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EMG signal decomposition: how can it be accomplished and used?

Dan Stashuk

Department of Systems Design Engineering, University of Waterloo, Ontario, Canada

Abstract

Electromyographic (EMG) signals are composed of the superposition of the activity of individual motor units. Techniques exist for the decomposition of an EMG signal into its constituent components. Following is a review and explanation of the techniques that have been used to decompose EMG signals. Before describing the decomposition techniques, the fundamental composition of EMG signals is explained and after, potential sources of information from and various uses of decomposed EMG signals are described. © 2001 Elsevier Science Ltd. All rights reserved.

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1. Introduction

Some electromyographic (EMG) signals, detected using selective indwelling electrodes, can be decomposed into their constituent motor unit action potential trains (MUAPTs). The MUAPTs that contribute to an EMG signal provide information regarding the temporal behaviour and morphological layout of motor units that are active during muscle contraction. Such information can assist in the diagnosis of various neuromuscular disorders and in the development of a better understanding of healthy, pathological, ageing or fatiguing neuromuscular systems. Fig. 1 conceptually presents the process of EMG signal decomposition and depicts the relationship between a decomposed EMG signal and the activity of individual motor units.

The decomposition of an EMG signal and the useful analysis of the resultant information involve the application of signal processing and pattern recognition algorithms and were first reported by De Luca and co-workers [11,12,41,42]. In this presentation the fundamental concepts and aspects involved in the successful decomposition of an EMG signal will be described and discussed. These will include assumptions and methods upon which decomposition is based and related limitations of all decomposition techniques. Specific ways in which EMG signal decomposition may be used for either clinical or research purposes will also be described.

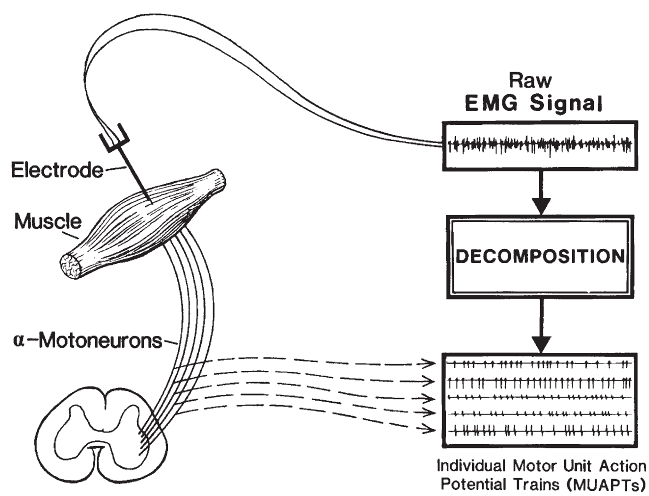

Fig. 1. EMG signal decomposition is the process of discovering the significant constituent MUAPTs that contribute to a detected EMG signal (from DeLuca et al. [11]).

2. EMG signal composition

In order to appreciate the concepts involved with decomposing an EMG signal it is essential to be familiar with the composition of an EMG signal [50,69].

2.1. MFAP

A muscle fibre action potential (MFAP), which is a fundamental component contributing to a detected EMG signal, results from the propagation of an action potential

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(AP) along the excitable membrane of a muscle fibre. Let the waveform resulting from the detection of the AP travelling along the ith fibre of a motor unit be called $\mathrm{MFAP}_i(t)$. The characteristics of $\mathrm{MFAP}_i(t)$ will depend upon the diameter of the fibre, the speed with which it conducts APs (its conduction velocity), its location relative to the detection electrode and the configuration of the detection electrode. Larger diameter fibres create larger MFAPs. APs conducted more slowly create MFAPs that have longer durations. The magnitude and high frequency content of a MFAP decrease as the distance between the electrode and fibre or the surface area of the electrode increase [2,39,46].

2.2. MUAP

The fibres of a muscle are not excited individually. They are controlled together in groups, called motor units. Formally, a motor unit is an alpha-motoneuron, its axon and all of the muscle fibres it innervates. As such, individual MFAPs are, under normal circumstances, not detected. Instead a summation of all of a motor unit's MFAPs or a motor unit action potential (MUAP) is detected. Let $\mathrm{MUAP}_j(t)$ be the potential detected when the jth motor unit fires.

$$\mathrm{MUAP}_j(t)=\sum_{i=1}^{N_j}\mathrm{MFAP}_i(t-\tau_i)s_i \qquad (1)$$

where τ_i is the temporal offset of $\mathrm{MFAP}_i(t)$; N_j is the number of fibres in motor unit j; s_i is a binary variable used to represent neuromuscular junction function that has a value of 1 if fibre i fires and 0 if the fibre is blocked (i.e. does not fire).

τ_i, the temporal offset of the ith fibre, is dependent on the location of its neuromuscular junction and its conduction velocity. N_j represents the size of the motor unit. The number of fibres within a motor unit can theoretically determine the size of the MUAP. However, because of the attenuation of MFAP size with distance to the detection electrode, the size of the MUAP is in practice often dependent on the location and diameter of the closet few fibres. This is usually the case when detecting the signal with small or micro electrodes such as concentric needle (CN), monopolar needle (MN) or single fibre needle (SFN) electrodes. This can also be the case when detecting signals using large or macro electrodes, such as surface or needle cannula electrodes, but this situation occurs less often. Therefore, the number of fibres close to the detection electrode and their diameters determine, for the most part, the shape of a MUAP. Fig. 2 depicts the composition of a MUAP as the summation of individual MFAPs.

The conduction delay (τ_i) for each fibre of the motor unit will fluctuate from motor unit discharge to discharge primarily due to variation in the time required by the

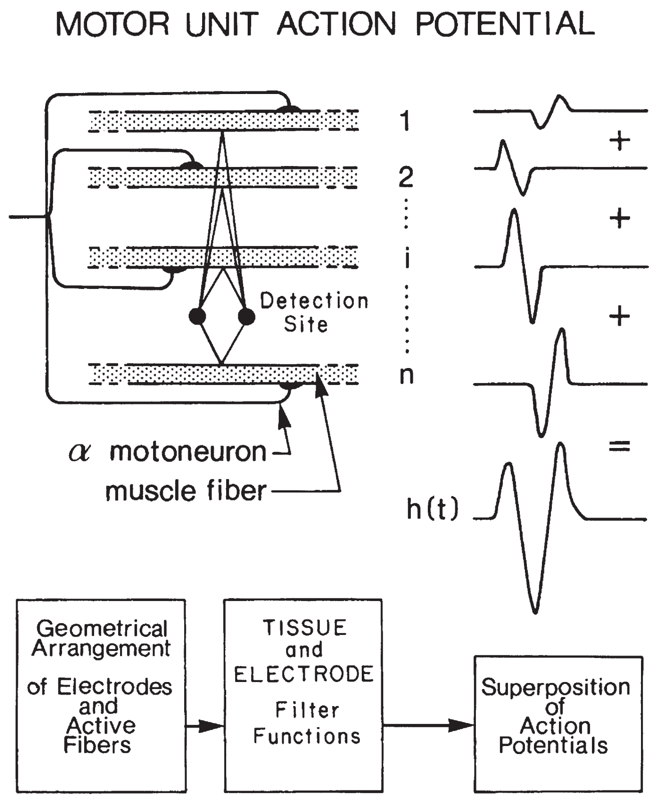

Fig. 2. A MUAP is composed of the summation of the MFAPs of its component muscle fibres. The location of a muscle fibre relative to the electrode, the surface area and configuration of the electrode and the diameter of the fibre greatly affect its contribution. MUAPs for a particular motor unit vary due to variable times of MFAP initiation, variable muscle fibre conduction velocity and possibly relative electrode movement (from Basmajian and DeLuca [2]).

neuromuscular junction of the fibre to depolarize its post-synaptic muscle fibre membrane and initiate the propagation of a MFAP. This in turn will cause the shapes of the MUAPs of a motor unit to biologically vary across its discharges. In general, MUAP waveforms will vary in shape due to variations in the delays of the fibre potentials (affecting τ_i), possible changes in the position of the electrode relative to the muscle fibres (affecting MFAP_i), and the possibility of a particular fibre failing to fire (affecting s_i). These variations are the source of stochastic biological variability in the MUAP waveform.

2.3. MUAPT

Motor units must fire repeatedly to maintain or increase the force generated by a muscle. As such, during a sustained contraction each motor unit generates multiple MUAPs. The collection of MUAPs generated by one motor unit, positioned at their times of occurrence or separated by their inter-discharge intervals (IDIs) is called a motor unit action potential train.

$$\mathrm{MUAPT}_j(t)=\sum_{k=1}^{M_j}\mathrm{MUAP}_{jk}(t-\delta_{jk}) \qquad (2)$$

where $\mathrm{MUAPT}_j(t)$ is the MUAPT of the jth motor unit; $\mathrm{MUAP}_{jk}(t)$ is the MUAP generated during the kth firing of the jth motor unit; M_j is the number of times the jth motor unit fires; δ_{jk} is the kth firing time of the jth motor unit.

Due to biological variations in the shape of a motor unit's MUAP, each $\mathrm{MUAP}_{jk}(t)$ will be unique. As the level of contraction increases the number of motor units active (i.e. the number of MUAPTs) and the number of MUAPs in each train per second will increase. In addition, larger motor units, that produce larger MUAPs per se, will be become active as the level of force increases [2].

2.4. Composite EMG signal

An electrode in a volume-conducting medium measures the electric potential field. Due to the property of superposition of electric fields, the electrode will measure the net electric potential, which is the spatial and temporal sum of potential contributions from all excited muscle fibres (of any motor unit). Therefore, the composite EMG signal is simply the summation of the MUAPTs of all recruited motor units.

$$\mathrm{EMG}(t)=\sum_{j=1}^{N_m}\mathrm{MUAPT}_j(t)+n(t) \qquad (3)$$

where: $\mathrm{MUAPT}_j(t)$ is the jth MUAPT; N_m is the number of active motor units; $n(t)$ is the background instrumentation noise.

Fig. 3 presents both an anatomical and physiological model relating to the detection of an EMG signal.

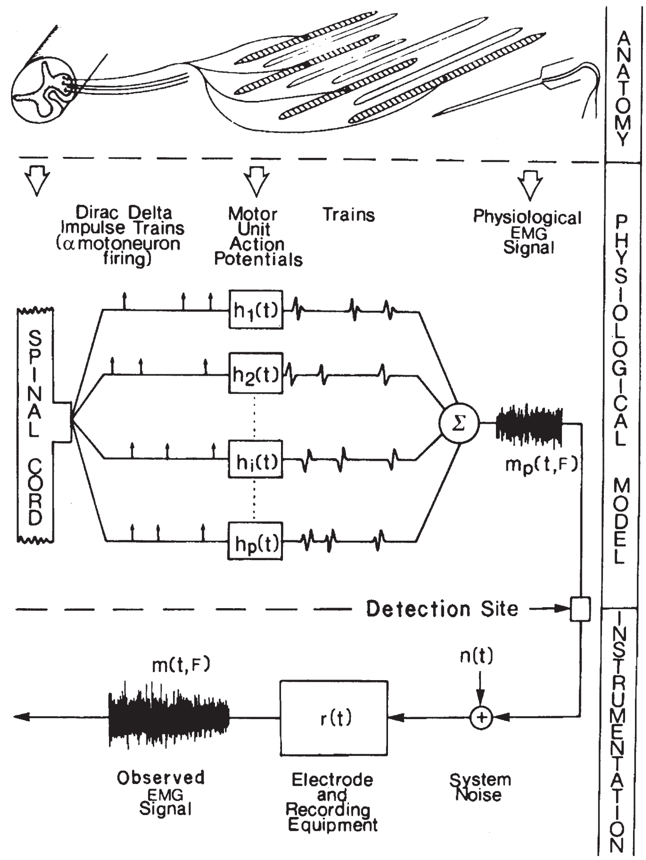

Fig. 3. Physiological and mathematical model for the composition of a detected EMG signal (from Basmajian and DeLuca [2]).

Theoretically, an EMG signal is composed of contributions from all active fibres in the muscle. However, due to the radial separation between distant muscle fibres and the electrode detection surface, the amplitude and high frequency content of MFAP contributions from distant fibres may be attenuated below the level of the background noise. At such low levels these MFAPs, by themselves, cannot be discriminated from noise. However, the superposition of small MFAP contributions with many other similar and coherent contributions, as occurs during the detection of a MUAP using an electrode with a large detection surface, can be recognized. As such, the contributions to an EMG signal that can be practically considered are dependent on the position of the electrode relative to the active muscle fibres and the physical characteristics of the electrode. For instance, an electrode with a small detection surface placed very close to a single muscle fibre can primarily detect the electrical activity of just this one fibre and thus the activity of a single motor unit. Alternately, for a larger detection surface, there will be many fibres that are equally close, yielding many equally sized contributions and thus making it impossible to selectively detect the activity of single fibres and difficult to distinguish the activity of single motor units.

Therefore, the shapes of the MUAPs within the MUAPTs contributing to a detected signal and the number of motor units that can be considered to be contributing MUAPTs with significant MUAPs depend on the configuration of the detection electrodes and their location relative to the contributing muscle fibres. As such, signals detected by electrodes with small surface area or micro-electrodes, such as CN, MN or SFN electrodes, are considered to be composed primarily of contributions of relatively high frequency content and from relatively few motor units with few fibres close to the electrode. Alternately, signals detected by electrodes with large surface area or macro-electrodes, such as surface or needle cannula electrodes, are considered to be composed primarily of contributions of relatively low frequency content and from a larger number of motor units with many of their fibres close to the electrode. Consequently, in signals detected with micro-electrodes, isolated MUAP occurrences and contributions of individual fibres to MUAPs can be easily detected and it is therefore possible to decompose these signals. On the other hand, in signals detected with macro-electrodes, it is more difficult to detect isolated MUAP occurrences and impossible to detect the contributions of individual fibres to MUAPs and therefore more difficult to decompose these signals.

3. How can an EMG signal be decomposed?

3.1. Basic assumptions

EMG signal decomposition is the process of resolving a composite EMG signal into its constituent MUAPTs. The two basic assumptions regarding the ability to decompose an EMG signal are that all of the discharges (i.e. MUAPs) of the motor units significantly contributing to the composite signal can be detected and that each detected MUAP can be correctly associated with the motor unit that created it. This requires methods for detecting MUAPs and recognizing detected MUAPs. To detect MUAPs some characteristic of their shape, that is common to all MUAPs, must be used to identify their occurrence within the composite signal. To recognize detected MUAPs requires that the MUAPs produced by the same motor unit must be more similar in shape than the MUAPs produced by different motor units and that differences in MUAP shapes can be determined. To recognize detected MUAPs also requires that the MUAPs of each motor unit occur enough times, by themselves (i.e. not at the same time as MUAPs of other motor units), so that the respective shapes of the MUAPs for each active motor unit can be determined. Considerations and constraints that govern the design and use of a decomposition system and the several tasks involved in accomplishing the decomposition of an EMG signal including segmentation, clustering, supervised classification, superposition resolution, and the discovery of temporal relationships between MUAPTs are discussed below.

3.2. Signal acquisition

3.2.1. Choice of electrodes

As discussed in Section 2.4, to obtain detailed, or *micro*, spatial and temporal information about the fibres of a motor unit, signals need to be acquired with electrodes that have small, selective detection surfaces such as MN, CN, SFN or wire electrodes. In contrast, to obtain information regarding the overall size and fibre spatial distribution of a motor unit, or *macro* information, signals must be acquired with electrodes that have large, non-selective surfaces such as overlying surface electrodes or indwelling macro [61] or conmac [34] electrodes. Therefore it is useful to acquire signals from at least two instrumentation channels. One channel acquires a *micro* signal detected by a MN, CN, SFN or wire electrode with an appropriate passband and sampling rate. The second channel could acquire a *macro* signal detected by an overlying surface or indwelling macro or conmac electrode with an appropriate passband and sampling rate. The *micro* signal is decomposed into its MUAPTs and the *macro* signal can be analyzed in conjunction with the results of the micro signal decomposition using triggered averaging techniques [61]. Additional micro signals, to improve the ability to discriminate between the MUAPs of different motor units [10,38,41,42], or additional macro signals, such a muscle force, could also be acquired.

3.2.2. Protocol of signal detection

The type of electrode, electrode positioning, profile of muscle contraction and muscle selected all affect the complexity and decomposability of the acquired signal. To ensure that a micro signal of adequate sharpness (slope) and signal to noise ratio is obtained the micro-electrode should be initially positioned, in a minimally contracting muscle, to detect MUAPs of maximum amplitude and sharpness. This ensures that the electrode is close to active muscle fibres which in turn will cause the detected MUAPs to be more distinct, with respect to the noise and each of the various active motor units, than if the electrode was not close to any active muscle fibres. In this way, MUAP amplitude and sharpness are two key factors of signal quality that should be maximized if possible. The subject is then instructed to, as isometrically as possible, increase the level of muscle contraction to the desired level. When at the desired level of contraction, data acquisition is initiated. If the decomposition system can process signals acquired during force changing contractions, data acquisition can be started immediately after needle positioning. Generally, the peak level of force is below 50% of maximal voluntary contraction (MVC) and the contractions must still be as isometric as possible to minimize needle movement which usually requires that the rate of change of force be $<$10%MVC/s. Signal complexity at a certain %MVC level of contraction is related to a number of physiological factors such as: the number of motor units in the muscle, muscle fibre diameter; the density of motor unit muscle fibres; motor unit recruitment thresholds and motor unit rate coding strategies. Smaller muscles, such as the first dorsal interosseous, compared to larger muscles, such as the biceps brachii, have fewer motor units, tend to have low as opposed to a broad range of recruitment thresholds and use large amounts of rate coding. Therefore, for comparable %MVC contractions, smaller muscles will on average generate more complex signals than signals detected in larger muscles [2].

3.2.3. Interesting EMG signal attributes

The ideal EMG signal decomposition system should be able to deal with signals with the following attributes:

1. five or more MUAPTs;
2. non-stationary MUAPs shapes usually due to electrode movement;
3. variable MUAP shapes due to variability in the operation of neuromuscular junctions and background biological noise due to the activity of other motor units;
4. two or more motor units with similar MUAP shapes;
5. frequent superpositions of MUAPs;
6. non-stationary motor unit firing pattern statistics; and
7. intermittent recruitment and decruitment of motor units.

3.2.4. Selection of sampling rate

The Nyquist sampling theorem predicts that the minimal rate at which a signal can be sampled without the loss of information is twice its maximum frequency content. This suggests that if a signal is bandlimited to 5 kHz, as are most EMG signals, a sampling rate as low as 10 kHz could be used. However, if this minimal rate were to be used signal interpolation techniques, either in the time or frequency domains, would be required to obtain sufficient temporal resolution when comparing signal component shapes and for adequate graphical display. Sampling at a 25 kHz rate is a compromise between extreme oversampling, which can require specialized hardware, and sampling at the minimal rate, which may require signal interpolation.

3.3. Segmentation of the composite signal (detecting MUAPs)

The first step in the decomposition of an acquired EMG signal is to detect all of the MUAPs generated by motor units active during signal acquisition. However, in practice, the MUAPs of motor units with no fibres close to the detection surface will be of low amplitude, composed of primarily low frequency components and very similar in shape. Therefore, it is very difficult to consistently assign such MUAPs to their correct MUAPT and it is easy to miss occurrences of such MUAPs when they occur in close temporal proximity to larger MUAPs. Consequently, it is necessary to select and consistently detect only those MUAPs that can be subsequently successfully assigned. Several different methods have been devised to segment the signal into sections that contain significant MUAPs. All of these methods are based on defining some detection threshold based on some statistic computed using the composite signal. Most algorithms, when the signal characteristics produce a statistic value above the threshold value, select a fixed length section that is subsequently assumed to be a candidate MUAP for classification. Other methods select variable length sections assumed to contain significant MUAP contributions [23,24,38,40,49,77,78]. Either way, methods for determining what has actually been detected and properly aligning and representing it for further processing must be incorporated into the decomposition system. This is because any detected signal section may in fact be an isolated MUAP, the superposition of MUAPs from two or more motor units, only a portion of a single MUAP or a spurious noise spike.

Some detection schemes are applied to the raw or bandpass filtered micro signal and are based on amplitude [4,20,41,51] or signal variance thresholds [24,49,77,78]. Others, applied to the raw signal, use a combination of both slope and amplitude thresholds [65,67]. One consistent method of selecting segments that contain MUAPs that can be consistently correctly assigned is to consider the slope of the micro-EMG signal [23,38,40] or the micro-EMG signal after it has been passed through a low pass differentiator [27,28,36,43,46,75]. In general, bandpass filtering and low-pass differentiators shorten the duration of MUAPs, which reduces their temporal overlap and therefore reduces the number of superimposed waveforms. They also reduce the amplitude of the many similarly-shaped MUAPs of different motor units that do not have fibres close to the electrode. This filtering can remove non-discriminative, low frequency information and make it easier to discriminate between the MUAPs of different motor units by reducing the variability of the MUAP shapes. Fig. 4 shows the effects of first and second order difference filtering. After filtering the MUAPs have shorter durations and some of the non-discriminative baseline noise is removed.

The thresholds set for detection are either pre-set, to select MUAPs with a fixed set of characteristics [23,51,65,67], or they are determined by the characteristics of the signal and noise components of the analyzed micro-EMG signal. Of those that are based on estimates of the signal and noise components some use absolute noise-based thresholds [36,38,40,43,49] while others use thresholds that are relative to the largest signal components [4,24,48,75]. This latter approach reduces the chance of small MUAPs being ‘lost’ in larger ones but also introduces a possible bias against smaller MUAPs. Independent of how the significant signal segments are detected they must be some how aligned. During segmentation, most systems initially align detected waveforms using peak values either of the raw or slope signal. However, major initial alignment errors can sometimes not be corrected during later alignment attempts and can cause classification problems. Methods of alignment during segmentation, when there is little contextual information, need to be developed and evaluated. Fig. 5 shows a section of an EMG signal that has been filtered and then segmented. In this example the

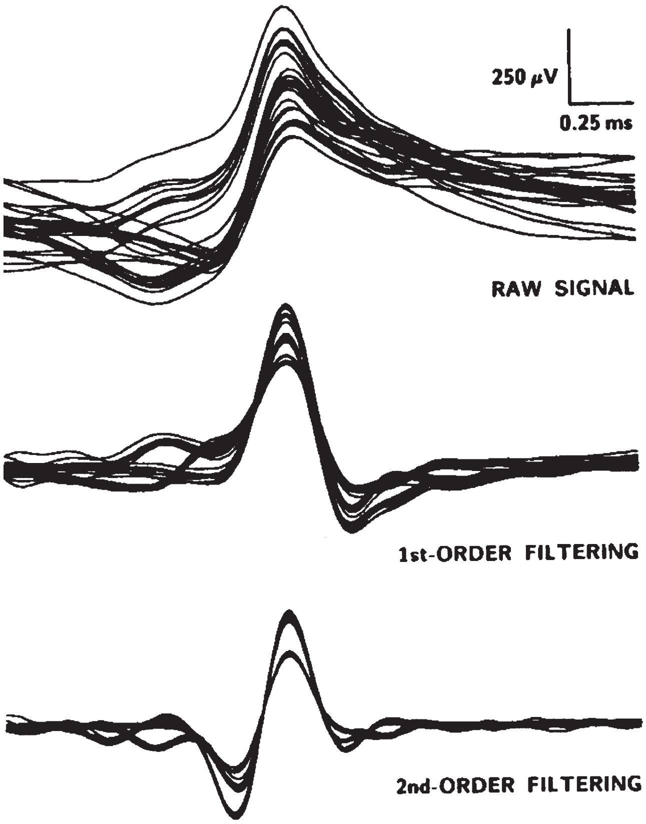

Fig. 4. The affects of bandpass filtering on the shapes and distinguishability of MUAPs (from McGill and Dorfman [44]). Notice that following low-pass differentiation the MUAP durations have reduced and the MUAPs created by each of the three contributing motor units can be more easily discriminated.

detected MUAPs have also been classified. The number above a detected MUAP represents the MUAPT or motor unit to which it was assigned.

3.4. Feature extraction for pattern recognition

The detected MUAPs must be represented using a vector for pattern recognition. The characteristics of the MUAPs used for this representation are called features. The multi-dimensional space composed of all possible feature values is called the feature space.

3.4.1. Feature space considerations

Following is a list of a number of factors to be considered when deciding on the optimal way to represent an object (MUAP) for pattern recognition.

1. What are the storage and computational requirements of the feature vectors? (How many features are there? i.e., what is N?)
2. What is the computational effort required to extract or compute the feature values?
3. What is the signal to noise ratio and variance of each feature?
4. What is the amount of correlation between features?
5. What is the discriminative power of the feature representation?
6. What is the sensitivity of the representation to waveform alignment?
7. What is the effect of MUAP superpositions on the feature values?
8. What is the effect of MUAP shape variability on the feature values?

3.4.2. Feature spaces

A number of different feature spaces have been used to represent muaps for signal decomposition. A list of some of them follows.

1. Using morphological statistics such as peak to peak voltage, number of phases, duration, number of turns, etc [24,40,51,65].
2. Representation in the frequency domain using Fourier transformation coefficients [43,67].
3. Representation using coefficients obtained from a transformation (e.g. a wavelet basis) [20,77,78].
4. Representation using the time samples of the band-pass filtered signal [4,23,24,36,38,41,49].
5. Representation using the time samples of the low-pass differentiated signal [27,48,75].

3.5. Clustering of detected muaps

3.5.1. Objectives

Clustering, in general, is the partitioning of a set of objects into a number of groups or clusters. Any member of a group should be more *similar* to the other members of its group than it is to the members of any other group. The exact number of groups is not known before hand and each cluster has a prototypical shape that is called the cluster mean or template which is also initially unknown. Within the context of EMG signal decomposition, a clustering algorithm has two main objectives. One is to determine the correct number of motor units contributing significant MUAPs to the composite EMG signal (i.e., the number of significant MUAPTs). The other is to assign as many MUAPs as possible to their correct MUAPT so that the prototypical or mean MUAP shape of each contributing motor unit can be determined. However, every MUAP assigned to the wrong MUAPT increases the probability of more errors and supervised classification results (see Supervised Classification of Detected MUAPs subsection below) will be more successful if based on accurate clustering results. Therefore, it is more important that the clustering results are accurate and that superimposed MUAPs are ignored than it is for all detected MUAPs to be assigned. As such, a clustering algorithm does not need to consider all of the

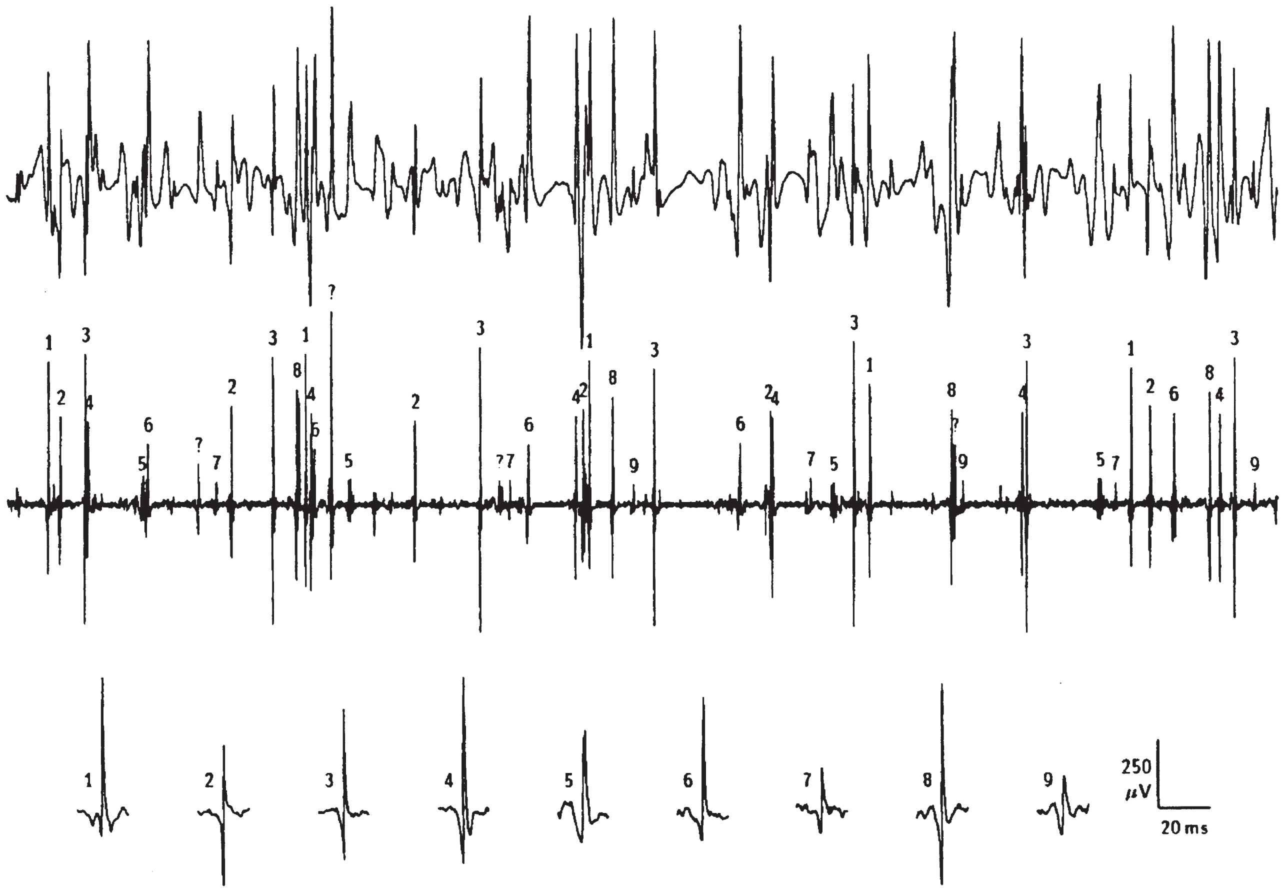

Fig. 5. Example MUAP detection using an EMG signal which has been low-pass differentiated (from McGill and Dorfman [44]). The top trace shows a raw, biceps-brachii concentric-needle detected EMG signal segment. The middle trace shows the same segment after second-order low-pass differentiation filtering and indicates the detected significant MUAPs. The bottom trace shows the MUAP waveforms of the motor units significantly contributing to the shown EMG segment.

detected MUAPs nor classify all MUAPs considered. Rather, it needs to discover all of the MUAPTs significantly contributing to the signal and it should be conservative and try to minimize the number of erroneous classifications. In addition, because during later stages of the decomposition it is easier to merge two trains into one than it is to split one train into two, over estimation of the number of MUAPTs is preferred to underestimation.

3.5.2. Distance measure

Clustering decisions are based on some measure of the similarity or dissimilarity between MUAP shapes. The most often-used dissimilarity measure is called the Euclidean distance, which is defined as follows.

Let $\boldsymbol{X}_i$ denote the ith N-dimensional pattern (MUAP)

$\boldsymbol{X}_i=(x_{i1}, x_{i2},\ldots,x_{iN})^{\mathrm{T}}$

The Euclidean distance between two objects in an N-dimensional feature space is then:

$$d^2(\boldsymbol{X}_i, \boldsymbol{X}_k)=(\boldsymbol{X}_i-\boldsymbol{X}_k)^{\mathrm{T}}(\boldsymbol{X}_i-\boldsymbol{X}_k)=\sum_{j=1}^{N}(x_{ij}-x_{kj})^2 \qquad (4)$$

Let $\boldsymbol{M}_k$ denote the N-dimensional mean or prototype pattern (MUAP) of the kth cluster (MUAPT)

$\boldsymbol{M}_k=(m_{k1}, m_{k2},\ldots,m_{kN})^{\mathrm{T}}$.

The Euclidean distance between an object and a cluster mean in an N-dimensional feature space is then $d^2(\boldsymbol{X}_j, \boldsymbol{M}_k)$.

3.5.3. Classical clustering techniques

Hierarchical techniques initially assume that each object is a cluster and compute the distances between all pairs of objects and store the results in a distance matrix. There are two basic hierarchical techniques known as complete and single linkage, respectively. In complete-linkage techniques, the two most similar objects are combined into one cluster and replaced by its mean shape. The distance matrix for the reduced number of objects is then recalculated. This process of joining objects and recalculating the distance matrix is repeated until only a single object (cluster) remains. Tracking this process creates what is called a dendrogram. If the dendrogram is cut at some level of dissimilarity, K clusters will be created with all of the objects represented by each of the K remaining means assumed to belong to each respective cluster. These techniques are referred to as complete-linkage because objects are compared to cluster mean values and therefore clustering decisions are based on all of the elements of any particular cluster. Various complete-linkage hierarchical techniques differ based on how they combine objects and compute their mean values. Hierarchical single-linkage techniques are similar to complete-linkage techniques in that they also use a distance matrix. However, cluster membership is based on the single closest individual object and not a cluster mean. This type of clustering is also known as nearest-neighbour clustering. Both hierarchical techniques do not depend on the order in which the objects are considered for classification. However, all of the data must be considered at once which is computationally expensive for large data sets. Furthermore, thresholds must be chosen for cutting the dendrograms to determine the appropriate number of clusters [35]. With regard to EMG signal decomposition, selecting appropriate thresholds that are suitable for a wide variety of signals can be problematic because of the variety of EMG signals that may be encountered.

Partitioning methods are an alternate class of clustering techniques. Given a known number of clusters K, partitioning methods attempt to create a clustering set partition (C_1, C_2,...C_K), where C_i represents the set of objects that belong to the ith cluster, that minimizes a specified objective function. Often the function to be minimized is the squared error defined as:

$$E_k^2=\sum_{k=1}^{K} e_k^2=\sum_{k=1}^{K}\sum_{X_i\in C_k}(\boldsymbol{X}_i-\boldsymbol{M}_k)^{\mathrm{T}}(\boldsymbol{X}_i-\boldsymbol{M}_k) \tag{5}$$

In all partitioning methods some method must be used to determine the number of partitions or clusters and initial estimates of the cluster means. Once the number of clusters is decided and their initial means are selected each object is then simply assigned to the cluster with the most similar mean.

$$\boldsymbol{X}_i\in C_c \text{ if } d^2(\boldsymbol{X}_i, M_c)<d^2(\boldsymbol{X}_i, \boldsymbol{M}_k),\ \ k=1,2,\ldots,K,k\neq c \tag{7}$$

The mean value of each cluster can be updated after each assignment or at the end of a pass through all of the data. Multiple passes through the data are required until the cluster means are suitably stable. With partitioning methods the order in which the objects are classified can change the results. However, only the cluster means and one object need to be considered at any one time which reduces the computational complexity. The K-means and ISODATA clustering algorithms are two examples of partitioning methods [35]. Sequential clustering techniques, such as leader-based clustering, can be considered special cases of the partitioning method. Sequential clustering techniques make a single pass through the data using the initial object considered as an initial cluster template and fixed thresholds of similarity to assign subsequent objects to the closest template, update the current template or to use the current object being classified to initialize a new template.

3.6. Clustering algorithms used for EMG signal decomposition

Most clustering algorithms used for EMG signal decomposition have been based on the single-linkage or nearest-neighbour concepts [4,13,20,23,26,36,38,40,49, 77,78]. Pattichis et al. [51] used a modified complete-linkage technique that was not based on traditional distance metrics but rather used successively applied range criteria for each MUAP feature considered. Others have used partitioning methods such as a modified K-means technique [71] and the leader-based approach [36,41,43,48,65]. Self-organizing neural nets with learning vector quantization have been used [4] as well as a recurrent neural network [27,28]. For many of these applications the standard Euclidian distance is normalized in some way by the energy of the waveforms being compared [4,26,36,38,40,41,77,78]. Guiheniuc [24] and McGill et al. [43] instead adjust acceptance thresholds based on MUAP size. Distance normalization and threshold adjustment account for the higher biological variability expected for larger MUAPs. Stashuk and Qu [71] consider a portion of the detected MUAPs and actively use MUAP shape as well as firing pattern information, if it is available, to determine the number of MUAPTs and to make classification decisions. The firing pattern information is calculated using algorithms developed specifically to deal with sparse MUAPTs that will have missed motor unit discharges and may also include erroneous motor unit discharges [72]. LeFever and DeLuca [41], via a hazard function, also actively used firing pattern information. Many other methods passively use firing pattern information to detect misclassifications, classification errors and to possibly merge MUAPTs [23,24,26–28,36,40,43,67]. Several other distance-measure modifications have been used: Gerber et al. [23] use an L_1, area instead of energy based, distance measure; Nandedkar et al. [48] first compare maximum slope and amplitude of MUAPs to be compared and if suitably similar then calculate their distance measure; Fang et al. [20] use only the maximal difference between corresponding wavelet transform coefficients; and Stashuk and Naphan [68] compared probabilistic inference-based classification with classical distance measures.

One of the most important aspects of any clustering algorithm are the thresholds used for cutting dendograms to determine the number of clusters or for making decisions to classify candidate MUAPs or to use them to initiate new templates. This is because superimposed MUAP waveforms being considered for classification must be identified for subsequent resolution and they must not be used to update cluster templates. In this regard, many methods use fixed a priori determined thresholds based on shape similarity [4,41,43,51,65], firing pattern [20] or both [38,48,67]. Alternately some methods use thresholds that are dependent on the specific EMG signal being decomposed [23,27,40,49,71]. In general, data-driven thresholds should lead to more robust performance across a variety of EMG signals. In essentially all cases, a minimum number of occurrences within a MUAPT are used in validating a train and in identifying superimposed waveforms. Fig. 6 presents typical clustering results.

3.7. Supervised classification of detected MUAPs

Some of the decomposition techniques apply supervised classification methods as well as clustering or unsupervised methods [13,23,24,27,28,75]. In general, supervised classification algorithms use sets of assigned objects to characterize the number of classes expected and the properties of each class so that unassigned objects can be more efficiently assigned. Therefore, once estimates for the number of active motor units and the shapes of their prototypical MUAPs are available (these estimates are usually based on clustering results) the complete set of detected MUAPs can be classified using supervised classification techniques. For supervised classification, the MUAPs are often represented as they are for clustering [23,75], however, some schemes use expanded feature sets [13,24].

3.7.1. Possible steps for supervised classification

1. Check the clustering results for obvious errors.
2. Select the most discriminative feature space and/or features.
3. Derive effective prototypes for each class.
4. Derive thresholds for shape similarity which suit the data.
5. Estimate the firing pattern statistics for each class.
6. Attempt to classify unassigned MUAPs given shape and firing pattern statistics for each class.
7. Given new classifications, update MUAP shape prototypes and firing pattern statistics for each class.
8. Merge classes that are from presumably the same generating motor unit.
9. Split classes that contain MUAPs from presumably more than one motor unit.
10. Repeat steps 6,7,8 and 9 until no more classifications are made.

3.7.2. Possible factors affecting supervised classification

Two major factors affecting supervised classification performance are the variability of the MUAPs within a MUAPT as well as the similarity of MUAPs from different trains. MUAP shape variability is caused by two

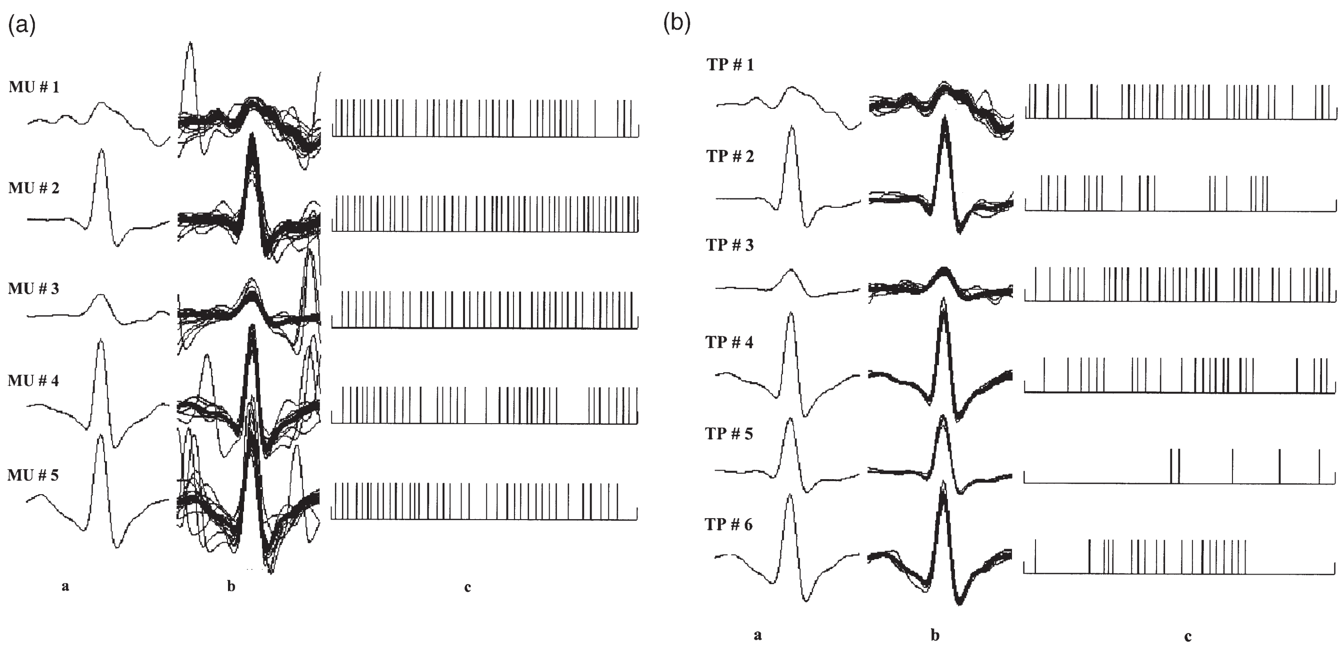

Fig. 6. Example output of a clustering algorithm that uses both shape and firing pattern information (from Stashuk and Qu [71]). For a 5 s analysis interval (a) presents the manually-determined gold standard results; (a) template plots; (b) shimmer plots of assigned MUAPs; (c) firing time plots. Gaps in the firing time plots are caused by unresolved MUAP superpositions. (b) The clustering algorithm results (a), (b) and (c) as in (a). Clusters 2 and 5 are duplicates and together represent the activity of MU No. 2. They were created due to signal nonstationarity and could be merged by a supervised classification algorithm.

main conditions, signal noise and signal non-stationarity. The greatest source of noise is interference caused by the MUAPs of other motor units that are active at the same time or nearly the same time as when a MUAP is detected. This includes the relatively few motor units with fibres close to the detection electrode which cause what are called MUAP superpositions, as well as the larger number of motor units throughout the muscle which contribute more temporally diffuse background noise. A second source of noise, which is generated entirely within a given motor unit and would be evident even if only a single motor unit was active, is due to the variability in the time required at the neuromuscular junctions to depolarize its muscle fibre membranes (*jitter* [56]). This variability results in variable arrival times of the constituent MFAPs of a MUAP at the electrode and causes the shape of the MUAP to vary from discharge to discharge. This biological variation is sometimes called *jiggle* [64]. The third and smallest source of noise is due to the instrumentation required to amplify the detected voltages. Signal non-stationarity occurs if the electrode moves relative to the fibres, which in turn causes the shapes of the MUAPs to change. This is usually seen as a trend over time. Despite the several sources of MUAP shape variability the MUAPs of two different motor units can still be remarkably similar if they have similar muscle fibre geometries. This is especially true if they each have a relatively small number of very close fibres. Supervised classification algorithms must be able to deal with both MUAP shape variability within a MUAPT and be able to consistently discriminate between similarly shaped MUAPs generated by different motor units.

An additional performance factor to consider is firing pattern information. If a supervised classification algorithm is to use firing pattern information, either passively or actively, it must also take into account factors that affect the validity of any firing pattern statistics estimated. Several factors affect the accuracy of firing pattern statistic estimates, such as:

1. classification error rate;
2. classification identification rate;
3. minimum number of IDIs in the estimation sample; and
4. the inherent variability of the firing pattern in the estimation interval.

Therefore, the estimation intervals used to determine firing pattern statistics must consider the stationarity of the firing patterns, this is obviously most important when analyzing signals detected during force variable contractions. In addition, the degree to which firing pattern information is used in making classification decisions should match the level of confidence about the information used.

3.7.3. Desired attributes of a supervised classification algorithm

Following is a list of desirable attributes of a supervised classification algorithm:

1. robust performance across a variety of suitable EMG signals with minimal computational cost;
2. ability to perform despite having small, imperfectly-labelled training sets after clustering;
3. ability to decompose despite background noise and biological variability;
4. minimal use of arbitrary thresholds of similarity and minimal sensitivity to any required thresholds;
5. prudent use of firing pattern information to complement shape-based classification;
6. robust use of shape and temporal information given non-stationarity;
7. multi-pass algorithm to allow classification context to grow iteratively;
8. valid stopping criteria for iterative process;
9. ability to merge classes which correspond to the same motor unit;
10. ability to split classes which correspond to more than one motor unit;
11. ability to decouple low-assignment rate/low-error rate tradeoff as much as possible;
12. accuracy and completeness of classification; and
13. the ability to supply some measurement of confidence regarding the classification results.

Most of the EMG signal decomposition methods reported do not use a supervised classification algorithm. Instead, they attempt to classify all of the individual MUAPs using only clustering techniques. Gerber et al. [23] and Guiheniuc et al. [24], however, both use a single-pass supervised classification algorithm to classify individual MUAPs discovered in significant variable-length signal segments; Hassoun et al. [27,28] use a trained neural network to classifiy individual MUAPs; and Gut and Moschytz [25] model the EMG signal as an $[M+1]$-ary signalling system with inter-symbol interference and use a sparse-sequence constrained Viterbi algorithm and MUAP shape and firing pattern information to obtain a maximum a posteriori probability based estimate of the innervation sequences of the active motor units. Each of these algorithms use the results of an initial clustering stage to assist in making supervised classification decisions. In addition, Stashuk and Paoli [73] have developed a multi-pass certainty-based supervised classification algorithm that uses both shape and firing pattern information and which has many of the attributes listed above.

3.7.4. Certainty-based classification

Certainty-based classification uses a set of decision functions to combine shape and firing-pattern information to calculate a measure of the certainty with which a particular MUAP assignment can be made. The Certainty algorithm evaluates MUAP classification decisions with regard to the likelihood that they will be correct. Decisions that are deemed to be the best possible and to have requisite certainty are executed. MUAP assignment decisions whose calculated certainty is below a threshold value are not made. These unassigned MUAPs are often actually superimposed MUAPs. The certainty threshold used to make decisions does affect the number of decisions made and their accuracy. However, the results are not highly sensitive to its value. The Certainty algorithm is described and evaluated in detail elsewhere [50,73]. A brief description of the Certainty algorithm follows below.

Certainty is measured by combining the results of several decision functions. The first function measures the normalised Euclidean distance between a candidate MUAP and a prospective MUAPT template. The second function is the relative Euclidean distance, which is a measure of the distance of a candidate MUAP to its closest MUAPT template relative to the distance of the candidate MUAP to its second closest MUAPT template. The third decision function measures the firing time consistency of the candidate MUAP relative to the firing-pattern of a prospective MUAPT. Each decision function has a range of values from 0 to 1. The certainties of assigning a candidate MUAP to its closest MUAPT and to its second closest MUAPT are then calculated by multiplying the respective decision function values. The MUAP is assigned the MUAPT which has the greatest certainty value provided the value is greater than the certainty assignment threshold. Multiple passes through the set of detected MUAPs are made. With each pass, the certainty-based assignment of each MUAP is considered. During initial passes limited temporal information is available and only MUAPs with shapes similar to the template of a train are assigned. During later passes as more temporal information is developed the consistency of classifications with the established firing patterns become more important and more difficult assignment decisions can be made or earlier decisions modified. The iterations continue until a maximum number of iterations have been completed (usually 10) or until the percentage of MUAP assignment changes in total and the maximum percentage of changes within any specific train are both below specified threshold values. Attempts to track MUAP shape non-stationarity are made by calculating the MUAPT templates as moving averages of their assigned MUAPs using the certainties with which the respective MUAPs are assigned as weighting factors. At the end of each assignment pass at most two trains are merged if the average certainty of all the classifications within the merged train is greater than the average certainty of all the classifications of each individual train. The certainty model allows direct implementation of a robust, certainty-based assignment threshold. Instead of choosing a fixed distance threshold, or fixed threshold for IDIs, the information is combined to yield a measure of certainty. If the calculated certainty exceeds the minimal certainty the classification can be made. This design leads to robust performance across EMG signals. The minimal level of certainty required to make a MUAP assignment is independent of the particular signal being decomposed, yet the values of the certainties calculated for the assignment of each candidate MUAP are based on the characteristics of the specific signal being decomposed. The certainty algorithm can classify a high percentage of detected MUAPs and its performance is not sensitive to the certainty threshold used. Its performance is robust, it can deal with biological variability of the shapes of MUAPs within a MUAPT and it is able to discriminate between similar MUAPs generated by different motor units. The ability to consistently classify variably shaped MUAPs of a single motor unit and at the same time successfully discriminate between similarly shaped MUAPs from different motor units is one of the key qualities of the Certainty algorithm. Figs. 7 and 8 demonstrate the capability of the certainty algorithm to discriminate between very similar MUAPs from different MUAPTs and to allow a large amount of MUAP variability in a single MUAPT.

3.8. *Resolving superimposed MUAPs*

During muscle contraction motor units fire asynchronously and at variable firing rates (FRs), depending on their motor unit recruitment threshold and the level of muscle force being produced. When two or more motor units discharge at the same time or in close temporal succession, the detected potential is the algebraic summation of the individual potentials from these motor units and is termed a superimposed MUAP. During EMG signal decomposition, superimposed MUAPs need to be resolved into their constituent MUAPs if complete firing pattern information is to be obtained. Three different types of superimposed waveforms may be defined: *partially superimposed*, in which the MUAPs overlap without the peaks being obscured; *completely superimposed*, in which the peaks of the MUAPs combine to make one large peak; and *destructively superimposed*, in which the MUAPs are superimposed in such a way that their out-of-phase peaks are summed together and cancel each other. Fig. 9 provides examples of the various types of superimposed MUAPs.

Attempts to resolve superimposed MUAPs can be based on two fundamentally different strategies. The first is the *peel-off* or *sequential* approach, which is simply based on matching MUAPs, one at a time, with the superimposed waveform or a residual form of it. If a match is suitable the MUAP is assumed to have contributed to the superposition and subtracted from it. The cre-

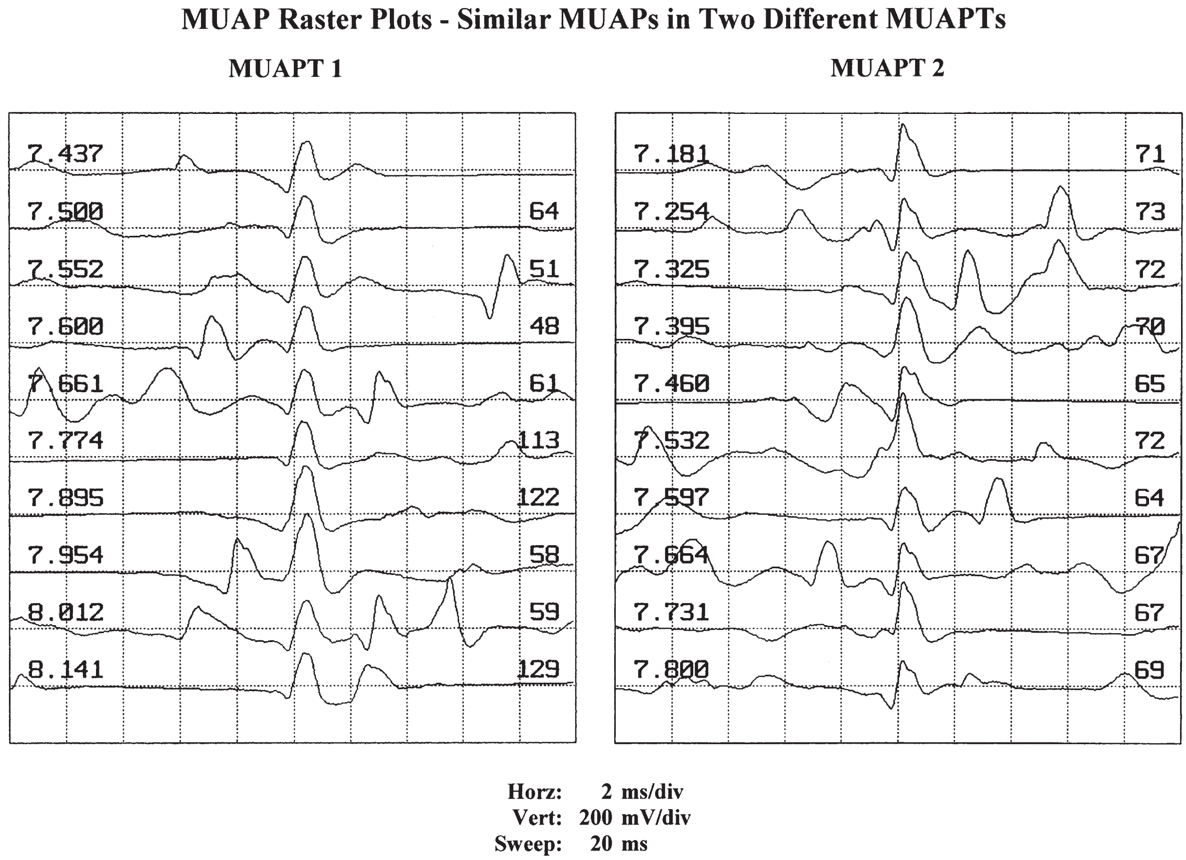

Fig. 7. Similar MUAPs in two different MUAPTs. Raster plots of two different MUAPTs are shown. Time of motor unit discharge in s is shown on the left and IDI in ms on the right of each column. The MUAPs in each train are similar in shape and firing pattern information is useful in discriminating between the MUAPs created by each motor unit (from Stashuk [74]).

ated residual waveform is then used to search for other contributing MUAPs. MUAP contributions can be assumed to be correct after each subtraction or the final residual can be used to accept the combination of subtracted MUAPs. A number of algorithms for resolving superimposed MUAPs using the peel-off approach have been reported [4,20,24,38,41]. These algorithms differ in how they align candidate templates with the superimposed waveform, the order in which they align and subtract templates and the thresholds used to accept suggested resolutions. Some methods align using MUAP peak values [24,41], while others use peak correlation values [4,20]. The methods used for matching and subtracting MUAPs include peeling-off: the MUAP waveform with the most similar amplitude first [24]; the MUAP that matches best [4]; the MUAP that produces the smallest residual signal [20]; or the MUAP with the best combination of smallest residual and most likely firing time [41]. Some methods accept proposed contributions individually, without resolving the complete superimposed waveform [4,20] while others only accept combinations of contributing MUAPs that can sufficiently account for the energy of the entire superimposed waveform [24,38,41].

The second strategy is the *modelling* approach, which is based on synthesizing superimposed waveform models by adding up combinations of MUAPT templates with different relative time shifts. Model synthesis and comparison is repeated until an optimal or acceptable match is obtained between one of the model superimposed waveforms and the actual superimposed MUAP. The peel-off approach is not very powerful when the superimposed waveforms exhibit destructive properties, whereas the modelling approach is theoretically capable of resolving all types of superimposed waveforms. The peel-off approach, however, is faster than the modelling approach. It requires $2NM$ tests to resolve a superimposed MUAP, whereas the modelling approach requires $N(N-1)M^2/2$, where N is the number of possibly contributing motor units and M is the number of time shifts considered for matching. Several modelling approaches have been reported [9,23,26,43]. All of these techniques are similar in that they reduce the space required to be searched by first selecting a subset of possibly contributing MUAPs, limit the number of assumed contributing MUAPs to 2 or 3, initially align the MUAPs using either peak values [43] or maximal correlation [9] and use optimization techniques to solve for the model parameters.

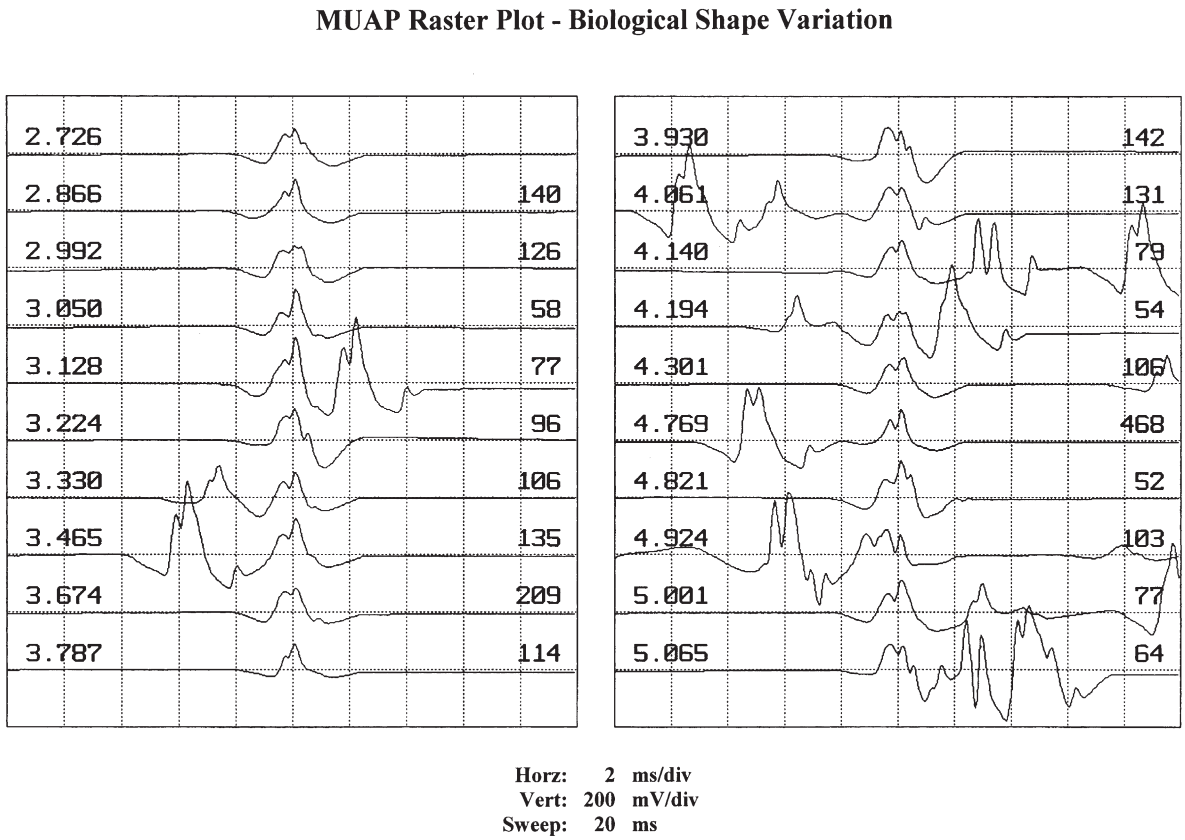

Fig. 8. MUAPT with variable MUAPs due to biological variation. A raster plot, similar to Fig. 7, shows the MUAPs of a single MUAPT. The variability in MUAP shapes is due to biological variability in the times of arrival at the electrode detection surface of the individual MFAPs significantly contributing to the detected MUAPs. Relative and absolute shape criteria, firing pattern information and data driven assignment thresholds help in discovering this train (from Stashuk [74]).

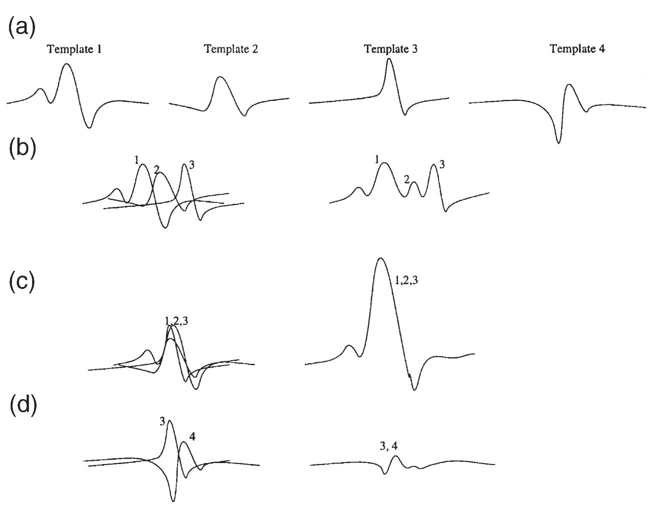

Fig. 9. MUAP superposition definitions. Four MUAP waveforms and their superpositions for different time shifts are shown. (a) The MUAP waveforms; (b) partially superimposed waveforms; (c) completely supeimposed waveforms; (d) destructively superimpoosed waveforms (from Etawil and Stashuk [19]).

The superimposed waveform is resolved using the best fitting, optimized model.

Most peel-off methods do not search for the minimal residual that could be created by a combination of contributing MUAPs. The first combination which creates a below threshold residual is usually accepted. Furthermore, each alignment and subtraction step is completed without considering previous steps. Therefore, errors made during each step of a peel-off algorithm can greatly affect subsequent steps and lead to an incorrect or unsuccessful resolution. Alternatively, modelling approaches can have a large search space and consequently be excessively computationally expensive. To avoid these problems methods based on limited modelling and parameter optimization have been developed [19,40,49]. These methods combine the peel-off and modelling strategies. A list of possible MUAP combinations is constructed and limited MUAP alignment optimizations are performed to search within the list for the best match. The list can be composed of a limited number of combinations that provide the best match [49] or knowledge extracted from the EMG signal being decomposed can be used to construct the list [19,40]. Loudon et al. [40]

use net energy, MUAPT firing pattern information and a rule-based expert system. Etawil and Stashuk [19] use template energy and firing pattern information both within and across MUAPTs to prioritize the constructed list and direct the search. In an attempt to find the minimal residual, both of these techniques alter the order in which MUAP templates are subtracted and Etawil and Stashuk [19] use intermediate searches to refine alignment. Fig. 10 shows the resolution of some example superimposed MUAPs.

If only mean FR and FR variability during constant contractions are to be studied, algorithms for the resolution of superimposed MUAPs are not essential in the clinical use of EMG signal decomposition systems [72]. However, as the use of firing-pattern information becomes more important, the clinical importance of resolving superimposed MUAPs will also increase and as computing power available in the clinic increases it will become more practical to consider resolving superimposed MUAPs. Nonetheless, for the detailed analysis of motor unit firing patterns required for the study of the basic mechanisms of motor unit control, superimposed MUAPs must be resolved.

3.9. Discovering temporal relationships between MUAPTs

3.9.1. Defining and measuring MUAPT interdependence

During and after MUAP classification it is important to determine the temporal relationships between MUAPTs. MUAPTs can be modelled as stochastic point processes. If each discharge of a motor unit is independent of previous and future firings and identically distributed, its MUAPT can be modelled as a renewal point process. Such modelling represents the discharge times or the intervals between discharge times of MUAPTs as random variables [52]. The random variables representing the activity of two MUAPTs can be either independent or dependent [53]. If they are independent the firing times of one train have no affect or are not related to the firing times of the other train. On the other hand, if the trains are dependent the firing times of one train are affected or related to the firing times of the other train. Three kinds of dependent behaviour defined as *linked*, *exclusive* or *synchronised* are possible. Linked trains fire with a definite, essentially constant interval relative to each other, such as when a single, long-duration MUAP is consistently multiply-detected as two or more distinct MUAPs each representing only a portion of the single MUAP. Exclusive trains never fire together. This is to say that the absolute difference between the firing times of any two MUAPs each selected from a different train is never less than some threshold amount (say 25 ms for example). If two trains are exclusive they may have been created by the same motor unit and erroneously separated into two trains by the classification algorithms. Synchronised trains have behaviours somewhere in between linked and exclusive and probably represent a true biological tendency of motor units to have dependent firing behaviours. Relationships between spike trains have been studied using recurrence histograms [53], but this analysis requires assumptions regarding the probability distributions of the bins of the resulting histograms. Mutual information is a non-parametric measure of the interdependency between two random variables [58]. The tendency of two MUAPTs to fire together or not can be determined by studying the probabilities of either MUAPT or both MUAPTs firing within an analysis window randomly positioned in time. Considering MUAP durations and peak motor unit FRs a window of 25 ms duration is sufficient [3,5]. A discrete random variable representing the event of a MUAPT firing within an analysis window can be defined to have a value of 1 if a firing of a MUAPT is in the analysis window and 0 if it is not. Assuming A and B are such discrete random variables representing MUAPT_i and MUAPT_j, respectively, of a selected pair of trains the interdependency redundancy of the trains can be measured. The interdependency redundancy can then be used along with the train individual and joint probabilities to determine if the trains are independent or dependent and if dependent whether they are mutually exclusive or linked [75,79,80].

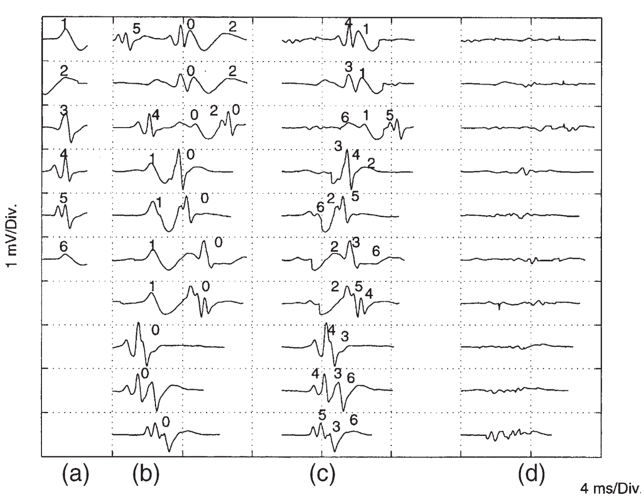

Fig. 10. Example MUAP superposition resolutions: (a) candidate template MUAP waveforms; (b) signal segments containing a superimposed MUAP and other classified MUAP waveforms; (c) resolved superimposed MUAPs with other classified MUAPs removed; (d) residuals (from Etawil and Stashuk [19]).

3.9.2. Importance of discovering temporal relationships between MUAPTs

By using a fixed number of samples to represent a detected MUAP, portions of complex, long-duration MUAPs can be detected as separate MUAPs. Multiplydetecting such MUAPs simplifies MUAP clustering and supervised classification. However, algorithms that discover temporal relationships between MUAPTs, whose MUAPs represent portions of multiply-detected MUAPs, must be applied to determine the correct number of active motor units. Furthermore, during detection there is no contextual information available to allow efficient MUAP alignment. As such, if a MUAP has two peaks of similar amplitude with less than approximately 1 ms temporal separation, slight biological variation in the shape of the MUAP may cause the peak used to define its firing time and therefore its alignment to vary. This can also occur for single peaked MUAPs if the biological variability is great. Exhaustive alignment searches may overcome these detection problems but they are computationally expensive at it can be more efficient to have MUAPTs containing such disparately-detected MUAPs to be processed by dedicated algorithms that determine any existing temporal relationships between MUAPTs. The mutual information based interdependency redundancy measure described above, applied to pairs of the MUAPTs created following clustering and supervised classification is able to successfully discover relationships which exist between trains detected in EMG signals. Trains associated with multiply-detected MUAPs are found to be linked and subsequently considered a single train. Trains associated with disparately-detected MUAPs are found to be exclusive and are made candidates for merging. Therefore, the application of a temporal-relationships discovering algorithm often allows the number of MUAPTs discovered following signal decomposition to more closely match the number of motor units consistently contributing significant MUAPs to the composite EMG signal. However, in some research situations it may not be appropriate to excessively use such temporal information.

3.10. Evaluating EMG signal decompositions

3.10.1. Evaluation criteria

The accuracy, extend and speed with which a system can decompose an EMG signal are the most important criteria for evaluation. Accuracy refers to the percentage of assigned MUAPs that are correctly assigned. Extent refers to the percentage of the total number of MUAPs that contributed to the composite signal that are actually detected and assigned including the resolution of superimposed MUAPs. Speed simply refers to the length of time required for the decomposition and subsequent post-processing to be completed and includes both computer and operator time. Which of these criteria is the most important depends on the area of application. For clinical use, accuracy and speed are most important. For research applications, accuracy and extent may be more important.

3.10.2. Quantitatively evaluating EMG signals decompositions

For the quantitative evaluation of developed EMG signal decomposition systems and as a means to obtain correct and complete EMG signal decompositions (at least to the limits of an experienced operator) computer-aided graphical display systems have been developed to manually decompose EMG signals [20,23,25,26,40,41,75]. These algorithms are used to create 'gold standard' decomposition files. They allow superimposed MUAPs to be resolved and only the experience and perseverance of the operator limit the accuracy of the results obtained. The results of edited (gold standard) output files can then be compared to the results of files created automatically by a decomposition algorithm to determine the accuracy and extent of signal decompositions. An alternate approach for validating the decomposition of real EMG signals, used by LeFever and DeLuca [42], was to independently decompose two signals simultaneously detected by separate electrodes placed close to each other in a contracting muscle. Common trains discovered in each signal were compared for consistency with any discrepancies considered as errors. This approach is biologically the most consistent but it is very time consuming and requires a special detection protocol. Decomposition systems need to be evaluated using signals detected from normal as well as diseased muscle. However, to date the number of systems tested using pathologic EMG signal data are small [26,28]. Many decomposition systems have also been evaluated using simulated EMG signals [20,28,40,42,45]. The use of simulated data is the only way to have unquestionable information about the actual composition of the signals decomposed. Therefore, using simulated data provides accurate performance results. However, the degree to which the simulated signals match real data, especially with respect to MUAP variability within the MUAPTs can limit their usefulness. A new simulation algorithm developed especially for the evaluation of decomposition algorithms can overcome most of these drawbacks [21]. Whether evaluated with real or simulated data, the consistency of the performance of a system across a variety of representative signals is very important [25,75].

3.10.3. Qualitatively evaluating EMG signals decompositions

A qualitative evaluation of the adequacy of an EMG signal decomposition can be made by viewing raster plots of the MUAPs assigned to each MUAPT (see Figs. 7 and 8). From the raster plots the number of assignment errors can be approximated. Another way to qualitatively assess some EMG signal decompositions is to view IDI histograms and estimates of the instantaneous FR as a function of time (see Fig. 11). MUAPTs that contain many errors will have large variations in their IDIs and especially their instantaneous FRs as a function of time.

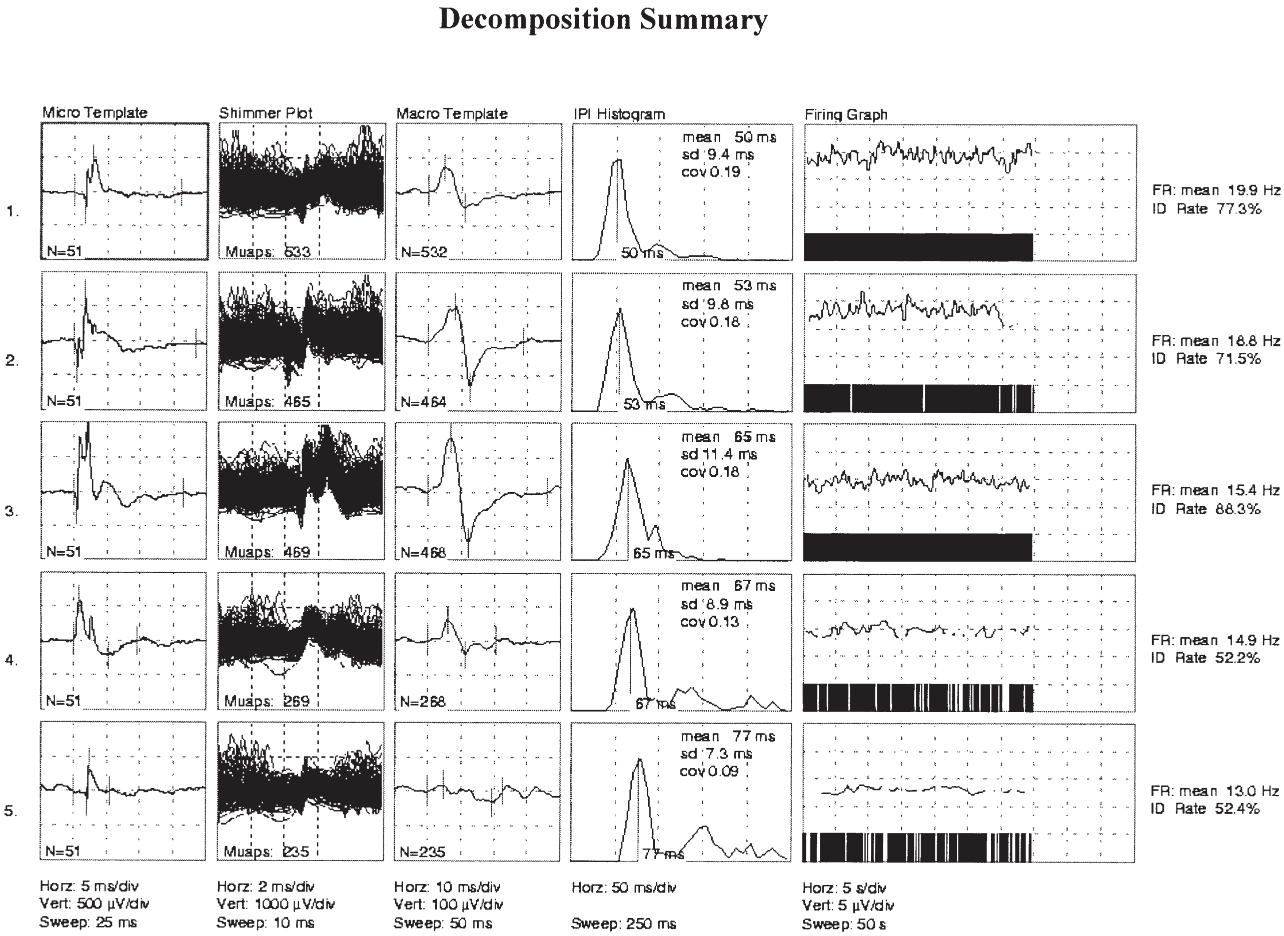

Fig. 11. Decomposition summary: the results of the decomposition of a typical micro signal and subsequent further analysis of the micro and macro signals. In the first column, the prototypical micro MUAPs along with the numbers of isolated MUAPs used for their estimation are displayed for each MUAPT. The individual MUAPs assigned to each MUAPT are drawn, on top of each other, in the shimmer plots shown in the second column. The third column displays the macro MUAPs obtained by ensemble averaging along with the number of firings used in each average. The final two columns present IDI histograms and MUAPT discharge times and instantaneous firing rate plots, respectively (from Stashuk [74]).

If two trains have been erroneously merged into one this can very often be seen by viewing IDI histograms and FR plots [75]. However, in some research situations the IDI plots will not be useful because assuming pseudo-regular motor unit firing patterns may not be appropriate.

4. How can decomposition results be used?

The results of the decomposition of an EMG signal can be used to assist in the diagnosis, treatment and further study of neuromuscular disorders from a functional point of view. In addition, information about the operation and control of skeletal muscles and the effects of disease, ageing and fatigue can be obtained. Following are descriptions of some of these specific uses.

4.1. Quantitative needle (micro) EMG

In a normal muscle the fibres of a motor unit are randomly distributed throughout a roughly circular area of about 5–10 mm in diameter called the motor unit territory. The morphology of the motor units of a muscle change with disease. With myopathic diseases, the numbers of fibres in motor units are reduced, as are the diameters of the fibres. With neuropathic diseases, the number of motor units is reduced but the sizes of the remaining motor units are increased. This means that the motor units have larger numbers of fibres and that the fibres are no longer randomly spatially distributed. These morphological changes in the structure of motor units result in changes in the shapes of their detected MUAPs [5]. Characterizing these MUAP changes can be used to aid in the diagnosis and treatment of some neuromuscular disorders [1,3,4,31,33,44,47,48,51,54,60,62–65,76]. Various statistics of the MUAP shapes, calculated from a representative sample of MUAPs detected in a muscle of interest, are used to quantify their characteristics [66]. The typical sample size is 20.

Therefore, given a set of MUAPTs, one for each motor unit that contributed significant MUAPs to the original composite signal, the prototypical MUAP shape for each train can be estimated. Mean, median [48], mode [70], statistical [65] and interference cancelling [43] averaging techniques have been used to reduce the interfering activity of other motor units when estimating the prototypical MUAP. Examples of prototypical CN-detected MUAPs can be seen in the first column of Fig. 11. Given a prototypical MUAP, its duration, peak-to-peak voltage, number of phases and turns, area and area to amplitude ratio can be calculated using standard algorithms [62] and used to characterize the MUAP so that the effects of disease may be detected [54]. In addition to calculating parameters of the prototypical MUAPs, using acceleration processing, fibre density can be estimated [74]. Fibre density [56] is an estimate of the density of fibres within a motor unit and is based on the average number of muscle fibres that contribute significant MFAPs to MUAPs detected at various sites throughout a muscle. Using decomposition techniques, a set of 20 or more representative MUAPs can be more quickly and easily collected than compared to using simple level or window triggering, which requires a higher level of subject co-operation and the completion of many more contractions. In addition, MUAPs can be obtained during higher level contractions, which should provide a sample of MUAPs that better represents the studied muscle's motor unit population. However, when analyzing signals detected during higher levels of contraction it is important to be aware of any possible sampling bias against smaller MUAPs that may exist in the decomposition system. It is also very important to have an effective method of estimating the prototypical MUAP so that a relatively noise-free baseline can be achieved for the calculation of MUAP parameters, especially duration. Morphological MUAP parameters and fibre density estimates should allow clinically important information to be obtained. However, because of the different MUAP sampling and estimation procedures involved with decomposition-based methods, separate normative data must be collected for comparison when making clinical decisions.

4.2. Measuring the stability of MUAP shapes

The ensemble of MUAPs comprising a MUAPT represents the repeated discharges of a motor unit. As such, the analysis of the variability of the shapes of the MUAPs within a MUAPT can provide information regarding the stability of the operation of the neuromuscular junctions [56,64] of a motor unit. Jitter [56] is a measure of the variability of the time of arrival at the detecting electrode of two individual MFAP components of a MUAP. To improve the chances of detecting significant individual MFAPs, jitter and fibre density measurements are usually based on MUAPs detected using SFN electrodes. Jiggle [64] is a measure of the average variation between motor unit discharges of the individual voltage samples used to represent a MUAP, normalized by the energy of the MUAP. Jitter and jiggle measures provide information regarding the operation of the neuromuscular junctions of a motor unit. Simulation studies have suggested that information closely related to the activity of individual muscle fibres that are contributing significant MFAPs to the MUAPs of a motor unit can be obtained if MUAP accelerations are analyzed [74]. Therefore, up to 50 isolated-MUAP occurrences can be selected from each MUAPT. Given a set of isolated-MUAPs selected from a MUAPT, the acceleration of a prototypical or template MUAP can be calculated. The number of sufficiently sharp acceleration peaks with amplitude significantly larger than the estimated acceleration noise can be used as the fibre count. Fibre count is similar to fibre density, which is measured using SFN potentials. It represents the number of motor unit fibres in close proximity to the electrode. Fibre count measurements, using CN or MN electrodes, have the potential of providing similar information as fibre density measurements made with SFN electrodes and they can be obtained more easily. If there are at least two significant peaks in the MUAP acceleration template, the mean consecutive difference (MCD) between the corresponding peaks across the ensemble of MUAP accelerations can be calculated as an estimate of the jitter of a pair of the motor unit's neuromuscular junctions. As with SFN potentials, to be confident that a single fibre pair is being considered, the peaks tracked throughout the ensemble must be stable and not bifurcate. Finally, the jiggle of the isolated MUAPs and the Ajiggle of their accelerations can also be calculated. Ajiggle is a statistic similar to jiggle but applied to the accelerations of an ensemble of MUAPs. Ajiggle measures the amount of shape variation across the selected ensemble of MUAP accelerations. The fact that it is less affected than jiggle by the baseline shifts that occur in signals acquired during higher levels of contraction combined with the strong relationship between MUAP acceleration and individual fibre activity may make it a useful source of information.

As an example, Fig. 12 displays a micro MUAP prototype or template for a selected motor unit above its corresponding acceleration template that was calculated by median estimation using the ensemble of isolated MUAP accelerations displayed to the left in the acceleration raster. The double lines shown in the acceleration template plot represent the estimated level of noise in the acceleration estimates. The acceleration template has four peaks that are significantly larger than the estimated acceleration noise, whose positions in time correspond to distinct changes in the MUAP template shape and that probably correspond to contributions from single or small groups of muscle fibres. Within the raster of MUAP accelerations each of these four respective peaks occur with consistent shape even though its position in time may vary. At the scale displayed this is only evident

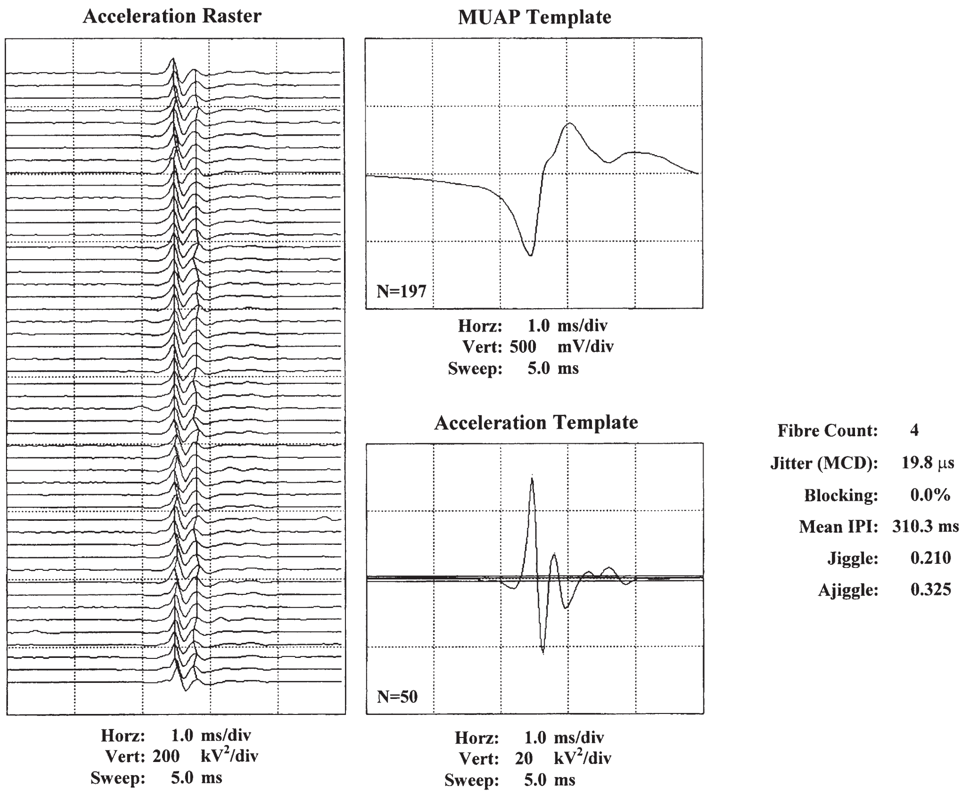

Fig. 12. Acceleration jitter summary: a raster of isolated MUAP accelerations selected from a MUAPT are displayed on the left. The micro MUAP template or prototypical waveform is shown at the top right. Bottom right shows the acceleration template, which is calculated using median estimation across the ensemble of MUAP accelerations shown in the acceleration raster plot. The set of double lines in the acceleration template plot represents the level of noise present in the MUAP accelerations (from Stashuk [74]).

for the two larger peaks, but at lower scales the stability of the two smaller peaks can be confirmed. Thus, as with potentials obtained with a SFN electrode, it is reasonable to assume that these peaks represent the activity of individual muscle fibres. The tracking of the two largest peaks across the ensemble is shown in the acceleration raster. No blocking was found and an MCD value of 19.8 μs was measured. Collecting jitter and fibre density data using SFN electrodes requires much skill on the part of the physician and co-operation on the part of the subject. It would be advantageous to be able to obtain similar information using a CN or MN and using a decomposition algorithm in place of a simple level or window trigger.

4.3. Motor unit firing and recruitment patterns

Before motor unit firing pattern information obtained from an EMG signal decomposition system is to be used or interpreted, the limitations of the decomposition system used must be taken into account. The expected performance level of the decomposition algorithms with regard to completeness and accuracy, whether the decomposition algorithms have resolved superimposed MUAPs and whether or not manual editing was completed will determine the expected completeness and accuracy of the firing pattern information available. This in turn will determine how the information can be used. If the information is complete and accurate detailed firing pattern analysis can be performed. If the firing pattern data is not complete or contains errors the level of analysis may be limited to the study on mean values and variabilities [57]. While information about mean values and variabilities may be suitable for clinical use it is more likely that detailed information will be required for research based investigations. Once the expected quality of the firing pattern data is determined, the level and type of contraction created during signal acquisition is of course another important consideration when interpreting firing pattern information. Were FRs changing to create a varying force profile? Were motor units being recruited or decruited? Obviously, if the force of a contraction is also measured more detailed information can be obtained. Nevertheless, electrode movement leading to the apparent 'loss' and possible 'reappearance' of MUAPs must be considered when determining motor unit recruitment and decruitment. Essentially, if the signal is not stationary with respect to MUAP shape, recruitment and decruitment is difficult to confidently determine.

While considering the above limitations, many studies of motor unit firing patterns have been successfully completed and have lead to the following concepts for motor unit control during constant or slowly force-changing isometric contractions [2,6,14]:

- common drive and the onion skin effect
- FR decay and muscle diversification (large versus small muscles)
- synchronization and train interdependencies (affects of disease, ageing and fatigue)
- individual motor unit and subject mean FRs

Motor unit control properties are also being studied during dynamic contractions [38,59] in aged [18,32,37] subjects and in subjects suffering from neuromuscular disorders [17,22].

In all of these situations the use of a suitable decomposition system can greatly facilitate the process. Suitable in this case is dependent on the motor control questions being considered which indirectly determines the types of contractions studied, the types of EMG signals detected and ultimately the type of decomposition system required.

In general, for each MUAPT obtained following signal decomposition the basic firing pattern of the motor unit can be characterized by an IDI histogram along with estimates of its mean IDI and of the standard deviation (STD) and coefficient of variation (COV) of its IDIs. Because there may be erroneous and missed motor unit firings present in the trains a technique that recognizes and ignores erroneous IDIs (either too short or long) should be used [72]. If the firing patterns change significantly with time, it is important to select a suitable analysis interval to ensure stationary during the analysis interval and to move the analysis interval to track changes in the firing patterns. During stationary analysis intervals, the motor unit's average FR can be calculated as the inverse of its current mean IDI. A motor unit's instantaneous FR, at each of its discharge times, can be estimated as the inverse of a Hamming weighted average of 10 valid IDIs centred about the current discharge time; where a valid IDI has a value within 3 STDs of the current mean IDI. As an example, Fig. 11 shows, for each of the MUAPTs obtained following the decomposition of an EMG signal, the times of a motor unit's discharges, its instantaneous FR, an IDI histogram and calculated firing pattern statistics. In addition, the identification (ID) rates, calculated as the percentage of expected firings detected where the number of expected firings is estimated as the product of the mean FR times the length of time that the motor unit was active, are displayed.

Mean, STD and MCD FR values will depend on the exact level of force generated. To characterize a muscle's mean FR at a particular contraction level subject mean FRs can be calculated across 15–20 motor units that are active at a specified level of force [6]. For clinical evaluations, ways to standardise the level of force generated during signal acquisition without the need of additional instrumentation need to be developed. Given standardized levels of force production, increased or reduced values of various firing pattern parameters are expected for various clinical disorders. As such these parameters may be useful indicators of specific disease states. In any event, assuming a constant level of force or by analyzing small stationary signal epochs throughout a force varying contraction, the COV value may be used as a measure of the stability of neural control or the ability of the motor units to be consistently active. Motor unit firing patterns have been similarly studied in hemiparesis [22] and these techniques could be used to study the affects of other neuromuscular disorders.

4.4. Macro MUAPs

Stalberg [61] first introduced the concept of ensemble or spike triggered averaging a macro signal using individual motor unit firing times as triggers. His original macro electrode was a 15 mm length of cannula centred around a SFN detection surface used to acquire the micro signal triggering potentials. Following signal decomposition, the concepts introduced by Stalberg can be extended to use the firing times of the multiple motor units represented in the obtained MUAPTs. For each MUAPT, the motor unit firing times can be used as triggers for locating 100 ms epochs in the macro detected signal (detected using surface or indwelling needle cannula electrodes). Each located interval can be ensemble averaged to extract the motor unit's macro MUAP. The duration, peak-to-peak voltage, area and the negative peak amplitude, area and duration of each macro MUAP can be calculated and displayed along with the macro MUAP waveform [75]. Example surface detected macro potentials can be seen in the third column of Fig. 11. The size parameters of the macro MUAPs, such as peak to peak voltage or area are related to the overall size of the contributing motor unit. This is certainly true when using indwelling macro electrodes such as Stalberg's original 'macro' electrode or a conmac [34] electrode. When using surface electrodes, the depth of the motor unit in the muscle can confound these relationships. Nevertheless, the surface detected macro MUAPs are still useful sources of motor unit size information [15,55]. They have also been related to the level of muscle activity [7] in a manner that is consistent with Henneman et al.'s [29,30] size principle.

4.5. Electrotonic twitch

The combination of macro information with micro and/or firing pattern information may provide new information regarding how a muscle is structured and how it is controlled for force production. One such combination, electrotonic twitch [8], the product of macro

MUAP area and motor unit mean FR, promises to relate the size and average activity of motor units to their average force contribution. If area is used to represent the size of the macro-MUAP the resulting units for the electrotonic twitch values are volts (V) or micro volts (μV). For a given muscle, the average macro MUAP size times the average motor unit mean FR results in an average electrotonic twitch that can be used to predict the average force produced by the muscle. Conwit et al. [8] calculated average values using data from 10 to 15 motor units sampled using EMG signal decomposition techniques at the same level of force to produce average electrotonic twitch values that could be used to provide a reliable estimate of muscle force (r^2=0.70). In addition, the distribution of individual motor unit electrotonic twitch values for a representative sample of motor units within a muscle active at slight to moderate levels of force will reflect the motor unit size and FR patterns for a muscle. Such distributions could be used to detect shifts in the capability of a muscle to produce force, or shifts in the way in which muscle force is produced. Both of these may be useful for studying changes in the neuromuscular system.

4.6. Motor unit number estimation (MUNE)

The electrical response of a muscle to the stimulation of its motor nerve detected using overlying surface electrodes is called a compound muscle action potential (CMAP) or M-wave. The CMAP represents the activity of all of the motor units of a muscle whose axons were excited by the stimulus. If the stimulus is supramaximal all of a muscles motor units will be activated and a maximum CMAP or M-wave will be detected. Therefore, the maximal CMAP represents the electrical activity of all of a muscle's motor units. The activity of an average sized motor unit can be represented by an average surface-detected MUAP (S-MUAP). The average S-MUAP can be determined by averaging over a representative sample of S-MUAPs. An estimate of the number of motor units in a muscle can be obtained by dividing the value of a size-related parameter of the maximum CMAP by the corresponding value for the average S-MUAP. A size-related parameter may be the peak-to-peak voltage or the area. For the estimate to be valid the maximal CMAP and the sample of S-MUAPs used to calculate the average S-MUAP must have been detected using the same electrode configuration. In addition, the motor units sampled to calculate the average S-MUAP must be representative of the muscle's motor unit population [16].

To obtain a motor unit number estimate using EMG signal decomposition techniques the following steps need to be completed:

1. Obtain a maximal CMAP using a surface electrode positioned over the motor point of the muscle of interest.
2. Using the same surface electrode collect a series of macro and micro signals during a series of moderate muscle contractions. Before each muscle contraction re-position the micro electrode to detect the activity of differing sets of motor units.
3. Decompose each micro signal and for each MUAPT calculate the corresponding macro-MUAP (S-MUAP).
4. Once a set of at least 20 S-MUAPs have been obtained, align each S-MUAP using its onset and calculate an average S-MUAP.
5. Divide the area or peak-to-peak voltage of the maximal CMAP by the corresponding value of the average S-MUAP.

Estimates obtained via EMG signal decomposition techniques may be biased to high values because the motor units sampled will for the most part be smaller lower threshold units because EMG signals detected during only moderate muscle contractions and not during a full range of muscle contractions are studied. Nonetheless, the results are more representative than those obtained using spike-triggered averaging based on level or window triggering, much more quickly and easily obtained and may still be clinically useful.

5. Current status, concluding remarks and summary

5.1. Current status

EMG signal decomposition is a complicated process that requires several signal processing and pattern recognition steps. The results of an EMG signal decomposition can be used in a variety of ways and an abundant amount of useful information can be obtained. Many different approaches to EMG signal decomposition have been reported and new systems are currently under development. Several of the approaches, which focus on clinical application, have resulted in the development of algorithms that are being successfully utilized [48,49,65,75]. For example, the multi-algorithm, multi-pass decomposition system reported by Stashuk [75] is able to successfully decompose a variety of EMG signals with up to over a 130 MUAPs per second. The resulting decompositions are based on a single channel micro signal and are usually consistently accurate across an ensemble of signals and for each signal, sufficient information is provided to accurately calculate various quantitative EMG parameters of clinical interest. Most of the clinically oriented systems, in an effort to provide clinically acceptable decomposition and analysis times, do not attempt to resolve superimposed MUAPs. With the availability of increasingly faster processors the resolution of superimposed MUAPs may become clinically feasible and studies involving the benefits of resolving superimposed MUAPs are on going. While further improvements to clinically oriented systems could be made, at present, these systems provide a convenient and robust method for collecting clinically useful quantitative information and further developments would not have an immediate clinical impact. On the other hand, with regard to systems that can be used to provide information for more involved research applications further developments that would have an immediate impact on the use of these systems can be suggested. These systems are required to provide more detailed information and as such must resolve superimposed MUAPs and be able to accurately determine motor unit firing patterns including the precise times of recruitment and decruitment. All of the current systems applied for research purposes require some degree of operator interaction to select detection and assignment thresholds, confirm superposition resolutions or assess decomposition quality and to determine firing pattern validity. Any improvements that reduce the amount of operator interaction and therefore reduce the time required to decompose and analyze a detected EMG signal would be important.

5.2. Concluding remarks

For clinical and research purposes, micro and macro EMG signals can be used in conjunction with the decomposition results to calculate quantitative micro and macro MUAP and firing pattern parameter values. The combination of micro and macro MUAP parameters with the micro MUAP ensemble and firing pattern parameters allows more comprehensive information regarding the morphological and operational state of the neuromuscular system studied to be obtained. The micro MUAP parameters relate to the distribution of relatively few fibres that are situated close to the micro electrode. The macro MUAP parameters relate to the distribution of all of the fibres of a motor unit. The micro MUAP ensemble parameters relate to the operation of the neuromuscular junctions of a motor unit and to the density of motor unit fibres close to the micro electrode. The firing pattern parameters relate to the control and operation of the motor units.

In total, the parameters described provide quantitative information that can be used to assist in the clinical diagnosis and treatment of neuromuscular disorders, whether this be achieved by using multiple univariate tests or multivariate discriminate analysis [54] or by searching for outliers [63]. In addition, this expanded set of parameters can be used to study basic motor unit physiology in normal and diseased neuromuscular systems or the affects of ageing and fatigue. Results obtained from using EMG signal decomposition systems to this point are only preliminary. No comprehensive data set exists that could be used to systematically study neuromuscular system changes. More data needs to be collected and analyzed. The potential usefulness of the various parameters described must be further investigated.

5.3. Summary

Basic aspects regarding the composition of EMG signals and methods for EMG signal decomposition have been discussed. The various steps involved in the decomposition of an EMG signal have each been described and important aspects regarding each of these steps have been discussed. The uses of EMG signal decomposition results both for the diagnosis and management of neuromuscular disorders and for further research to better understand neuromuscular physiology and the affects of disease, ageing and fatigue have been presented. The value of acquiring and analyzing both micro and macro signals and in analyzing MUAP ensembles, to obtain information about the local and global aspects of a motor unit, has been described.

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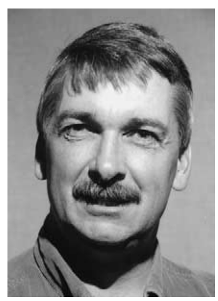

Daniel W. Stashuk received a B.ASc. degree in electrical engineering from the University of Waterloo, Waterloo, Ont., Canada, in 1978 and M.Eng and Ph.D. degrees in electrical engineering from McMaster University, Hamilton, Ont., Canada, in 1982 and 1985, respectively. From 1985 to 1988 he held the position of Research Assistant Professor at Boston University Neuro-Muscular Research Center and was supervisor of the Motor Unit Laboratory. Since 1988 he has been a faculty member with the Department of Systems Design Engineering at the University of Waterloo and currently has the rank of Associate Professor. He is interested in the detection and analysis of biological signals, especially the detection and analysis of electromyographic signals for tbe extraction of clinically relevant information. Dr Stashuk is a member of the Canadian Medical and Biological Society and the Engineering in Medicine and Biology Society of the IEEE.