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CHAPTER 3

Update on the decomposition and analysis of EMG signals

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INTRODUCTION

During the past decade, numerous efforts directed at developing methods for quantitatively analyzing needle EMG signals have been reported. Most efforts have been concerned with computerization of parameter measurements of the motor unit action potential waveform. They essentially provide a powerful and potentially objective means of performing scientific and clinical measurements. LeFever and De Luca (1978) originally reported a technique which employed communication theory concepts to decompose electromyographic (EMG) signals into their constituent motor unit action potential trains (MUAPTs). Details of the technique and computer algorithms have been described (LeFever and De Luca, 1982; Mambrito and De Luca, 1983, 1984). This computer-aided operator-interactive technique provided accurate measurement of the concurrently active motor units' discharge times and the ability to estimate their time-changing firing rates. The firing rates of motor units provide useful information about the neuromuscular system and should be helpful in the diagnosis of clinical disorders. Accurate motor unit discharge time information also allows for the extraction of motor unit morphological information via the trigger averaging of simultaneously acquired concentric needle or cannula detected signals.

The concepts of separating an EMG signal into its constituent MUAPTs is presented in Fig. 1. Development of the procedure has been focused by its two main goals: to provide a tool for researchers to efficiently study motor unit properties and behavior, and to assist clinicians in assessing and monitoring the state of a patient's neuromuscular system. Development has also been constrained by two major considerations: accuracy and convenience of use.

Overall system accuracy is most important for it provides the basis on which the results are judged and determines the practicality of their subsequent use. A philosophy of maintaining accuracy at a level of 98% has been adopted. Lower accuracy provides confusing and possibly deceptive information that may lead to inappropriate clinical diagnoses and scientific misstatements. All contemplated modifications had to comply with the accuracy requirement.

Convenience of use is essential for the technique to have any clinical feasibility and will determine the amount of use the technique receives as a tool. Convenience is determined by the amount of time involved in acquiring suitable EMG signal data and performing the decomposition. Modifications have been made to the contraction protocols and signal detection electrodes which increase the percentage of data collections containing stable EMG signals, thus reducing the time required to obtain suitable data. Alterations have been made to the data sampling and compression routines

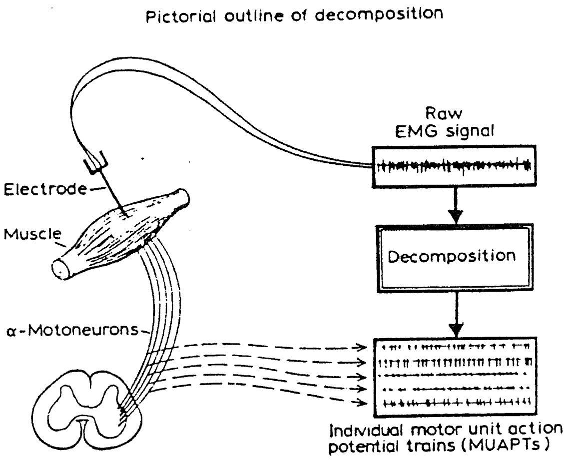

Fig. 1. A schematic representation of the decomposition of an EMG signal into its constituent motor unit action potential trains. (From De Luca et al., 1982)

which allow additional continuous data channels to be acquired so that additional information can be obtained. More efficient signal filtering algorithms have been implemented to precondition the signals for the decomposition algorithm. Attempts to increase the speed of the decomposition consisted of improving the algorithms' computational efficiency and introducing rudimentary concepts of artificial intelligence to reduce required operator interactions. In this chapter the decomposition procedure is first reviewed, then the modifications made to each facet of the procedure are outlined. This is followed by descriptions of the methods used to analyze the individual motor unit firing times resulting from an EMG signal decomposition and discussions of the importance of the information obtained.

DECOMPOSITION REVIEW

The accurate determination of individual motor unit activity and that of groups of concurrently active motor units, requires the measurement of the EMG activity associated with muscle contraction using selective multichannel indwelling electrode configurations. Suitably detected composite EMG signals can be analyzed and separated into their constituent MUAPTs by utilizing the EMG signal acquisition and decomposition technique reported by Mambrito and De Luca (1983, 1984). These reports described procedures by which three channels of EMG signals are detected using a specialized quadri-filar indwelling electrode configuration and a passband of 1 – 10 kHz. The three channels of information are used to represent the motor unit action potentials (MUAPs) arising from each motor unit active in the immediate area of the electrode. The detected EMG signals are initially recorded on FM tape, then digitized, compressed and placed in permanent digital storage. The digital EMG signals are then decomposed into their constituent MUAPTs.

Decomposition is performed by a computer-based operator-interactive algorithm. The algorithm scans the EMG signal and identifies MUAPs. Each MUAP is then classified as being created by a particular motor unit. This classification is based on a comparison of the MUAP's shape to those of the templates of candidate motor units and consideration of the probability of each motor unit firing at the time the MUAP was detected. The motor unit with the best combination of similar template shape and high firing probability is selected. Motor unit templates are representative MUAP shapes for each candidate motor unit. The selected motor unit's template and firing statistics are updated with each appropriate MUAP classification. The selected motor unit's current template is then subtracted from the EMG signal and scanning for the next MUAP begins. This approximate removal of each identified MUAP allows processing of the entire signal above the specified scan threshold. Superpositions of several MUAPs are resolved into their component motor unit templates by special routines. Operator interaction is sought to determine the composition of unknown waveshapes. The operator classifies a questioned shape as a superposition of specific existing motor unit templates or as a new motor unit template. The use of three channels of information for the representation of MUAP and motor unit template shapes is critical to the successful classification of candidate waveforms, for this provides sufficiently unique representations of an individual motoneuron's MUAP to allow the firing times of each different motor unit to be consistently and accurately discriminated. A simplified flow chart of the EMG signal decomposition algorithm is presented in Fig. 2. The main components are connected by heavy black lines.

The decomposition procedure was proven accurate by independently decomposing EMG signals obtained simultaneously using two electrodes separately inserted into a common muscle volume. The signals from each electrode were then independently decomposed. The firing times of motor units present in both signals, determined by each decomposition, were identical (Mambrito and De Luca, 1983, 1984). An example output, resulting from the decomposition of an EMG signal with 11 concurrently active motor units, is displayed in Fig. 3. The EMG signals were detected from a first dorsal interosseous muscle during an isometric ramped force contraction. The individual firing times of each motor unit are represented by vertical bars. The muscle force produced during the contraction is shown as the solid black line.

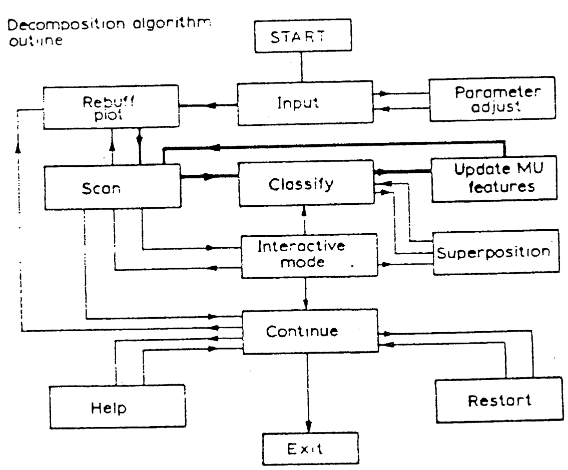

Fig. 2. Simplified flow chart of the decomposition algorithm. Routines connected with the heavy lines are performed more frequently.

DECOMPOSITION MODIFICATIONS

As outlined earlier (LeFever and De Luca, 1982; Mambrito and De Luca, 1983, 1984), the decomposition procedure can be divided into four major segments: signal acquisition, data sampling and compression, signal conditioning, and the decomposition algorithm. Modifications have been incorporated into each segment of the procedure to improve the overall system performance in terms of decreasing the time required to perform a decomposition while maintaining the decomposition accuracy.

Signal acquisition

The EMG signal acquisition system remains essentially the same as described by Mambrito and De Luca (1983, 1984). Three channels of information are acquired to provide the necessary discrimination between the MUAPs of the contributing motor units. However, two significant changes have been made. A variety of electrode configurations are now available. A certain configuration is chosen to best suit the intent of the signal collection and the properties of the muscle studied. In addition, a signal quality monitor is used to constantly measure the amplitudes and slopes of the detected MUAPs to ensure adequate signal content and stability.

Originally, EMG signals were detected using needles containing an electrode configuration consisting of a cluster of four 75 μm diameter detection surfaces arranged in a square with approximately 200 μm sides and located 2 mm from the tip of the needle cannula. Currently, needles containing electrode configurations of four 50 μm diameter detection surfaces arranged in a square with 150 μm sides and located 7.5 mm from the tip of the needle cannula, are also available for signal acquisitions. Fig. 4 schematically shows the electrode detection configurations available. The potentials measured at each detection surface are individually buffered and various combinations of detection surface potentials (bipolar or monopolar) can be input to the differential amplifiers

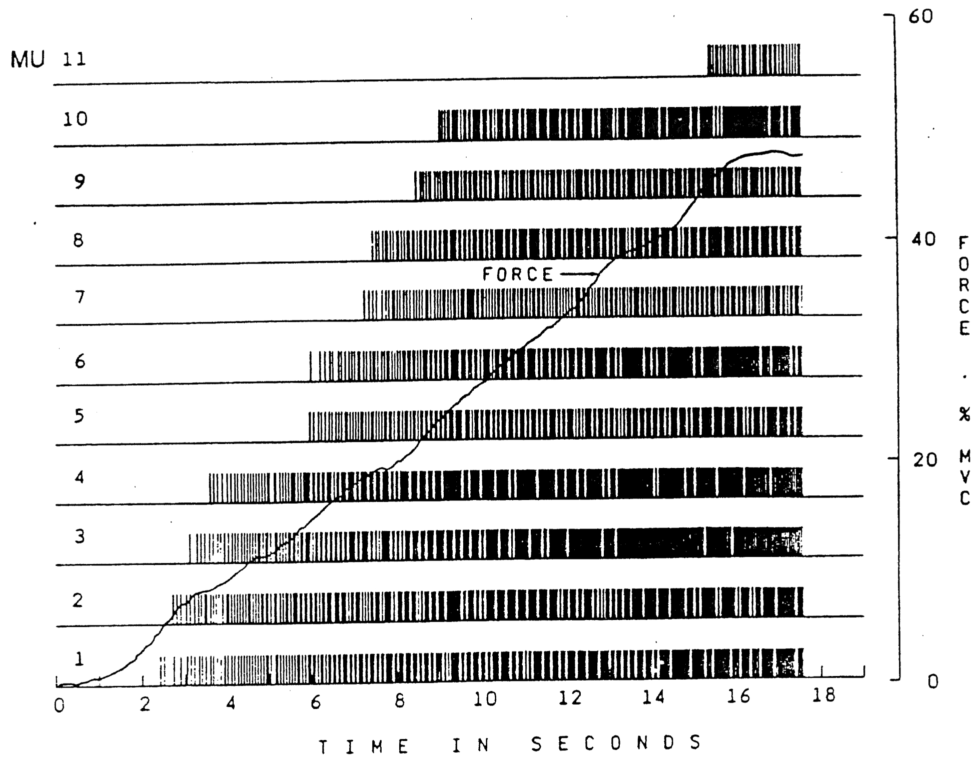

Fig. 3. Individual MUAPTs of eleven concurrently active motor units are displayed along with the corresponding muscle force. The discharge times of each individual motor unit are depicted by vertical bars. The solid line represents the muscle force created.

whose outputs define the MUAPs for each of the three channels. The second configuration has two distinct features. First, the position of the detection surfaces (7.5 mm from the cannula tip) is better suited for the electrode to be used for macroEMG studies which are described more fully later. Second, because of its smaller detection surface areas and inter-surface distances it is considerably more selective. It acquires EMG signals composed of the contributions from fewer motor units and MUAPs which are more likely to be composed of the contributions from fewer muscle fibers per motor unit and therefore of shorter duration. The result is an EMG signal which is more easily decomposed. This configuration is especially useful for studying EMG signals obtained during high level contractions in small muscles where motor unit density is high. However, for studying low to moderate level contractions of larger muscles the original less selective configuration is still preferred.

During data collection the signal quality of the selective needle signals is now constantly surveyed with the signal quality monitor equipment package. This equipment electronically monitors the slope and amplitude of the selective needle signals and visually indicates their levels by a light display. A more complete description of this hardware may be found in Stashuk (1985). Amplitude and slope criteria are used to initially position the electrode detection surfaces suitably close to at least one muscle fiber of the motor units studied. Amplitude values greater than 1 mV with slope values greater than 6 V/s are typical limits. Such signal amplitude and slope criteria ensure that suitable MUAPs of substantial amplitude and slope are measured.

Data collection is not initiated until, at minimal force, both the signal slope and amplitude criteria are met. The monitoring continues throughout the contraction to determine if the signals detected remain stable. Stable signals contain MUAPs whose shapes do not change significantly and represent the activity of a fixed population of motor units. Signal instability is primarily caused by needle movement or neuromuscular jitter. Therefore, if the amplitude and slope criteria are not consistently met or exceeded throughout a contraction, excessive needle movement is assumed, the data is rejected and another collection is attempted.

Data sampling and compression

The detected EMG and force signals are recorded on FM tape at a speed of 30 in/s. The analog signals are then converted and transferred off-line to digital storage. When the signal potential (on any one of the three channels) is above an operator-set threshold, MUAPs are assumed to be present and the signal epoch is placed in permanent digital storage. A complete time reference of events is provided by also storing the amount of time between stored signal epochs, represented by the number of samples skipped. No information pertinent to the decomposition process is lost. The data collection-compression operation greatly reduces the amount of digital storage and subsequent digital signal processing required to perform a signal decomposition. By replaying the recorded signals at reduced speeds, the collection-compression algorithm indirectly sampled the three channels of data to be compressed at a rate of 50 kHz and also indirectly, simultaneously and continuously sampled one or two force signal channels at a rate of 500 Hz.

The data collection-compression algorithm has been revised to increase its operational efficiency. The overall program speed has been increased to

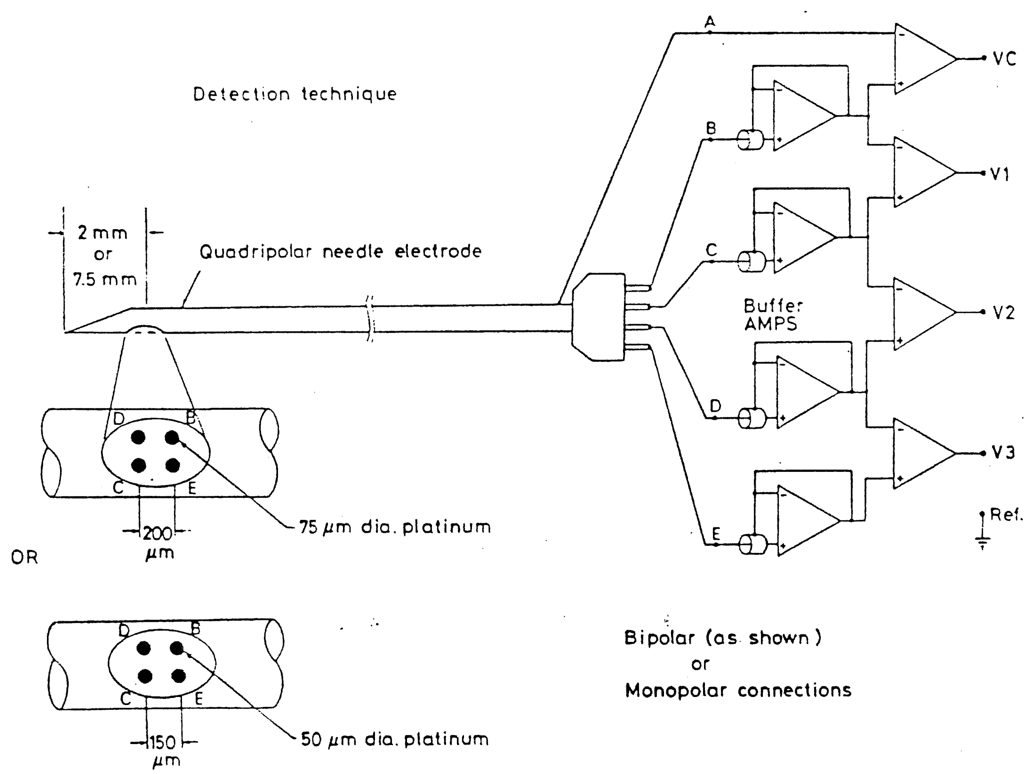

Fig. 4. Available needle electrode configurations with typical buffering connections.

allow for the simultaneous continuous sampling and storage of additional data channels and the use of higher continuous data sampling rates. Currently, the algorithm is capable of simultaneously collecting and compressing three channels of data at a 50 kHz indirect sampling rate and also continuously collecting three additional channels of data, each at an individual indirect rate of up to 5 kHz. This has made possible the acquisition of additional continuous EMG signals and force signals. This capability has provided a means for studying and comparing simultaneously acquired macro-EMG potentials recorded from both a needle cannula and an overlying surface electrode (Stashuk and De Luca, 1986).

Signal conditioning

The analog high pass filtering at 1 kHz, performed during signal acquisition, is effective in substantially reducing both the amplitude and the time duration of slow rise time MUAP waveforms recorded from fibers distant from the detection surfaces of the electrode. However, it is sometimes useful to further reduce the degree of superposition among MUAPs by further shortening their time durations. In such cases, a 51 point symmetric Hamming window, finite impulse response digital filter was used. The filter chosen most often had a 2 kHz to 7 kHz bandpass.

Filtering with the Hamming windows required significant amounts of time due primarily to the filter length. An alternate method of reducing MUAP durations and attenuating distant activity consists of the use of first or second order difference filters (McGill and Dorfman, 1985; Usui and Amidror, 1982). First order difference filters essentially replace the input waveforms with estimates of their slopes or time differentials. Second order filters are equivalent to a second pass through a first order filter. The main advantages of difference filters are the small number of filter coefficients used, which allow rapid output signal computation (first order 2, second order 4), and the effective reduction of MUAP durations which are obtained. The equations presented by McGill and Dorfman (1985) were modified as shown below to account for the higher than Nyquist sampling rates used.

First order difference filter:

$$X_t = Y_{t+n} - Y_{t-n} \tag{1}$$

Second order difference filter:

$$X_t = Y_{t+2n} - Y_{t+n} - Y_t - Y_{t-n} \tag{2}$$

where, Y_t is the sampled raw data, X_t is the sampled filter data, n is a factor chosen between 1 and 5 to account for the greater than Nyquist sampling rate.

As n increases from 1 towards 5 the amount of filtering performed is reduced. Second order filtering more severely attenuates low frequency MUAP content. Typically first order filters using n equal to 3 produce MUAPs most suited for the decomposition process. Results of filtering are displayed in Fig. 5. MUAPs which are superimposed and difficult to identify in the raw signal occur individually in the filtered data and are easily identified. The main advantage of difference filtering is its great computational efficiency.

Decomposition algorithm

As earlier discussed the decomposition algorithm uses both MUAP shape and motor unit firing probabilities to classify a candidate MUAP as belonging to or being created by a specific motor unit. The use of a combination of shape and temporal information in the classification of detected MUAPs, was suggested by the similarity of the decomposition problem to a common problem in the field of communications: the determination of one of many signal sources for a received signal, which uses maximum a posteriori probability receiver theory (Van Trees, 1968).

The similarity although is not complete. The decomposition problem has many other factors controlling a correct classification. For this reason MUAP classifications are not automatically made

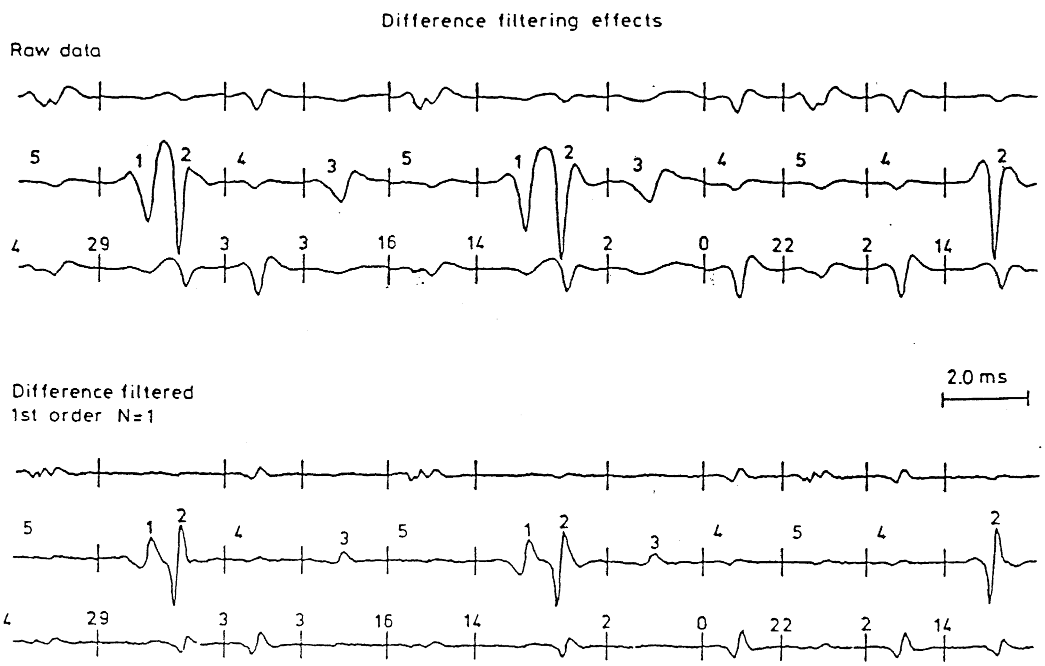

Fig. 5. Unfiltered three channel representations of MUAPs are displayed at the top. The result of difference filtering these MUAPs are shown at the bottom. MUAP durations are reduced and MUAP superpositions are more easily resolved. The numbers between the MUAPs are skipped interval markers. They represent the amount of time during which, the EMG signal was not stored. The numbers over each MUAP are motor unit assignment numbers.

by the algorithm unless the shape similarity between a candidate MUAP and the chosen motor unit template are suitably close. A MUAP and a chosen motor unit template are suitably close when the quantitative measure of their shape similarity (the distance measure) falls within an acceptance region. When an automatic classification can not be made, the algorithm goes into an interactive mode. The operator is informed of the algorithms determination of the most appropriate motor unit choice and asked to respond. LeFever et al. (1982) discuss in detail what considerations and possible actions an operator has at this point.

Initially the size of the acceptance region was fixed at the onset of the decomposition. It could be manually adjusted by the operator during the decomposition, but to do so was time consuming. The fixed acceptance region was sometimes too strict and other times too lax. Automatic classification of a MUAP would not be made to the best candidate motor unit when its template had poor shape similarity, even when the MUAP was detected when the firing probability for that motor unit was high. The operator would be queried only to agree with the algorithm's choice, a considerable waste of time. Conversely, a MUAP assignment could be automatically accepted if the distance measurement was within the fixed acceptance region even when based on firing statistics, the assignment would be apparently erroneous. This also would create a situation in which time-consuming operator interaction was required.

A variable size acceptance region has now been incorporated into the algorithm in an attempt to rectify these situations. The acceptance region becomes larger if the firing statistics support the assignment and it becomes smaller if the converse is true. The determination of whether the firing statistics support a classification or not is based on the difference between the resulting interpulse interval (IPI) and the mean IPI of the chosen motor unit. This difference is expressed in units of standard deviations of the IPI for the chosen motor unit. The variable acceptance region has considerably reduced the number of interactions sought with the operator allowing the decomposition to proceed more quickly without reducing the accuracy of the process.

Several modifications have been made which also affect the way in which the decomposition algorithm interfaces with the operator. The display of the candidate motor unit templates and the three channels of EMG signal currently being processed were rearranged to allow the operator to monitor the ongoing classifications more easily and respond to algorithm queries more quickly. Algorithm modifications were made which allowed the operator to suspend decomposition if needed, and to resume the decomposition, at the same state, at a later time. Also, the ability to restart the decomposition at any previous time in the contraction to correct any possible misclassifications was implemented. These features greatly increase the perceived ease of decomposition. Fig. 6 shows an example of a typical graphics screen during decomposition. The information across the bottom is displayed at the operator's request when the algorithm is seeking input and often provides in-

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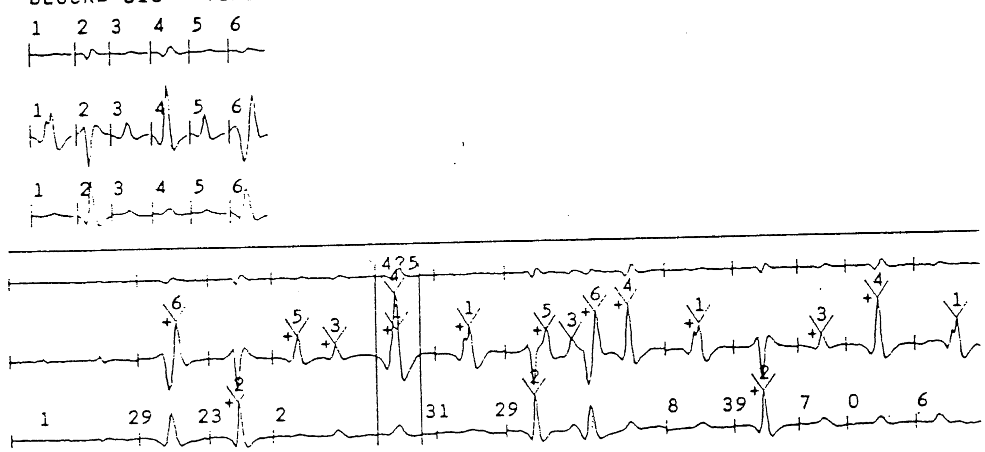

MU	NORM IPI	DEV (SD)	MEAN IPI	ABSOLUTE DISTANCE	NORM DIST	HAZD PROB	WGTD PROB	MAP DIST
1	1.38	1.65	47.1	0.13E+08	12.98	0.062	0.42	13.40
2	0.12	8.13	56.9	0.86E+07	6.45	0.000	5.39	11.83
3	0.03	10.00	63.9	0.17E+08	38.48	0.000	12.78	51.26
4	1.25	1.25	55.1	0.35E+07	2.37	0.077	0.39	2.76
5	0.03	10.00	83.8	0.11E+08	18.85	0.000	12.78	31.63
6	0.35	3.44	92.2	0.12E+08	6.52	0.000	1.47	7.99

Fig. 6. An example of the visual display presented to the operator during a signal decomposition. The middle of the display includes the three channel representations of the MUAPs to be classified in this portion of the EMG signal. The numbers between the MUAPs represent the amount of time during which the EMG signal was not stored (the amount of time skipped). The current shapes of the templates of the MUAPs of the candidate motor units are displayed at the top left and the corresponding elapsed time during the contraction along with the file name is displayed at the top. The algorithm automatically classified the MUAPs up to the displayed question mark. The operator was then queried for assistance. The operator responded with a request for pertinent statistical information (displayed across the bottom), then manually classified the MUAP in question. The algorithm then successfully completed the classifications for the rest of the currently displayed page automatically. Constant visual feedback of the algorithm's selected classifications is provided by the numbers placed at each MUAP peak. A plus sign next to the motor unit number indicates that the MUAP was used to update the template of the MUAP of the motor unit to which it was classified.

formation needed to quickly determine proper MUAP classifications.

General algorithm modifications were made to provide better documentation and to make more efficient use of the buffering capabilities of a Vax 11/750 computer system. The data buffering alterations decreased the amount of time required to manipulate the collected EMG signals and search for suitable MUAPs. It also allowed the current segments of EMG signals being processed to be more rapidly plotted on the graphics terminals.

Up to a 50% reduction in the amount of time required to perform an EMG signal decomposition has been achieved. Thus, current decomposition times typically range from 30 s to 3 min/s of acquired EMG data depending on its complexity and stability. These times are of course still not clinically acceptable. However, with the application of currently available specialized data acquisition hardware, more efficient mathematical processors and high speed graphics terminals, combined with the implementation of additional artificial intelligence routines, clinical applicability is a distinct possibility.

INDIVIDUAL MOTOR UNIT FIRING TIMES ANALYSES

The output of the decomposition algorithm provides accurate information about the recruitment and firing times of individual motor units throughout a contraction as is demonstrated in Fig. 7. The individual firing times of four concurrently active first dorsal interosseous motor units are represented by vertical bars. The corresponding muscle force is shown as the solid black line. An example

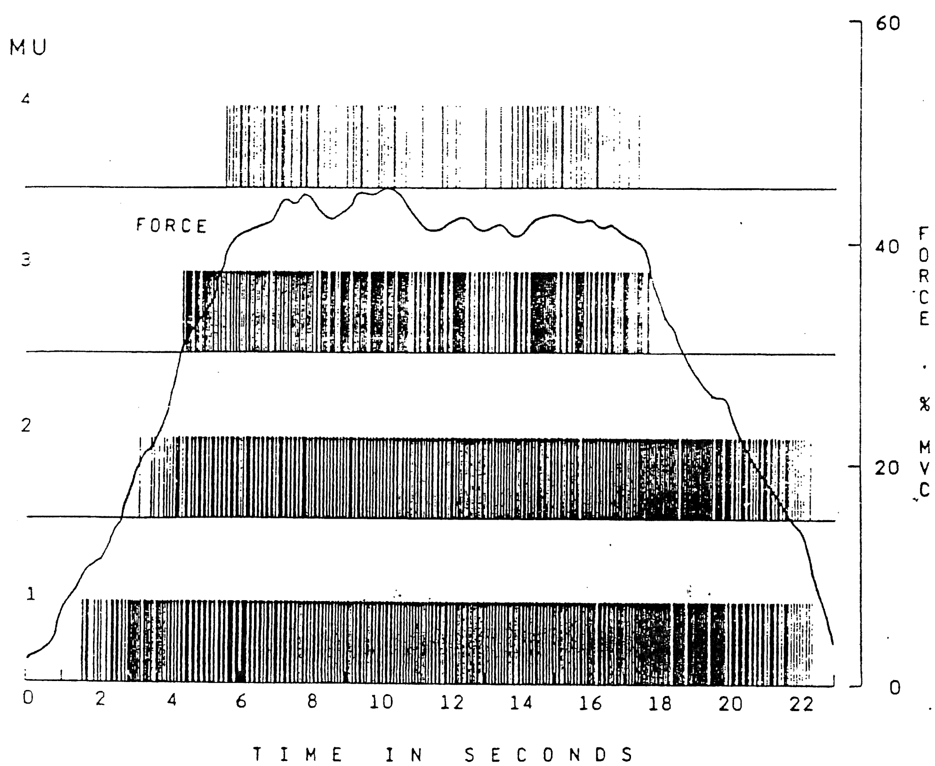

Fig. 7. Individual MUAPTs of four concurrently active motor units, are displayed along with the corresponding muscle force. The discharge times of each individual motor unit are depicted by vertical bars. The solid line represents the muscle force created.

depicting the activity of only four motor units is displayed for the purpose of clarity in the subsequent displays, which were produced using these firing times and are discussed later in this section. Such accurate temporal information provides a basis for many useful subsequent forms of data analysis. The actual firing times of the individual motor units can be compared with those of other motor units to test for the existence of synchronous behavior. Discharge times used as synchronous triggers in ensemble averaging applications result in estimates of concentric needle, cannula or surface electrode detected MUAPs. The individual motor unit firing times may also be used to estimate motor unit firing rates. The firing rates of the motor units may then be cross-correlated to determine the amount of common modulation which occurred during various contraction protocols.

Synchronization studies

Synchronous behavior of motor units is considered as the tendency for pairs of motor units to contract with preferred relative latencies. Preferred latencies are those which occur more often than would be expected if the motor units were discharging independently.

Rigorous statistical methods are used to determine if cross-interval histogram peaks (Perkel et al., 1967) infer statistically significant interdependence or synchronization of motor unit pairs. A cross-interval histogram clearly displaying synchronization between motor units nos. 1 and 2 of Fig. 7, within the ± 5 ms latency is shown in Fig. 8. Cross-interval histograms represent the probability of one motor unit of a chosen motor unit pair firing before or after the firing of the other motor unit. Flat histograms represent independent discharge times. Peaks in the histograms reveal

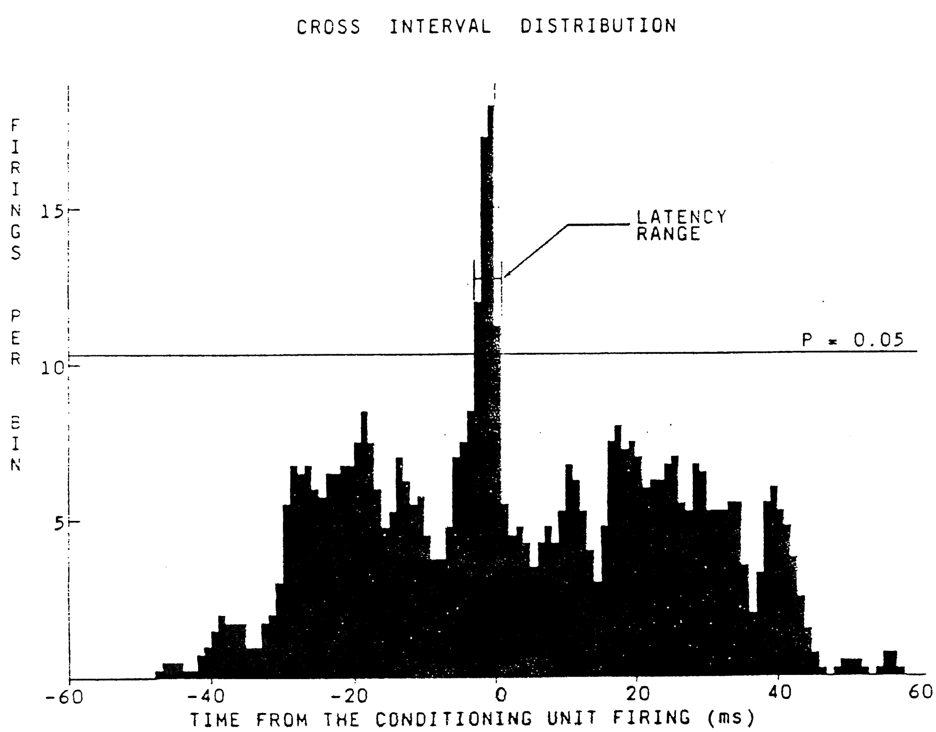

Fig. 8. An example cross-interval histogram with a peak showing considerable synchronous activity for a motor unit pair. The latency range defines the width of the peak. Peak area is an indicator of the intensity of the synchronous behavior. The horizontal line represents the 95% level of significance for one sided tests of the null hypothesis that the motor units of the chosen pair are firing independently.

preferred inter-discharge latencies. The solid line across the histogram represents the 95% confidence limit for a one sided test of rejecting the null hypothesis of independent behavior of the motor unit pair.

The latencies of the significant histogram peaks and the latency ranges (peak widths) are computed to describe the temporal relationships of the synchronous behavior. The amount of synchronization for each motor unit pair, over the determined latency ranges, is expressed in normalized units. The normalized units are calculated as the average difference, over the latency range, between the histogram values and the expected histogram value, measured in units of expected standard deviation (Griffith and Horn, 1963). The percentage of motor unit pairs studied expressing synchronous behavior can also be measured. The overall amount of synchronous behavior in each muscle studied is summarized by a synchronization level. This level is calculated as an average normalized unit value times the percentage of motor unit pairs which had interdependent discharge times.

Measurements of the amount of synchronous motor unit firing behavior, during a variety of force protocols, in a number of human muscles, have been made. Muscles studied include: first dorsal interosseous (FDI), deltoid, tibialis anterior (TA), extensor carpi radialis longus (ECRL), extensor carpi ulnaris (ECU), extensor pollicis longus (EPL) and flexor pollicis longus (FPL). These measurements indicated that more than 40% of the motor unit pairs examined exhibited synchronization at some time during the contraction unlike the results of Kranz and Baumgartner (1974) and Shiavi and Negin (1975) for similar contraction protocols. The latencies of the synchronous behavior were most often within $\pm$ 5 ms and they had an average latency range of about 4 ms. Synchronization at longer latencies (< -5 or $> +5$ ms) also occurred, but to a lesser degree. At similar contraction levels, the deltoid muscle showed lower amounts of synchronization than the FDI which had lower amounts than the TA. Synchronization level increased with contraction level in the deltoid and FDI. The analysis of motor units in synergist (ECRL and ECU) and antagonist (FPL and EPL) muscle pairs revealed a greater interdependence of firing times for motor unit pairs chosen within rather than across the muscles, although clear indications of synchronization between motor units pairs chosen across muscles were commonly evident. The possible clinical significance of various amounts of synchronous behavior is yet to be determined.

Ensemble averaging concentric needle, cannula and surface detected signals

When large detection surfaces are used for the recording of EMG signals, or during high levels of force, individual MUAPs are usually detected superimposed along with the action potentials of other active motor units. Estimates of their true detected shapes are only available via the ensemble averaging process. During ensemble averaging, the uncorrelated contributions of other active motor units are reduced. Thus, an ensemble averaged MUAP is an estimate of the MUAP, as detected by the detection surfaces used, of the individual motor unit whose discharge times were used to extract it. The larger the number of triggers used for the averaging process, the better the resulting estimate.

When concentric needle, cannula or surface detected EMG signals are simultaneously acquired along with the multi-electrode signals, the discharge times of the individual motor units obtained from the decomposition process can be used as triggers for ensemble averaging. Such ensemble averaging can produce clean concentric needle MUAPs, and cannula or surface detected macroMUAPs (Stålberg, 1983). A MUAP corresponding to each motor unit whose discharge times were tracked during the decomposition is available. Motor units active only at high levels of contraction can be studied and compared with other lower threshold units using this data.

Cannula and surface detected macroMUAPs represent the electrical activity of most of the fibers of a motor unit and therefore contain information that reasonably estimates the size of the individual motor unit whose discharge times are used for the ensemble averaging process. The motor unit size is related to the peak-to-peak voltage of the ensemble averaged MUAPs, but is more directly dependent on its area (Nandedkar and Stålberg, 1983). Ensemble averaged concentric needle potentials represent the actual MUAP shapes of individual motor units better than single event recordings. The shapes are more suitable for clinical analysis because the background noise, from other active motor units, has been diminished by the averaging process.

Cannula signals were simultaneously detected from an FDI muscle along with multichannel selective surface signals during an isometric contraction following a trapezoidal shaped trajectory with 10% MVC/s sides and a 5 s long plateau at a 40% MVC level. The selective surface signals from this contraction were used by the decomposition algorithm to determine the individual firing time histories of eight motor units. The histories of four selected motor units are displayed in Fig. 7. Fig. 9 displays the four macroMUAPs corresponding to the motor units whose discharge times are shown in Fig. 7. The peak-to-peak voltages and macroMUAP areas are given in Fig. 9 along with the motor unit's mean IPI. Fig. 9 along with Fig. 7 provide an opportunity to directly compare motor unit sizes with their recruitment threshold and firing time behavior.

This collective view clearly shows that the smaller, earlier recruited motor units (no. 1 and no. 2) fire more rapidly, while the larger, later recruited motor units (no. 3 and no. 4) fire more slowly. This demonstrates an apparent paradox in motor unit firing behavior, at least during isometric contractions with slowly changing or constant force levels. The smaller, earlier recruited motor units are usually composed of slow twitch fibers yet they fire more rapidly than the larger,

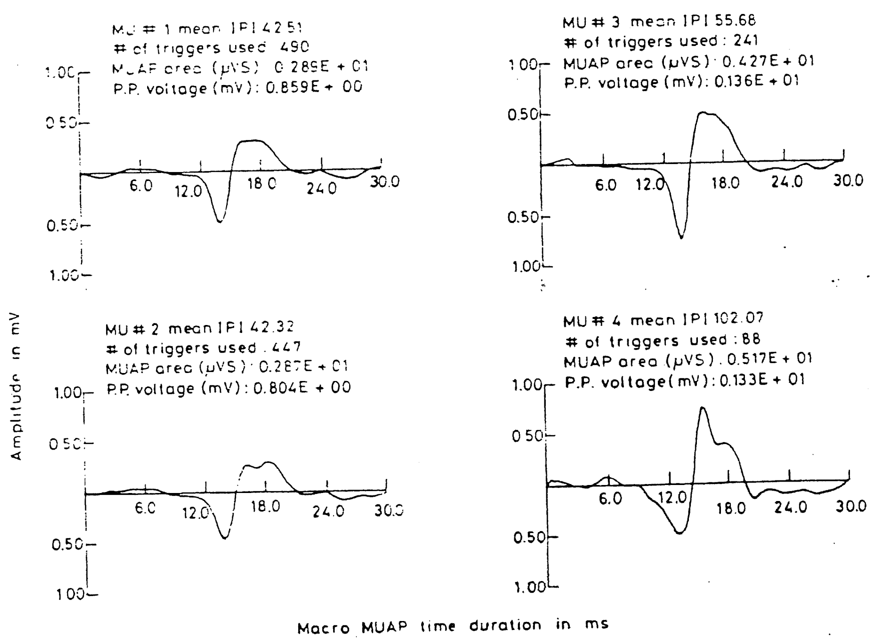

Fig. 9. Four macroEMG potentials estimated from ensemble averaging a cannula detected EMG signal. The cannula signal was detected during a contraction of a FDI muscle along with selective surface multi-channel signals. The corresponding individual motor unit firing times used as triggers for the averaging were obtained via EMG signal decomposition of the multichannel signals and are displayed in Fig. 7. The area and peak-to-peak voltages of the macropotentials are also displayed.

later recruited motor units which are usually composed of fast twitch fibers (see chapter 8 of this volume). Clinically, any changes to the control properties of motor units, which can be studied with signal decomposition and ensemble averaging techniques as outlined above, could prove to be significant. Nonetheless, the ability to simultaneously obtain ensemble averaged concentric needle potentials or macroMUAPs, for groups of motor units, typically 5 – 8, would be clinically useful.

Motor unit firing rate estimation

The firing times of an individual motor unit may also be used to estimate the motor units firing rate and to map any firing rate fluctuations as a function of time. We use one of two methods to estimate a motor unit firing rate. One method models the MUAPTs as unity height Dirac delta impulse trains. The impulse trains are then sampled at fixed intervals. The resulting zero-one sequences are then convolved with smoothing filters of fixed length. The output of the convolution process represents the firing rate estimates. The other method uses the inverse of a weighted average of a fixed number of IPIs at each firing of the motor unit as an estimate of the firing rate. These estimates are then linearly interpolated to provide the sampling resolution desired for time mapping of the firing rate estimates. For estimating a firing rate at a specific point in time, both methods use future and past firing time information. Common weighting sequences used for convolutions and averaging are Hamming, Hanning or rectangular. The symmetry of these sequences ensures that equal amounts of future and past information are used. Hamming and Hanning data windows are well suited because they apply the greatest weights to the motor unit firing times or IPIs closest to the corresponding time of the estimate and smaller weights further away from the time of the estimate.

The firing intervals of motor units may be modelled as renewel processes with low coefficients of variation. Thus, firing rate estimates filter out both some stochastic process variability and some bias modulations in the excitability of the motor unit. A fixed length of time over which an estimate is based can therefore determine the actual temporal (spectral) content of the modulation variation tracked, but the amount of statistical error present in each estimate will be variable and dependent on the firing rate of the motor unit. On the other hand, if a fixed number of IPIs are used to obtain an estimate, a constant statistical error is present in the estimate; however, a variable amount of temporal smoothing (filtering) is performed, depending on the firing rate of the motor unit. Determination of the best method, convolving over a fixed period of time or averaging a fixed number of IPIs, requires further study and may very well be dependent on the type of analysis ultimately to be performed.

Fig. 10 displays individual motor unit firing rate estimates obtained using the firing times of the FDI motor units displayed in Fig. 7. The firing rates shown were estimated by convolving a fixed length (400 ms) Hamming window with the zero-one sequence created by sampling the MUAPTs modelled by unity height Dirac delta impulse trains at 10 ms intervals. Evident in the figure are the consistently higher firing rates of the earlier recruited motor units compared to the later recruited motor units. The clinical relevance of motor unit firing rates and firing rate variability is an area that needs further investigation.

Common drive measurements

Cross-correlation analysis of suitably bandpass filtered firing rate estimates can provide information about the degree of commonality in the modulation of the net excitation of selected motor unit pairs. Successful cross-correlation analysis requires at least 98% accurate EMG signal decompositions for consistent results (Shaivi and Negin, 1973). This type of analysis has led to the determination of *common drive* (De Luca et al., 1982; De Luca, chapter 8 of this volume).

Cross-correlation analysis is performed by selecting an interval during the contraction of at least

5 s duration. Whenever possible, the interval is selected at a time when no additionally recruited motor units are observed. Within this interval, the motor unit firing rate estimates are then processed to remove the DC component so that only the fluctuations are analyzed. This is achieved by band-pass filtering with a digital filter algorithm and then removing any remaining mean value. The filter algorithm used has a low pass cutoff frequency of 0.75 Hz with a 24 dB/octave low pass rolloff and a high pass cutoff frequency of 10 Hz with a 12 dB/octave high pass rolloff. The discrete Fourier transforms of each filtered record are then computed using a fast Fourier transform algorithm. The cross-correlation between pairs of firing rates is obtained by multiplying the discrete Fourier transform of one element of the pair with the complex conjugate of the discrete Fourier transform of the second element of the pair, and then taking the inverse transformation of the product. The cross-correlations have a resolution which depends on that of the firing rate estimates. Typically the resolution is 10 ms.

The results of a cross-correlation analysis performed with FDI motor unit pairs is displayed in Fig. 11. The pairs were selected from the motor units whose firing rate estimates are displayed in Fig. 10. The results show significant amounts of cross-correlation with consistent near zero lags. This is a strong indicator of the common drive of motor units. Such measurements have been made over a wide range of muscles and during a variety of contraction protocols. Common drive among the motor units of a muscle is consistently found

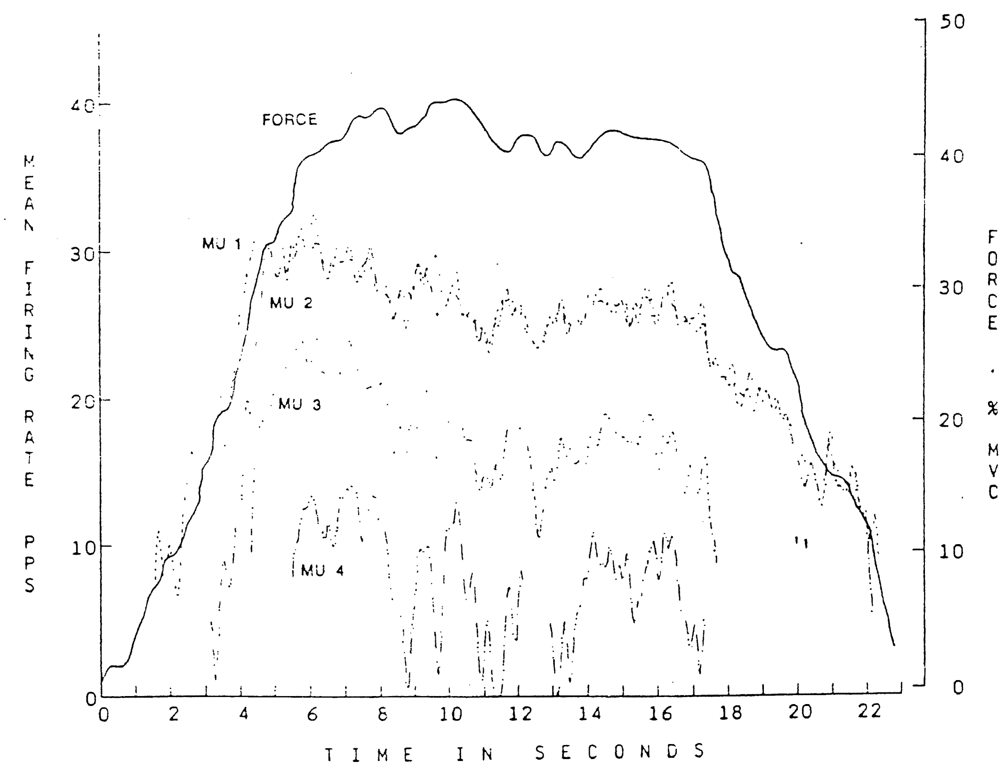

Fig. 10. The individual motor unit firing times displayed in Fig. 7 were converted to continuous time, firing rate estimates by convolving their corresponding MUAPTs with a 400 ms Hamming window and are pictured. The motor unit firing rate plot for each motor unit, scaled in pulses/s (PPS), is represented by different dot-dashed lines and numbered accordingly. The corresponding muscle force scaled in % MVC is depicted by the solid black line.

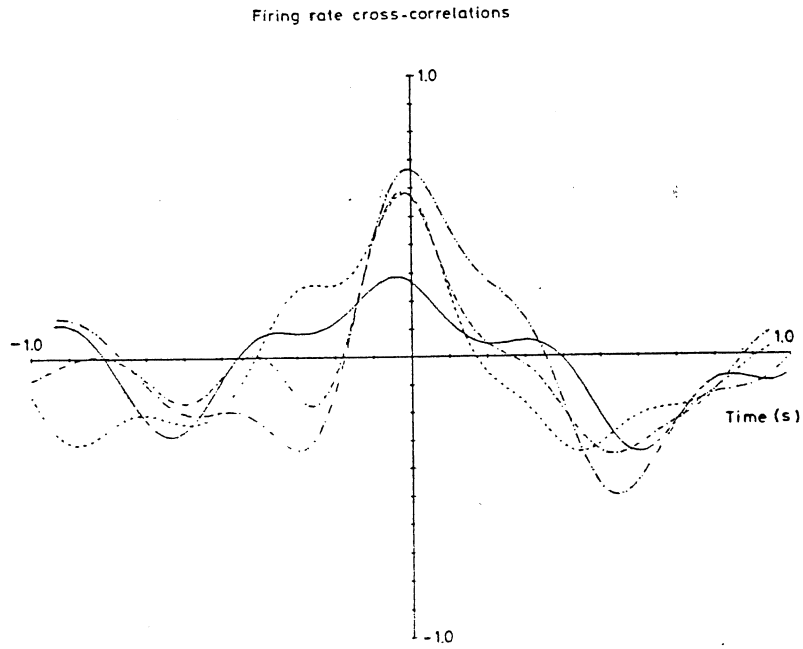

Fig. 11. The results of cross-correlating pairs of motor unit firing rate estimates are shown. The firing rate estimates displayed in Fig. 10 were used.

and common drive between motor unit pairs chosen across muscles has also been measured (De Luca and Mambrito, 1987). Common drive measurements are higher in tibialis anterior muscle with a mean peak cross-correlation value of 0.72 ± 0.13 than in first dorsal interosseous muscle which has a mean value of 0.6 ± 0.16 (Kamen et al., 1987). Common drive has also been found in patients with clinical disorders (see Jabre, chapter 17 of this volume). However, the overall clinical relevance of common drive measurements must be further investigated.

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