Statistics of Inter-spike Intervals as a Routine Measure of Accuracy in Automatic Decomposition of Surface Electromyogram

Xiaogang Hu, Nina L. Suresh, Brian Jeon, Henry Shin, William Z. Rymer

Abstract— **Automated motor unit (MU) decomposition algorithms of surface electromyogram (EMG) have been developed recently. However, a routine estimate of the decomposition accuracy is still lacking. The objective of this preliminary study was to examine the statistics of the inter-spike intervals (ISIs) of the identified MUs as a measure of the decomposition accuracy, such that the ISI analysis can be used as a routine procedure to assess the accuracy of the surface identified MU spike timings. A surface EMG recording and decomposition system was used to record EMG signals and extract single MU activities from the first dorsal interosseous muscle of three healthy individuals. The estimated ISI statistics were cross-validated with decomposed MUs from simultaneous intramuscular EMG recordings. Our preliminary results reveal that the distribution of the ISIs, specifically the deviation from the Gaussian distribution as represented by secondary peaks at the short or long ISIs, can provide information regarding the spurious errors and missed firing errors in the decomposition. In addition, the variability (coefficient of variation) of the ISIs also correlated inversely with the decomposition accuracy. These findings show that the ISI statistics can be used to assess the spike timing accuracy of the identified MUs from surface EMG decomposition algorithms.**

I. Introduction

Motor unit (MU) firing patterns are typically obtained using invasive intramuscular recordings, and the yield of the MU is also low. Recently, noninvasive skin surface EMG recordings and automatic MU decomposition techniques have been developed [1-5]. These methods allow extractions of a large number of simultaneously active MUs in a large force range. Although promising, the validity of these approaches cannot be readily assessed routinely.

Accordingly, the objective of this study was to examine the firing statistics of the identified MUs in order to evaluate the accuracy of a surface EMG (sEMG) decomposition algorithm (dEMG) based on sEMG recordings from a five-pin sensor array [5]. The output of the decomposition algorithm consists of the firing times and action potential templates of a large number of MUs identified from the sEMG signals over a large range of muscle contraction levels. The validity of this decomposition algorithm has previously been assessed using a 'reconstruct-and-test' approach (in which reconstructed EMG signals from the real sEMG signals were decomposed and compared with the original decomposition results) [5] and a 'spike triggered averaging' approach (in which the action potentials of individual MUs were estimated, and the consistency of the estimated action potentials were evaluated) [6, 7]. However, both validation methods could not identify the missed firing errors of the MUs. A more rigorous two-source validation procedure has been performed [8]. In this study, the surface and intramuscular EMG signals were recorded simultaneously and were then decomposed independently using two separate decomposition algorithms. Although the two-source validation provides a definite assessment of the decomposition accuracy, this procedure cannot be performed routinely during sEMG recordings of different muscles in different experimental conditions. Therefore, an accuracy assessment tool that can be used to evaluate the decomposition results on a regular basis is necessary to ensure reliable estimate of the MU firing properties.

During steady state muscle contractions, the recruited MUs discharge at stable firing rates with ISIs following a Gaussian distribution [9], and deviations from this distribution can signify potential identification errors. In MU decomposition, there are two types of errors. First, spurious errors (false positives) are the identified action potentials that are not present in the real action potential train. These errors can lead to reduced ISIs, which may produce a secondary peak at the short ISIs in the ISI distribution. Second, missed firing errors (false negatives) are existed action potentials in the sEMG signal that are missed by the decomposition algorithm. These errors can lead to large ISIs, which may create a secondary peak at the long ISIs in the ISI distribution. Therefore, these secondary ISI peaks on either side of the main peak can provide information about the nature of the identification errors. In addition, both spurious and missed firing errors can increase the variability of the ISIs, which is also a sign of potential decomposition errors.

In this preliminary study, we examined the ISI distribution of the decomposed MUs from the sEMG signals, and the ISI distribution of MUs from the intramuscular recordings were used as the true distribution to cross-validate the estimated ISI statistics. The variability of the ISIs was also calculated. Specifically, the coefficient of variation (standard deviation normalized by the mean) of the ISIs was correlated with the decomposition accuracy. These measures can serve as potential tools to assess the decomposition accuracy of the decomposed MUs to ensure that the estimated MU firing properties are reliable.

*Research supported by the National Institutes of Health of the USA (Grant #: R24 HD50821-07).

Xiaogang Hu is with the Sensory Motor Performance Program of the Rehabilitation Institute of Chicago (email: xiaogang.hu@northwestern.edu)

Nina L. Suresh is with the Sensory Motor Performance Program of the Rehabilitation Institute of Chicago (email: n-suresh@northwestern.edu)

Brian Jeon is with the Sensory Motor Performance Program of the Rehabilitation Institute of Chicago (email: bjeon6@johnshopkins.edu)

Henry Shin is with the Department of Biomedical Engineering of Northwestern University (email: hshin@u.northwestern.edu)

William Z. Rymer is with the Rehabilitation Institute of Chicago and the Department of Physical Medicine and Rehabilitation of Northwestern University (email: w-rymer@northwestern.edu)

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

II. METHODS

A. Subjects

Three healthy subjects without any neurological disorders participated in the study. For each subject, intramuscular and surface EMG activities were recorded simultaneously from the first dorsal interosseous (FDI) muscle during the abduction/flexion of the index finger. All subjects gave informed consent via the protocols approved by the Institutional Review Board of Northwestern University.

B. Experimental Setup

Subjects were seated upright in a Biodex chair with their arm resting comfortably on a support (Figure 1). To minimize the activity of the unrecorded muscles, their forearm was casted and the wrist was fixed with a brace onto a ring mount attached to the support. In doing so, the forearm was also completely pronated and the wrist was in neutral position with respect to flexion and extension. The index finger was isolated by extending the little, ring, and middle fingers away and placed in line with the long axis of the forearm to form a 0 degree metacarpophalangeal joint angle. The thumb was placed at approximately 60 degrees away from the index finger. The proximal phalanx of the index finger was securely attached to the six degrees-of-freedom load cell (ATI, Inc., Apex, NC). The abduction and flexion forces from the load cell were low-pass filtered at 200 Hz and sampled at 1 kHz.

The intramuscular EMG (iEMG) was recorded with Teflon-coated double-stranded wires (bifilar 50 µm, California Fine Wire, Grover Beach, CA). The fine-wire was only exposed at the tip for maximal recording selectivity. The wire was then inserted into a 30-gauge hypodermic needle and the tip was bent to form a barb. The bipolar iEMG signals were amplified, band-pass filtered from 20 Hz to 20 kHz, and sampled at 20 kHz using the Bagnoli sEMG system (Delsys, Inc., Boston, MA).

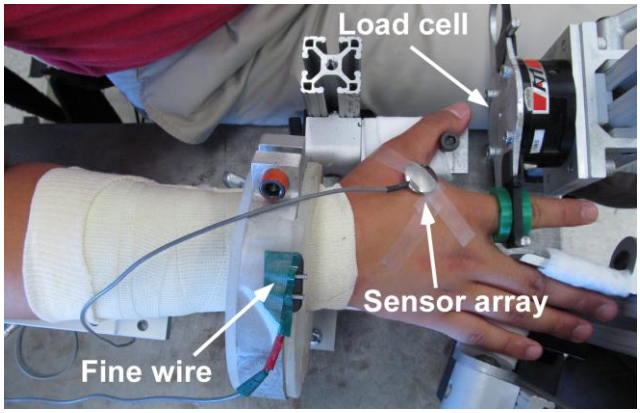

Fig. 1: Experimental setup. A surface sensor array and a fine-wire electrode were used to record EMG activities of the FDI muscle. Isometric finger force was recorded using a load cell.

The superficial layer of the skin was properly cleaned using abrasive alcohol pads and adhesive tape. After the fine-wire had been placed in the muscle, the surface sensor array was placed above the FDI muscle close to the fine-wire entry point.

The sEMG was recorded with the surface sensor array (Delsys, Inc., Boston, MA). The surface sensor array has 5 cylindrical pins with 5mm diameter arranged in a rectangle with one pin in the center. Pairwise differentiations of the pins produce four channels of sEMG. The sEMG signals were then amplified and filtered from 20 Hz to 2 kHz and sampled at 20 kHz using the same Bagnoli sEMG system used for the fine-wire recording.

C. Procedures

The subjects were asked to follow an isometric force trajectory of trapezoidal shape using abduction and/or flexion of their index finger. The trapezoidal force trajectory was composed of a 5-second resting period, a slow ramp-up segment, a 12-second steady force period, a short ramp-down segment, and a 3-second resting period. To ensure reliable decomposition of the iEMG using EMGlab [10], the steady-state force was limited to low levels (approximately 5 to 15% of maximum force), determined by the degree of discriminable MU patterns in the iEMG signal. The subjects were asked to hold a force level when one MUAP train was visible on iEMG. This force level was then used as the lower bound for force. 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 motor units. The upper bound for force was set to be just below this level. Using this approach, the constant-hold force (abduction and/or flexion) ranged from 0.2 to 8 N across the subjects.

D. Data Analysis

sEMG signals were decomposed using the dEMG decomposition algorithm (version 1.0.0.31) [5] to obtain firing times of each MU and four MU action potential templates corresponding to the four channels of raw sEMG. The iEMG signals were decomposed using EMGlab (version 1.03) [10]. The raw iEMG was passed through EMGlab to obtain a number of automatically decomposed MUs, which were then manually inspected for correctness. For maximum accuracy, MUs with multiple superpositioning in the iEMG signal, which prevented the editor from correctly identifying the MU firing events, were discarded.

In order to identify MUs common to both sEMG and iEMG signal, first, spike triggered averaging was performed on the iEMG signal using the firing time output of the decomposed sEMG MUs. When the averaged waveform displayed a clear MUAP above the baseline noise, it is possible that the MU was recorded on both the iEMG and sEMG. Second, the raw sEMG and raw iEMG signals were aligned to visually identify time locked MUAPs especially during the recruitment and de-recruitment stages (up-ramp and down-ramp portion of the trial). After these two steps were used to qualitatively find MUs common to both sEMG and iEMG, for each MU, an event correlation histogram between the spike trains from iEMG and sEMG was constructed to confirm that the MU was truly common between the two recordings. Because each decomposition method has a different placing method of the time of a firing event, and because there may be a difference in the distance between the muscle fiber and the two electrodes, the

decomposed spike timings of surface and iEMG signals were shifted to have maximum agreement.

For each identified common MU, the inter-spike intervals (ISIs) between the firings, the mean firing rates (MFRs) were calculated from both sEMG and iEMG. Then, ISIs from all MUs within a single trial were pooled together to examine the accuracy of the decomposition system. First, ISI histogram of all MUs within a single trial was constructed for both iEMG and sEMG. The ISI histograms were overlaid on top of each other for comparison. In addition, the accuracy of the identified surface MU spike trains was calculated as:

$$Accuracy = \frac{N_{Correct}}{N_{Correct} + N_{FP} + N_{FN}}$$

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

After the common MUs have been identified, the ISI distribution was constructed and compared between the two sources. Moreover, the correlation between the accuracy of sEMG firing output and the CV of ISIs of surface identified MUs was studied to examine if CV of ISIs is a good indicator of the decomposition accuracy. Pearson's correlation coefficient between the CV of ISI and decomposition accuracy was calculated from all of the MUs from all subjects pooled together. In addition, a linear fit was conducted to quantify the general trend.

III. Results

From the three subjects, a total of 54 trials were analyzed, and a total of 67 common MUs were examined. The number of trials, the number of MUs, the minimum and maximum accuracy, and the mean accuracy for each subject are summarized in Table I.

TABLE I. MU DECOMPOSITION ACCURACY

Subjects	Trials	MUs	Min Acc	Max Acc	Avg Acc
1	19	24	76.25%	100%	93.82%
2	15	21	77.78%	100%	93.77%
3	20	22	82.19%	100%	98.22%

Note: Trials: number of trials analyzed. MU: number of MUs identified. Min/Max/Avg Acc: Minimum/Maximum/Average Accuracy of MU spike identification of each subject.

After accuracy of each MU has been computed, the ISI were calculated and a histogram of ISI was created for each of the MU. The visual inspection of histograms showed that the distribution of ISI generally follows a Gaussian distribution (Fig. 2). For MUs with high accuracy, the ISI histogram of the sEMG MUs (blue traces) matched the ISI histogram of the iEMG MUs (red traces) very closely. However, the ISI histogram of the sEMG MUs showed deviations for the MUs with lower decomposition accuracy. If there were many false positives, the distribution of ISI had a longer tail or a secondary peak on the left side of the main peak of the distribution, due to the shorter ISI around the false positive firing events. On the other hand, if there were many false negatives, the distribution of ISI had a longer tail or a secondary peak on the right side of the main peak of the distribution due to the longer ISI resulting from missed firing events.

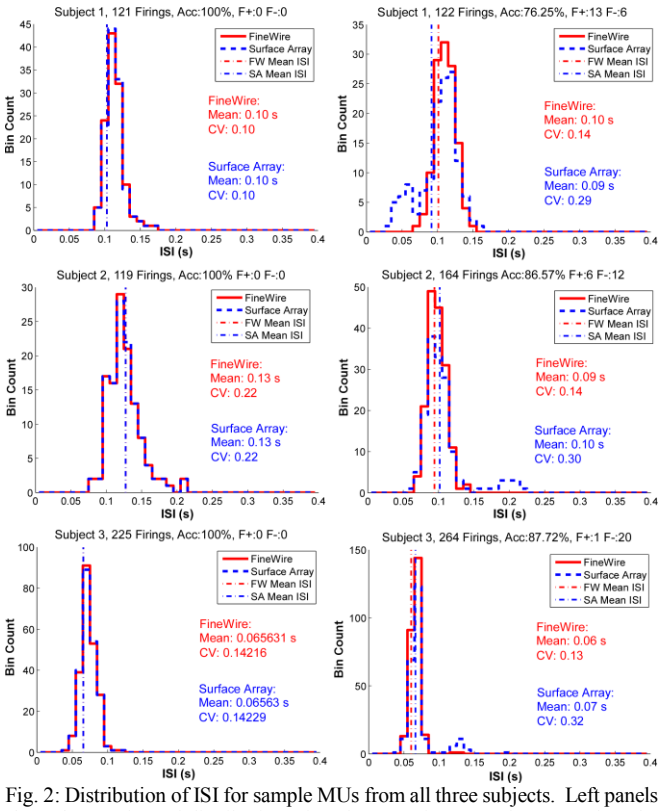

Fig. 2: Distribution of ISI for sample MUs from all three subjects. Left panels show the overlapped distribution of ISI between iEMG and sEMG when the accuracy was 100%. Right panels show the visible differences between the two distributions when the accuracy was relatively low. Acc represents accuracy; 'F+' represents false positives; and 'F-' represents false negatives. In the legend, 'FW' represents fine-wire; and 'SA' represents surface array.

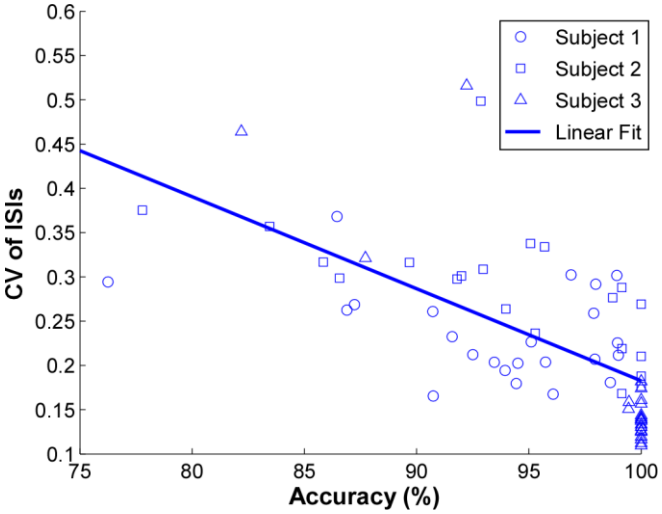

Fig. 3: CV as a function of accuracy shows a negative correlation (Pearson's correlation coefficient: -0.65, p<0.001).

The CV of ISI was also calculated as the index of the variability or dispersion of the ISI. Then, the CV was correlated with the decomposition accuracy to examine the possible relation between the two variables (Fig. 3). Pearson's correlation coefficient for the relationship was -0.65 ($p<0.001$). These results confirm that the decomposition errors can lead to increased firing variability.

IV. Discussion

This preliminary study examines the distribution and variability of ISIs of decomposed MUs from sEMG signals, in order to assess whether ISI statistics can be used to evaluate the decomposition accuracy of the identified MUs. When cross-validated with simultaneously recorded intramuscular EMG signals, the analyses of ISI statistics can provide information regarding the MU decomposition accuracy in steady state muscle contractions, during which the ISI of MU firings follow a Gaussian distribution [7, 9], and the intramuscular MU firing ISIs also followed a Gaussian distribution in the current study as shown in Figure 2. Therefore, a deviation of the ISI distribution from a Gaussian distribution can signify decomposition errors. A long tail or a secondary peak in short ISIs is a sign of spurious errors, and a long tail or a secondary peak in long ISIs is a sign of missed firing errors. Additionally, the decomposition errors also lead to increased variability of firings during steady state contractions, and the CV of ISIs correlated inversely with the decomposition accuracy. Our preliminary results show that the ISI statistics can be used as an assessment tool to routinely evaluate the spike timing accuracy of decomposed MUs from sEMG signals.

In this study, intramuscular EMG recordings and decomposition were used to verify the ISI statistics so as to establish the true ISI distributions and the actual decomposition accuracy. It should be noted that intramuscular recordings are not necessary during routine ISI analysis. Actually, it is not realistic to assess the decomposition accuracy using the two-source method (where only a sub-sample of the decomposed MUs were evaluated), and the analyses of ISI statistics only from sEMG decomposition results would provide an efficient way to evaluate the firing accuracy of all the decomposed MUs. Clearly, further investigations are necessary to quantify the ISI distribution and examine higher-order moments (such as skewness and kurtosis of the distribution) as well as fit the distribution with a multi-modal Gaussian function, in order to better predict the decomposition errors.

The muscle contractions in the current study were constrained at low levels, largely because the intramuscular recordings and decomposition only work effectively at low levels of muscle contractions. This can limit the analysis of the ISI distribution. As shown in Figure 3, two MUs had CV of ISI around 0.5, and the decomposition accuracy was still acceptable (around 93%). Such high CV values in real ISIs are due to the fact that these MUs were discharging at their recruitment rate, which may show a large degree of fluctuations [11]. Therefore, the ISI analysis may have false alarms that can eliminate the MUs with very low firing rates.

Overall, the analyses of ISI statistics can provide information regarding the decomposition accuracy and the nature of the error of a sEMG decomposition system. These analyses can be used routinely to assess the system performance in different experimental conditions. Although the current study was based on a particular decomposition algorithm [5], these types of analysis can be readily applied to other decomposition algorithms, when the MU discharge rate was stable or the level of muscle contraction was steady.

References

[1] C. J. De Luca, A. Adam, R. Wotiz, L. D. Gilmore, and S. H. Nawab, "Decomposition of surface EMG signals," *Journal of Neurophysiology,* vol. 96, pp. 1646-57, Sep 2006.

[2] A. Holobar and D. Zazula, "Multichannel blind source separation using convolution kernel compensation," *IEEE Transactions on Signal Processing,* vol. 55, pp. 4487-4496, Sep 2007.

[3] B. U. Kleine, J. P. van Dijk, B. G. Lapatki, M. J. Zwarts, and D. F. Stegeman, "Using two-dimensional spatial information in decomposition of surface EMG signals," *Journal of Electromyography and Kinesiology,* vol. 17, pp. 535-48, Oct 2007.

[4] R. Merletti, A. Holobar, and D. Farina, "Analysis of motor units with high-density surface electromyography," *Journal of Electromyography and Kinesiology,* vol. 18, pp. 879-890, Dec 2008.

[5] S. H. Nawab, S. S. Chang, and C. J. De Luca, "High-yield decomposition of surface EMG signals," *Clinical Neurophysiology,* vol. 121, pp. 1602-15, Oct 2010.

[6] X. Hu, W. Z. Rymer, and N. L. Suresh, "Assessment of validity of a high-yield surface electromyogram decomposition," *J Neuroeng Rehabil,* vol. 10, p. 99, Sep 23 2013.

[7] X. Hu, W. Z. Rymer, and N. L. Suresh, "Motor unit pool organization examined via spike triggered averaging of the surface electromygram," *Journal of Neurophysiology,* vol. 110, pp. 1205-1220, 2013.

[8] X. Hu, W. Z. Rymer, and N. L. Suresh, "Accuracy assessment of a surface electromyogram decomposition system in human first dorsal interosseus muscle," *J Neural Eng,* vol. 11, p. 026007, Apr 2014.

[9] H. P. Clamann, "Statistical analysis of motor unit firing patterns in a human skeletal muscle," *Biophys J,* vol. 9, pp. 1233-51, Oct 1969.

[10] K. C. McGill, Z. C. Lateva, and H. R. Marateb, "EMGLAB: an interactive EMG decomposition program," *Journal of Neuroscience Methods,* vol. 149, pp. 121-33, Dec 15 2005.

[11] J. Duchateau and R. M. Enoka, "Human motor unit recordings: origins and insight into the integrated motor system," *Brain Research,* vol. 1409, pp. 42-61, Aug 29 2011.