Accuracy assessment of a surface electromyogram decomposition system in human first dorsal interosseus muscle

Xiaogang Hu¹, William Z Rymer¹,² and Nina L Suresh¹

¹ Sensory Motor Performance Program, Rehabilitation Institute of Chicago, Chicago, IL, USA
² Department of Physical Medicine and Rehabilitation, Feinberg School of Medicine, Northwestern University, Chicago, IL, USA

E-mail: xiaogang.hu@northwestern.edu

Received 25 November 2013, revised 22 December 2013
Accepted for publication 23 January 2014
Published 21 February 2014

Abstract

Objective. The aim of this study is to assess the accuracy of a surface electromyogram (sEMG) motor unit (MU) decomposition algorithm during low levels of muscle contraction. Approach. A two-source method was used to verify the accuracy of the sEMG decomposition system, by utilizing simultaneous intramuscular and surface EMG recordings from the human first dorsal interosseous muscle recorded during isometric trapezoidal force contractions. Spike trains from each recording type were decomposed independently utilizing two different algorithms, EMGlab and dEMG decomposition algorithms. The degree of agreement of the decomposed spike timings was assessed for three different segments of the EMG signals, corresponding to specified regions in the force task. A regression analysis was performed to examine whether certain properties of the sEMG and force signal can predict the decomposition accuracy. Main results. The average accuracy of successful decomposition among the 119 MUs that were common to both intramuscular and surface records was approximately 95%, and the accuracy was comparable between the different segments of the sEMG signals (i.e., force ramp-up versus steady state force versus combined). The regression function between the accuracy and properties of sEMG and force signals revealed that the signal-to-noise ratio of the action potential and stability in the action potential records were significant predictors of the surface decomposition accuracy. Significance. The outcomes of our study confirm the accuracy of the sEMG decomposition algorithm during low muscle contraction levels and provide confidence in the overall validity of the surface dEMG decomposition algorithm.

Keywords: surface electromyogram, motor unit decomposition, two-source, validation, motor unit

(Some figures may appear in colour only in the online journal)

Introduction

Information regarding single motor unit (MU) firing patterns is typically obtained using intramuscular electromyogram (iEMG) recordings with a needle or fine-wire inserted into the muscle of interest. Recently, skin surface recording techniques capable of recording extractable MU activity from EMG recordings have been developed. Based on these non-invasive recording techniques, a number of MU decomposition methods have been developed, where single MU firings can be extracted from surface EMG (sEMG) interference patterns using automatic decomposition algorithms [1–5]. However, certain characteristics of sEMG (e.g., excessive superposition and shape similarity of action potential waveforms) pose potential challenges to these decomposition algorithms. As it is difficult to validate the accuracy of the surface decomposition methods with visual inspection, there has been continuing skepticism about the general validity of the approach [6, 7].
Accordingly, the purpose of this study was to assess the accuracy of a sEMG decomposition algorithm (dEMG algorithm, previously referred to as PDsEMG) based on EMG recordings from a five-pin sensor array [5]. The array electrode has the advantage that, after differential signal processing, the duration of the recorded action potentials is relatively short, thereby minimizing the possibility of occurrences of action potential superposition. The decomposition algorithm represents an advance over earlier intramuscular MU decomposition approaches [8, 9], as it has gone through several improvements over the course of its development [1, 10, 11]. The output of the decomposition algorithm provides the firing times and action potential templates of a large number of MUs extracted from the sEMG over a large range of muscle contraction levels. However, the accuracy of the decomposition algorithm has not been thoroughly assessed by users outside of the developers, and the validity of the decomposition results has also been questioned [6, 7]. Accordingly, the objective of this study was to assess the accuracy of the dEMG algorithm in performing MU decomposition from a sEMG signal recorded from the first dorsal interosseous (FDI) muscle using the array electrode. To assess accuracy and thereby validity, we used the secure ‘two-source’ method at low contraction forces [1, 12, 13].

The two-source method involves simultaneous recordings of sEMG and iEMG signals; the EMG signals are then decomposed independently. Given that the iEMG decomposition techniques have widely been accepted as reliable and that iEMG decomposition can be manually corrected for near perfect accuracy, the degree of agreement of common MUs between the decomposition results will reflect the accuracy of the sEMG decomposition. In the current study, we recorded sEMG and iEMG signals simultaneously from the FDI muscle during low-level contractions. The accuracy of the commonly identified MUs from both recording sites was compared. We also assessed the degree of discharge timing alignment between random pairs of intramuscular and surface MUs as well as between random pairs of surface MUs in order to get an estimate of the timing accuracy just by chance and an estimate of the discharge synchrony between MUs. We then determined the factors that can influence the surface decomposition accuracy, which in turn can potentially help us to predict the spike accuracy of the surface decomposed MUs using the dEMG decomposition algorithm.

Materials and methods

Participants

Nine neurologically intact individuals (five male, four female) volunteered to participate in this study. Both iEMG and sEMG activities of the FDI muscle were recorded simultaneously during isometric abduction and/or flexion of the index finger. The participants gave informed consent via protocols approved by the Institutional Review Board under the Office for the Protection of Human Subjects at Northwestern University.

Experimental setup

Participants were seated upright in a Biodex chair with their upper arm resting on a support (figure 1(A). To minimize contributions of unrecorded muscles, the forearm was immobilized in a brace and placed in a ring-mount interface attached to an elbow rest. The forearm was placed in full pronation and the wrist was held neutral with respect to flexion/extension. The little, ring and middle fingers were extended away from the index finger and rest on a support surface. The thumb was secured at an approximately 60° angle to the index finger. The index finger was placed in line with the second metacarpal and the long axis of the forearm creating a 0° metacarpophalangeal joint angle. The proximal phalanx of the index finger was cast and fixed to a ring–mount interface attached to a six degrees-of-freedom load cell (ATL Inc., Apex, NC). The recorded forces from the abduction/adduction and flexion/extension directions were low-pass filtered (cutoff = 200 Hz) and digitized at a sampling frequency of 1 kHz.

Intramuscular EMG recordings. iEMG data from the FDI muscle were recorded with Teflon-coated double-stranded wires (bifilar 50 μm, California Fine Wire, Grover Beach, CA) (figure 1(B)). The fine-wires were cut to expose only the cross-section to increase the recording selectivity. The wire was then inserted into a 30-gauge hypodermic needle and the wire tip was bent to form a barb. The bipolar iEMG signals were amplified, band-pass filtered (20 Hz to 2 kHz) and sampled at 20 kHz using the Bagnoli sEMG system (Delsys, Inc., Boston, MA).

Surface EMG recordings. Prior to the needle insertion, the subject’s skin was prepared by cleaning the superficial layers with adhesive tape to ensure proper electric contact and low baseline noise, and the skin was then cleaned with alcohol pads. After the fine-wire had been placed in the muscle, the surface sensor array (Delsys, Inc., Boston, MA) was placed above the FDI muscle close to the fine-wire entry point (figure 1(B)). The surface sensor array consisted of five cylindrical probes (0.5 mm diameter) as shown in figure 1(C). The probes are located at the corners and at the center of a 5 × 5 mm square. Pairwise differentiation of the five electrodes yields multiple channels of sEMG signals. The sEMG sensor and a reference electrode were connected to four channels of the Bagnoli sEMG system (the same as the fine-wire recording). The sEMG signals were amplified and filtered with a bandwidth of 20 Hz to 2 kHz. The signals were sampled at 20 kHz and stored on a computer for decomposition processing.

Procedures

The subjects were asked to produce a trapezoidal isometric force contraction via abduction and/or flexion of their index fingers, about the second metacarpophalangeal joint. The trapezoid trajectory contains five segments: a 5 s quiescent period for sEMG baseline noise calculation, a slow ramp-up, a constant-hold force for 12 s, a brief ramp-down and a final 3 s quiescent period. To ensure reliable decomposition
results of the iEMG using EMGlab [14], the steady-hold force was limited to low levels (approximately 5–15% of maximum force). The steady-hold force was determined based on the degree of discriminable MU patterns in the iEMG signals. The subjects were asked to hold a force level when one motor unit action potential (MUAP) train was visible in the iEMG. They were then asked to increase the steady-hold force until dense interference patterns had been recorded in the iEMG such that the experimenter could not visually identify discriminable MUs, just below this level would be the upper bound for force. Using this approach, the constant-hold force (abduction and/or flexion) ranged from 0.2 to 8 N across the subjects.

Data analysis

The sEMG signals were decomposed using the dEMG decomposition algorithm (version 1.0.0.31) developed by De Luca and colleagues [5]. The decomposition algorithm consists of two stages. For both stages, the four channels form a $1 \times 4$ vector and are used simultaneously to identify different MUAPs.

The first stage involves MUAP template creation, matching and updating. First, the algorithm identifies as many template shapes as possible from the peaks of the EMG data. When similar shapes are identified consistently for a set number of times, a template is initiated by averaging the similar shapes.

Second, the matching of MUAP templates goes through a maximum \textit{a posteriori} probability classifier that uses the information of the correlation between the templates and the EMG signal, the amplitude of action potential and the remaining energy of the EMG signal. The MUAP templates are subsequently updated through a weighting process, in which a larger weighting is assigned to the existing old template and a smaller weighting is assigned to the new action potential shape. The second stage also identifies which MUAPs within complex superposition best matches the signal shape, and for which the coefficient of variation (CV) of the ISI of these MUs reaches a minimum. The output of the decomposition algorithm consists of the spike times and action potential templates of individual MUs. Given that there are four channels of sEMG signals, each decomposed MU has four representations of the template.
 waveform. More detailed information of the algorithm is described in [5].

The iEMG signals recorded in this study, were decomposed using EMGlab (version 1.03) developed by McGill and colleagues [14]. EMGlab is a program written in Matlab (The Mathworks, Natick, MA) specifically for the decomposition of iEMG signals. It provides a number of automatic decomposition procedures combined with a graphical interface that allows manual inspection and editing. In the automatic step, the raw EMG signal is high-pass filtered first to increase the sharpness of the spike. The spikes are then detected using a threshold crossing method. The waveforms that crossed the threshold are then classified using a template matching algorithm in the frequency domain [15], and the template is also updated recursively using a weighted average. The irregularity of the interspike interval of the identified MUAP trains is then analyzed manually to correct potential spurious and missing spike errors.

The complex superposition between multiple units is resolved using a ‘peel off’ procedure beginning from the larger spikes to the smaller ones, with an objective function of minimizing the residual energy of the signal and the variability of the interspike interval of firing spikes. In the manual interaction step, the individual spike times are verified, and spurious and missed firings are corrected using the graphical user interface based on the residual of the signal and the firing properties of the spike train (e.g., unusually large or small interspike intervals are typically signs of possible errors).

The iEMG signals recorded in our experiment were first decomposed using the automatic procedures of EMGlab, and then an experienced editor manually inspected and edited the results to make sure that the decomposed spike timings were 100% accurate. To ensure accurate decomposition of iEMG signals, recordings of MUs with excessive superposition in the iEMG trace which the editor was not able to manually separate were discarded to avoid inaccurate spike identifications. This constraint is the major limiting factor on the muscle contraction (force) levels during the experiment, as well as the number of iEMG/sEMG pairs for accuracy analysis.

Three steps were then followed to identify the common MUs between the sEMG and iEMG signals. First, spike-triggered averaging from the iEMG was performed based on all the identified spike trains from the sEMG signal in order to identify possible common MUs recorded in both recording sources. A clearly visible waveform average above baseline noise signifies possible common MUs. Second, the sEMG and iEMG signals were aligned to visually identify consistent time-locked action potentials especially at the initial recruitment and final de-recruitment stages. The spike-triggered average waveform of the iEMG was then compared with the time-locked individual action potentials in the iEMG signal. Only the intramuscular MUAPs with clearly visible waveform averages were decomposed later. These first two steps were used to qualitatively identify matched pairs of MUAP trains. Finally, an event correlation histogram between the iEMG and sEMG spike trains was calculated to further confirm the common MU pairs, and the pair with the largest correlation peak was regarded as identifying the same MU. Given that the spike event placement criteria may be slightly different between decomposition algorithms, and given that there may be consistent timing offsets between the spike trains from intramuscular and surface recording sites, the decomposed spike timings of sEMG and iEMG signals were aligned to have the maximum degree of agreement.

In order to estimate the range of accuracy arising just by chance, we also performed the accuracy calculation for all random pairs between the intramuscular and surface MUAP trains as well as the spike timing alignment between the surface MUAP trains identified in the same contraction.

For each pair of common MU spike trains, three accuracy assessments were then performed: the entire contraction duration, the ramp-up stage that lasted 2–4 s and the steady-hold stage that lasted approximately 12 s. The ramp-up stage may have greater variability in the MUAP shape for a given MU due to possible displacement between the electrodes and the muscle fibers, posing a greater challenge to the decomposition algorithm. The steady-hold stage could have a greater number of superpositions between MUs, due to a greater number of active MUs. This poses a different challenge to the algorithm. Therefore, it was necessary to assess the decomposition accuracy for each stage separately. For completeness, we also assessed the accuracy of both stages combined.

The accuracy of the identified surface MU spike trains was calculated as

\[
\text{Accuracy} = \frac{N_{\text{Correct}}}{N_{\text{Correct}} + N_{\text{FP}} + N_{\text{FN}}}.
\]

\(N_{\text{Correct}}\) is the number of correctly identified firings (i.e., the firings that were identified within ±5 ms agreement both on the sEMG and iEMG), \(N_{\text{FP}}\) is the number of false positives and \(N_{\text{FN}}\) is the number of false negatives. A false positive is defined as a sEMG firing that did not match any firings within ±5 ms identified from the iEMG signal, or a sEMG firing that is further away from the iEMG firing, when multiple surface firings have been identified within ±5 ms of the iEMG firing. A false negative is defined as an iEMG firing that did not match any firings within ±5 ms identified from the sEMG signal.

We then identified factors that could possibly influence the decomposition accuracy.

1. Signal-to-noise ratio (SNR). The SNR of individual MUs was calculated. The action potential waveforms of the sEMG were estimated by the spike-triggered averaging of a 10 ms window of the sEMG using the spike timings from the iEMG signals during the steady-hold stage of 12 s. The SNR was calculated as the ratio between the peak–peak (P–P) amplitude of the estimated waveform and the P–P amplitude of the baseline noise during the first 5 s quiescent period. Given that there are four channels of waveform representations for the same MU, the norm of SNR across four channels was calculated as an index.

2. Muscle contraction level. The force level in Newton (abduction and flexion) during steady-hold was calculated as an estimate of the muscle contraction level.

3. steadiness of muscle contraction. The CV (standard deviation divided by mean) of force during steady-hold was used to quantify the variation of muscle contraction.
(4) Variation of MUAP shape record. The recorded MUAP shape may be distorted by electrode–muscle fiber displacement and superpositions between MUs. To quantify the recorded MUAP shape variations, a 10 ms sEMG segment around the spike events (±5 ms) was extracted, and the root mean squared (RMS) value of the segment at each channel was then calculated. The CV of RMS was used to quantify the overall shape variation due to superposition with other MUAPs and variations of the MUAP itself. The CV of P–P amplitude of the 10 ms sEMG segments was also calculated as a second estimate of shape variations. The CV of RMS and CV of P–P amplitude was calculated for the entire contraction, ramp-up stage and steady-hold stage, respectively.

Statistical analysis

A multiple-linear regression was performed to assess the relation between the decomposition accuracy and the factors including SNR, muscle contraction level, steadiness of contraction and variation of the recorded MUAP waveform. To ensure normality of the data, the accuracy number and SNR (bounded from 0 to 1) was transformed using the arcsine-square-root transformation, and the CV value (lower bounded by 0) was logarithmically transformed. A one-way repeated measures ANOVA was also performed on the transformed accuracy at different stages of the contraction.

Results

Among the nine subjects, a total of 252 trials were analyzed. 1443 MUs were identified from the sEMG recordings with an average of 5.8 ± 1.5 MUs per trial. A total of 119 MUs that were common to both iEMG and sEMG recordings were identified.

Two exemplar trials are displayed in figures 2 and 3. One channel of iEMG and four channels of sEMG signals recorded during a relatively low force contraction trial (7.89 N) are shown in figure 3(A).
In this trial, the decomposition accuracy was 91.89% in steady state contraction. The zoomed window from 15 to 16.5 s is displayed in figure 3(B). Even though a higher degree of superposition in the sEMG signal was observed in figure 2, the sEMG decomposition algorithm can still decompose most of the spike trains reliably.

In order to estimate the range of accuracy arising just by chance, we also performed the accuracy calculation for all random pairs between the intramuscular and surface MUAP trains identified in the same contraction. All the identified spikes were used during this calculation. As shown in figure 4(A), most of the random pairs had timing accuracy (shown in blue bars) below 20%. Among these random pairs, the best matching pairs (shown in red bars) that were identified as the common MUs had a degree of timing agreement well above the accuracy distribution of the remaining random pairs.

In addition, we estimated the level of synchronization between MU pairs identified from the sEMG signal. Specifically, we estimated the timing alignment between random pairs of surface MUAP within a contraction, using the same accuracy measure as before. Our objective was to examine whether the same MU action potential was identified multiple times. As shown in figure 4(B), the proportion of timing agreement between pairs of surface MUAP trains were below 20% for most of the MU pairs.

The accuracy assessment of the sEMG decomposition based on the total pool of 119 in-common MUs is summarized in figure 5. We calculated the accuracy distribution, based on all the identified spikes (figure 5(A)), during the ramp-up stage (figure 5(B)) and during the steady state contraction (figure 5(C)). The median accuracy for all the identified spikes was 94.81% with an interquartile range (IQR) of 8.72%, and the minimum accuracy was 77.78%. The median accuracy during the ramp-up stage was 95.65% with an IQR of 12.38%, and the minimum accuracy was 70.23%. The median accuracy during the steady state contraction was 95.07% with an IQR of 8.42%, and the minimum accuracy was 74.14%. The ANOVA results did not show any significant difference between the accuracy at different stages of the task ($F(2, 236) = 1.57; p = 0.211$).

Regarding the nature of the errors, the percentage of missed firing errors (false negatives) was an average of 57.8% of the total error during ramp-up stage and 60.5% during the steady state force. The percentage of spurious errors (false positives) was on average 42.2% during ramp-up and 39.5% during steady state force.
Figure 4. (A) Distribution of spike timing accuracy between random pairs of surface and intramuscular MUAP trains in individual contractions. The best matching pairs are shown in red bars. (B) Distribution of spike timing alignment between random pairs of surface MUAP trains within individual contractions.

The cumulative probability of the accuracy at different stages was calculated and shown in figures 5(D)–(F). When all the spikes were considered among all the MUs (figure 5(D)), 15.13% of the decomposed MUs had accuracy below 85%, 27.73% of the MUs had accuracy below 90% and 57.14% of the MUs had accuracy below 95%. When the spikes during the ramp-up stage were considered (figure 5(E)), 18.48% of the MUs had accuracy below 85%, 35.29% of the MUs had accuracy below 90% and 51.26% of the MUs had accuracy below 95%. When the spikes during steady state contraction were considered (figure 5(F)), 12.61% of the MUs had accuracy below 85%, 24.37% of the MUs had accuracy below 90% and 52.94% of the MUs had accuracy below 95%.

Among all the common MUs, the mean firing rate during steady state contraction was 11.38 ± 2.40 Hz. The estimation error in mean firing rate (defined as the absolute difference in mean firing rate between the surface and intramuscular spike trains normalized by the intramuscular mean firing rate) as a function of the decomposition accuracy is illustrated in figure 6. Only 9 out of all the 119 MUs had an estimation error greater than 10%. When a cutoff accuracy threshold of 90% was selected, the estimation error upper bound was found at 10%. The error upper bound was at approximately 13%, when an accuracy threshold of 85% was selected. Note that the estimation error could be low even with low accuracy, and this is likely due to the fact that the numbers of false positive and false negative errors are comparable, so that the averaged mean firing rate is still an accurate estimate. Overall, our results suggest that the mean firing rate estimate is reliable in the majority of the decomposed MUs.

In order to identify the different factors that could have influenced the decomposition accuracy, we identified multiple variables that would quantify the appropriate characteristics of the sEMG and force signals. The results of the multiple-linear regression between the decomposition accuracy and the identified factors are summarized in table 1. The regression model showed that the SNR of the individual MUAPs and CV of the P–P amplitude of the EMG segments were significant predictors of accuracy in all the three sets of accuracy assessments. Namely, a higher SNR and a lower CV would predict a higher accuracy. The CV of RMS was also a significant predictor (i.e., an inverse relation) of accuracy during the ramp stage. Surprisingly, the force level (either flexion force or abduction force ranging from 5% to 15% of maximum force) was not a significant predictor of the accuracy, and similar results were found regarding the CV of force.

Discussion

The objective of this study was to assess the accuracy of a sEMG decomposition system [5] in decomposing the sEMG signal (recorded from the FDI muscle) into discrete MU trains, during low levels of isometric force contractions. The two-source method was used to verify the spike accuracy of the sEMG decomposition system, using the intramuscular MU train as the gold standard. iEMG and sEMG signals were recorded simultaneously and decomposed independently. The degree of agreement of the decomposed spike timings was assessed on three segments of the EMG signals (i.e., all the decomposed spikes, the spikes during force ramp-up and the spikes during steady state force). Our results show that the median accuracy among the 119 MUs was approximately 95%, and the accuracy was not statistically different between the different segments of the sEMG signals. Although the numerical accuracy number was slightly lower during ramp-up stage (i.e., the lower bound of the accuracy was lower than steady state, and the percentage of MUs with accuracy lower than 85% and 90% was higher than steady state). The regression function revealed that the SNR of the MUAPs and variations in MUAP were significant predictors of spike identification accuracy. In general, the outcomes of this study affirm the validity and accuracy of this type of sEMG decomposition algorithm, and provide confidence in the overall utility of the decomposition system at the relatively low force levels that we have tested.
In the field of MU decomposition, a variety of iEMG decomposition algorithms have been proposed [8, 14, 16–18]. Due to the complexity and potential instability of EMG signals, the lower bound of iEMG decomposition accuracy ranged from approximately 65% to 88% [16, 17, 19] with manual error corrections, although the accuracy can also reach up to 100% with manual editing in some of the decomposed MUs.

**Figure 5.** Accuracy assessment at different segments of the sEMG signal. (A) Accuracy of all the identified spikes. (B) Accuracy of the spikes during the ramp-up stage. (C) Accuracy of the spikes during steady state. (D) Cumulative probability of the accuracy of all the identified spikes. (E) Cumulative probability of the accuracy during the ramp-up stage. (F) Cumulative probability of the accuracy during steady state.

**Figure 6.** Estimation error in mean firing rate as a function of the decomposition accuracy. Each circle represents a motor unit. The horizontal dash–dotted line represents the 10% estimation error, and the two vertical dash–dotted lines represent the decomposition accuracy of 85% and 90%, respectively.
Regarding the sEMG decomposition algorithm tested in the current study, a preliminary two-source testing on an earlier version of this algorithm has been described [1]. Specifically, three common MUs were identified in a single 30% of maximum force contraction of the tibialis anterior muscle. After manual corrections on the sEMG and iEMG decomposition results, the overall decomposition accuracy was 97.6%. With a much larger sample size and without manual editing on the sEMG decomposition, our current results were able to reach comparable decomposition accuracy on an improved version of the decomposition algorithm, and a new design of the sensor array.

Our results were also comparable to the accuracy assessment of a different sEMG decomposition algorithm [13, 20]. This convolution kernel compensation algorithm was based on recordings from high-density (HD) sEMG electrodes with 60 to approximately 90 channels. The reported average accuracy ranged from 84% to 92% depending on the recording muscle. Based on the two-source verifications, both algorithms provide reliable decomposition results. However, there are substantial methodological differences in the accuracy assessment procedures for the two techniques.

First, the accuracy assessment previously performed [13, 20] only assessed the accuracy of a 10 s segment of the HD sEMG segment during steady state contractions, whereas the present study assesses the accuracy of all the decomposed MU spike events for the entire duration of the trial (each trial ranges from approximately 16 to 22 s) including the ramp-up contractions. During the ramp-up contraction, the muscle fiber shorts progressively; as a result, the recorded MUAP shape and amplitude may vary, which poses great challenge to the decomposition algorithm. However, analysis of the accuracy of this stage is necessary when MU recruitment or other discharge statistics are the point of interest [21, 22]. Our results revealed that the accuracy during the ramp-up stage was still comparable to the steady state contractions, which provides confidence in the accuracy of the decomposed firings during varying force contractions.

Second, previous studies have used an error band of ±0.5 ms to determine whether the spike timings of the sEMG agree with the iEMG spike timings, whereas in our current study, an error band of ±5 ms was used to determine the degree of agreement; in addition, a smaller error band of ±2 ms was tested and the high accuracy level was retained. Such a large error band was used because of the possible imprecise placement of spike timings when resolving excessive superpositions of multiple MUAPs.

### Accuracy prediction

When the characteristics of the sEMG signals and the MUAPs were examined, the SNR of the MUAP and shape variations in the MUAP collectively can predict the decomposition accuracy. Previous validation studies of iEMG decomposition have also shown that the SNR of the MUAP correlate with the decomposition accuracy [19]. In the current study, the lowest steady state accuracy (74.14%) unit had a SNR of 0.87, much lower than any other sEMG decomposition study has reported thus far. The SNR of the MUAP record can be determined by the fiber–electrode distance, the baseline noise level and the actual electrical amplitude of the MUAPs. The MUAP shapes in the EMG record can be distorted significantly by superposition with other MUAPs. The shape variation of an MUAP in itself may arise naturally during the recording process (e.g., a position shift of the electrodes with respect to the muscle fibers and potential impedance change of the electrode–electrolyte interface [23]). Variations may also arise from the fact that not all the muscle fibers within a MU are activated simultaneously by the motoneuron [24] and that the muscle fiber conduction velocity can fluctuate due to temperature changes in the focal muscle region [25, 26]. All these factors pose challenges to the sEMG (even iEMG) decomposition algorithms in general. Therefore, to minimize decomposition errors, it is important to ensure high signal quality during data acquisition.

For example, when using the sEMG decomposition algorithm, it is recommended that the SNR of the EMG signal for accurate decomposition should be high (e.g., >4) and baseline noise should be low (e.g., P–P amplitude <20 μV). The recommendations also include avoidance of abrupt changes in muscle contraction to minimize fiber–electrode shift, a stable sensor array position and close electrode–skin contact.

| Table 1. Multiple-linear regression between accuracy and characteristics of the sEMG and force signals. Regression function is: accuracy = β1 × SNR + β2 × CV Fx + β3 × CV Fy + β4 × RMS + β5 × CV P–P. β, represents the coefficient of the regression function, t-stat represents the t-statistic of β, SNR represents the signal-to-noise ratio, Fx represents the abduction force of the index finger, Fy represents the flexion force of the index finger, CV Fx represents the coefficient of variation (CV) of Fx, CV Fy represents the coefficient of variation (CV) of Fy, CV RMS represents the CV of the root mean square value of the 10 ms EMG segments and CV P–P represents the CV of the peak–peak (P–P) amplitude of the 10 ms EMG segments. |
|---|---|---|---|---|---|
| Total | Ramp state | Steady state | | | |
| | β | t-stat | p-value | β | t-stat | p-value | β | t-stat | p-value |
| Constant | 1.615 | 31.911 | 0.000 | 1.748 | 22.043 | 0.000 | 1.623 | 30.319 | 0.000 |
| SNR | 0.011 | 3.142 | **0.002** | 0.013 | 2.729 | **0.007** | 0.010 | 2.568 | **0.012** |
| Fx | 0.003 | 0.376 | 0.707 | 0.011 | 1.044 | 0.299 | 0.003 | 0.341 | 0.734 |
| Fy | −0.031 | −1.207 | 0.230 | −0.065 | −1.935 | 0.056 | −0.010 | −0.338 | 0.736 |
| CV of Fx | 0.018 | 1.418 | 0.159 | 0.013 | 0.820 | 0.414 | 0.014 | 1.052 | 0.295 |
| CV of Fy | −0.016 | −1.275 | 0.205 | −0.027 | −1.653 | 0.101 | −0.006 | −0.418 | 0.677 |
| CV of RMS of MUAP | −0.025 | −0.777 | 0.439 | −0.070 | −2.697 | **0.008** | −0.013 | −0.456 | 0.649 |
| CV of P–P | −1.745 | −6.446 | **0.000** | −1.118 | −5.724 | **0.000** | −1.727 | −6.344 | **0.000** |
contact during sEMG recordings. The SNR measure in our regression analysis was not calculated based on the raw EMG signal but rather on the MUAP, a much more stringent criterion.

The multiple-linear regression analysis also revealed that the force level was not a significant predictor of accuracy. Typically, a higher force would mean a larger number of recruited MUs and a higher discharge rate, therefore, a higher degree of superposition between MUAPs. This lack of significance could possibly arise from the nature of the decomposition algorithm. Specifically, when initiating a MUAP template, the algorithm requires a minimum number of $N (N > 6)$ uncontaminated MUAPs for a 30 s EMG signal epoch [5]. The superposition of multiple MUAPs is then solved in a utility maximization process via suprasegmental analysis over the entire EMG segment, which can provide template separation accuracy well above 95% on complex sEMG data [10].

**Limitations of the current study**

One limitation of the current study was that the accuracy of only a small fraction of the decomposed MUs could be examined. A total of 1443 MUs were identified from the sEMG decomposition, and the accuracy of only 119 (8.2%) common MUs was assessed. The accuracy of the remaining MUs could not be readily evaluated. This is because the total pool of common units proved to be very small (1–2 common MUs per trial), a similar observation that has been reported by other two-source studies [13, 20]. The reason for the relative paucity of common units is likely due to the selectivity of recording volume of both the surface and intramuscular sensors. Nonetheless, the assessed 119 MUs represent a random sample of the MU population in the FDI muscle. Thus, our results suggest that the decomposition of the remaining MUs will also be accurate.

The other limitation of the two-source method is that the muscle contraction was constrained to low levels in order to avoid excessive MUAP superposition in the iEMG signal. This is necessary so that the iEMG can be decomposed accurately and manually verified spike-by-spike. Even though the sEMG decomposition can handle contraction levels up to the maximum level, the accuracy of the sEMG decomposition at moderate and high contraction levels cannot be verified using this two-source method. Additionally, only the FDI muscle was used to assess the decomposition accuracy. Clearly, further study is necessary to thoroughly assess the decomposition accuracy at higher muscle contraction levels from multiple muscles.

**Conclusions**

Using the two-source method, our study was able to confirm that the results of this sEMG decomposition algorithm were highly accurate, at least during low levels of muscle contraction. The outcome of this study provides confidence for the users when using the surface decomposition system at relatively low muscle contraction levels, and also confirms the general validity of the decomposition algorithm and it is not generating erroneous MUAP trains. In addition, based on our regression analysis results, to ensure accurate decomposition, a high signal quality should be guaranteed during sEMG recordings.

**References**

[7] De Luca C J and Nawab S H 2011 Reply to Farina and Enoka: the reconstruct-and-test approach is the most appropriate validation for surface EMG signal decomposition to date J. Neurophysiol. 105 983–4


[22] Duchateau J and Enoka R M 2011 Human motor unit recordings: origins and insight into the integrated motor system Brain Res. 1409 42–61


