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Decomposition and quantitative analysis of clinical electromyographic signals

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Abstract

Procedures for the quantitative analysis of clinical electromyographic (EMG) signals detected simultaneously using selective or *micro* and non-selective or *macro* electrodes are presented. The procedures first involve the decomposition of the micro signals and then the quantitative analysis of the resulting motor unit action potential trains (MUAPTs) in conjunction with the associated macro signal. The decomposition procedures consist of a series of algorithms that are successively and iteratively applied to resolve a composite micro EMG signal into its constituent MUAPTs. The algorithms involve the detection of motor unit action potentials (MUAPs), MUAP clustering and supervised classification and they use shape and firing pattern information along with data dependent assignment criteria to obtain robust performance across a variety of EMG signals. The accuracy, extent and speed with which a set of 10 representative 20–30 s, concentric needle detected, micro signals could be decomposed are reported and discussed. The decomposition algorithms had a maximum and average error rate of 2.5% and 0.7%, respectively, on average assigned 88.7% of the detected MUAPs and took between 4 to 8 s. Quantitative analysis techniques involving average micro and macro MUAP shapes, the variability of micro MUAPs shapes and motor unit firing patterns are described and results obtained from analysis of the data set used to evaluate the decomposition algorithms are summarized and discussed.

Keywords: Quantitative EMG; EMG Signal Decomposition; Motor unit action potentials; Motor unit firing patterns; Macro EMG

1. Introduction

The quantitative analysis of the motor unit action potentials (MUAPs) of individual motor units detected using monopolar needle (MN), concentric needle (CN) or single fibre needle (SFN) electrodes can provide important information for the diagnosis and treatment of neuromuscular disorders [1–6]. Statistics, based on a motor unit's average MUAP shape, are calculated from a representative sample of motor units, usually of size 20, from a muscle of interest to extract morphological information regarding the size and fibre distributions of its motor units. Common statistics used with regard to MN and CN MUAPs include duration, amplitude, number of phases and turns, area, amplitude-area ratio, spike duration and size index [1–5]. The variability or jitter, of the temporal intervals between significant peaks within SFN MUAPs is analyzed to assess the functional stability of a muscle's neuromuscular junctions, while the average number of significant peaks is used to estimate the density of motor unit fibres in close proximity to the detection-surface [6].

Traditionally, such MUAPs are often obtained using level or window triggering during slight muscle contraction. Recently however, several clinical EMG signal decomposition systems have been introduced [7–12] and at least three are currently available on commercial clinical EMG systems and have published reference values [10–15]. EMG signal decomposition resolves a composite EMG signal into its constituent motor unit action potential trains (MUAPTs). The resulting MUAPTs rep-

Abbreviations: EMG, electomyographic; CN, concentric needle; MN, monopolar needle; SFN, single fibre needle; MUAPT, motor unit action potential train; MUAP, motor unit action potential; MFAP, muscle fibre action potential; IPI, inter-potential-interval; FR, firing rate; MVC, maximum voluntary contraction; STBC, shape and temporal based clustering; RMS, root mean square; STD, standard deviation; COV, coefficient of variation; pps, pulses per second.

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resent the individual activities of a population of concurrently active motor units. Consequently, analysis of the MUAPTs can provide information regarding motor unit firing patterns and the stability of the MUAPs within each MUAPT in addition to the standard morphological information based on statistics of the average MUAP shapes. The stability of MUAPs within a MUAPT, or jiggle, can provide information related to that obtained using SFN MUAPs [16].

The decomposition of an EMG signal is a difficult task. The characteristics of each signal depend on the type of electrode used, its position relative to the muscle, the level of contraction and the clinical state of a subject's neuromuscular system. EMG signal decomposition algorithms must therefore be capable of providing robust performance across signals with widely varying characteristics. A system of algorithms for signal decomposition will be described and results of the evaluation of their performance across a wide spectrum of EMG signals will be presented. A brief description of the overall decomposition system has been presented earlier [17] and detailed explanations and evaluations of several of its key aspects have also been previously reported [18–21]. However, the entire system has not been previously described in detail nor has its performance been reported. In addition, methods of analyzing the stability of the MUAPs within a MUAPT and combining the results of the decomposition of signals detected with selective or *micro* electrodes with signals acquired simultaneously using non-selective or *macro* electrodes will be introduced.

2. Methods

Following are descriptions of the major components of the EMG signal decomposition and analysis system.

2.1. Data acquisition

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 or SFN 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 [22] or conmac [23] electrodes. Therefore, signals from two instrumentation channels are acquired. The first channel acquires a *micro* signal detected by a standard MN, CN or SFN electrode with an appropriate passband and sampling rate. The second channel acquires 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 is then analysed in conjunction with the results of the micro signal decomposition. Provided that the *micro* signal is acquired with a sampling rate of at least 12.5 KHz, the exact details of the data acquisition system will not greatly affect the decomposition and subsequent analysis results.

To ensure that a micro signal of adequate sharpness and signal to noise ratio is obtained, the micro electrode is initially positioned, in a minimally contracting muscle, to detected MUAPs of maximum amplitude and sharpness. 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 and the subject attempts to maintain a constant level of contraction until data acquisition is ended.

2.2. Decomposition of the micro signal

2.2.1. Signal preconditioning and MUAP detection

MUAPs are detected using a method similar to that of McGill et al. [10]. The composite signal is bandpass filtered using a first-order difference filter and a coefficient (typically 1.5) times the root mean square (RMS) value of the filtered signal, calculated over an initial 1 s interval, is used as the detection threshold. The filtered signal is scanned for locations where the detection threshold is exceeded. Once a MUAP is detected, its firing time is defined by the location of the maximum value found within the next 1 ms. The search for subsequent MUAPs then continues 1 ms past the firing time of the currently detected MUAP.

2.2.2. Clustering of detected MUAPs

Once a set of MUAP firings have been detected, the number of active motor units contributing MUAPs to the set and the prototypical shape of each motor unit's MUAP must be determined. Initially no a priori information regarding the number of motor units or their average shapes is available. Therefore, clustering or non-supervised classification must first be applied. In addition it cannot be assumed that each detected MUAP actually represents the MUAP of a single motor unit. A detected MUAP may actually represent the superposition of the MUAPs from two or more motor units. For each MUAP firing time, the signal samples on each side of it can be used as features to represent the MUAP. For the analyses presented in this report, the 32 first-order difference-filtered signal samples evenly spaced over 2.56 ms interval centred on the MUAP firing times were used to represent the detected MUAPs for clustering. The goal of the clustering algorithm is to accurately determine the number of active motor units and for each active motor unit its average or prototypical MUAP shape. The clustering algorithm does not have to analyse the entire composite signal nor does it have to assign every detected MUAP. In fact only the MUAPs detected within a specified portion of the composite signal, called the clustering interval and typically of 5 s duration, are clustered using a modified K-means shape- and temporal-based clustering algorithm (STBC) [18]. The STBC algorithm does not use fixed assignment criteria but instead uses assignment criteria that are based on the detected MUAP data. No critical parameter values need to be set a priori. The algorithm uses motor unit firing-pattern statistics estimated using an error-filtered estimation (EFE) algorithm [19]. The major steps in the STBC algorithm include initialisation, learning, classification, splitting and merging. Initialisation involves using the central 3 s of the clustering interval to obtain an initial estimate of the number of active motor units (clusters) and of the prototypical shape of the MUAP of each cluster. The learning phase considers the MUAPs in the initialisation interval and uses K-means clustering [24]. Firing pattern inconsistencies, determined using the error-filtering estimation (EFE) technique [19], are used to establish new clusters and the K-means algorithm is re-applied until the clustering is stable. After K-means clustering, the cluster cores are selected using Forgy's criteria [24], MUAPs not in a cluster core or in small cluster cores (<3 members) are ignored. To increase the number of members in the clusters, unassigned MUAPs in the clustering interval are then assigned to clusters using data-driven individual-cluster assignment criteria. Cluster splitting using a 2-mean clustering algorithm is then applied to any cluster containing a firing-pattern inconsistency. Cluster splitting continues until no inconsistencies exist in any cluster. Clusters are merged using heuristic distance and firing-pattern based rules. Classification, splitting and merging are repeated until no clusters are split or merged. For a more detailed description and evaluation see [18,19].

2.2.3. Supervised classification of MUAPs

Once estimates for the number of active motor units and the shapes of their prototypical MUAPs are available the complete set of detected MUAPs can be classified using supervised classification techniques. For the analyses presented in this report, for supervised classification, the MUAPs were represented as they were for clustering (see Section 2.2.2). The supervised classification algorithm applied in this system 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 certainty that they will be correct. Certainty is measured by multiplying together the results of three decision functions each having values that range from 0 to 1. One is based on normalised distance between a candidate MUAP and a prospective MUAPT template, one uses relative 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 and one measures the firing time consistency of the candidate MUAP relative to the firing-pattern of a prospective MUAPT. The MUAP is assigned to the MUAPT which produces the greatest certainty value provided the value is greater than the certainty assignment threshold (typically 0.02). MUAPs whose maximum calculated certainty is below the threshold value are not assigned. These unassigned MUAPs are often actually superimposed MUAPs. 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. 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. Changing MUAP shapes, which can be caused by small needle movements, are tracked by calculating the MUAPT templates as weighted moving averages of their assigned MUAPs, weighted using the certainties with which the respective MUAPs are assigned. After each assignment pass MUAPTs are merged if the average certainty of the merged train is greater than the average certainty of each individual train. 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 [20].

2.2.4. Discovering MUAPT temporal relationships

2.2.4.1. 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 [25]. The random variables representing the activity of two MUAPTs can be either independent or dependent. 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, synchronised or exclusive are possible. Linked trains fire with a definite, essentially constant interval relative to each other, such as a main MUAP spike and its satellite or when a MUAP is consistently multiply-detected as two or more distinct MUAP sections. Exclusive trains never fire together. 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 [26], but this analysis requires assumptions regarding the probability distributions of the bins of the resulting histograms. Mutual information is a nonparametric measure of the interdependency between two random variables [27]. The tendency of 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, expected MUAP satellite latencies and peak motor unit firing rates (FRs) a window of 25 ms duration is sufficient. 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 $\mathrm{MUAPT_i}$ and $\mathrm{MUAPT_j}$ respectively, of a selected pair of trains. The mutual information between A and B is defined as:

$$I(AB)=H(A)+H(B)-H(AB) \tag{1}$$

where:

$H(A)=-\Sigma^{n}_{i=1}\, p_i \log p_i$ entropy of random variable A,
$H(B)=-\Sigma^{m}_{j=1}\, p_j \log p_j$ entropy of random variable B,
$H(AB)=-\Sigma^{n}_{i=1}\,\Sigma^{m}_{j=1}\, p_{ij} \log p_{ij}$ joint entropy of random variables A and B,
$p_i=P[A=a_i]$, $i=1,\ldots,n$ discrete probability distribution of A,
$p_j=[B=b_j]$, $j=1,\ldots,m$ discrete probability distribution of B,
$p_{ij}=P[A=a_j,\, B=b_j]$ discrete joint probability distribution of A and B,
$n=m=2$, $a_1=b_1=0$ and $a_2=b_2=1$.

To compute $I(AB)$ each of the above entropies must be computed which in turn requires that each of the above probabilities be computed.

The probability of a firing of a $\mathrm{motor\ unit_i}$ within a randomly positioned analysis window is:

$$p_i=\frac{N_iW}{T_i} \tag{3}$$

where: N_i is the number of firings in the $\mathrm{MUAPT_i}$; W is the width of the analysis window; T_i is the total time over which $\mathrm{motor\ unit_i}$ was active.

The joint probability of $\mathrm{motor\ unit_i}$ and $\mathrm{motor\ unit_j}$ firing in the analysis window is

$$p_{ij}=\sum_{k=1}^{n_{ij}}\frac{W-\Delta t_k}{T_{ij}} \tag{4}$$

where: W is the width of the analysis window; Δt_k is the time interval between the k^{th} firing in $\mathrm{MUAPT_i}$ and $\mathrm{MUAPT_j}$; n_{ij} is the number of firings in $\mathrm{MUAPT_i}$ and $\mathrm{MUAPT_j}$ such that $\Delta t_k<W$; T_{ij} is the total time over which $\mathrm{motor\ unit_i}$ and motor unit, were simultaneously active.

A statistic of known distribution for determining whether the level of mutual information between to random variables is significant is the interdependency redundancy measure [28,29] which is defined as:

$$R(AB)=\frac{I(AB)}{2NH(AB)} \tag{5}$$

where: $I(AB)$ is the mutual information between variable A and B; $H(AB)$ is the joint entropy of variable A and B; N is the minimum number of occurrences of A and B ($=n_{ij}$ of Eq. (4)).

$R(AB)$ is χ^2 distributed with $(n-1)(m-1)$ degrees of freedom (where $n=m=2$ in this application). Therefore, the calculated value of $R(AB)$ can be compared to a χ^2 distribution with 1 degree of freedom at the desired level of confidence to determine if two MUAPTs are dependent.

2.2.4.2. Classifying MUAPT temporal relationships

The interdependency redundancy is used to classify temporal relationships between trains. At the end of each supervised assignment pass the existing MUAPTs are considered in pairs and the interdependency redundancy measure for each pair is calculated. If its value is less than 3.84 (95% confidence level) the trains are considered independent. If its value is greater than 3.84 the trains are considered dependent. When the trains are considered dependent, if its value is greater than 10.84 (99.9% confidence limit) and the ratio of the product of the individual train probabilities p_i and p_j respectively, to the train joint probability p_{ij}, is less than 0.5, the trains are classified as linked and considered as a single train during post-decomposition analysis. When the trains are considered dependent, if the ratio of the product of the individual train probabilities, to the train joint probability, is greater than 2 the trains are classified as mutually exclusive and are further considered for merging.

2.2.5. Resolution of superimposed MUAPs and further MUAP classification

Although algorithms for the resolution of superimposed MUAPs have been developed and evaluated [21] they have not yet been deemed necessary in the clinical use of this system. As such they will not be further discussed in this report. However, as the use of firing-pattern information becomes more important, the importance of resolving superimposed MUAPs will also increase. In addition, as computing power available in the clinic increases it will become more practical to consider resolving superimposed MUAPs. Studies investigating the effects of including such algorithms on the usefulness of the results obtained are ongoing.

2.3. Micro and macro signal analysis following signal decomposition

2.3.1. Micro MUAP analysis

Given a MUAPT for each motor unit that contributed significant MUAPs to the original composite signal the prototypical MUAP shape can be estimated. Mean, median [11], mode [30], statistical [12] and interference cancelling [10] averaging techniques have been used to reduce the interfering activity of other motor units when estimating the prototypical MUAP. Currently, the system described here uses isolated MUAPs and mode estimation [30], over a 50 ms interval centred on each MUAPs peak slope, to calculate the prototypical MUAP. An isolated MUAP is defined as one that occurs isolated in time by at least 3 ms from any other detected MUAP and with a shape close to that of the prototypical MUAP. Isolated MUAPs are used to better estimate the spike portion of the prototypical MUAP. Given the prototypical shape, its duration, peak-to-peak voltage, number of phases and turns, area and area to amplitude ratio are calculated using standard algorithms [31]. For the results presented in this report, a 25 μV threshold was used to define a turn and a phase had to have amplitude of at least 20 μV and duration of at least 240 μs. The values of MUAP parameters along with the prototypical MUAP waveform for each MUAPT extracted from a composite EMG signal are presented in a clinical or micro MUAP summary, as shown in Figs. 1 and 2, respectively. Markers identifying the onset, end and peak values can be manually adjusted if necessary.

2.3.2. Micro MUAP ensemble analysis

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 [6,16] of a motor unit. In an attempt to obtain information more closely related to the activity of the individual muscle fibres that are contributing significant muscle fibre action potentials (MFAPs) to the MUAPs of a motor unit, the accelerations of the MUAPs are analyzed [32]. Such analysis provides information regarding the density of fibres within a motor unit as well as the operation of its neuromuscular junctions. For each MUAPT, up to 50 isolated MUAP occurrences are selected. Given a set of isolated MUAPs, a prototypical MUAP acceleration is calculated via median averaging [30]. The number of significant peaks in the acceleration template is used as an estimate of the number of nearby fibres contributing significant MFAPs to the MUAPs of the motor unit [32]. If there are at least two significant peaks the mean consecutive difference (MCD) [6] between the two sharpest peaks across the ensemble is calculated as an estimate of the jitter of a pair of the motor unit's neuromuscular junctions. The jiggle [16] of the isolated MUAPs and their accelerations are also calculated. Summaries, similar in format to Fig. 2, containing shimmer plots of the ensembles of selected MUAPs or their accelerations for each MUAPT can be displayed. Fig. 3 shows details of the calculations for the MUAP ensemble of one MUAPT. A similar acceleration jitter summary can be viewed for each MUAPT. The members selected within the ensemble can be manually edited and if less than 25 isolated MUAPs are available within a MUAPT the ensemble statistics calculated are ignored.

2.3.3. Firing pattern analysis

For each MUAPT the temporal pattern of its discharges are characterised by a histogram and estimation of the mean inter-potential-interval (IPI) and the standard deviation (STD) and coefficient of variation (COV) of the IPIs. Because there are erroneous and missed motor unit firings present in the trains an error filtering estimation (EFE) technique that recognises and ignores erroneous IPIs (either too short or long) is used [19]. The EFE technique was shown to produce accurate mean and standard deviation estimates even when up to 50% of the firings of a MUAPT are missing [19]. A motor unit's average FR is calculated as simply the inverse of its mean IPI. A motor unit's instantaneous FR, at each of its discharge times, is estimated as the inverse of a Hamming weighted average of 10 valid IPIs centered about the current discharge time. A valid IPI has a value within 3 standard deviations of the mean IPI. The identification (ID) rate is calculated as the percentage of expected firings detected. 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. The times of a motor unit's discharges can be displayed along with its instantaneous FR, a histogram of its IPIs and calculated firing pattern statistics in a decomposition summary as shown in Fig. 4. A clinical summary also presents firing pattern statistics, as shown in Fig. 1, and

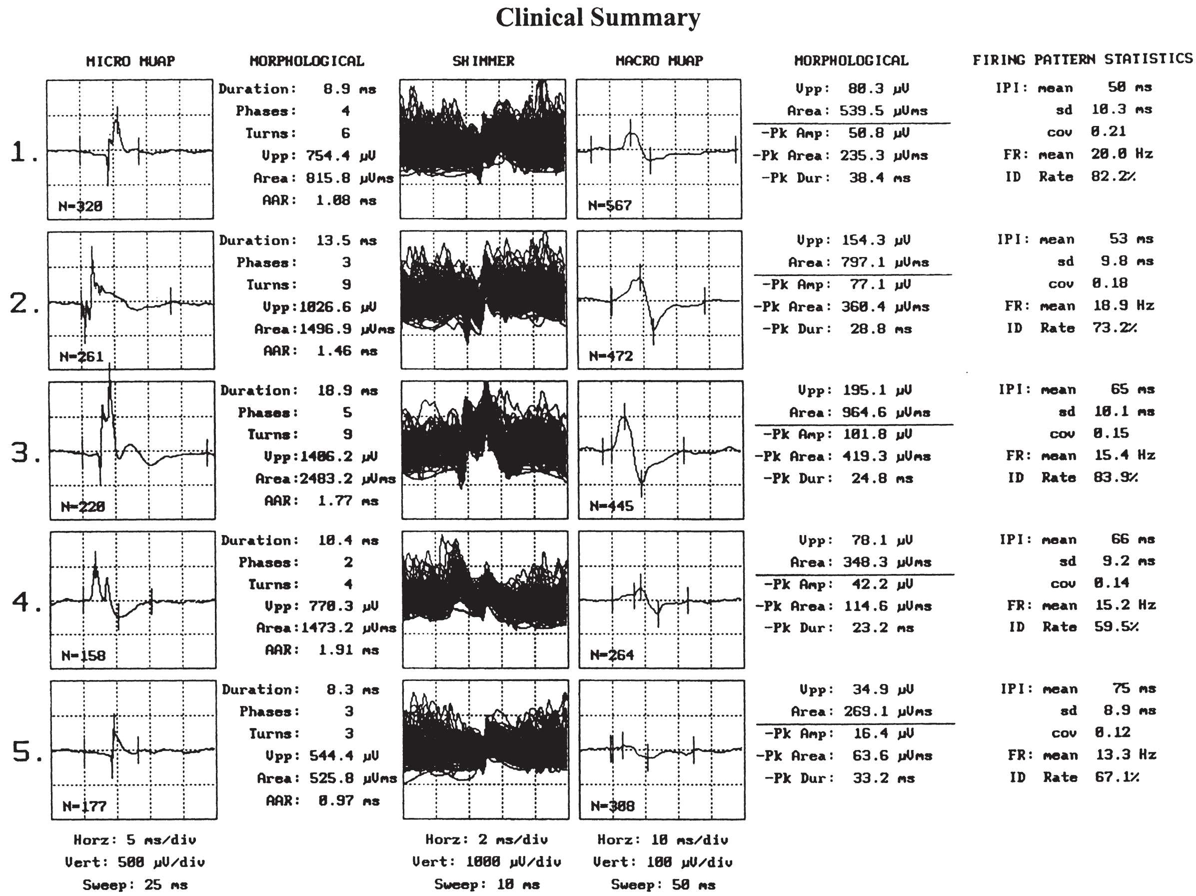

Fig. 1. Clinical Summary: the results of the decomposition of a typical micro signal and subsequent further analysis of the micro and macro signals. The left most column contains plots of the calculated prototypical micro MUAPs. The location of significant landmarks (onset, positive and negative peak and end) and the number of isolated MUAPs used in the estimation of the prototypical waveforms are also indicated. The micro MUAP parameter values are displayed to the right of the waveforms. The individual MUAPs assigned to each MUAPT are drawn, on top of each other, in the shimmer plots shown in the third column. The fourth column displays the macro MUAPs obtained by ensemble averaging along with the number of firings used in each average. The final two columns present the macro MUAP and firing pattern parameter values for each train, respectively.

a firing-pattern data display for each MUAPT train, similar in format to Fig. 2, is also available.

2.3.4. *Macro potential analysis*

For each MUAPT the motor unit firing times are used as triggers for locating 100 ms epochs in the macro detected signal (detected using surface or indwelling needle cannula electrodes). Each located interval is ensemble averaged to extract the motor unit's macro MUAP [22]. The duration, peak-to-peak voltage, area and the negative peak amplitude, area and duration of each macro MUAP are calculated and can be displayed along with the macro MUAP waveform in a clinical summary as shown in Fig. 1. In addition, a decomposition summary displays the macro MUAP waveforms, as shown in Fig. 4, and a macro-MUAP data display for each MUAPT train, similar in format to Fig. 2, is also available. Markers identifying the onset, end and peak values can be manually adjusted if necessary. An additional parameter, called the electrotonic twitch, that relates to the average contribution of a motor unit to the muscle force generated and is defined as the product of the motor unit's macro MUAP area and its mean FR is also calculated.

3. Results

Ten sets of EMG signals detected during slight to moderate levels of contraction, corresponding to approximately 10 to 25% of maximum voluntary contraction (MVC), of the extensor digitorm communis (EDC) muscle of normal subjects were used for evaluation and to present exemplary normative data. EMG signals were detected from 4 healthy subjects ranging in age from 25 to 72 years. The typically 20–30 s long micro and macro signals were detected using CN and overlying 1 cm by 3 cm surface electrodes (Ag-AgCl with adhesive, conductive gel) and acquired at sampling rates of 25 KHz and 5 KHz, respectively. The CN was

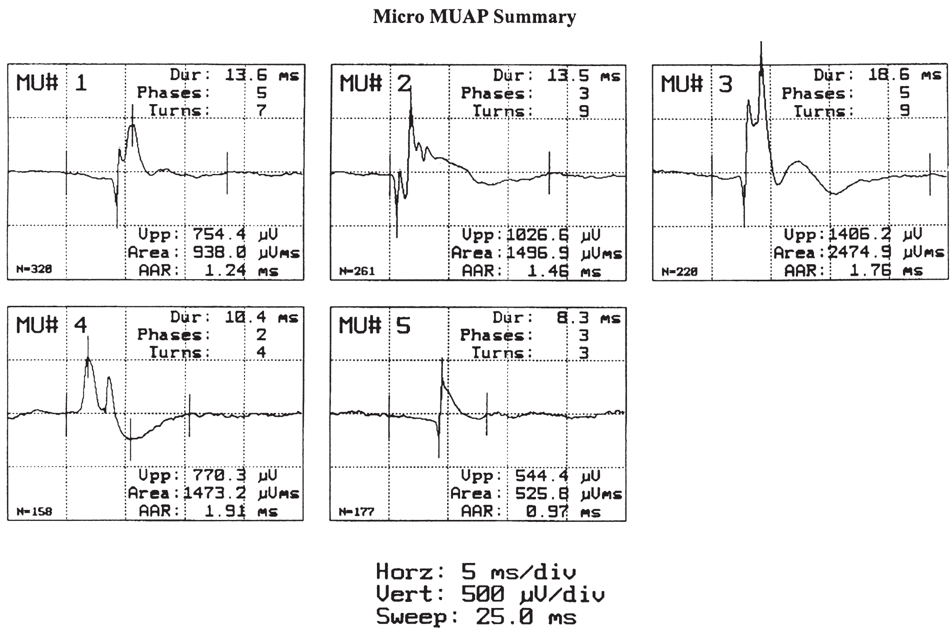

Fig. 2. Micro MUAP Summary: a detailed view of the micro MUAPs shown in Fig. 1 are displayed along with their associated parameter values. The location of significant landmarks (onset, positive and negative peak and end) and the number of isolated MUAPs used in the estimation of the prototypical waveforms are also indicated.

positioned and the muscle was contracted as described in the Data Acquisition section.

In the decomposition summary, shown in Fig. 4, a summary of the results obtained following the decomposition of a typical signal is presented. The consistency of the assigned MUAPs and the level of background interference can be seen in the shimmer plots shown in the second column. The individual MUAPs within a specific train can also be viewed in a MUAP raster plot as shown in Fig. 5. The ability of the EFE algorithm [19] to ignore erroneous IPIs and determine accurate mean and standard deviation values can be seen in the IPI histogram plots displayed in Fig. 4. A decomposition summary display, though similar to a clinical summary, is necessary because it is used in conjunction with MUAP raster plots for individual MUAPTs, as in Fig. 5, to quickly determine qualitatively the validity of a decomposition. Trains with large numbers of errors and their corresponding parameter values can be designated as invalid and therefore not included in subsequent motor unit summary or population statistics.

3.1. Micro signal decomposition results

Decomposition of the complete 20–30 s acquired of each micro signal took between 4 to 6 iterations of the Certainty algorithm and between 4 to 8 seconds running in DOS on a 166 MHz pentium based machine. The first 5 seconds of each micro signal were manually decomposed, including the resolution of superimposed MUAPs, by an experienced operator using a computer-based graphical display algorithm. The manual decomposition results were assumed to be the *gold standard* and were compared with those obtained automatically by the decomposition routines. The results of this comparison are presented in Table 1. The ten files considered had varying levels of electrical activity. The number of MUAPs represent the total number of motor unit discharges evident in the 5 s intervals manually analysed, including MUAPs contributing to superimposed MUAPs that were resolved during manual decomposition. The discharge rate in pulses per second (pps) is simply the number of MUAPs divided by the 5 s analysis interval length. The degree of complexity of the interference patterns was not always related directly to the level of muscle activity or to the level of the detection threshold. The degree of interference pattern complexity was instead more closely related to the discharge rate. The files were therefore labelled in ascending order based on their discharge rate. The number of trains in Table 1 represents the number of classes remaining after supervised classification. The number of motor units represents the number of classes remaining after MUAPT temporal relationships were considered. In every case, the number of motor units exactly agreed with the number of motor units found, by manual decomposition, to be consistently contributing MUAPs to the composite signal. The number of trains and the number of motor units contributing to the signals were related to the discharge rate.

The number of MUAPs detected represents the number of MUAPs detected using the reported detection threshold. The % of missed detections represents the percentage difference between the number of MUAPs and

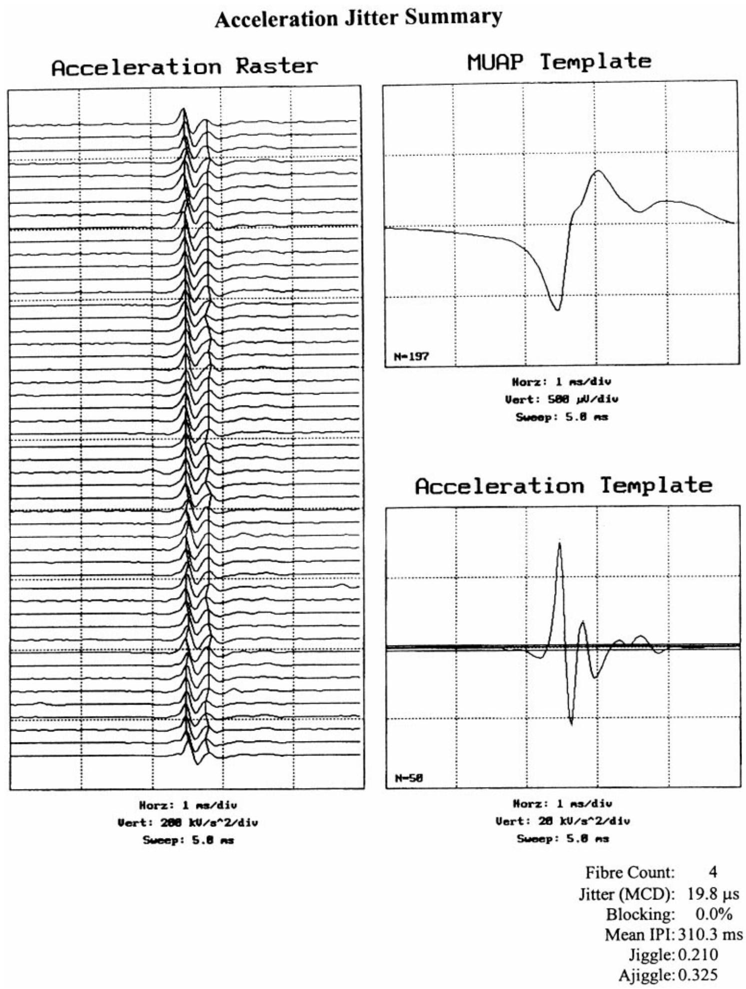

Fig. 3. Acceleration Jitter Summary: a raster of isolated MUAP accelerations selected from a MUAPT are displayed on the left. The micro MUAP template or prototypical waveform is shown at the top right. Bottom right shows the acceleration template, which is calculated using median estimation across the 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.

the number of MUAPs detected. On average 14.8% of the occurring MUAPs were not detected. This is partly due to superimposed MUAPs that were detected as single MUAPs and partly because some small MUAPs were not detected using the current simplistic detection algorithm. The certainty-based supervised classification algorithm used does not attempt to assign all of the detected MUAPs. Rather, it only makes MUAP classifications that had an above threshold amount of certainty. Using a certainty assignment threshold of 0.020 the % of detected MUAPs that could be assigned (assignment rate %) for each file is presented in Table 1. The average assignment rate was 88.7%. MUAP assignments that did not agree with those assigned manually were considered erroneous. The percentage of MUAPs assigned that were erroneous is also reported for each file (error rate %). The maximum and average error rates were 2.5% and 0.7%, respectively. An ideal situation is to have 100% assignment and 0% error rate. A measure of quality is then to have consistently high assignment and low error rates, respectively. Fig. 6 shows that, except for the most complex interference patterns studied, as the discharge rate increased, the assignment rate remained consistently high while the error rate remained low.

3.2. Quantitative EMG results

A total of 58 MUAPTs were obtained from the decomposition of the 10 micro EMG signals. Table 2 shows the number of MUAPTs that were suitable for calculating the various parameters along with a summary of these calculations, which includes the mean, standard deviation, maximum and minimum values of the parameters organized into groups as described in the Methods section above. Forty-one MUAPTs (73%) had accelerations with at least one pair of peaks suitable for jitter analysis, while 55 had at least one significant peak which thus resulted in a non-zero fibre count and 54 had sufficient acceleration values to calculate the jiggle of the MUAP accelerations. Some macro signals were not

Decomposition Summary

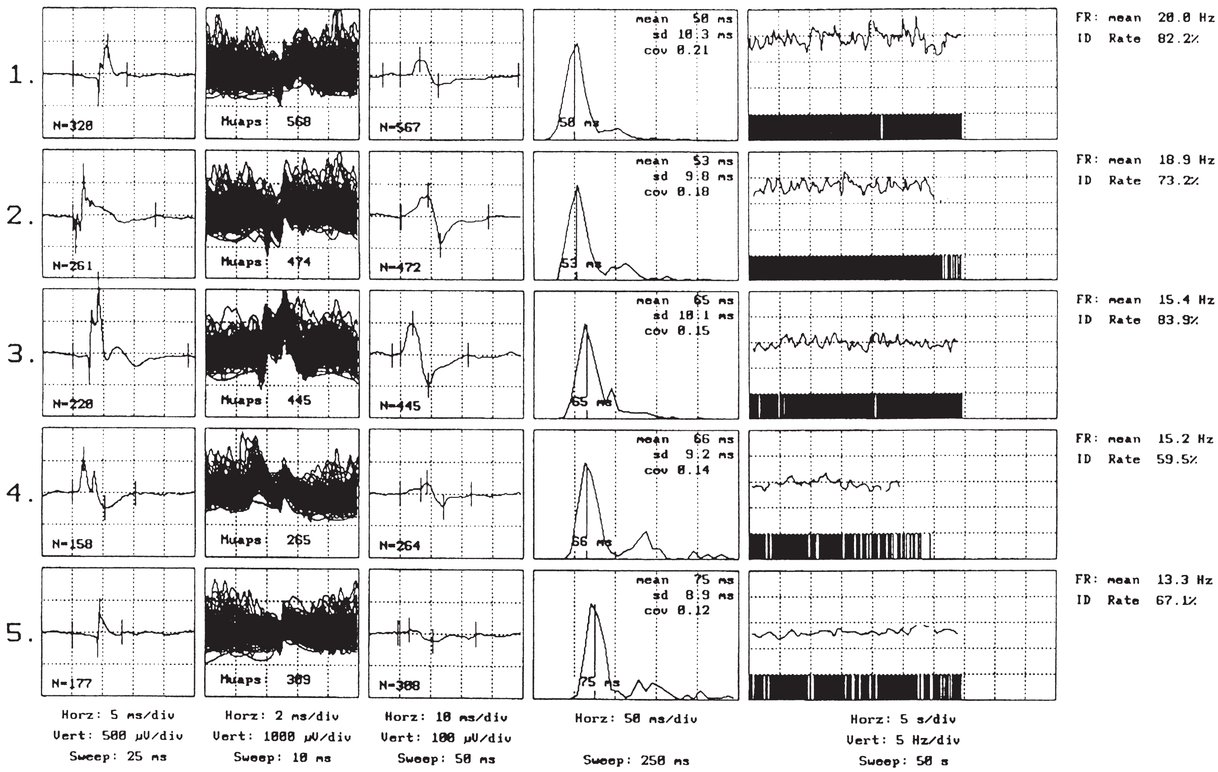

Fig. 4. Decomposition Summary: the results of the decomposition of a typical micro signal and subsequent further analysis of the micro and macro signals. In the first column, the prototypical micro MUAPs along with the numbers of isolated MUAPs used for their estimation are displayed for each MUAPT. 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 IPI histograms and MUAPT discharge times and instantaneous firing rate plots, respectively.

available for some contractions and therefore only 47 MUAPTs could be analysed for macro parameters.

The micro signals were detected using CN electrodes in the EDC muscle. Except for higher numbers of turns, values in Table 2 are similar to values presented for other muscles similarly analysed using decomposition algorithms [11–15]. The increased number of turns is due to the smaller threshold value used in defining a turn (25 μV). The jiggle mean and standard deviation values are larger than those originally reported [16]. This was caused by large baseline fluctuations present in the micro signals detected during the relatively high levels of contraction studied. Ajiggle had lower mean and standard deviation values than jiggle. The mean CN jitter values were in the normal range [33] of values obtained using SFN electrodes and no blocking was measured. The mean and standard deviation of the fibre count values were greater than similar fibre density measures obtained with SF electrodes [33].

The mean IPI was 65 ms, which corresponded to a mean FR of 16.1 pps. The mean standard deviation and coefficient of variation (COV) of the IPIs was 12.9 and 0.19 respectively, while the mean FR MCD was 0.29. The average identification (ID) rate, without any attempt to resolve superimposed MUAPs, was 66.7%. The average number of MUAPs in each MUAPT was 268.

The macro signal was detected using surface electrodes overlying the EDC muscle. The macro MUAPs ranged from 23 to 195 μV in peak-to-peak amplitude with duration ranging from 13.6 to 45.6 ms. Electrotonic twitch values ranged from 2.07 to 15.54 μV with a mean value of 6.46 μV.

4. Discussion

4.1. EMG signal decomposition

Robust performance is very important for clinical application. The decomposition system presented successfully decomposed a variety of EMG signals with up to over 130 MUAPs per second. Decompositions were consistently accurate and for each signal sufficient information was provided to accurately calculate the various quantitative EMG parameters of interest even though superimposed MUAPs were not resolved. Due to memory constraints the current DOS implementation spends significant time accessing various data files. A Windows-

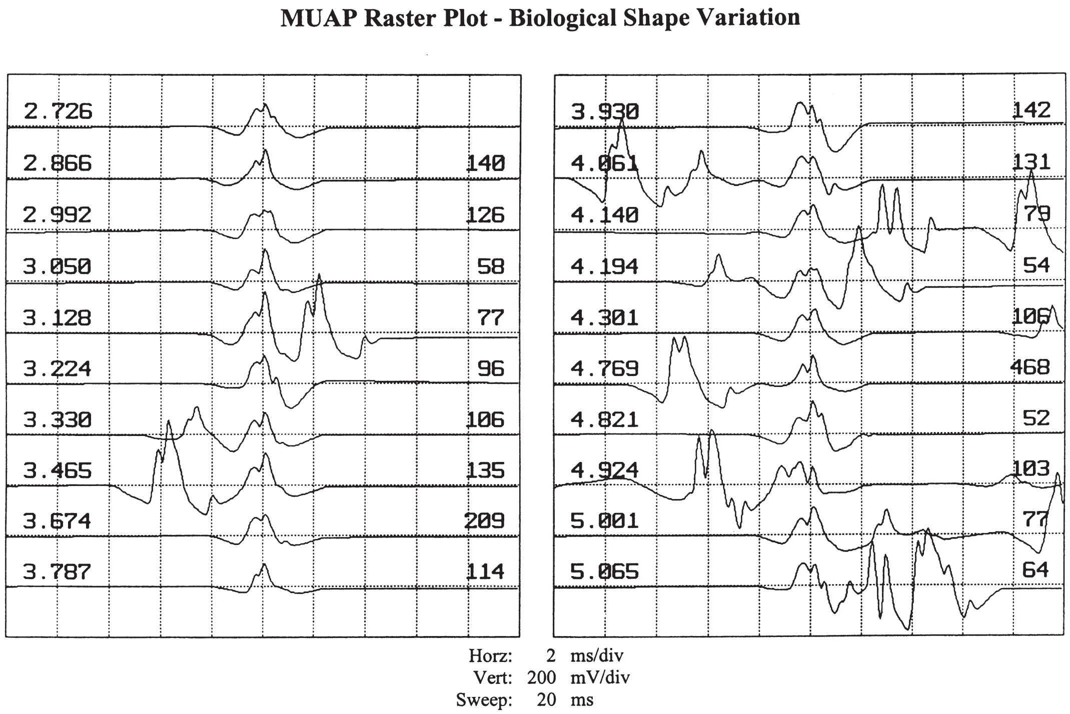

Fig. 5. MUAP Raster Plot — Biological Shape Variation: the individual MUAPs assigned to a MUAPT are displayed in a raster plot format. The numbers on the left and right of each column represent times of occurrence of the MUAPs in s and IPIs in ms, respectively. The motor unit represented by the MUAPT shown had an irregular firing-pattern because it was intermittently recruited throughout the contraction and the shapes of its MUAPs varied considerably. Nevertheless, the Certainty algorithm was able to successfully assign its MUAPs to the MUAPT shown.

Table 1
Results of decomposing 10 EMG signals detected from the EDC muscles of normal subjects during slight to moderate (10 to 30% MVC) levels of contraction[a]

File	No. of trains	No. of MUs	No. of MUAPs	Discharge rate (pps)	Detection threshold (V/s)	No. of MUAPs detected	% of Missed firings	Assignment rate (%)	Error rate (%)
1	4	4F	326	65.2	0.62	255	21.8	94.5	0.0
2	6	4F 1Sp	342	68.4	0.42	309	9.6	85.8	0.6
3	5	5F	419	83.8	0.53	380	9.3	95.3	0.0
4	8	5F 1Sp	433	86.6	0.65	372	14.1	90.6	1.3
5	6	5F 1Sp	453	90.6	0.65	398	12.1	89.7	0.0
6	6	5F	470	94.0	0.33	385	18.1	87.0	0.3
7	7	5F	538	107.6	1.20	491	8.9	86.6	0.6
8	8	5F	563	112.6	0.32	451	19.9	82.9	0.0
9	11	8F	660	132.0	0.99	547	17.1	93.2	1.6
10	8	8F	671	134.2	0.65	558	16.8	81.0	2.5
Mean	6.9		487.5	97.5	0.6	414.6	14.8	88.7	0.7
STD	2.0		119.3	23.9	0.3	97.8	4.7	4.8	0.9

[a] No. of trains is the number of MUAPTs considered during classification. No. of MUs is the actual number of motor units contributing significant MUAPs to the composite signal decomposed. F indicates the corresponding MUAPT was full. Sp indicates the corresponding MUAPT was sparse. No. of MUAPs is the number of motor unit discharges during the 5s analysis interval. Discharge Rate is the average, aggregate rate of motor unit discharges during the 5s analysis interval measured in pulses per second (pps). Detection threshold is the volt/s value used on the filtered EMG signals to detect MUAPs. No. of MUAPs Detected is the number of MUAPs detected during the 5 s analysis interval. % of missed firings is the percentage of motor unit discharges that were not detected or assigned. Assignment rate is the percentage of detected MUAPs assigned to a MUAPT. Error Rate is the percentage of detected MUAPs erroneously assigned. The mean and standard deviation (STD) values of appropriate data are also shown.

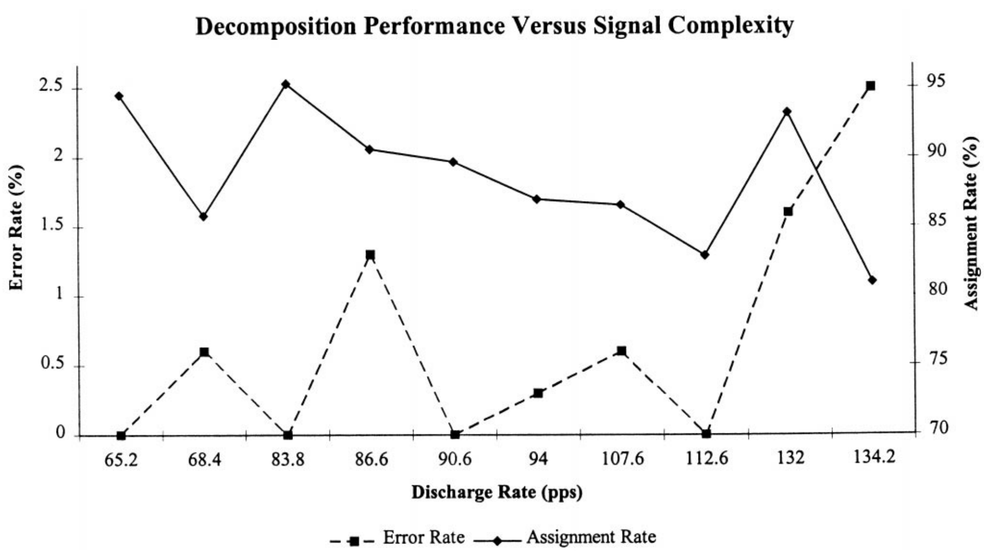

Fig. 6. Decomposition Performance Versus Signal Complexity: the accuracy (left axis — error rate %) and extent (right axis — assignment rate %) to which signals were decomposed are plotted against the complexity of the signal (Discharge rate pps).

Table 2
Summary of the results of processing the MUAPTs obtained following the decomposition of the 10 EMG signals reviewed in Table 1[a]

Group	No. of MUAPTs	Parameter	Units	Mean	STD	Max	Min
Micro MUAPs	56	V_{pp}	μV	502	275	1406	159
		Duration	ms	11.4	3.8	24.2	4.0
		Phases		3.30	0.93	7.00	2.00
		Turns		4.96	2.25	11.00	2.00
		Area	μV*ms	693	507	2611	141
		Area/ampl	ms	1.37	0.51	2.63	0.51
MUAP Ensembles	55	Jiggle		0.68	0.35	1.82	0.20
	54	Ajiggle		0.23	0.08	0.39	0.09
	41	CN Jitter	μs	25.3	9.4	49.7	4.4
	41	% Blocking	%	0.0	0.0	0.0	0.0
	55	Fibre Count		3.04	1.39	6.00	1.00
Firing Patterns	56	Mean IPI	ms	65	16	146	50
		IPI STD	ms	12.9	7.7	51.3	5.8
		IPICOV	ms	0.19	0.07	0.36	0.10
		Mean FR	Hz	16.1	2.8	20.0	6.8
		FR MCD	Hz	0.29	0.15	0.90	0.12
		ID Rate	%	66.7	21.7	98.4	9.3
	57	# of MUAPs per MUAPT		268	137	568	33
Macro MUAPs	47	V_{pp}	μV	67	36	195	23
		Area	μV*ms	399	190	965	121
		Duration	ms	28.4	6.4	45.6	13.6
		Neg. peak ampl	μV	36	19	102	14
		Neg. peak area	μV*ms	159	81	419	41
	45	Electronic twitch	μV	6.46	3.46	15.54	2.07

[a] The parameters are grouped into categories: Micro MUAPs relates to the micro prototypical MUAPs; MUAP Ensembles relates to the ensembles of isolated micro MUAPs selected from the MUAPTs; Firing Patterns relates to the discharge patterns of the motor units; Macro MUAPs relates to the ensemble averaged macro MUAPs;. The parameter names and associated units are provided along with their mean, standard deviation(STD), maximum (Max) and minimum (Min) values.

based version and the use of faster processors will greatly reduce decomposition and analysis time such that the resolution of superimposed MUAPs may be clinically feasible. Studies involving the benefits of resolving superimposed MUAPs are on going. Discussion regarding the various aspects of the signal decomposition system follows.

4.1.1. Signal preconditioning and MUAP detection

The first step in EMG signal decomposition is to consistently detect MUAPs that can be subsequently successfully assigned. Several different methods have been devised to detect significant MUAPs, or to segment the EMG signal. Each uses a detection-threshold value of a statistic computed using the composite signal. When the statistic value is above the detection-threshold a significant MUAP is detected. Gerbers et al. [7] and Loudon et al. [8] estimate the activity of the EMG signal by summing the absolute difference between adjacent samples over a 1.5 ms window and compare this value to either a fixed [7] or data dependent threshold [8]. Nandedkar et al. [11] use 10% of the maximum low-pass filtered first derivative of the composite signal as a threshold. Stalberg et al. [12] use an absolute threshold criteria consisting of an amplitude of greater than 50 μV and a slope of greater then 0.3 V/s. All of these methods directly or indirectly use the first derivative of the signal. In similar fashion, the method presented here processes a first-order difference-filtered signal and uses a detection threshold, defined using the RMS value of the signal calculated over a 1 s interval, to detect MUAP occurrences. The detected MUAPs are then represented by the data samples of the filtered micro signal for clustering and supervised classification, which reduces the affects of baseline fluctuations and offsets. It also produces shorter duration MUAPs that are less likely to be superimposed and that have more consistent shapes, which in turn provides better discrimination between the MUAPs of the various MUAPTs.

4.1.2. Clustering of detected MUAPs

The shape and temporal based clustering (STBC) algorithm [18] provides both high assignment accuracy and high assignment rates while reducing the number of duplicate clusters and minimising the number of missed clusters. The STBC algorithm performance was robust across the variety of EMG signals studied because it does not depend on fixed and sensitive assignment thresholds. Rather, it utilises data dependent assignment thresholds and the results are not sensitive to the value of Forgy's cluster core selection parameter. The use of temporal information also allows similarly shaped MUAPs produced by different motor units to be correctly discriminated and assigned to separate clusters. The EFE algorithm [19] used to estimate the mean and standard deviation of a motor unit's IPIs consistently provided sufficiently reliable temporal information to allow the STBC algorithm to perform as intended, even when the partial MUAPTs available during clustering had missed and erroneous firings.

4.1.3. Supervised classification of MUAPs

The certainty model allows direct implementation of a robust, certainty-based assignment threshold. Instead of choosing a fixed distance threshold, or fixed threshold for IPIs, 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 provides 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. Advantages of the Certainty algorithm are discussed in detail and examples are provided eleswhere [20]. Briefly however, the certainty algorithm, when compared to other traditional algorithms, can, with relative accuracy, classify a high percentage of detected MUAPs and its performance is not sensitive to the certainty threshold used. Considering the signals studied in this report, its performance was robust, it could deal with biological variability of the shapes of MUAPs within a MUAPT and it was able to discriminate between similar MUAPs generated by different motor units. Fig. 5 presents an example of the degree of biological shape variability that could be successfully dealt with and Fig. 7 presents an example of two different MUAPTs whose similarly shaped MUAPs were successfully discriminated. 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.

4.1.4. 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. Multiply-detecting 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 proper MUAP alignment. As such, if a MUAP has two peaks of similar amplitude with less than approximately 1 ms temporal separation, biological variation in the shape of the MUAP may cause the peak used to define its firing time and therefore its alignment to vary. MUAPTs con-

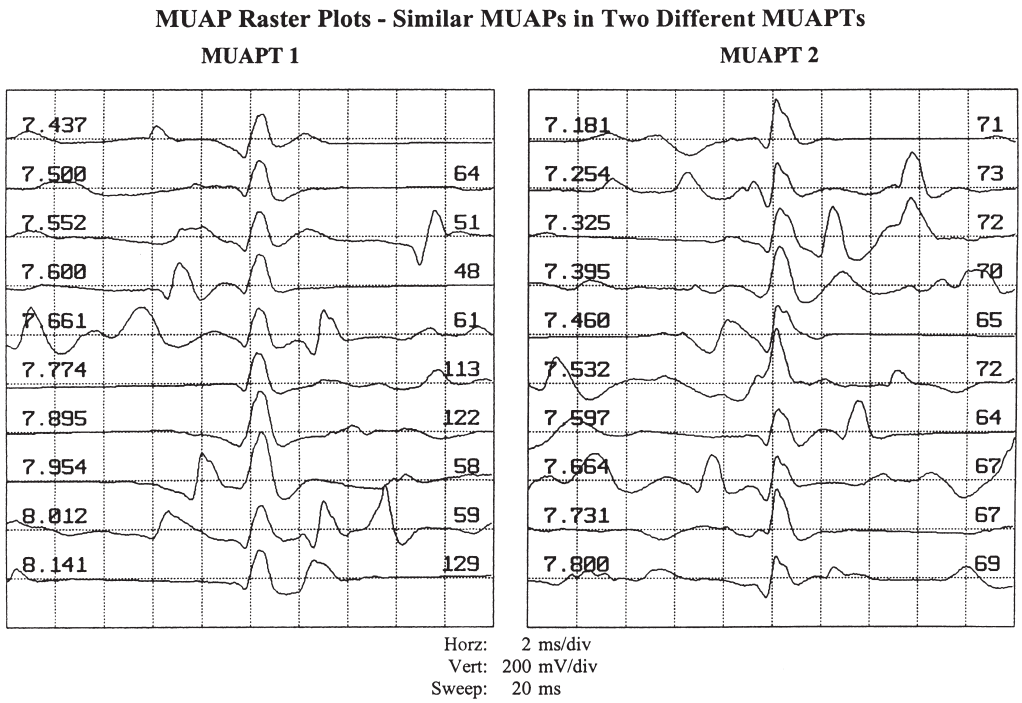

Fig. 7. MUAP Raster Plots — Similar MUAPs in Two Different MUAPTs: the individual MUAPs assigned to two different MUAPT are displayed using two columns in a raster plot format similar to Fig. 5. The prototypical MUAP shapes of these two MUAPTs are similar to each other. Temporal information helps to successfully discriminate between the discharges of these two motor units. In particular, MUAPT 1 has a MUAP at time 7.6 and 7.661 s, while MUAPT 2 has discharges at 7.597 and 7.664 s. In both cases, the interval between firings in the two trains is just 3 ms and can be used to confirm that these two trains represent the activity of two distinct motor units.

taining such disparately-detected MUAPs must also be processed by dedicated algorithms that determine any existing temporal relationships between MUAPTs. The mutual information based interdependency redundancy measure applied to the MUAPTs created following clustering and supervised classification was able to successfully discover all of the relationships which existed between the trains detected in the 10 EMG signals studied. Trains associated with multiply-detected MUAPs and MUAPs with satellites were found to be linked and subsequently considered a single train. Trains associated with disparately-detected MUAPs were found to be exclusive and were candidates for merging. The numbers of MUAPTs following the application of the temporal-relationships algorithm exactly matched the numbers of motor units consistently contributing MUAPs to the composite EMG signals as determined by the manual decompositions. Interdependency redundancy can also be used to detect and quantify synchronous motor unit behaviour. However, synchronous motor unit behaviour does not affect the accuracy of the decompositions and is currently of unknown clinical utility. It is therefore, currently not studied.

4.2. Quantitative EMG following signal decomposition

The original micro and macro EMG signals were used in conjunction with the decomposition results and to calculate quantitative micro and macro MUAP and firing pattern parameter results. The combination of micro and macro MUAP parameters with micro MUAP ensemble and firing pattern parameters is an attempt to provide more comprehensive quantitative information regarding the morphological and operational state of a studied neuromuscular system. This information 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 [34] or by searching for outliers [35]. In addition, this set of parameters could be used to study basic motor unit physiology in normal and diseased neuromuscular systems or the affects of ageing and fatigue. The results presented are from the study of just 10 contractions from 4 subjects. As such, they do not by themselves provide significant clinical information. More data needs to be collected and analysed. The results presented are intended to represent typical data that can be obtained by using the decomposition and analysis system described. The potential usefulness of the various parameters defined will be briefly discussed.

4.2.1. Micro MUAPs

Peak to peak voltage, duration, number of phases and number of turns have been suggested previously [31]. The threshold currently used for turns (25 μV) is similar to that used by Stewart et al. [1] but lower than used by others (50 [12] or 100 [11,14] μV). Assuming a turn should represent a significant change in voltage and considering the noise levels present in the averaged micro MUAPs this lower threshold level is justified and may provide additional diagnostic information. Area and area to amplitude ratio or MUAP thickness [5] are also calculated. Each of these micro MUAP parameters relate to the distribution of a relatively few fibres of a motor unit that are situated close to the micro electrode, see [36] for a more complete discussion.

4.2.2. Micro MUAP ensembles

Micro MUAP ensemble parameters relate to the operation of the neuromuscular junctions and to the density of motor unit fibres close to the micro electrode. The variability of the MUAPs within a MUAPT relates to the operation of the neuromuscular junctions of the fibres of the motor unit close to the micro electrode. One way of measuring this variability is MUAP jiggle [16]. An alternate measure is Ajiggle, which is a measure essentially similar to jiggle but applied to the accelerations of MUAPs. Ajiggle is less affected by baseline shifts that occur in signals acquired during higher levels of contraction. In addition, simulations suggest that the acceleration of a MUAP reveals the activity of muscle fibres close to the electrode, which are contributing significantly to the detected MUAP [32]. Fig. 3 demonstrates that this is also true for real MUAPs. The micro MUAP prototype or template for a selected motor unit is displayed along with the 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. It is evident that 4 significant peaks or groups of fibre contributions exist and that the positions of these peaks in time correspond to points in the MUAP template were distinct changes in its shape occur. Within the raster of MUAP accelerations each respective peak occurs with consistent shape even though its position in time may vary. At the scale displayed this is only evident for the two major peaks, but at lower scales the stability of the two smaller peaks can be confirmed. Thus, as with potentials obtained with an SF needle electrode, it is reasonable to assume that these peaks represent the activity of individual muscle fibres. The strong relationship between MUAP acceleration and individual fibre activity and its lower standard deviation values may make Ajiggle a useful source of information.

A second measure of the variation across the ensemble of MUAP accelerations that is related to neuromuscular junction performance is the MCD jitter [6] between the two sharpest peaks. The tracking of peaks across an ensemble is shown in the acceleration raster of Fig. 3. No blocking was found and an MCD value of 19.8 μs was measured. The fact that the CN jitter values obtained had a similar range as those obtained using SFN electrodes and that 41 out of 56 MUAPs (73%) had accelerations suitable for jitter measurement suggests that this may be a very useful parameter. Collecting jitter data using SF needle 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 electrode from slight to moderate level contractions.

The number of sufficiently sharp acceleration peaks with amplitude significantly larger than the estimated acceleration noise was defined as the fibre count. Fibre count is similar to fibre density, which is measured using SF needle potentials. It represents the number of motor unit fibres in close proximity to the electrode. The fibre count values were larger than corresponding fibre density values would be. This is probably due to the larger detection surface area of the CN electrode. Nonetheless, fibre count measurements, using CN or MN electrodes, have the potential of providing similar information as fibre density measurements and they can be obtained more easily.

4.2.3. Firing patterns

Firing pattern parameters relate to the control and operation of the motor units. The mean IPI and the STD and COV of the IPIs are calculated for each MUAPT using the EFE [19] algorithm along with the mean FR and FR MCD. Absolute firing pattern values will depend on the contraction force profile. However, assuming standardised force profiles, elevated or diminished values of these various parameters can be 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 analysing small 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.

4.2.4. Macro MUAPS

Macro MUAP parameters relate to the distribution of all of the fibres and size of a motor unit. Stalberg [22] first introduced the concept of ensemble averaging a macro signal using individual motor unit firing times as triggers. The analysis described here simply extends Stalberg's original idea to use the firing times of multiple motor units represented in the MUAPTs obtained following decomposition. The basic premise, as in Stalberg's original work, is that 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 [23] 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 [37]. They have been used for motor unit number estimation [17] and they have been related to the level of muscle activity [38]. The combination of macro information with micro and/or firing pattern information may provide new clinical insights. Electrotonic twitch, the product of macro MUAP area and motor unit mean FR, promises to relate the size and activity of motor units to the force generated by a muscle. The distribution of electrotonic twitch values within a muscle active at slight to moderate levels of force will reflect the motor unit size and firing rate patterns for a muscle and could be used to evaluate a muscle's ability to produce force.

5. Summary

The presented system for decomposing and analysing EMG signals is capable of extracting useful clinical information from simultaneously acquired micro and macro signals. Based on a set of 10 signals used for evaluation it was demonstrated that CN-detected micro signals could be decomposed with sufficient accuracy and speed to provide clinically useful parameter values relating to detailed aspects of the structure and function of the motor units of a muscle. In conjunction with the micro signal based parameters, a set of parameter values related to the macro signals, in this case detected with surface electrodes, could also be successfully obtained to represent more global information about the motor units of a muscle and how they were contributing to force production. Overall, the necessary parameter values can be obtained in a clinically viable time. Parameter values resulting from the analysis of the set of 10 signals and representing typical system performance were presented.

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