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Motor Unit Number Estimation Based on High-Density Surface Electromyography Decomposition

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Abstract

Objective—To advance the motor unit number estimation (MUNE) technique using high density surface electromyography (EMG) decomposition.

Methods—The K-means clustering convolution kernel compensation algorithm was employed to detect the single motor unit potentials (SMUPs) from high-density surface EMG recordings of the biceps brachii muscles in eight healthy subjects. Contraction forces were controlled at 10%, 20% and 30% of the maximal voluntary contraction (MVC). Achieved MUNE results and the representativeness of the SMUP pools were evaluated using a high-density weighted-average method.

Results—Mean numbers of motor units were estimated as 288 ± 132, 155 ± 87, 107 ± 99 and 132 ± 61 by using the developed new MUNE at 10%, 20%, 30% and 10–30% MVCs, respectively. Over 20 SMUPs were obtained at each contraction level, and the mean residual variances were lower than 10%.

Conclusions—The new MUNE method allows a convenient and non-invasive collection of a large size of SMUP pool with great representativeness. It provides a useful tool for estimating the motor unit number of proximal muscles.

Significance—The present new MUNE method successfully avoids the use of intramuscular electrodes or multiple electrical stimuli which is required in currently available MUNE techniques; as such the new MUNE method can minimize patient discomfort for MUNE tests.

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Conflict of Interest

None of the authors have potential conflicts of interest to be disclosed.

Keywords

Motor unit number estimation; electromyography; high-density; decomposition; bicep brachii

1. Introduction

Motor unit number estimation (MUNE) techniques are clinically useful by estimating the number of functioning motor units in a muscle, which can serve as a biomarker for the progression of motor neuron diseases or neuromuscular disorders. Various MUNE methods have been developed since the incremental counting technique was introduced in 1971 (McComas et al., 1971). The main limitation with the incremental counting technique is the problem known as “alternation”, which leads to an erroneous overestimation of the MUNE. This problem attributes to the procedure that all stimuli are applied at a single site of the nerve, which results in possible alternative activations of two or more motor neurons at an incremental stimulus and complicates the separation of single motor neurons.

The multiple-point stimulation (MPS) method was then developed to solve this problem by activating different single axons at different sites along nerves (Kadrie et al., 1976, Doherty et al., 1993). However, the MPS MUNE is not applicable to proximal muscles, as it is difficult to stimulate a proximal nerve at enough sites to obtain a sufficient amount of single motor unit potentials (SMUPs) (Gooch et al., 2014). This limitation also challenges the statistical method (Gooch et al., 2014), possibly because of the difficulty in steadily sustaining a large number of stimuli at several levels of intensity at proximal nerves that are often with a poor accessibility. Alternatively, the spike-triggered average (STA) method and its variation, the decomposition enhanced spike-triggered average (DE-STA) method, were developed to overcome this limitation (Doherty et al., 2003, Boe et al., 2004, Boe et al., 2005). The STA and DE-STA methods can be performed on both distal and proximal muscles, as SMUPs are obtained from voluntary contractions rather than multiple-points stimulation along nerve courses. However, the need of using intramuscular needle electromyography (EMG) electrodes to obtain the triggers for the construction of the SMUP pool in the STA or DE-STA methods makes them an invasive approach and demands much patient tolerance. A more advanced MUNE technique that is non-invasive and not limited to distal muscles will greatly help extend the applicability of current MUNE methods.

High density (HD) surface EMG techniques have become a powerful tool for clinical neurophysiology (Merletti et al., 2009, Van Dijk Johannes, 2012, Li et al., 2015, Yao et al., 2015). Non-invasive HD surface EMG recordings can be decomposed into constituent motor unit action potential trains which can be further employed to extract SMUPs in a non-invasive manner for MUNE studies. Many surface EMG decomposition algorithms have been developed over the last decade (Holobar et al., 2007a, b, Kleine et al., 2007, Ning et al., 2015, Chen et al., 2016) and undergone extensive investigations and validations (Holobar et al., 2010, Marateb et al., 2011, Almousa et al., 2015, Liu et al., 2015) in human. However, these algorithms have yet been applied to MUNE for the extraction of SMUP samples. Van Dijk and coworkers recently pioneered the application of the HD surface EMG in MUNE (van Dijk et al., 2008, Van Dijk et al., 2010a, van Dijk et al., 2010b). This method offered a

comprehensive way to calculate MUNE and evaluate the representativeness of SMUP samples based on the HD information. However, this HD MUNE was essentially based on the multiple-points stimulation and therefore the applicability to proximal muscles remains unmet.

In this study, we present a new MUNE method that combines our earlier experience in HD surface EMG decomposition (Liu et al., 2015, Ning et al., 2015) and advantages offered by existing HD MUNE methods (van Dijk et al., 2008). This new method is non-invasive in nature and not limited by the locations of muscle.

2. Methods

2.1. Subjects

A total of 8 healthy and physically active male subjects (mean age: 29 ± 4) participated in this study, and none of them has a history of peripheral nerve disease. The research protocol was approved by the local ethic committee and all subjects were fully informed of the purpose and goal of the study and gave informed consents. The biceps brachii muscles of the dominant hand were investigated.

2.2. Stimulating and recording systems

The musculocutaneous nerve was stimulated using the DS7 current stimulator (Digitimer Ltd, Welwyn Garden City, United Kingdom) with a bipolar stimulating electrode by an experienced physician (S.L.). High-density surface EMG signals of the biceps brachii muscles were recorded using two 2 flexible 8 × 8 arrays (TMSi, Enschede, The Netherlands) with an electrode diameter of 4.5 mm, and a center-to-center electrode distance of 8.5 mm, as shown in Figure 1a. This HD EMG grid showed great competency in our previous EMG analysis including EMG decomposition (Liu et al., 2015). The EMG signals were acquired by a 136 channel Refa amplifier (TMSi, Enschede, The Netherlands) at a sampling rate of 2048 Hz per channel and stored in a personal laptop for offline analysis.

2.3. Experimental Protocol

An earlier study demonstrated that the force level is an important factor to consider when utilizing voluntary contractions to provide SMUPs (Boe et al., 2005). Therefore, contraction force levels were rigorously controlled in our study. Each subject was seated upright in a mobile Biodex chair (Biodex, Shirley, NY) with a standard 6 degrees-of-freedom load cell (ATI Inc, Apex, NC) setup used to accurately record the isometric contraction force of the biceps brachii during flexion. The forearm and wrist were mounted on a plastic platform inside a fiberglass cast (Figure 1b). A ring-mount interface was used to strap the wrist in a partial pronation position. This standard position served to minimize spurious force contributions from unrecorded muscles. The skin above the biceps brachii muscle was slightly abraded and cleaned. Two EMG grids were placed adjacently over the muscle belly and longitudinally along the muscle fiber direction. Double-sided tapes with electrode-matched holes were used to stick the grid surface to the skin to enhance the electrode-tissue contact with the help of conductive gels. The reference electrode was placed on the skin above the elbow of the arm on the same side of the EMG grids. A strap ground electrode

was wrapped around the wrist on the contrary side. Monopolar surface EMG signals were obtained at each channel relative to the reference electrode.

The protocol to obtain the compound muscle action potential (CMAP) was adopted from our previous study (Li et al., 2014). Briefly, trial electrical stimulation was first performed in an attempt to determine the optimal stimulation position that produced the maximal evoked CMAP. After the optimal stimulation position was localized and fixed, a series of stimuli was delivered with the stimulus strength increasing manually from 5 mA (in increments of 5 mA) to the strength when a supramaximal response was reached. Each stimulus was a rectangular pulse with a width of 200μs. The supramaximal stimulation was repeated for three times and the largest one was chosen as the source for the CMAP signal. After the stimulation, participants were asked to perform maximal voluntary contractions (MVC) for three times with the contraction force vector in the x and z direction measured, as shown in Figure 1. The averaged force vector was taken as the effective MVC. Subsequently, the participants were asked to perform a series of voluntary contractions at different percentage levels of MVC with visual feedback displayed on the computer screen controlled by a load cell (Figure 1d). For each subject, voluntary contractions were performed at three levels (10%, 20% and 30% MVC) and repeated for 3 times at each level. Each repetition lasted approximately 8 seconds. Subjects were given sufficient recovery time between any two consecutive contractions to minimize fatigue. The order of the contraction levels were randomized by the operator prior to each session (Boe et al., 2006).

2.4. Data Analysis

All data analysis was performed offline using Matlab (The Mathworks, Natick, MA). The surface EMG recordings were digitally bandpass filtered (10–500 Hz). Channels with poor signal qualities due to bad contacts were visually identified and removed from analysis.

2.4.1 EMG decomposition—A number of signal decomposition methods such as the wavelet-based decomposition and blind source decomposition can be employed to decompose the surface EMG signals into their constituent motor unit action potential trains. The wavelet-based algorithms are challenged by the high superimposition of the motor unit action potentials (Gazzoni et al., 2004), which are frequently encountered in EMG signals at moderate contraction levels.

Our recently developed K-mean clustering convolution kernel compensation (KmCKC) algorithm provides a suitable candidate for this purpose and was employed in this study to decompose the high-density surface EMG signals into SMUPs (Ning et al., 2015). In the first step, the correlation matrix between the interferential measurements of all channels was calculated (Holobar et al., 2007a, b, Ning et al., 2015). This correlation matrix implicitly describes the firing patterns of all motor units (global pulse train) and can be further decomposed to extract the initial pulse trains (or trigger points) of different motor units through an appropriate selection of time instants to estimate the activity index of the global pulse train. The K-means clustering technique was then employed to cluster the firing instants of individual motor units via evaluating a distance function (Ning et al., 2015). During this process, the initial pulse train can be estimated by choosing an appropriate

number of clustered groups and time instants so that the firing instants of a single motor unit can be gathered into one group as completely as possible. Then an improved multi-step iterative convolution kernel compensation method was employed to update the estimated initial pulse train to improve the decomposition accuracy. The final results of the decomposition method provide the intelligent trigger points of each identified motor unit and their waveforms can be constructed using the spike-triggered averaging (STA) method. It should be noted that our method is essentially different from STA or DE-STA MUNE methods, as the spatiotemporal information from high-density EMG recordings was utilized to obtain intelligent triggers, avoiding the need of an invasive intramuscular needle electrode as used in DE-STA methods. Each decomposed SMUP was stored as an array with a window size of 205 samples (~ 0.1 seconds) at each of the 128 channels. For simplicity, we use $SMUP_i(k; t)$ to represent the signals of the k-th channel of the i-th SMUP as a function of time sample t, where $1 \le k \le 128$, $1 \le t \le 205$.

2.4.2 Elimination of multiples—First, all SMUPs obtained from the same repetition were compared by checking their firing sequences and waveforms. SMUPs with close firing sequences (difference < 1ms) or with similar waveforms were considered to originate from the same motor unit. This step was performed by the operator right after the decomposition results from each repetition were obtained. Then the entire SMUP pool, containing SMUPs from all repetitions of all MVCs, was systematically checked by calculating a modified channel-weighted correlation coefficient between any pair of SMUPs, as defined in Eq. (1):

$$M_{i,j}=\sum_{k=1}^{128}\left[W_{i,j}(k)\times Corr_{i,j}(k)\times Amp_{i,j}(k)\right] \quad (1)$$

where $W_{i,j}(k)$ is the weight assigned to the k-th channel (k = 1,2,…,128), $Corr_{i,j}(k)$ and $Amp_{i,j}(k)$ measure the similarity in the waveform and amplitude between the k-th channels of the i-th SMUP and the j-th SMUP, respectively. Their definitions are provided in Eqs. (2–4):

$$W_{i,j}(k)=\frac{A_i(k)\times A_j(k)}{\sum_{m=1}^{128}A_i(m)\times A_j(m)} \quad (2)$$

where $A_i(k)$ is the negative peak amplitude of k-th channel of the i-th SMUP and m is the dummy index used to calculate the sum of the negative peak amplitude product over all channels.

$$Corr_{i,j}(k)=corrcoef\ [SMUP_i(k;t), SMUP_j(k;t)] \quad (3)$$

where *corrcoef* calculates the correlation coefficient between these two channels. Before the calculation, the two SMUPs were aligned by their onset time, defined as the time of instants of the largest negative peak among all channels.

$$Amp_{i,j}(k)=\begin{cases} 1-\frac{|A_i(k)-A_j(k)|}{100\mu V} & if\ |A_i(k)-A_j(k)|<100\mu V \\ 0 & else \end{cases} \quad (4)$$

The introduction of this modified correlation coefficient was inspired by the work of van Dijk et al. (2008), who proposed the weighted-average method for the calculation of MUNE from high-density surface EMG signals. In addition to using correlation as a means to check multiples, we also introduced the criteria based on the SMUP size, which is defined as the largest negative peak amplitude among all channels throughout this study, given that correlation alone does not tell the differences in amplitudes. SMUPs obtained from higher MVC levels may have high correlations but differ greatly in SMUP sizes. In our study, we employed an empirical value of 100μV to design the criteria in Eq. (4). The preliminary results suggested that two SMUPs are likely the same if the modified correlation coefficient is over 0.9 and less likely if it is less than 0.8. All SMUPs with a modified correlation coefficient larger than 0.8 were visually judged by the operator by comparing their waveforms and residuals (van Dijk et al., 2008).

2.4.3 MUNE and SMUP pool representativeness—The MUNE and residual variance (RV) were calculated following a similar approach introduced in (van Dijk et al., 2008). First, all SMUPs in the pool were aligned by their onset instants. The mean SMUP was then obtained by averaging all SMUPs, yielding a high-density mean SMUP that is representative for the entire SMUP pool. This mean SMUP was later aligned with the CMAP at their onset instants. The calculation of the MUNE was described in Eq. (5):

$$MUNE=\sum_{k=1}^{128} w_{meanSMUP}(k)\frac{A_{CMAP}(k)}{A_{meanSMUP}(k)} \quad (5)$$

where $A_{CMAP}(k)$ and $A_{meanSMUP}(k)$ are the negative peak amplitudes of k-th channels of the CMAP signal and the mean SMUP signal, respectively; the weight function $w(k)$ for calculating the MUNE, as described in Eq. (6), can be interpreted as the particular case of Eq. (2), when the i-th and j-th SMUPs are both replaced by the mean SMUP.

$$w_{meanSMUP}(k)=\frac{A^2_{meanSMUP}(k)}{\sum_{m=1}^{128} A^2_{meanSMUP}(m)} \quad (6)$$

To evaluate the representativeness of the mean SMUP, the RV was calculated using Eq. (7):

$$RV = \frac{\sum_{m=1}^{128} [A_{CMAP}(m) - MUNE \times A_{meanSMUP}(m)]^2}{\sum_{m=1}^{128} A_{CMAP}^2(m)} \quad (7)$$

MUNE and RV were calculated separately at each MVC level as well as all MVCs. The CMAP was kept the same for all MUNE calculations.

3. Results

Main results achieved in this study are summarized in Table 1. The average CMAP across the eight subjects was 17.5 ± 3.3 mV. Initially, 1338 SMUPs were obtained from EMG decomposition results using the KmCKC algorithm, and 557 non-repeated SMUPs were kept after removing multiples for further analysis. For all eight subjects, at 10%, 20% and 30% MVCs, the mean number of SMUPs obtained from three repetitions was 23 ± 5, 23 ± 6 and 26 ± 7, with a mean SMUP size (measured as the amplitude of the largest negative peak among all channels) of 91.3 ± 42.6 μV, 192.5 ± 96.0 μV and 350.8 ± 208.6 μV, respectively. Figure 2 shows the distribution of the SMUP sizes after removing multiples from all MVC levels of all eight subjects. Figure 3 shows the overlapping plot of the SMUPs obtained from three contraction levels for one exemplary subject.

The mean MUNE values obtained at three contraction levels for all subjects were 288 ± 132, 155 ± 87 and 107 ± 99, respectively. When SMUPs from all MVC levels were used, the mean SMUP size and MUNE were 214.0 ± 124.2 μV and 132 ± 61.

The mean RVs of 9.3% ± 5.9%, 10.1% ± 7.0% and 9.1% ± 5.8% were achieved at 10%, 20% and 30% MVCs, respectively, with an accumulative mean RV of 9.6% ± 6.0% for all MVC levels. Figure 4 shows the overlapping plot of the mean SMUP and the CMAP for exemplary subjects.

4. Discussion

In this study, we developed a novel MUNE method based on non-invasive high-density surface EMG decomposition and evaluated its performance on the biceps brachii muscles in eight healthy subjects.

4.1. Decomposition and Representativeness

A large pool of SMUPs (mean number > 20) was collected at each MVC level, with a high representativeness (mean RV < 10%). The uniformly low RV values in all MVC levels suggest that a representative SMUP pool can be well constructed under a fixed MVC below 30%, as long as a sufficiently large SMUP pool size is feasible. When all MVC levels were considered, more than 60 non-repeating SMUPs were available to provide a reliable estimation of the mean SMUP. This is reflected in the overlapping plot of the CMAP and the scaled mean SMUP using SMUPs from all MVCs, as shown in Figure 4, where great

matches in waveforms are observed. The distribution of SMUP sizes across all subjects, as shown in Figure 2, is in accordance with previously reported studies (Galea et al., 2001, van Dijk et al., 2008).

It should be noted that the SMUP detection with the KmCKC algorithm is not exhaustive. This is actually a common challenge to all surface EMG decomposition methods (Holobar et al., 2007b, a, Li et al., 2015, Ning et al., 2015, Chen et al., 2016). We found that in our decomposition results, SMUPs detected at higher contraction levels were larger in amplitude than those detected at lower contraction levels, as shown in Figure 3. This is consistent with the findings in previous studies that undetected motor unit action potential usually comes from smaller motor units (Holobar et al., 2010).

4.2. MUNE

As the actual number of motor units in human biceps brachii muscles remains unavailable because of the difficulty in performing non-invasive anatomical count, we compared our results with previous MUNE studies on the same muscle. At the 10% MVC level, our MUNE is similar with the results reported in the literature (288 ± 132 vs. 272 ± 124) (Boe et al., 2006), in which the DE-STA MUNE was employed at the same MVC level. The MUNE value achieved in this study when all MVC levels are considered is close to the report of Galea et al. (2001) (132.3 ± 60.5 vs. 135.5 ± 64.6), in which an incremental stimulation method was employed. This similarity suggests that the SMUP pool obtained from an incremental stimulation may resemble the one constructed using SMUPs from voluntary contractions up to 30% MVC. By separating the SMUPs from different MVC levels, our results may explain the existing variations among reports employing different MUNE approaches when the same muscle group was studied (Gooch et al., 2014).

A decreasing trend of MUNEs against MVC levels was found, which is similar with the report of Boe et al. (2005), although a quantitative comparison was not available because different muscles were studied. We also find that the CMAP sizes established in our study (negative peak amplitude: 17.5 ± 3.3 mV) are much greater than reports of Boe et al. (2006) (negative peak amplitude: 11.9 ± 2.4 mV) and Calder et al. (2005) (peak to peak amplitude: 13.5 ± 4.1 mV). However, we tend to believe that this increase was more reliable because of the employment of the high-density surface EMG grid, which allowed the recording site with the largest evoked response to be detected. The small electrode size, which helped reduce the effect of action potential averaging over the skin surface (Van Dijk et al., 2009), is also believed to be a factor leading to a higher amplitude. Besides, cross-subject variations and sample size might play a role in causing this difference.

4.3. Significance

Although decomposition-based MUNE has been reported previously in DE-STA MUNEs (Doherty et al., 2003, Boe et al., 2004, Boe et al., 2005, Ives et al., 2014), one distinguishing feature of our new MUNE approach is that it avoids using invasive intramuscular needle electrodes to obtain the triggers of SMUPs (Gooch et al., 2014). The SMUPs are rather obtained from the spatiotemporal information provided by non-invasive HD surface EMG recordings using the KmCKC algorithm (Ning et al., 2015). Previous high-density MUNE

methods (van Dijk et al., 2008, van Dijk et al., 2010b) are inherently based on the multiple-points stimulation technique. This technique is limited to distal muscles, as the stimulation needs to be performed at multiple points along the course of the nerve, allowing the collection of multiple SMUPs and reducing the problem of “alternation” (Gooch et al., 2014). For proximal muscles, a very limited portion of the nerve is accessible for electrical stimulation, making multiple site stimulation unavailable and results susceptible to “alternation”. Our method extends the application of the high-density MUNE method to proximal muscles, as the collection of SMUPs does not rely on multiple point stimulation along the course of the nerve, but rather on the high-density surface EMG signals during voluntary contractions. The MUNE can be estimated for both the distal and the proximal muscles, as the high-density surface electrode grid can be placed flexibly on both muscles.

It is worth mentioning that the motor unit number index (MUNIX) approach has gained increasing popularity for its convenience in implementation (Nandedkar et al., 2010, Neuwirth et al., 2010) and its good reliability (Neuwirth et al., 2011). However, its performance is limited when a muscle has severe atrophy, as it cannot properly determine whether the decrease in MUNIX is accompanied with a reduction of the motor unit action potential amplitude (loss of muscle fibers) or an actual loss of motor units (Li et al., 2012, Li et al., 2016). Compared with MUNIX, MUNE approaches have the advantage that the MUNE results reflect the actual motor unit size and number, but they are less convenient in implementation. The HD-MUNE method proposed in our study can greatly improve the efficiency of MUNE implementation. Compared with traditional MUNE approaches, e.g., the MPS MUNE in which multiple-points stimulations are required or the DE-STA MUNE in which multiple needle insertions are needed, the proposed HD-MUNE method only requires a few voluntary contractions each of which lasts less than 10 seconds while still maintaining a high yield of SMUPs. The duration of the entire procedure could be further significantly reduced if contractions are only performed at one fixed MVC level, as long as the fixed MVC level is kept the same for the purpose of consistently tracking of the disease progression. In addition, with promising decomposition results achieved (Peng et al., 2015, 2016), we expect to apply this new MUNE method on pelvic floor muscles, the motor unit number of which plays an important role in the pathophysiology of pelvic floor disorders but has never been estimated.

4.4. Limitations

One limitation of this study is the lack of an assessment of the test-retest reliability. On one hand, it remains our next step to assess the reproducibility of this new approach for its further applications in clinical practices. On the other hand, the fact that the surface EMG decomposition algorithm has been extensively validated (Holobar et al., 2010, Marateb et al., 2011, Martinez-Valdes et al., 2015, Ning et al., 2015) provides a solid basis to the accuracy and reliability of this new MUNE method. A remaining question is at which force level the MUNE should be performed. Answer to this question would be of great clinical significance, as it allows the selection of the optimal force level that makes the MUNE results most sensitive to the disease progression. Nevertheless, the large variation in the MUNE with force levels revealed in this study provides insights into the physiology of MUNE, and thus we recommend MUNE to be performed in a consistent testing condition.

4.5. Conclusions

In conclusion, we presented a new MUNE method based on the high-density surface EMG decomposition that can non-invasively assess both distal and proximal muscles with a high yield of representative SMUPs. It is expected to extend the applicability of MUNE methods to more challenging clinical applications.

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Abbreviations

MUNE	Motor Unit Number Estimation
MPS	Multiple-Point Stimulation
STA	Spike-Triggered Average
DE-STA	Decomposition Enhanced Spike-Triggered Average
EMG	Electromyography
HD	High-Density
SMUP	Single Motor Unit Potential
CMAP	Compound Muscle Action Potential
MVC	Maximal Voluntary Contraction
CKC	Convolution Kernel Compensation
KmCKC	K-means clustering Convolution Kernel Compensation

References

Almousa S, Moser H, Kitsoulis G, Almousa N, Tzovaras H, Kastani D. The prevalence of urine incontinence in nulliparous female athletes: a systematic review. Physiotherapy. 2015; 101:e58.

Boe SG, Stashuk DW, Brown WF, Doherty TJ. Decomposition-based quantitative electromyography: Effect of force on motor unit potentials and motor unit number estimates. Muscle Nerve. 2005; 31:365–73. [PubMed: 15627267]

Boe SG, Stashuk DW, Doherty TJ. Motor unit number estimation by decomposition-enhanced spike-triggered averaging: Control data, test–retest reliability, and contractile level effects. Muscle Nerve. 2004; 29:693–9. [PubMed: 15116373]

Boe SG, Stashuk DW, Doherty TJ. Within-subject reliability of motor unit number estimates and quantitative motor unit analysis in a distal and proximal upper limb muscle. Clin Neurophysiol. 2006; 117:596–603. [PubMed: 16442341]

Calder KM, Hall L-A, Lester SM, Inglis JG, Gabriel DA. Reliability of the biceps brachii M-wave. J Neuroeng Rehabil. 2005; 2:33. [PubMed: 16332261]

Chen M, Zhou P. A Novel Framework Based on FastICA for High Density Surface EMG Decomposition. IEEE Trans Neural Syst Rehabil Eng. 2016; 24:117–27. [PubMed: 25775496]

Doherty TJ, Brown WF. The estimated numbers and relative sizes of thenar motor units as selected by multiple point stimulation in young and older adults. Muscle Nerve. 1993; 16:355–66. [PubMed: 8455648]

Doherty TJ, Stashuk DW. Decomposition-based quantitative electromyography: Methods and initial normative data in five muscles. Muscle Nerve. 2003; 28:204–11. [PubMed: 12872325]

Galea V, Fehlings D, Kirsch S, McComas A. Depletion and sizes of motor units in spinal muscular atrophy. Muscle Nerve. 2001; 24:1168–72. [PubMed: 11494269]

Gazzoni M, Farina D, Merletti R. A new method for the extraction and classification of single motor unit action potentials from surface EMG signals. J Neurosci Methods. 2004; 136:165–77. [PubMed: 15183268]

Gooch CL, Doherty TJ, Chan KM, Bromberg MB, Lewis RA, Stashuk DW, et al. Motor unit number estimation: A technology and literature review. Muscle Nerve. 2014; 50:884–93. [PubMed: 25186553]

Holobar A, Minetto MA, Botter A, Negro F, Farina D. Experimental analysis of accuracy in the identification of motor unit spike trains from high-density surface EMG. IEEE Trans Neural Syst Rehabil Eng. 2010; 18:221–9. [PubMed: 20144921]

Holobar, A.; Zazula, D. ICA 2007. Springer; 2007a. Gradient convolution kernel compensation applied to surface electromyograms; p. 617-24.

Holobar A, Zazula D. Multichannel blind source separation using convolution kernel compensation. IEEE Trans Signal Process. 2007b; 55:4487–96.

Ives CT, Doherty TJ. Influence of needle electrode depth on DE-STA motor unit number estimation. Muscle Nerve. 2014; 50:587–92. [PubMed: 24639081]

Kadrie H, Yates S, Milner-Brown H, Brown W. Multiple point electrical stimulation of ulnar and median nerves. J Neurol Neurosurg Psychiatry. 1976; 39:973–85. [PubMed: 1003242]

Kleine BU, van Dijk JP, Lapatki BG, Zwarts MJ, Stegeman DF. Using two-dimensional spatial information in decomposition of surface EMG signals. J Electromyogr Kinesiol. 2007; 17:535–48. [PubMed: 16904342]

Li S, Liu J, Bhadane M, Zhou P, Rymer WZ. Activation deficit correlates with weakness in chronic stroke: Evidence from evoked and voluntary EMG recordings. Clin Neurophysiol. 2014; 125:2413–7. [PubMed: 24747057]

Li X, Holobar A, Gazzoni M, Merletti R, Rymer WZ, Zhou P. Examination of Poststroke Alteration in Motor Unit Firing Behavior Using High-Density Surface EMG Decomposition. IEEE Trans Biomed Eng. 2015; 62:1242–52. [PubMed: 25389239]

Li X, Nandedkar SD, Zhou P. Modified motor unit number index: A simulation study of the first dorsal interosseous muscle. Med Eng Phys. 2016; 38:115–20. [PubMed: 26639774]

Li X, Rymer WZ, Zhou P. A simulation-based analysis of motor unit number index (MUNIX) technique using motoneuron pool and surface electromyogram models. IEEE Trans Neural Syst Rehabil Eng. 2012; 20:297–304. [PubMed: 22514208]

Liu Y, Ning Y, Li S, Zhou P, Rymer WZ, Zhang Y. Three-dimensional innervation zone imaging from multi-channel surface EMG recordings. Int J Neural Syst. 2015; 25:1550024. [PubMed: 26160432]

Marateb HR, McGill KC, Holobar A, Lateva ZC, Mansourian M, Merletti R. Accuracy assessment of CKC high-density surface EMG decomposition in biceps femoris muscle. J Neural Eng. 2011; 8:066002. [PubMed: 21975280]

Martinez-Valdes E, Laine C, Falla D, Mayer F, Farina D. High-density surface electromyography provides reliable estimates of motor unit behaviour. Clin Neurophysiol. 2015; doi: 10.1016/j.clinph.2015.10.065

McComas A, Fawcett PRW, Campbell M, Sica R. Electrophysiological estimation of the number of motor units within a human muscle. J Neurol Neurosurg Psychiatry. 1971; 34:121–31. [PubMed: 5571599]

Merletti R, Botter A, Troiano A, Merlo E, Minetto MA. Technology and instrumentation for detection and conditioning of the surface electromyographic signal: state of the art. Clin Biomech. 2009; 24:122–34.

Nandedkar SD, Barkhaus PE, StÅlberg EV. Motor unit number index (MUNIX): principle, method, and findings in healthy subjects and in patients with motor neuron disease. Muscle Nerve. 2010; 42:798–807. [PubMed: 20976783]

Neuwirth C, Nandedkar S, Stålberg E, Barkhaus PE, de Carvalho M, Furtula J, et al. Motor Unit Number Index (MUNIX): A novel neurophysiological marker for neuromuscular disorders; test–retest reliability in healthy volunteers. Clin Neurophysiol. 2011; 122:1867–72. [PubMed: 21396884]

Neuwirth C, Nandedkar S, StåLberg E, Weber M. Motor unit number index (MUNIX): a novel neurophysiological technique to follow disease progression in amyotrophic lateral sclerosis. Muscle Nerve. 2010; 42:379–84. [PubMed: 20589888]

Ning Y, Zhu X, Zhu S, Zhang Y. Surface EMG Decomposition Based on K-means Clustering and Convolution Kernel Compensation. IEEE J Biomed Health Inform. 2015; 19:471–7. [PubMed: 25486655]

Peng Y, He J, Khavari R, Boone T, Zhang Y. PD24-03 identification of innervation zones of the pelvic floor muscle from noninvasive high-density intra-vaginal/rectal surface EMG recordings. J Urol. 2015; 193:e487.

Peng Y, He J, Khavari R, Boone T, Zhang Y. Functional mapping of the pelvic floor and sphincter muscles from high-density surface EMG recordings. Int Urogynecol J. 2016; In press. doi: 10.1007/s00192-016-3026-4

Van Dijk J, Lowery M, Lapatki B, Stegeman D. Evidence of potential averaging over the finite surface of a bioelectric surface electrode. Ann Biomed Eng. 2009; 37:1141–51. [PubMed: 19319681]

Van Dijk J, Verhamme C, Van Schaik I, Schelhaas H, Mans E, Bour L, et al. Age -related changes in motor unit number estimates in adult patients with Charcot–Marie–Tooth type 1A. Eur J Neurol. 2010a; 17:1098–104. [PubMed: 20443982]

Van Dijk Johannes P. High-density surface EMG: Techniques and applications at a motor unit level. Biocybern Biomed Eng. 2012; 32:3–27.

van Dijk JP, Blok JH, Lapatki BG, van Schaik IN, Zwarts MJ, Stegeman DF. Motor unit number estimation using high-density surface electromyography. Clin Neurophysiol. 2008; 119:33–42. [PubMed: 18037342]

van Dijk JP, Schelhaas HJ, Van Schaik IN, Janssen HM, Stegeman DF, Zwarts MJ. Monitoring disease progression using high -density motor unit number estimation in amyotrophic lateral sclerosis. Muscle Nerve. 2010b; 42:239–44. [PubMed: 20544934]

Yao B, Zhang X, Li S, Li X, Chen X, Klein CS, et al. Analysis of linear electrode array EMG for assessment of hemiparetic biceps brachii muscles. Front Hum Neurosci. 2015; 9:569. [PubMed: 26557068]

Highlights

- The novel MUNE method employs high density surface EMG decomposition to characterize SMUP signals.
- A large number (>20) of SMUPs can be obtained at each contraction with a good match with the CMAP.
- The new MUNE works for proximal muscles without intramuscular electrodes or multiple stimuli.

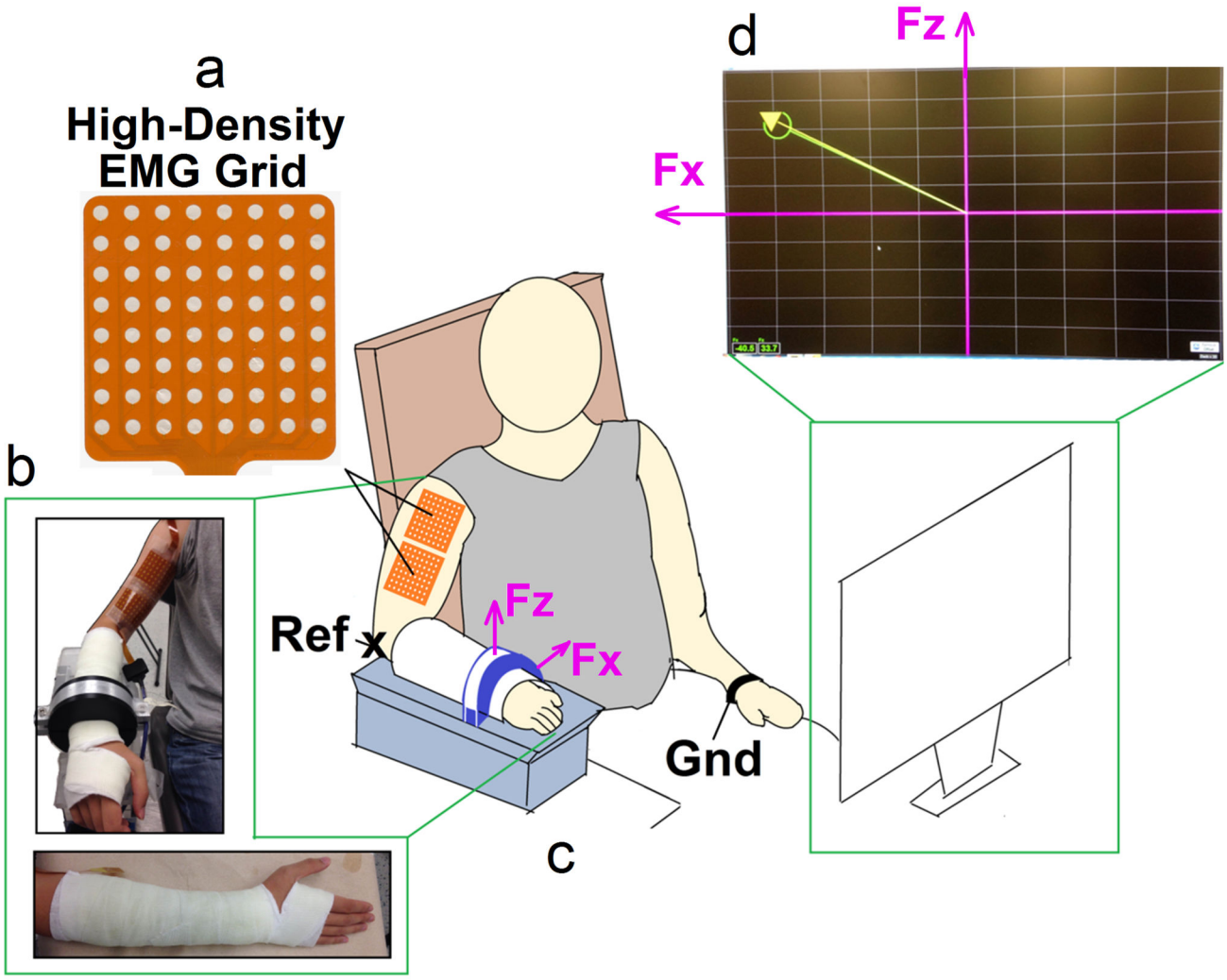

Figure 1.

Illustration of the experimental setup. (a) the high-density surface EMG grid, (b) the arm and hand cast and the wrist strap force sensor, (c) subject position and (d) the computer screen with visual feedback for the subject to match the force vector (yellow arrow) towards the target MVC position (green circle).

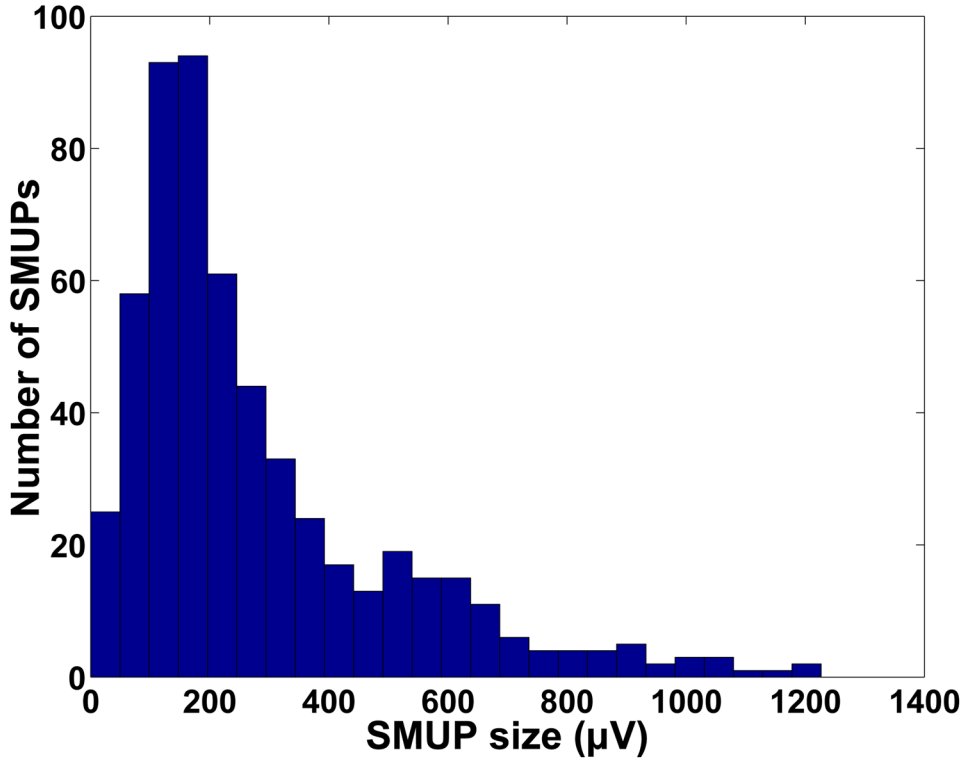

Figure 2.
Histogram of all SMUP sizes for all eight subjects. The SMUP size was represented by the largest negative peak amplitude among all channels.

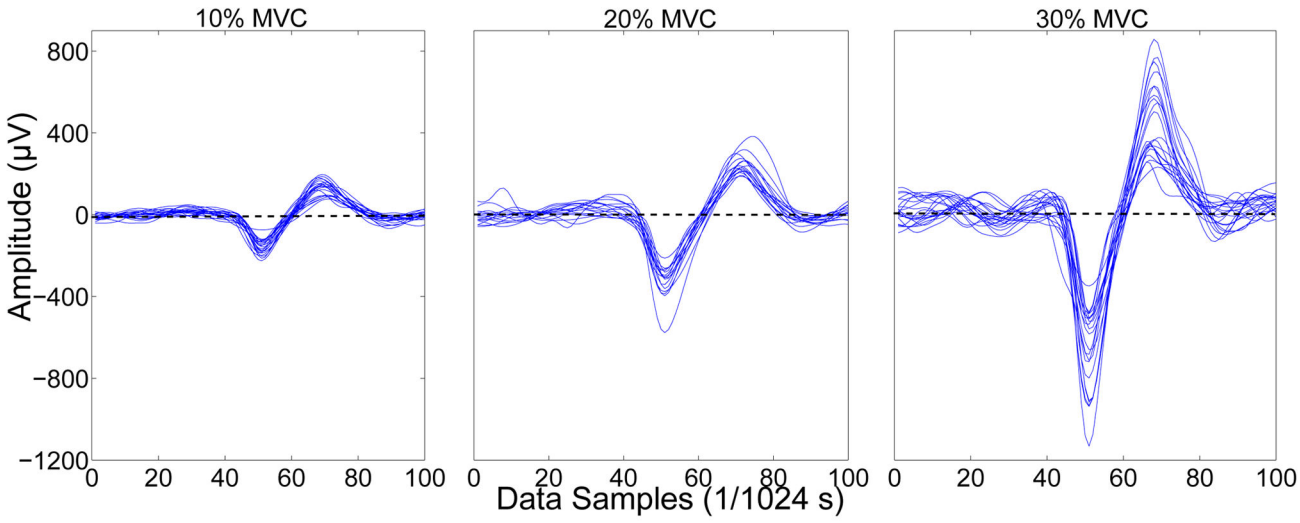

Figure 3.

Overlapping plot of SMUPs obtained at three contraction levels for subject 6 (with multiples removed) in one channel. Note that the difference in waveform between SMUPs at 10% MVC is less obvious due to the selection of uniform scale in amplitude.

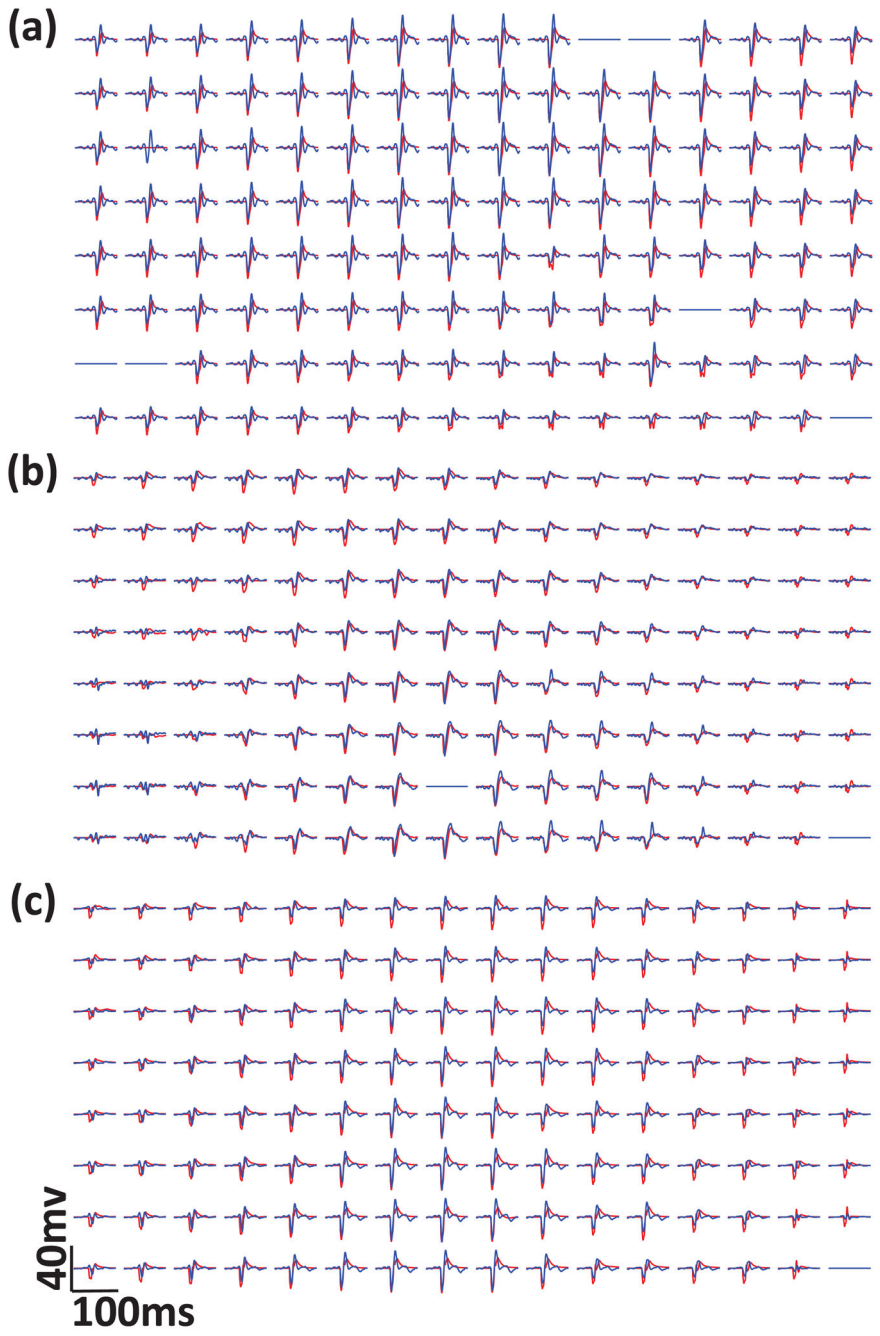

Figure 4.

Spatiotemporal profiles of the mean SMUP (blue) and CMAP (red) for (a) subject 1, (b) subject 5 and (c) subject 6. The mean SMUP was scaled to the CMAP by the ratio of their largest negative peak amplitudes for a better comparison. All three MVC levels were considered when constructing the mean SMUP. Channels with bad signal qualities were removed and not displayed.

Table 1

Individual subject mean CMAP and SMUP sizes, RV, MUNE at 10%, 20%, 30% and all MVC levels for the biceps brachii.

		10% MVC			20% MVC			30% MVC			All MVCs (10% – 30%)		
Subject	**CMAP**	**SMUP (No.)**	**RV (%)**	**MUNE**	**SMUP (No.)**	**RV (%)**	**MUNE**	**SMUP (No.)**	**RV (%)**	**MUNE**	**SMUP (No.)**	**RV (%)**	**MUNE**
1	20.0	65.4 (19)	2	358	115.6 (20)	6	230	131.2 (21)	3	194	104.1 (60)	4	246
2	16.3	88.5 (28)	14	178	189.6 (30)	24	106	443.1 (34)	22	45	251.0 (92)	23	78
3	19.9	52.7 (18)	18	442	116.9 (30)	13	177	196.8 (35)	14	112	135.3 (83)	14	159
4	10.7	30.8 (20)	16	522	83.7 (13)	12	194	148.5 (25)	9	90	90.2 (58)	11	153
5	15.3	89.3 (35)	11	227	181.3 (25)	15	124	193.2 (12)	6	100	111.6 (47)	8	177
6	17.9	145.7 (22)	5	168	275.6 (16)	6	90	556.7 (21)	7	45	327.0 (59)	6	76
7	17.6	166.8 (22)	6	129	400.0 (29)	7	56	748.2 (31)	7	31	469.1 (82)	7	49
8	22.0	91.0 (22)	2	279	177.5 (24)	2	137	388.7 (29)	6	77	226.9 (75)	4	120
Mean	17.5	91.3 (23)	9.3	288	192.5 (23)	10.1	155	350.8 (26)	9.1	107	214.0 (70)	9.6	132
S.D.	3.3	42.6 (5)	5.9	132	96.0 (6)	7.0	87	208.6 (7)	5.8	99	124.2 (15)	6.0	61

*CMAP in mV, SMUP in μV

*CMAP and SMUP sizes are represented by the largest negative peak among all channels