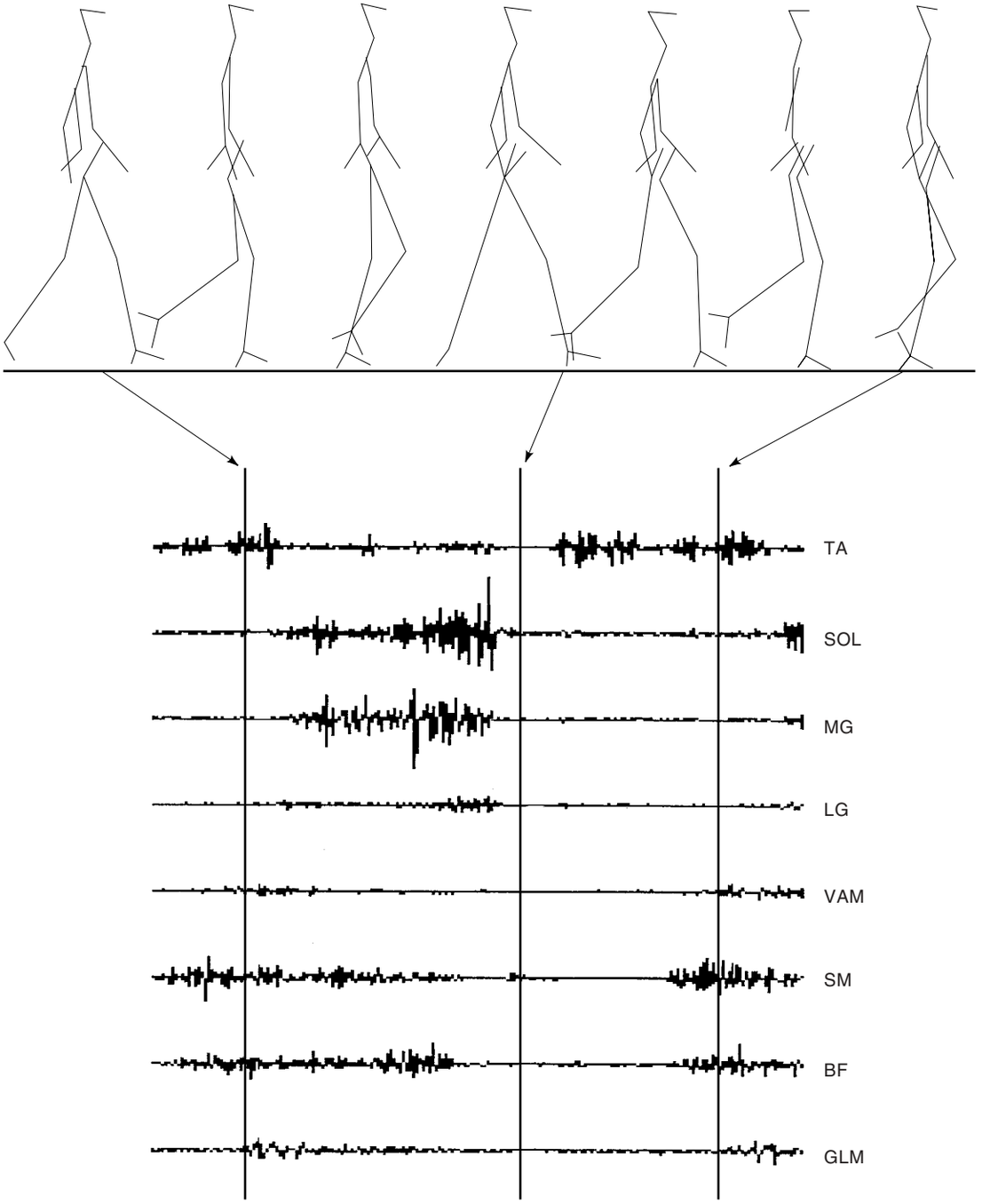


Figure 11. Example of surface EMG detected from a group of muscles during gait of a normal human subject. TA, tibialis anterior; SOL, soleus; MG, medial gastrocnemius; LG, lateral gastrocnemius; VAM, vastus medialis; SM, semitendinosus; BF, biceps femoris; GLM, gluteus maximus (courtesy of Dr. Carlo Frigo, Centro di Bioingegneria Politecnico di Milano and Fondazione Don Gnocchi).

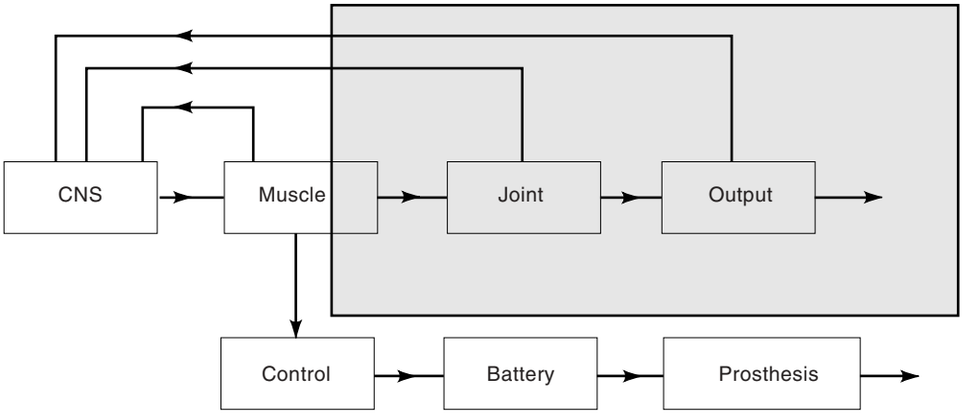


Figure 12. Block diagram showing relationship between normal and myoelectric control systems (shaded area is removed in amputation surgery) [from Parker and Scott (36)].

gies have been developed based on the EMG signals present in normally occurring activation patterns of agonist/antagonist group of muscles. The essence of this approach is to select from the EMG an appropriate feature set whose values are (a) repeatable for a given muscle group activity pattern and (b) sufficiently different across patterns to allow for reliable classification.

The early work in this direction used several EMG channels, and the feature set consisted of the binary 1 or 0 depending on whether or not a channel's EMG activity exceeded a threshold. The use of multiple EMG channels causes significant electronic hardware reliability problems and difficulties for the prosthetist in prosthesis fabrication. Thus the single EMG channel has become the goal and standard for pattern-based EMG multifunction controllers. That recognizable and repeatable EMG patterns can be obtained from a single channel is due to the differing contributions by individual agonist/antagonist muscles to the total channel EMG during different muscle activation patterns. Graupe et al. (37) were among the first to demonstrate this, and others have followed up to produce a new generation of EMG controllers. Not only is the single-channel system more reliable and easily fabricated, but it also has reduced size and cost. The reliability and size advantages were significant factors in the success of self-contained limb prostheses. Function selection performances of 80 to 90% have been obtained for five-function controllers.

Other recent developments have been in the direction of multifunction EMG controllers which allow simultaneous operation of several functions. The major challenge in this work is to obtain sufficient simultaneous and preferably independent EMG inputs which can be generated without excessive burden on the operator. To this end, artificial neural networks (ANN) have proven very successful in EMG pattern classification, and they are of particular significance in this application because of their trainability, adaptability, and robustness.

The EMG spectral components of a single-channel EMG can form a feature vector as input to an ANN, and the ANN can be trained under supervision to recognize members of a set of spectra corresponding to the functions of a multifunction prosthesis (38). Alternatively, a time-domain feature set can be used as the ANN input. Hudgins et al. (39) have demonstrated that the initial 300 ms of dynamic contraction EMGs contain deterministic components that are repeatable in time and which differ over contraction functions (see Fig. 13). Thus time samples from these deterministic components can form feature sets for an ANN trained to classify by function. A 30:8:4 perceptron ANN-based controller is used in this application and is currently implemented on a TMS320 DSP micro for clinical testing.

An approach to prosthesis control with significant promise is to estimate from EMGs the biomechanical variables of a joint model and to drive the mechanical prosthesis accordingly [see Wood et al. (40)]. Such an approach can incorporate stiffness control in which the stiffness (or compliance) of the prosthetic limb is made to match that of the limb model for a given client.

MODELING OF EMG SIGNALS; MODEL-BASED INTERPRETATION OF ARRAY SIGNALS

Many anatomical and physiological parameters of a muscle are not accessible and cannot be measured directly. However, they are accessible in a model simulating EMG signals and EMG variables and may be changed until the simulated observable EMG variables and parameters match the experimental ones. When the matching is obtained, it is likely that the parameters of the model have values similar to those that cannot be measured directly from the real system. This conclusion must always be taken with caution since (a) a model always implies approximations and simplifications that may affect the results and (b) there may be more than one set of model parameters that provide a good fit of the experimental data. Motor unit action potential models have been developed by many researchers among which are P. Rosenfalck (41) and N. Dimitrova (42). The model described in Fig. 14(a) is based on the work of Gootzen et al. (43) and has been used to investigate and explain some experimental findings. An application example is provided by Fig. 14(b), which shows 10 firings of the same MU of a healthy biceps brachii during a low-level voluntary contraction. The signals are detected bipolarly from a 16-contact linear array.

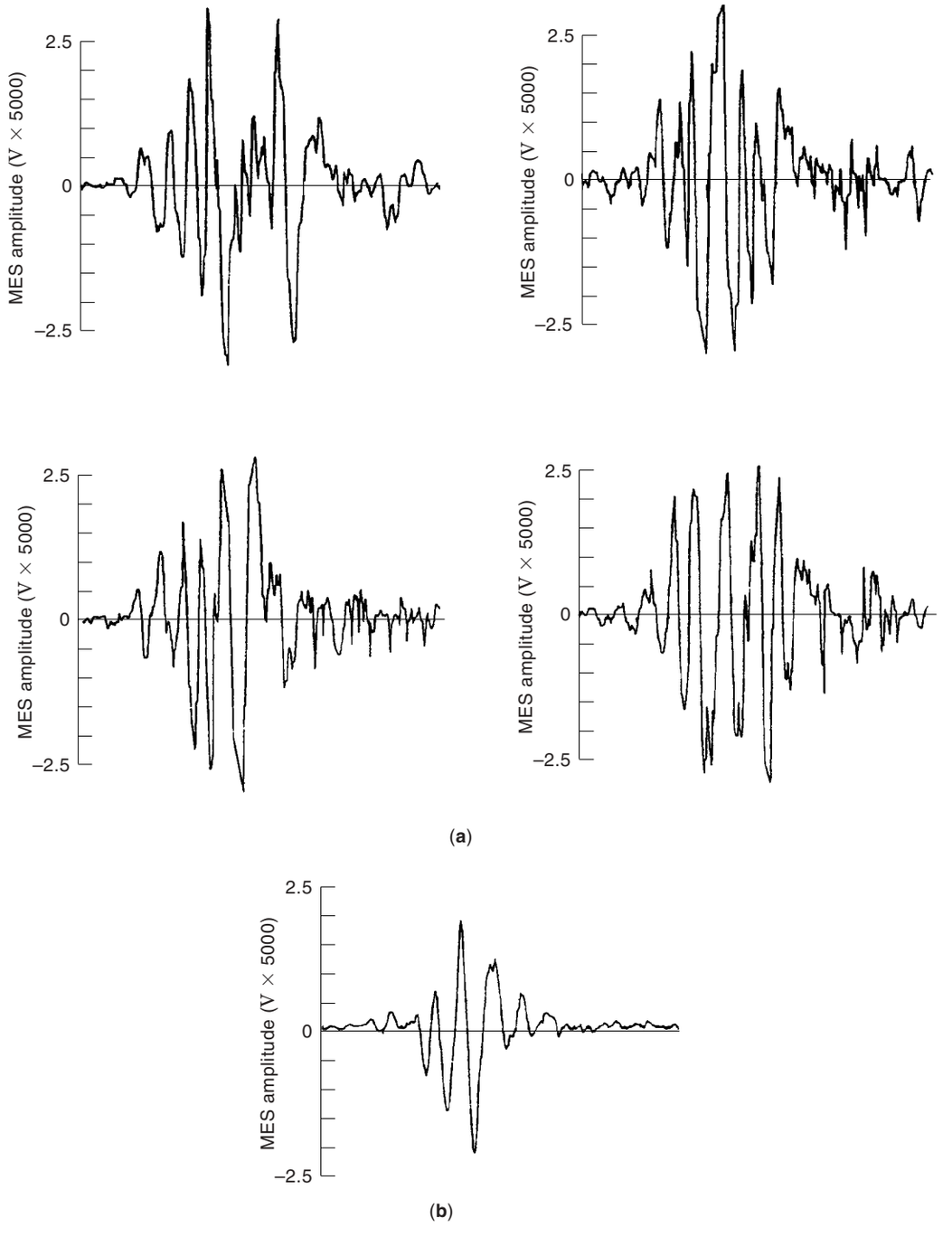
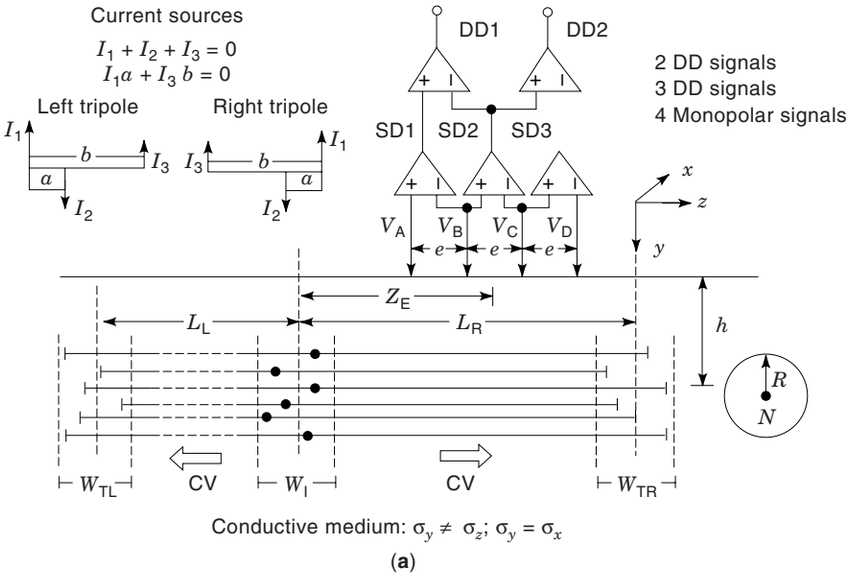
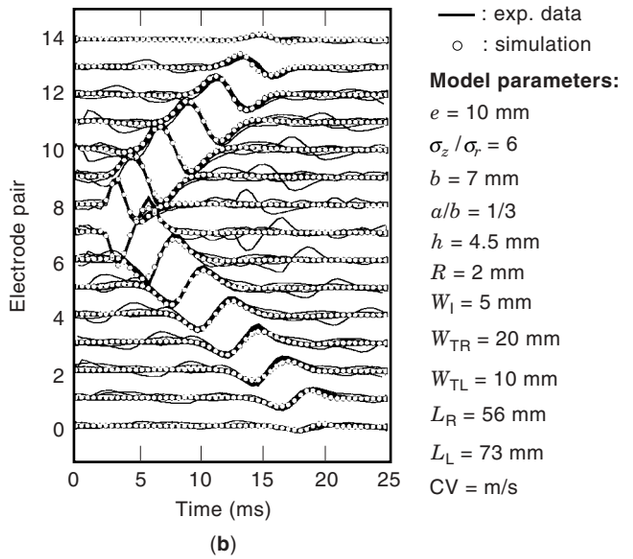


Figure 13. Initial 300 ms of EMG obtained from bipolar differential measurement with electrodes over biceps and triceps during elbow flexion. (a) Four 300 ms records and (b) the ensemble average of sixty 300 ms records demonstrating the deterministic component of the initial phase [from Hudgins et al. (35)].

The 10 firings are selected during a time interval of 1.5 s, are aligned and superimposed, and are similar enough to justify the assumption that they belong to the same MU. The results of the simulation (open circles) are superimposed and the indicated model parameters provide an estimate for anatomical features of the MU, conduction velocity, and anisotropy of the tissue. Future research might lead to the development of systems for the automatic identification of the most likely set of parameters for individual MUs and make them available to the neurologist for diagnostic evaluation.



(**a**)



(**b**)

Figure 14. (a) Model for the simulation of surface EMG signals and of their variables. Schematic structure of the model of a single motor unit. The motor unit has N fibers uniformly distributed in a cylinder of radius R at depth h. The axis of this cylinder may present an angle with respect to the skin plane and with respect to the z axis. The neuromuscular junctions are uniformly distributed in a region W_I, and the fiber–tendon terminations are uniformly distributed in two regions W_{TR} and W_{TL}. A right and a left current tripole originate from each neuromuscular junction and propagate to the fiber–tendon termination, where they become extinguished. The conduction velocity is the same in both directions and for all fibers of a motor unit but may be different in different motor units. Each of the voltages V_A, V_B, V_C, and V_D is the summation of the contributions of each tripole. (b) Example of simulation of 10 superimposed firings of a motor unit detected during a low-level contraction of a healthy biceps brachii muscle with a linear 16 contacts array. Pair 14 is proximal, pair 0 is distal.

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