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Journal of Neuroscience Methods xxx (2005) xxx–xxx

JOURNAL OF NEUROSCIENCE METHODS

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EMGLAB: An interactive EMG decomposition program

Kevin C. McGill [a,*], Zoia C. Lateva [a], Hamid R. Marateb [b]

[a] *Rehabilitation R&D Center, VA Palo Alto Health Care System, 3801 Miranda Ave, Palo Alto, CA 94304, USA*
[b] *Electronics and Computer Research Center, Isfahan University, Isfahan, Iran*

Received 15 December 2004; received in revised form 22 April 2005; accepted 22 April 2005

Abstract

This paper describes an interactive computer program for decomposing EMG signals into their component motor-unit potential (MUP) trains and for averaging MUP waveforms. The program is able to handle single- or multi-channel signals recorded by needle or fine-wire electrodes during low and moderate levels of muscular contraction. It includes advanced algorithms for template matching, resolving superimpositions, and waveform averaging, as well as a convenient user interface for manually editing and verifying the results. The program also provides the ability to inspect the discharges of individual motor units more closely by subtracting out interfering activity from other MUP trains. Decomposition accuracy was assessed by cross-checking pairs of signals recorded by nearby electrodes during the same contraction. The results show that 100% accuracy can be achieved for MUPs with peak-to-peak amplitudes greater than 2.5 times the rms signal amplitude. Examples are presented to show how decomposition can be used to investigate motor-unit recruitment and discharge behavior, to study motor-unit architecture, and to detect action potential blocking in doubly innervated muscle fibers.

Keywords: EMG; Decomposition; Motor-unit potential; Spike train; Muscle architecture; Double innervation; Common drive

1. Introduction

The electromyographic (EMG) signal recorded by a needle or fine-wire electrode is made up of trains of motor-unit potentials (MUPs), and thus provides a potentially rich source of information about motoneuron discharge behavior and motor-unit (MU) organization (Basmajian and De Luca, 1985). To obtain this information, it is necessary to sort out the activity of multiple simultaneously active MUs, a process known as decomposition. Before the advent of computers, simple EMG signals were sometimes decomposed manually by identifying distinctively shaped MUPs on traces photographed at high-sweep speed (Desmedt, 1983). Computer methods have now been developed to mechanize various aspects of this process (Lefever and De Luca, 1982; McGill et al., 1985; Haas and Meyer, 1989; De Luca, 1993; Stashuk, 2001; Zennaro et al., 2003). However, some degree of human oversight is still necessary to decompose moderately complex EMG signals completely and with consistent reliability.

The goal of full decomposition is to detect all the MUs that are active in a signal and to identify every one of their discharges. In reality, most EMG signals contain a continuum of activity, ranging from large MUPs that can be clearly distinguished to small ones that blend into and help constitute the background noise. Thus, the number of MUP trains that can be fully identified depends to some extent on the amount of effort one is willing to expend. Most EMG signals also contain frequent superimpositions. These occur when two or more MUs discharge at nearly the same time and their MUPs overlap. Full decomposition requires the ability to resolve such superimpositions.

Full decomposition is important in the study of MU discharge behavior. While it is possible to obtain complete discharge patterns for one or two MUs using single-unit recording techniques (Bigland and Lippold, 1954; Datta and Stephens, 1990), and to estimate certain global discharge

Abbreviations: EMG, electromyogram; IDI, inter-discharge interval; IFR, instantaneous firing rate; MN, motoneuron; MU, motor unit; MUP, motor-unit potential; MVC, maximum voluntary contraction

* Corresponding author. Tel.: +1 650 493 5000x64477; fax: +1 650 493 4919.
E-mail address: mcgill@rrdmail.stanford.edu (K.C. McGill).

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doi:10.1016/j.jneumeth.2005.05.015

parameters, such as mean firing rate, from incomplete discharge patterns (Stashuk and Qu, 1996), full decomposition of multi-unit signals provides a way to obtain complete discharge patterns of multiple, simultaneously active MUs. This information in essential in studies of MU coordination (Andreassen and Rosenfalck, 1980; De Luca and Erim, 1994; Adam and De Luca, 2003) and short-term synchronization (Datta and Stephens, 1990; Nordstrom et al., 1992).

Another application in which full decomposition is important is the study of muscle architecture (Lateva and McGill, 2001). The location of a MU's motor endplate and muscle/tendon junction can be estimated from the latencies of the onset and terminal wave of the MUP waveform. These features tend to be quite small, and signal averaging is needed to detect them reliably. Full decomposition makes it possible to average the MUP waveforms of multiple MUs from a single signal. Full decomposition is also useful for studying discharge irregularities such as those associated with doubly innervated muscle fibers (Lateva et al., 2002). Full decomposition makes it possible to detect such irregularities even in busy signals by subtracting out the activity of the other MUPs that are not of interest.

This paper describes an interactive decomposition program called EMGLAB that we developed and have used successfully to decompose hundreds of EMG signals from various muscles of the hand, arm, leg, and back. The program provides the capability to inspect, fully decompose, and obtain high-signal-to-noise-ratio MUP waveforms from moderately complex single- and multi-channel EMG signals recorded using conventional needle or fine-wire electrodes. The program also facilitates the identification and analysis of variable MUP components, such as potentials from doubly innervated muscle fibers. The program includes a convenient graphical interface in addition to advanced template-matching algorithms. It is written in Matlab (The Mathworks, Natick, MA), which facilitates the exportation of MUP waveforms and discharge patterns for further analysis. The use of the program is illustrated by examples from studies of MU behavior and architecture.

2. Methods

The section describes the main features of EMGLAB. The signals shown in the figures were recorded from normal subjects. The recordings were approved by the Stanford University Committee on the Use of Human Subjects in Research, and each subject gave informed consent.

2.1. EMG recordings

Although EMGLAB can be used to analyze signals recorded by various types of electrodes, all the signals reported here were recorded using monopolar needle or fine-wire electrodes. Monopolar electrodes are useful in both behavioral and architectural studies because they sample a broad muscle cross-section and because they are able to record MUP components with low-spatial gradients, including the onset, and terminal wave. The signals were referred to a surface electrode placed over the muscle or one of its tendons. A wide amplifier bandwidth (5 Hz–5 kHz) was used to capture low-frequency MUP components. The signals were sampled at a rate of 10 kHz. Contractions were kept below 30–40% of maximum voluntary contraction (MVC) to ensure signal decomposability. Signal quality and complexity were monitored at recording time by listening for a crisp sound and by looking for an appropriate balance between sharp spikes and flat baseline after 1 kHz high-pass filtering.

The fine-wire signals were recorded using 50 μm-diameter stainless steel wires insulated except for 1 mm at the tip. To increase the likelihood of obtaining signals of acceptable quality, the wires were inserted in pairs with their recording surfaces offset by 2 mm. Recordings were made either from both wires individually or from the single wire that gave the better signal quality. Although fine-wire electrodes cannot be repositioned as needle electrodes can, they have the advantage that—after a few initial contractions during which they "work themselves in," and as long as the joint configuration remains relatively unchanged—they tend to maintain the same position within the muscle, thus making it possible to record from the same set of MUs throughout the course of a long experiment involving multiple contractions.

2.2. Decomposition overview

EMGLAB provides a convenient graphical interface as well as a number of automatic procedures for decomposing and inspecting EMG signals. The computer screen is divided into four panels (see Fig. 1) that show a segment of the EMG signal, the templates of the identified MU spikes, the discharge patterns of the identified MUP trains, and a close-up of the signal for resolving superimpositions. Manual decomposition functions can be performed using the graphical interface. For example, new templates can be formed by dragging spikes from the signal panel to the template panel, and spikes in the signal panel can be identified either by dragging specific templates over them or by shift-clicking on them to have the program determine the best-fitting template. Graphical commands are also available for undoing identifications; deleting, reordering, and merging templates; deleting points from the discharge panel; and selecting and adjusting the template configuration in the close-up panel.

The decomposition process typically proceeds in the following way. First, the program reads in the initial 2 s of the EMG signal and automatically creates templates for all the spikes that occur at least three times with a high-degree of similarity. Then, the program tries to automatically classify the remaining spikes in this 2-s interval using template matching. Depending on the complexity of the signal, these automatic procedures may or may not achieve a full decomposition. The signal is then inspected manually to complete the decomposition and verify the results. This may require sev-

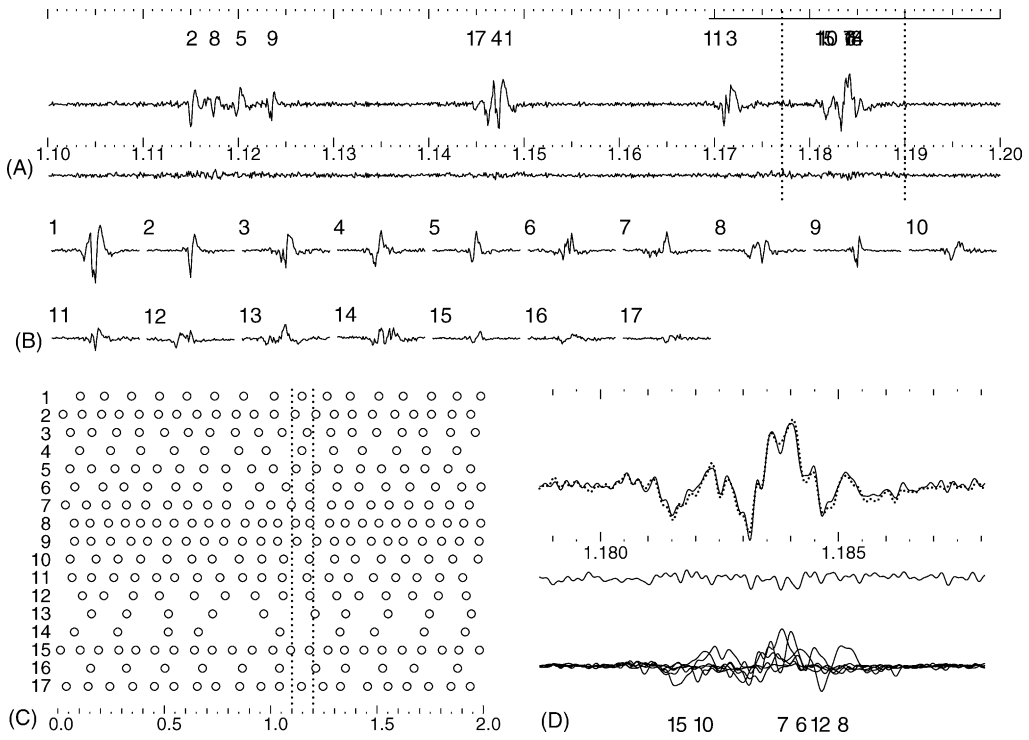

Fig. 1. EMGLAB computer screen analyzing an EMG signal from the brachioradialis muscle. (A) Signal panel, showing a segment of the EMG signal (high-pass filtered at 1 kHz, top trace) and the residual signal after template matching (bottom trace). The numbers at the top indicate the identified MU discharges. The horizontal line shows the interval in which a discharge of MU 15 is expected. The vertical lines indicate the interval displayed in the close-up panel. (B) Template panel, showing the templates of the identified MUs. (C) Discharge panel, showing the identified discharge times of each MU. The vertical lines indicate the interval displayed in the signal panel. (D) Close-up panel, showing a segment of the EMG signal at an expanded scale (top trace), a configuration of templates selected to match it (bottom traces and numbers), the sum of the templates (top dotted trace), and the residual (center trace). All the time scales are in seconds from the start of the signal.

eral passes back and forth through the data. Once this initial 2-s interval has been fully decomposed, the next 2 s are read in and analyzed using the existing set of templates, and so on.

The accuracy of the decomposition is assessed subjectively in two main ways. The first way is by inspecting the lower trace in the signal panel (Fig. 1A). This trace shows the residual that remains after the templates of the identified MUs have been subtracted from the signal. A small residual indicates a good fit between the templates and the signal, whereas a large residual indicates an incomplete or incorrect identification. The second way of assessing accuracy is by inspecting the identified discharge patterns (Fig. 1C). Full, regular patterns provide confidence that the decomposition is correct, whereas gaps, extra discharges or uneven intervals are signs of possible decomposition errors. The goal is to achieve a flat residual signal and smooth, regular discharge patterns, which together indicate a complete and accurate decomposition.

2.3. Signal panel

The signal panel makes it possible to scroll through and inspect the EMG signal in close detail (Fig. 1A). The signal is displayed in its entirety, rather than just the spikes that exceed a certain threshold. This makes it easier to see the temporal relationships between spikes and spike components and decreases the chances of overlooking small but important signal details.

The signal can be displayed either unfiltered or after digital high-pass filtering. For decomposition, a 1 kHz high-pass filter is usually used. This flattens the signal baseline and sharpens the MUPs into narrow spikes, making them easier to detect and distinguish. For averaging, the unfiltered signal is used in order to capture the entire MUP waveforms.

2.4. Templates

The default template length is 12.8 ms, which is long enough to hold most MUP spikes, including small outlying components. For MUPs with more than one distinct component, separate templates can be created for each component to reduce residual noise from inter-component jitter. Slow changes in spike shape are tracked by periodically re-averaging the templates. Re-averaging is performed over a 2-s window, using median averaging to reduce the noise caused by interference from other MUPs.

When a template is dragged to a spike in the signal panel, the program automatically aligns the template with the spike to minimize the resulting residual. From the operator's point

of view, the template seems to snap into place. The alignment is performed to sub-sampling-interval precision (0.01 ms) using interpolation to eliminate residual error due to time quantization (McGill and Dorfman, 1984).

2.5. Discharge patterns

In many signals, timing information is helpful for decomposition. During steady and slowly changing contractions, MUs usually discharge with fairly regular inter-discharge intervals (IDIs) (Fig. 1C). This regularity may not be apparent at the beginning of a decomposition when only a few scattered discharges have been identified, but it becomes clear as more of the discharge pattern is filled in. Once several of a MU's adjacent discharges have been identified it becomes possible to estimate the mean IDI, which, in turn, helps determine where to look for the subsequent discharges. As the discharge pattern becomes completely filled in, discrepancies in the pattern stand out clearly as indicators of possible errors.

To help locate the discharges of a selected MU, the program displays bars in the signal panel that indicate the MU's expected discharge times (Fig. 1A). Bars are shown before and after each of the MU's already identified discharges. Their locations and lengths are based on the MU's estimated firing statistics over a 2-s window. Since the identified discharge pattern might contain misses or false positives, IDIs that are much longer or shorter than the median IDI are excluded from the statistics calculation.

The discharge patterns can be displayed either as spike trains (as in Fig. 1C) or as smoothed instantaneous firing rates (IFRs) (Fig. 2). The smoothed IFR is obtained by forming the piecewise constant function equal to the reciprocals of the IDIs and then smoothing with a 2 Hz zero-phase-shift low-pass filter. In some contractions, the IFRs of the different MUs exhibit synchronous fluctuations, which are thought to reflect fluctuations in the common drive to the motoneuron pool (De Luca and Erim, 1994). Consistency among the fluctuation profiles of the identified MUP trains provides another source of confidence about decomposition accuracy.

It should be mentioned that not all signals exhibit the same degree of discharge regularity. MUs near their recruitment thresholds can fire intermittently, and some individuals, and perhaps some muscles, exhibit less regularity and less fluctuation synchrony than others.

2.6. Resolving superimpositions

One of the most difficult aspects of EMG decomposition is resolving superimpositions (De Figueiredo and Gerber, 1983; Etawil and Stashuk, 1996). In a signal with 15 active MUs, each firing at a mean rate of 15 Hz, a third of all discharges will occur within 1 ms of another discharge, and there will be about 15 instances per second in which four different discharges occur within the same 4-ms interval. When this happens, the individual MUPs sum together to produce a superimposition. Depending on the precise timing, superimpositions can range in complexity from partial ones in which the individual constituents are still largely recognizable, to full ones in which the constituents are unrecognizable because of constructive or destructive interference (Fig. 3).

EMGLAB is able to resolve many superimpositions during the automatic template-matching phase by identifying larger spikes and "peeling them off" to reveal smaller spikes in the residual. Superimpositions that are not resolved in this way must be resolved manually. This is done in the close-up panel (Fig. 1D), which displays the superimposition at an expanded scale and allows different sets of templates to be selected and adjusted to find the best fit.

The program can also be instructed to determine the optimal alignment for the selected set of templates. This turns out to be a difficult problem because of the large number of possible ways that the templates can be aligned. The algorithm used by EMGLAB essentially considers every possible alignment, using a branch-and-bound approach to try the most likely alignments first and to stop once it can be determined that none of the remaining alignments could do better than the ones already tried (McGill, 2002). Interpolation is used

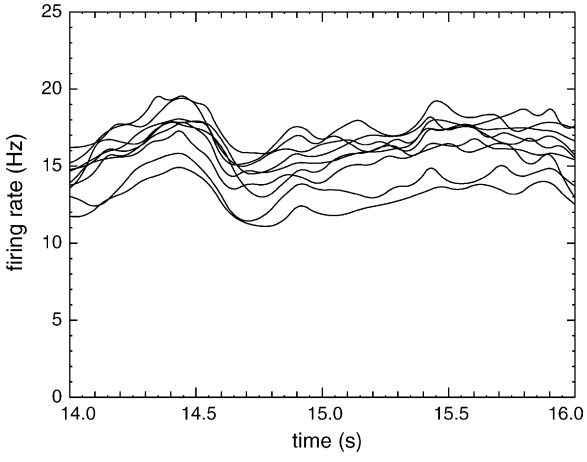

Fig. 2. Discharge panel, showing the discharge patterns plotted as instantaneous firing rates (IFRs) (different data from Fig. 1).

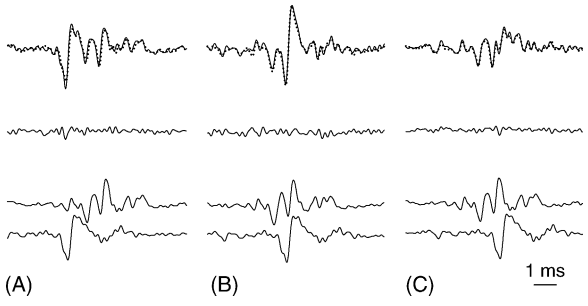

Fig. 3. Three very different looking superimpositions from the same two MUs. (A) Partial superimposition. (B) Constructive interference. (C) Destructive interference. Each set shows the superimposition (top solid), templates (bottom), reconstruction (top dotted), and residual (middle). All the signals have been interpolated to an effective sampling rate of 100 kHz.

to reduce time-quantization errors. The algorithm is able to resolve complicated superimpositions involving six or more MUPs quite efficiently, even in cases of destructive interference and different sized MUPs.

The templates involved in a superimposition can usually be determined, or at least narrowed down, by inspecting the discharge patterns to see which MUs are expected to fire at the time in question. The program does not attempt to try all the different possible combinations of templates, because that would be prohibitively time consuming. It would also often lead to the wrong result. The reason is that it is often possible to find incorrect sets of templates that provide a better fit to the superimposition than the correct set does. The incorrect sets usually include too many templates, which, because of the extra degrees of freedom, can be aligned to match some of the background noise as well as the superimposition itself.

2.7. Multiple channels

Signals recorded simultaneously from multiple sites in a muscle can provide a wider sampling of MU activity and a more complete characterization of MU architecture than the signal from a single site. Decomposing multi-channel signals is challenging, especially when the electrodes are relatively far apart.

Some MUs may be detected in more than one channel, while others may be detected in only a single channel. Spikes in different channels that correspond to the same MU can be recognized by the fact that they always occur in a time-locked relationship. The temporal offset between the spikes will depend on the conduction delay between the recording sites, which can be as much as 10–15 ms for sites that are 5 cm apart. The inter-channel offset can also exhibit a variability or jitter from discharge to discharge. In normal subjects, this jitter is due primarily to fluctuations in muscle-fiber conduction velocity (Stålberg and Sonoo, 1994). The jitter is greater for sites that are farther apart, and it can be as much as ± 0.5 ms. Because of this jitter, the discharge times of the spikes in one channel provide only a rough estimate of the discharge times of the spikes in another channel. Therefore, EMGLAB keeps separate lists of discharge times for every channel.

Multi-channel signals are decomposed in EMGLAB in a sequential fashion. When the operator is ready to begin decomposing a new channel, the program first uses spike-triggered averaging to determine whether any of the spikes in the new channel are time-locked to MUP trains that have already been identified in other channels. If such spikes are found, the program creates templates for them and imports their discharge patterns from the other channels, adjusting the times to compensate for the inter-channel offset. The program then attempts to correct for the inter-channel jitter by re-aligning the templates with the individual discharges. Any activity that remains must be due to new MUs that were not previously detected in other channels. This activity is then decomposed in the usual way.

The multiple views of MUs provided by multi-channel signals can be useful for MU identification (Lefever and De Luca, 1982). A particular discharge or even an entire MUP train that is difficult to identify in one channel may be much easier to identify in another. A good strategy is to decompose the larger MUPs in all the channels first, then identify the smaller MUPs that correspond to these larger MUPs in other channels, and only then decompose the remaining small MUPs. Multiple channels can also be decomposed independently and then the results cross-checked to assess decomposition accuracy, as described more fully below.

2.8. MUP waveforms

The MUP waveform recorded by a monopolar electrode is a temporal record of the electrical events that take place during a MU action potential. In particular, the onset, spike, and terminal wave of the MUP mark, respectively, the initiation of the action potential at the endplate, its propagation past the electrode, and its termination at the muscle/tendon junction (Stålberg et al., 1986). Thus, by measuring the relative latencies between these MUP features it is possible to estimate the architectural organization of the MU (Lateva and McGill, 2001). This approach provides one of the few available methods for studying the architectural organization of individual MUs in vivo.

To study muscle architecture, it is important to obtain an accurate estimate of the complete MUP waveform, including its onset and terminal wave. These features tend to be low-frequency, and so are much better seen in the unfiltered signal than in the high-pass filtered signal used for decomposition. They are also often quite small in amplitude, and so signal averaging is usually needed to detect them reliably. EMGLAB uses an averaging algorithm that estimates and subtracts out the effect of the interference from the other MUPs to achieve signal-to-noise ratios much higher than those obtained using simple averaging (McGill et al., 1985). In this way, EMGLAB is able to obtain MUP averages acceptable for architectural analysis from 10 or 20 s long epochs, even in fairly complex and noisy signals.

It should be noted that the MUP waveform is not perfectly constant from discharge to discharge. Rather, it varies somewhat in shape and duration, due primarily to fluctuations in muscle-fiber conduction velocity (Stålberg and Sonoo, 1994). This is related to the inter-channel jitter between spikes recorded at different electrode sites. As a consequence, averages of MUPs with widely separated components (either in the same or in different channels) can be considerably different depending on which component is used for aligning the individual traces. For example, for the MUP with a late satellite potential shown in Fig. 4, the average computed by aligning on the main component brings the main component into sharp focus but blurs the satellite potential (Fig. 4A). By the same token, aligning on the satellite potential brings it into focus but blurs the main component (Fig. 4B).

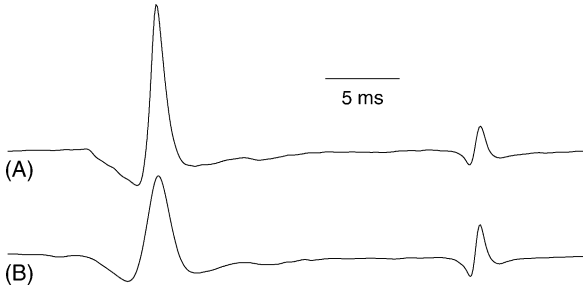

Fig. 4. Two different averages of a MUP with a satellite potential obtained by aligning on the main component (A) or the satellite potential (B). The MUP onset and the main spike are captured more sharply in (A). The satellite potential is captured more sharply in (B).

3. Results

3.1. Typical decomposition

The steps involved in the decomposition process can be understood more fully with reference to Fig. 5, which shows the results of the initial automatic decomposition procedure for the signal of Fig. 1. This EMG signal was recorded during a moderately strong contraction of the brachioradialis muscle (this particular signal does not contain any irregularities related to doubly innervated fibers). The program detected 12 MUs, and identified their discharge patterns well enough to be able to estimate the mean IDIs for most of them (but not, e.g., MU 12). The program may also have made some mistakes. For example, the short IDI of MU 7 near 0.7 s suggests a possible misidentification.

The decomposition was completed manually. The strategy used was to fill in the incomplete discharge patterns, beginning with the larger MUs and working to the smaller ones. For example, the horizontal bar indicates the expected location of a discharge of MU 1, based on the timing of its surrounding discharges. The most likely location is the spike at 1.148 s. When MU 1 was aligned with this spike, it gave a good fit, and the operator recognized the residual to be an occurrence of MU 4. Proceeding in this way, the operator filled in the discharge patterns of all the MUs to finally achieve the decomposition shown in Fig. 1. Note that the superimposition at 1.184 s involved 6 MUs. The operator guessed which MUs were involved from the discharge patterns. The alignment algorithm was able to achieve a very close match, confirming that these MUs were indeed involved and establishing their precise discharge times (Fig. 1D).

During the course of the decomposition, the operator noticed and made templates for five additional MUs that had not been detected initially. The smallest of these, MU 17, was only slightly larger than the baseline noise, but it had a distinctive shape and could be confidently recognized in all but a few instances. In those instances the expected discharge times coincided with superimpositions of other MUPs and the occurrences of MUP 17 could not be located unequivocally because of the residual noise.

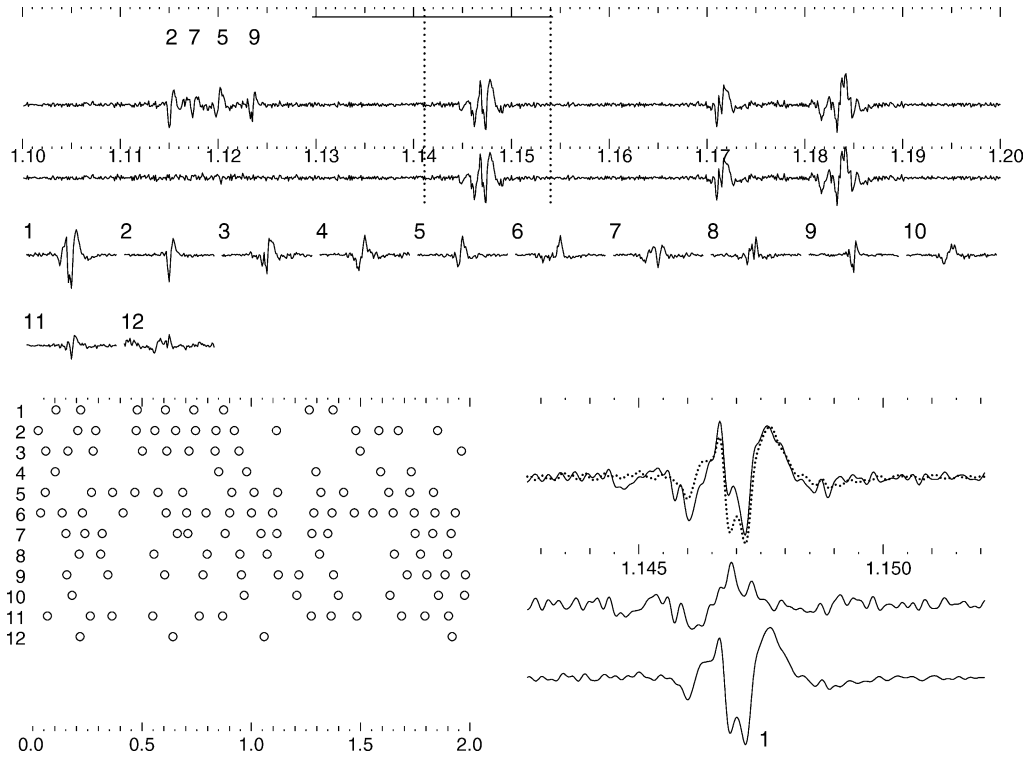

Fig. 5. EMGLAB screen after the initial automatic decomposition procedure for the signal of Fig. 1. The decomposition is incomplete and needs to be completed manually. The horizontal line in the signal panel shows the expected discharge time of MU 1. In the close-up panel, the template of MU 1 has been aligned with the spike at 1.148 s. The residual can be recognized as an occurrence of MU 4.

The validity of the decomposition in Fig. 1 can be judged by the small amplitude of the residual signal and the regularity of the discharge patterns. The residual is everywhere smaller than all but the smallest templates, making it very unlikely that any of the discharges of the larger MUs were misidentified. All the discharge patterns except for MUs 13, 14, and 16 contain regular intervals with no obvious gaps or extra discharges. The discharge patterns of MUs 13, 14, and 16 were slower and less regular than the others, but a careful recheck of the gaps failed to find that any discharges had been overlooked. This type of slow, less regular pattern is characteristic of MUs discharging near their recruitment thresholds, and so there is no reason to suspect that the decomposition is not substantially correct.

3.2. Objective validation

Because EMG decomposition is complicated and subjective, it is important to assess its accuracy in an objective way (Farina et al., 2001). The decomposition accuracy of a particular signal can be gauged by cross-checking with another signal recorded simultaneously from a nearby site in the same muscle (Mambrito and De Luca, 1984). Some of the activity in the two signals will come from the same set of MUs, although the signals themselves will be quite different. The cross-checking approach is based on the assumption that wherever independent decompositions of two separate signals agree about the identity and precise timing of a particular discharge, then that identification is probably correct. Otherwise, both decompositions would have to be in error by exactly the same amount, which is highly unlikely given the different characteristics of the two signals. On the other hand, wherever the two decompositions disagree, then at least one of them must be wrong.

This technique is illustrated in Fig. 6, which shows segments of the signal of Fig. 1 and a second signal that was recorded simultaneously from the other wire of the fine-wire pair. The two wires had been inserted together using a single hypodermic needle, and their recording surfaces were separated by about 2 mm due to different barb lengths. The signals were decomposed independently, i.e., without using any information from one signal during the decomposition of the other. A total of 17 MUP trains were identified in one signal, and 13 in the other. A comparison of the discharge patterns revealed that 10 pairs of trains were time-locked and hence corresponded to the same 10 MUs. These trains exhibited inter-channel offsets, but very little inter-channel jitter because of the close proximity of the two electrodes.

The number of decomposition errors was determined by counting the number of discharges for which the two decompositions disagreed by more than ±0.5 ms (after correcting for the intra-channel offset). Over the entire 10 s epoch, five

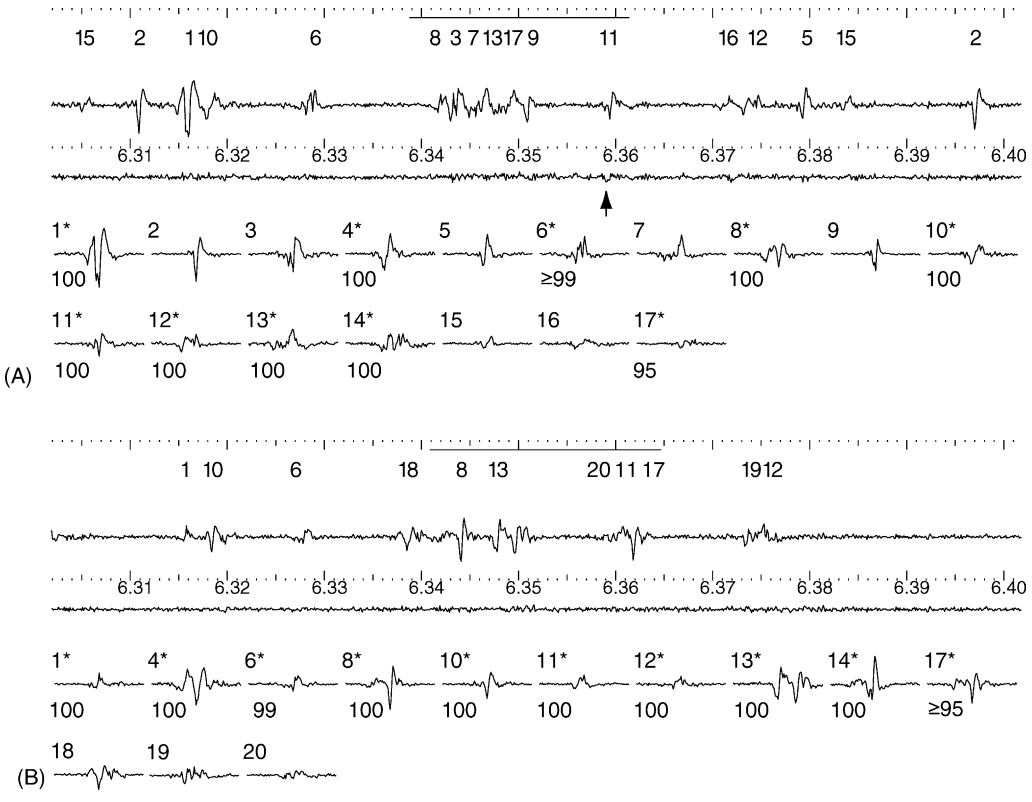

Fig. 6. Assessment of decomposition accuracy. (A) Decomposition of a segment of the EMG signal of Fig. 1. (B) Decomposition of the corresponding segment of a signal recorded simultaneously from a nearby site in the same muscle. The MUs marked with stars were detected in both signals, although with different templates and different amplitudes in each signal. The numbers under the templates indicate the estimated decomposition accuracy of those MUs in the two signals. The arrow at 6.36 s in signal A indicates the actual discharge time, based on signal B, of a misidentified instance of MU 17.

errors were found for MU 17, one for MU 6, and none for the other eight MUs. Assuming that the errors were probably made in the signal in which the MU had the smaller spike, this allowed us to estimate the identification accuracy (the number of correct identifications divided by the total number of discharges) for 18 of the MUPs in the two signals (see Fig. 6). These results agree with a more extensive validation study that showed that an identification accuracy of 98% or greater can generally be expected for MUPs that have peak amplitudes greater than 2.5 times the overall rms signal amplitude (McGill et al., 2004).

None of the errors involved missing discharges or false positives, because those types of errors were noticed and corrected during decomposition. Instead, all the errors involved slight misplacements of small MUPs, usually when they were involved in superimpositions with larger MUPs. These errors were typically less than 5 ms in magnitude, and they had only a small effect on the smoothed IFR profiles. One of the largest errors can be seen in Fig. 6A. A discharge of MU 17 was expected in the interval indicated by the horizontal bar. The operator located it in the spike at 6.35 s, but signal 5B shows that it actually occurred during the spike at 6.36 s. This particular error can be attributed to human error, since the operator failed to notice the actual discharge in the residual at 6.36 s. Other errors were attributable to low-signal-to-noise ratio.

3.3. Recruitment and discharge behavior

An example of using EMG decomposition to study MU discharge behavior is shown in Fig. 7. EMG signals were recorded from two separate fine-wire electrodes in the medial gastrocnemius muscle during an isometric ramp contraction. The electrodes were inserted 1 cm apart in a direction oblique to the muscle-fiber axis. The signals were decomposed and, to make the results from the two electrodes more comparable, only those MUs that had spike amplitudes greater than 20 μV peak-to-peak were accepted for further analysis. Since spike amplitude decreases with distance, this was roughly equivalent to including only those MUs that had at least one fiber within a certain fixed distance of one or the other electrodes. This gave a total of 16 MUs, 7 of which were detected only at one site, 7 only at the other site, and 2 at both sites.

Fig. 7A shows the recruitment patterns at the two sites. These plots were obtained by simply counting the number of MUs that were active in each signal at each instant in time. The MUs that were detected at both sites were included in both counts. It can be seen that the recruitment profiles were numerically similar, and that they closely resembled the force profile. This can be interpreted to mean that the MUs were homogeneously distributed in terms of their recruitment thresholds in the vicinity of the two electrodes, and that each electrode sampled a comparable, representative cross-section of muscle tissue.

The smoothed IFRs of the MUs are shown in Fig. 7B. The IFRs fluctuated considerably, but they all followed a common pattern that presumably reflects the pattern of the common

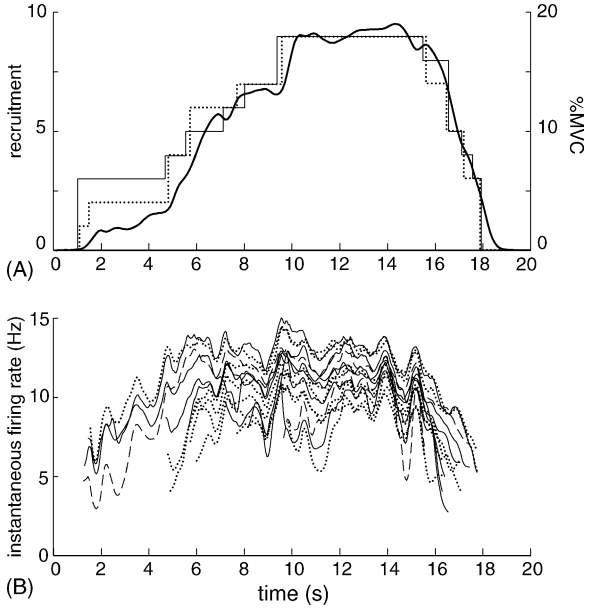

Fig. 7. (A) Muscle force (heavy) and MU recruitment estimated at two sites (thin, dotted) during a ramp contraction of the medial gastrocnemius muscle. Recruitment was estimated by counting the number of MUs that were active at each instant in time. (B) Instantaneous firing rate (IFR) profiles of the MUs during the contraction. MUs detected only at one site or the other are indicated by solid or dotted lines. Two MUs detected at both sites are indicated by dashed lines.

drive to the motoneuron pool (De Luca and Erim, 1994). The patterns of the IFR fluctuations of the MUs detected at the two different recording sites were indistinguishable, which bolsters confidence in the accuracy of the decompositions.

3.4. MUP averaging

The use of full decomposition to acquire high-accuracy MUP waveforms is illustrated in Fig. 8. Signals were recorded simultaneously from a pair of fine-wire electrodes in the semitendinosus muscle. A segment of the unfiltered signal

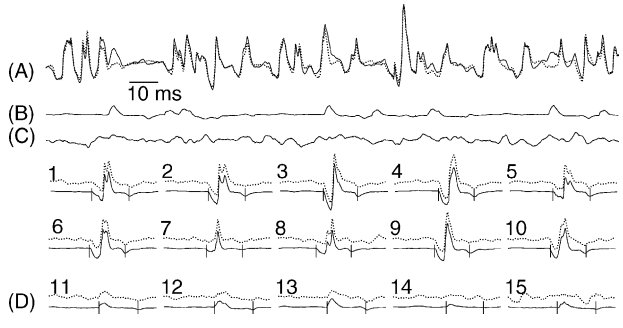

Fig. 8. MUP waveform averaging. (A) Unfiltered EMG signal from the semitendinosis muscle (solid) and reconstructed contribution of the 10 MUs that were decomposable in the signal (dotted). (B) Reconstructed contribution of five additional MUs decomposed from a nearby site. (C) Residual signal. (D) MUP waveforms obtained using averaging with (solid) and without (dotted) interference cancellation. The tics indicate the MUP onsets and terminal waves.

from one electrode is shown in Fig. 8A. 10 MUPs were fully decomposed in this signal, and an additional 5 MUPs were decomposed in the signal from the other electrode. The MUP waveforms were averaged from 10 s of data using the interference-cancellation algorithm (Fig. 8D, solid). For comparison, the simple averages (without interference cancellation) were also computed (Fig. 8D, dotted). It can be seen that the former averages have very flat baselines and clearly visible onsets and terminal waves (Fig. 8D, tics), whereas these features cannot be identified reliably in some of the waveforms obtained by simple averaging. Note also that even though MUs 11–15 were not decomposable in this signal, it was still possible to average their MUP waveforms using the discharge patterns from the other signal.

The completeness of the decomposition can be appreciated by looking at Fig. 8A–C. The dotted trace in Fig. 8A shows the reconstructed signal formed by summing together the MUP waveforms of MUs 1–10 at their detected discharge times. Fig. 8B shows the reconstruction for MUs 11–15, and Fig. 8C shows the residual. It can be seen that MUs 1–10 were responsible for most of the activity in the signal, and that their contribution has been completely accounted for by the decomposition. MUs 11–15 are farther away and make only a small contribution. The residual comes from other distant MUs whose broad MUPs sum together to make a low-frequency interference pattern, much like the surface EMG signal in which individual MUPs cannot easily be distinguished.

The noise reduction achieved using interference cancellation can be appreciated by noting that in simple averaging the entire signal essentially acts as noise, whereas with interference cancellation only the residual signal does. The availability of the second channel made it possible to cancel the interference from MUs 11 to 15, which provided a further, although in this case only slight, noise reduction.

3.5. MU architecture

An example of the use of MUP waveforms from different sites in a muscle to investigate muscle architecture is shown in Fig. 9. Signals were recorded from four pairs of fine-wire electrodes inserted at sites 2 cm apart along the proximodistal axis of the brachioradialis muscle. A total of 26 distinct MUs were identified. They fell into two classes, based on the spatial distribution of their MUPs across the four recording sites. A representative of each class is shown in Fig. 9A.

Several technical points should be made. The difference in amplitude of the MUPs at the different recording sites is due to the fact that the different electrodes ended up at different locations within the MU cross-sections. The initiations and terminal waves in Fig. 9 are smaller and more difficult to identify than those in Fig. 8. This is typical in brachioradialis, and is probably due to several factors, including small innervation ratios, long fiber lengths, and diffuse intrafascicular terminations. Nevertheless, since these features correspond to non-propagating components of the MUP (Stegeman et al., 1997), it is only necessary to identify them at one recording site. The correctness of these latency values was supported by the fact that similar values were found for the other MUPs in each class.

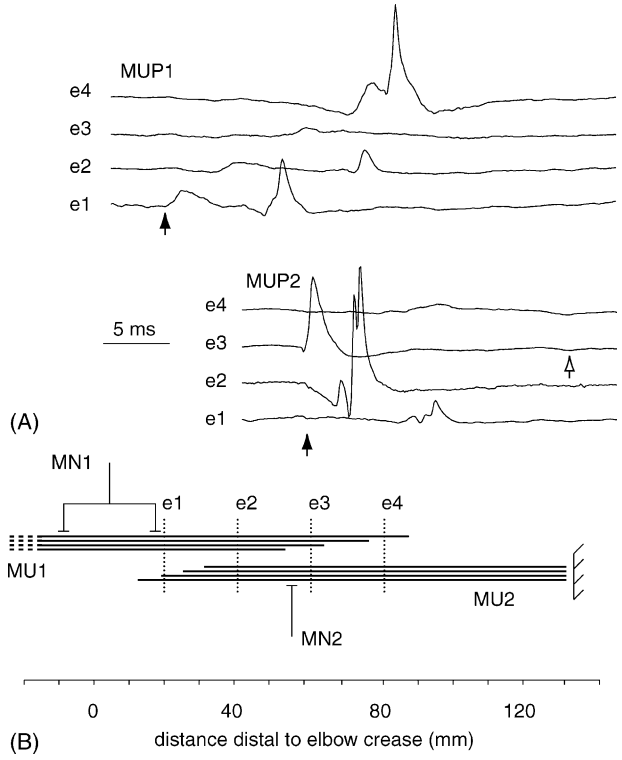

Fig. 9. MU architecture. (A) MUP waveforms of two MUs at four sites (e1–e4) along the proximodistal axis of the brachioradialis muscle. The solid arrows indicate the onsets and the open arrow indicates a terminal wave. (B) Estimated architectures of the two MUs. MN1 and MN2 indicate the motoneurons of the two MUs.

MUP 1 consisted of two waves, the first initiating near electrode site e1 and propagating distally at least as far as e4 with a conduction velocity of about 4 m/s, and the second following about 8 ms later but terminating before site e3. Assuming that the two waves were initiated at approximately the same time, the second wave must have originated about 30 mm proximal to e1. The lack of distinct terminal waves associated with either component suggests diffuse intrafascicular terminations.

MUP 2 consisted of a single main wave, although distinct spikes were visible at some recording sites, indicating a slight dispersion among the endplates locations or conduction velocities of the individual muscle fibers. The wave initiated near site e3 and propagated in both directions. A distinct terminal wave was visible 20 ms after the initiation, indicating a tendinous termination 80 mm distal to e3.

Thus, the overall architecture is that of a series-fibered muscle (Fig. 9B). MU 1 belongs to a proximal band of MUs that are innervated in two endplate zones near the elbow crease and that terminate intrafascicularly. MU 2 belongs to a distal band of MUs that are innervated in an endplate zone 60 mm distal to the elbow crease and that terminate at the

distal tendon. It would not have been possible to obtain this complete picture without the spatial information provided by the multiple recording sites.

3.6. Doubly innervated muscle fiber

The ability to subtract out the activity of certain MUs in order to highlight the activity of other MUs is illustrated in Fig. 10. The signal in Fig. 10A was recorded by a fine-wire electrode in the brachioradialis muscle. Decomposition revealed seven stable MUPs and two irregular ones. One of the irregular MUPs had gaps in its discharge pattern, and the other had an unstable waveform. In order to observe the behavior of the unstable MUPs more clearly, the activity of the stable MUPs was subtracted from the signal (Fig. 10B). The traces were aligned on the successive discharges of MU 1. MU 2 had a slightly higher discharge rate, so its discharges would be expected to occur somewhat earlier in each trace. In traces 3–5, MUP 2 did not occur at its expected discharge times (x's). In traces 6–8, MUP 1 was disrupted. This is the characteristic pattern of irregularities associated with a doubly innervated fiber (Lateva et al., 2002).

These irregularities can be explained in the following way (see Fig. 10C). MUs 1 and 2 shared a doubly innervated muscle fiber, the potentials of which were recorded both as MUP 2 and as the volatile component of MUP 1. The two endplates were about 30 mm apart, and the electrode was beyond the endplate of MU 1. Whenever MU 1 discharged less than about 25 ms before an expected occurrence of MUP 2 (as in traces 3–5), the leftward traveling action potential in the shared fiber collided with the action potential from MU 2 preventing it from reaching the electrode. Whenever MU 1 discharged shortly after MUP 2 (as in traces 6–8), the shared fiber was still partially refractory, and so its contribution to MUP 1 was delayed and attenuated. The ability to subtract out the activity of the other MUPs makes it possible to analyze these irregularities in some detail.

4. Discussion

4.1. Comparison with other methods

MU discharge patterns can be studied using both single- and multi-unit techniques. In single-unit studies, a highly selective electrode or a low-level of contraction is used to isolate the activity of a single MU (Bigland and Lippold, 1954; Datta and Stephens, 1990). The advantage of single-unit techniques is that the discharge pattern can be identified easily. The disadvantage is that only one MU can be studied at a time. Multi-unit techniques require more processing, but they yield information about multiple MUs, and, moreover, MUs that are active simultaneously.

EMG decomposition is employed somewhat differently in clinical and physiological applications. Clinically, EMG decomposition is used to diagnose neuromuscular disorders (Haas and Meyer, 1989; Stashuk, 2001). The goal is to quickly and automatically characterize MUPs and MUP trains in signals from low and moderate contractions. Clinical decomposition is primarily concerned with signals recorded by concentric and monopolar needle electrodes, although there is now interest in high-density surface electrode arrays as well (Kleine et al., 2000). Clinical decomposition methods need to be robust enough to deal with MUP instability in pathology, but they do not necessarily need to be able to achieve full decomposition.

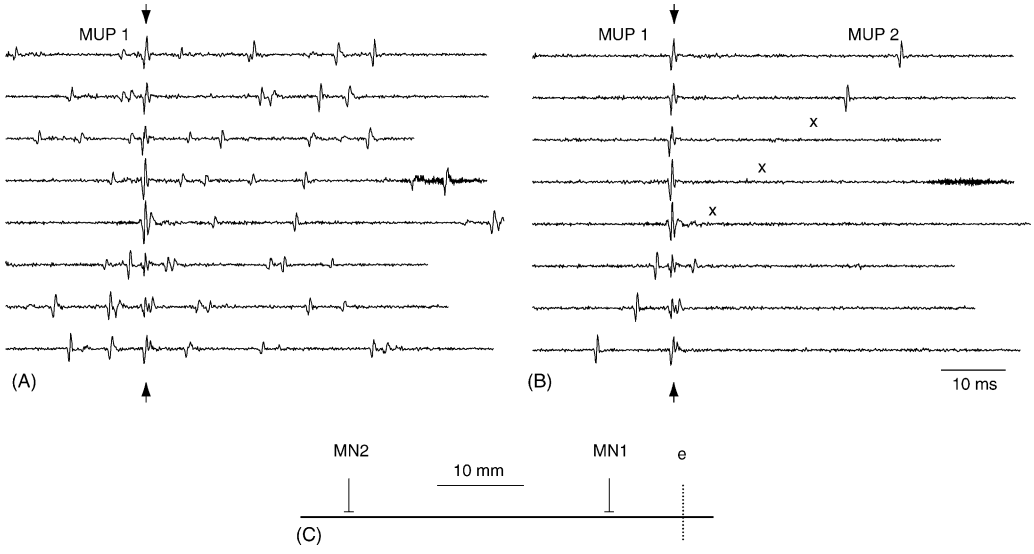

Fig. 10. Doubly innervated muscle fiber. (A) Consecutive traces of EMG signal (high-pass filtered) from the brachioradialis muscle, aligned by the discharges of MU 1 (arrows). (B) The same traces after subtracting out all the identified activity except for the discharges of MUs 1 and 2. The subtraction reveals irregularities indicative of a doubly innervated fiber: blocking of MUP 2 (x's) and disruption of MUP 1 (last three traces). (C) These irregularities are explained if MUP 2 and the volatile component of MUP 1 came from a single muscle fiber shared by both MUs. e indicates the electrode.

Although EMGLAB is not intended for routine clinical use, it is well suited for analyzing the types of signals recorded clinically, namely, single-channel signals recorded by conventional needle electrodes. The ability in EMGLAB to inspect individual discharges and subtract out interfering activity lends itself to investigations of the physiological mechanisms underlying electrophysiological phenomena. For example, we have used this ability to study the origin of satellite potentials in normal muscle (Lateva and McGill, 1999) and the mutual blocking behavior of action potentials in doubly innervated muscle fibers (Lateva et al., 2002, 2003).

In physiological applications, human interaction is often used to ensure full and accurate decompositions. The best known of these methods is the precision decomposition method (De Luca, 1993; Nawab et al., 2002; De Luca et al., 2004). It is specifically designed to analyze multi-channel signals recorded by a special quadrifilar needle electrode. This electrode uses multiple closely spaced recording surfaces to record highly selective signals from very close-by muscle fibers. This makes it possible to identify MUP trains during even the highest levels of contraction. Precision decomposition involves several automatic steps, but it relies on human supervision to complete and check the decomposition.

EMGLAB differs from precision decomposition in several ways. EMGLAB is able to analyze single-channel signals, including signals recorded using conventional needle and fine-wire electrodes. It uses interpolation rather than oversampling to achieve high temporal resolution, which permits a lower sampling rate (10 kHz compared to 50 kHz) and reduces storage requirements. The user interface is based on the continuous signal rather than just the spikes that exceed a threshold, which makes it easier to identify and analyze even small MUPs and MUP components. EMGLAB also displays the continuous residual signal to facilitate verification of decomposition completeness and accuracy.

Like some other methods, EMGLAB provides a "decomposition-triggered averaging" capability to extract MUP waveforms from the unfiltered EMG interference pattern. The fidelity of the averages is enhanced by interference cancellation. EMGLAB also includes several unique capabilities, including a robust algorithm for resolving complicated superimpositions and an ability to accommodate appreciable inter-channel jitter in signals from widely separated electrodes.

EMGLAB's facilities for reading, displaying, and interacting with EMG signals also make it an ideal platform for developing and testing new decomposition algorithms. The ability to manually check results provides an accurate way to assess algorithm performance.

4.2. Full decomposition

Full decomposition provides a complete accounting of every discharge in an EMG signal. This level of detail is not necessary in every application, but it may be needed for studying certain phenomena such as common MU discharge behavior, variability of MUP components, and MU architecture. Furthermore, by making sure that all the activity in a signal is fully accounted for, full decomposition also ensures that an unbiased and representative sampling of muscle activity is obtained from each recording.

Another advantage of full decomposition is that it provides an added measure of confidence in the accuracy of the results, in much the same way that the overall integrity of a completed jigsaw puzzle confirms the correct placement of the individual pieces. If a signal is only partially decomposed, one can never be entirely certain whether every other discharge might be missing from some discharge patterns or whether some MUs might have been overlooked altogether. However, when a signal is fully decomposed, with every discharge and superimposition accounted for to the level of the baseline noise by a set of physiologically realistic MUP trains, then those MUP trains can reasonably be considered to be substantially correct.

4.3. Decomposition accuracy

Most investigators would agree that the regular stereotypical discharges recorded in single-unit studies provide an unequivocal record of the discharge pattern of a single MU. Likewise, most investigators who have examined low- and moderate-level multi-unit EMG signals closely would agree that it is usually possible, given sufficient effort, to identify the discharge patterns of several MUPs with a high level of confidence.

Cross-checking studies like the one described here confirm that this confidence is warranted. EMG signals were recorded from two nearby sites in the same muscle. The signals contained activity from many of the same MUs, but the MUPs themselves and the non-common activity were quite different. Nevertheless, independent decompositions of the two signals agreed precisely on the timing of every discharge of eight large MUs. Thus, it is highly likely that all those discharges were identified correctly. The independent decompositions also showed that although some of the smaller discharges were identified incorrectly, most of them were identified correctly. These results confirm the subjective impression of experienced operators that the discharges of larger MUPs are by-and-large unambiguous and that smaller MUPs can be identified reliably enough to at least approximate their overall discharge patterns.

While it is not practical to validate every decomposition by cross-checking, results such as these can be used to estimate decomposition accuracy in signals of comparable complexity. For example, we expect that in signals that have been confidently decomposed by an experienced operator, MUPs with peak amplitudes greater than 2.5 times the rms signal amplitude will have been identified correctly to within ± 0.5 ms at least 98% of the time, but that MUPs with peak amplitudes between 1.0 and 2.5 times the rms signal amplitude will have been mislocated by up to ± 5 ms up to 10% of the time (McGill et al., 2004).

An objective assessment of decomposition accuracy is important for properly interpreting the scientific validity of decomposition results. It should be noted that different levels of accuracy may be called for in different applications. For example, a higher level of accuracy may be needed to estimate short-term synchronization than to estimate mean firing rate. It should also be noted that decomposition accuracy depends on both the MUP and the signal in which it occurs. The same level of accuracy cannot necessarily be expected for two different MUPs in the same signal, or for the same MUP in two different signals. Therefore, accuracy should properly be assessed for every individual MUP in every individual signal.

4.4. Human interaction

At present, EMGLAB still relies on manual interaction to accomplish full decomposition. The amount of manual effort needed is minimal for signals with eight or fewer MUP trains, which the program is largely able to decompose automatically. The effort is typically 10–20 min/s for signals with 9–12 MUP trains. More complex signals, multi-channel signals, and signals with volatile MUP components may take even longer.

We continue to develop EMGLAB's automatic procedures to make them more capable and reduce the amount of human involvement. Promising new approaches include the use of algorithms from coding and information theory (Gut and Moschytz, 2000; Koch and Loeliger, 2004) and techniques from artificial intelligence (Nawab et al., 2002, 2004).

In scientific investigations, however, a certain amount of "hands-on" inspection of individual data records is important in its own right. Not only does this help to ensure that the analysis and interpretation are consistent with the data, but it also widens the opportunity for new insights and discoveries. EMGLAB's ability to examine signals at different levels ranging from the discharge-to-discharge variations of individual MUP components to the seconds-long fluctuation patterns of MU populations provides a useful tool in this regard.

Acknowledgements

This work was supported by the Medical and Rehabilitation R&D Services of the US Department of Veterans Affairs (KM, ZL) and by the US National Institutes of Health (R01 AR049842) (KM, ZL).

References

Adam A, De Luca CJ. Recruitment order of motor units in human vastus lateralis muscle is maintained during fatiguing contractions. J Neurophysiol 2003;90:2919–27.

Andreassen S, Rosenfalck A. Regulation of the firing pattern of single motor units. J Neurol Neurosurg Psychiatry 1980;43:897–906.

Basmajian JV, De Luca CJ. Muscles alive: Their functions revealed by electromyography. 5th ed. Baltimore: Williams & Wilkins; 1985.

Bigland B, Lippold OCJ. Motor unit activity in the voluntary contraction of human muscle. J Physiol 1954;125:322–35.

Datta AK, Stephens JA. Synchronization of motor unit activity during voluntary contraction in man. J Physiol 1990;422:397–419.

De Figueiredo RJP, Gerber A. Separation of superimposed signals by a cross-correlation method. IEEE Trans Acoust Speech Signal Process 1983;31:1084–9.

De Luca CJ. Precision decomposition of EMG signals. Meth Clin Neurophysiol 1993;4:1–28.

De Luca CJ, Erim Z. Common drive of motor units in regulation of muscle force. Trends Neurosci 1994;17:299–305.

De Luca CJ, Nawab SH, Adam A, Roark RM, Manto MU, Wotiz R, et al. The second-generation precision decomposition system for EMG signals: an overview. In: Proceedings of 15th congress international society of electrophysiological kinesiology; 2004. p. 157.

Desmedt JE. Size principle of motoneuron recruitment and the calibration of muscle force and speed in man. In: Desmedt JE, editor. Motor control mechanisms in health and disease. Basil: Karger; 1983. p. 227–51.

Etawil H, Stashuk D. Resolving superimposed motor unit action potentials. Med Biol Eng Comput 1996;34:33–40.

Farina D, Colombo R, Merletti R, Olsen HB. Evaluation of intramuscular EMG signal decomposition algorithms. J Electromyogr Kinesiol 2001;11:175–87.

Gut R, Moschytz GS. High-precision EMG signal decomposition using communications techniques. IEEE Trans Signal Process 2000;48:2487–94.

Haas WF, Meyer M. An automatic EMG decomposition system for routine clinical examination and clinical research—ARTMUP. In: Desmedt JE, editor. Computer-aided electromyography and expert systems. Amsterdam: Elsevier; 1989. p. 67–81.

Kleine BU, Blok JH, Oostenveld R, Praamstra P, Stegeman DF. Magnetic stimulation-induced modulations of motor unit firings extracted from multi-channel surface EMG. Muscle Nerve 2000;23:1005–15.

Koch VM, Loeliger HA. Decomposition of electromyographic signals by iterative message passing in a graphical model. In: Proceedings of 26th IEEE engineering in medicine biology society conference; 2004. p. 65–8.

Lateva ZC, McGill KC. Satellite potentials of motor unit action potentials in normal muscles: a new hypothesis for their origin. Clin Neurophysiol 1999;110:1625–33.

Lateva ZC, McGill KC. Estimating motor-unit architectural properties by analyzing motor-unit action potential morphology. Clin Neurophysiol 2001;112:127–35.

Lateva ZC, McGill KC, Johanson ME. Electrophysiological evidence of adult human skeletal muscle fibres with multiple endplates and polyneuronal innervation. J Physiol 2002;544(Pt 2):549–65.

Lateva ZC, McGill KC, Johanson ME. Increased jitter and blocking in normal muscles due to doubly innervated muscle fibers. Muscle Nerve 2003;28:423–31.

Lefever RS, De Luca CJ. A procedure for decomposing the myoelectric signal into its constituent action potentials. I. Technique, theory, and implementation. IEEE Trans Biomed Eng 1982;29:149–57.

Mambrito B, De Luca CJ. A technique for the detection, decomposition and analysis of the EMG signal. Electroencephalogr Clin Neurophysiol 1984;58:175–88.

McGill KC, Dorfman LJ. High-resolution alignment of sampled waveforms. IEEE Trans Biomed Eng 1984;31:462–8.

McGill KC, Cummins KL, Dorfman LJ. Automatic decomposition of the clinical electromyogram. IEEE Trans Biomed Eng 1985;32:470–7.

McGill KC. Optimal resolution of superimposed action potentials. IEEE Trans Biomed Eng 2002;49:640–50.

McGill KC, Lateva ZC, Johanson ME. Validation of a computer-aided EMG decomposition method. In: Proceedings of 26th IEEE engineering in medicine biology society conference; 2004. p. 4744–7.

Nawab SH, Wotiz RP, Hochstein LM, De Luca CJ. Next-generation decomposition of multi-channel EMG signals. In: Proceedings of 24th IEEE engineering in medicine biology society conference; 2002. p. 36–7.

Nawab SH, Wotiz R, De Luca CJ. Second generation precision decomposition: challenges. In: Proceedings of 15th congress international society of electrophysiological kinesiology; 2004. p. 160.

Nordstrom MA, Fuglevand AJ, Enoka RM. Estimating the strength of common input to human motoneurons from the cross-correlogram. J Physiol 1992;453:547–74.

Stålberg E, Andreassen S, Falck B, Lang H, Rosenfalck A, Trojaborg W. Quantitative analysis of individual motor unit potentials: a proposition for standardized terminology and criteria for measurement. J Clin Neurophysiol 1986;3:313–48.

Stålberg EV, Sonoo M. Assessment of variability in the shape of the motor unit action potential, the "jiggle," at consecutive discharges. Muscle Nerve 1994;17:1135–44.

Stashuk D, Qu Y. Robust method for estimating motor unit firing-pattern statistics. Med Biol Eng Comput 1996;34:50–7.

Stashuk D. EMG signal decomposition: how can it be accomplished and used? J Electromyogr Kinesiol 2001;11:151–73.

Stegeman DF, Dumitru D, King JC, Roeleveld K. Near- and far-fields: source characteristics and the conducting medium in neurophysiology. J Clin Neurophysiol 1997;4:429–42.

Zennaro D, Wellig P, Koch VM, Moschytz GS, Laubli T. A software package for the decomposition of long-term multichannel EMG signals using wavelet coefficients. IEEE Trans Biomed Eng 2003;50: 58–69.