2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) | 979-8-3503-2447-1/23/$31.00 ©2023 IEEE | DOI: 10.1109/EMBC40787.2023.10340187

Semi-Automated Identification of Motor Units Concurrently Recorded in High-Density Surface and Intramuscular Electromyography

Dennis Yeung, Francesco Negro, and Ivan Vujaklija, *Member, IEEE*

***Abstract*— An increasing focus on extending automated surface electromyography (EMG) decomposition algorithms to operate under non-stationary conditions requires rigorous and robust validation. However, relevant benchmarks derived manually from iEMG are laborsome to obtain and this is further exacerbated by the need to consider multiple contraction conditions. This work demonstrates a semi-automatic technique for extracting motor units (MUs) whose activities are present in concurrently recorded high-density surface EMG (HD-sEMG) and intramuscular EMG (iEMG) during isometric contractions. We leverage existing automatic surface decomposition algorithms for initial identification of active MUs. Resulting spike times are then used to identify (trigger) the sources that are concurrently detectable in iEMG. We demonstrate this technique on recordings targeting the extensor carpi radialis brevis in five human subjects. This dataset consists of 117 trials across different force levels and wrist angles, from which the presented method yielded a set of 367 high-confidence decompositions. Thus, our approach effectively alleviates the overhead of manual decomposition as it efficiently produces reliable benchmarks under different conditions.**

***Clinical Relevance*— We present an efficient method for obtaining high-quality in-vivo decomposition particularly useful in the verification of new surface decomposition approaches.**

I. Introduction

The firing times of constituent motor units (MUs) heavily dictate force generation in skeletal muscles. Access to such information allows for improved characterization of neuromuscular control [1] and higher-fidelity human-machine interfacing [2] compared to amplitude measurements of rectified electromyography (EMG) which lacks specificity and is susceptible to amplitude cancellation effects [3].

The earliest methods of attaining MU firing times were invasive, either with concentric needle electrodes or fine-wire electrodes [4]. Surface decomposition techniques have since been developed to estimate MU spike trains (MUSTs) from high-density surface EMG (HD-sEMG) in a non-invasive manner [5], [6]. Typically, these algorithmic approaches work towards the compensation of MU action potentials (MUAPs) under the assumption of signal stationarity [2]. While some of these methods have only been validated via model simulations, comparisons with manually decomposed intramuscular EMG (iEMG) remain the "gold standard" for verification of their accuracy [7].

Recent developments have focused on extending surface decomposition to real-time dynamic applications where the stationarity assumption may no longer hold [8]. That is, changes to the joint condition may alter the volume conduction characteristics between neuromuscular junctions and recording electrodes, thereby altering MUAP manifestations at observation points. Current works have yet to be verified with the same degree of rigor as established batch decomposition techniques, however [8], [9]. As such, a database of concurrent HD-sEMG and iEMG recordings across non-stationary conditions can prove to be a valuable resource for the development and verification of robust, real-time decomposition algorithms. One difficulty in leveraging iEMG recordings, however, is the substantial effort required to manually decompose signals [7]. Though several automatic spike-sorting algorithms have been presented [10], [11], inspection by an experienced operator remains an integral step in obtaining a high-confidence decomposition. Given that in most cases only a subset of iEMG decomposed MUs can also be identified from concurrently recorded HD-sEMG signals [7], a partial decomposition of iEMG may be adequate for the purposes of verifying surface decomposition accuracy.

In this work, we present a semi-automated method for extraction of MUs with action potentials simultaneously present in iEMG and HD-sEMG. We verify this technique on a series of isometric contractions of the extensor carpi radialis brevis (ECRB) recorded from five subjects. To support the verification needs of more robust decomposition methods, this study incorporates trials that span a range of contraction intensities and joint configurations.

II. Methods

A. Subjects

Five subjects (four male, one female) participated in the experiment. Subjects were between the ages of 29 – 34 and were all right-handed. The study was approved by the local ethical board of Aalto University (approval number D/505/03.04/2022). Prior to the experiments all participants gave their written informed consent in accordance with the Declaration of Helsinki.

This work was supported in part by the Academy of Finland under Grant #333149 (Hi-Fi BiNDIng) and ERC-CoG "INcEPTION" (Grant agreement ID: 101045605; F.N.). (Corresponding author: D. Y. dennis.yeung@aalto.fi)

D. Y. and I. V. are with the Department of Electrical Engineering and Automation, Aalto University, Finland.

F. N. is with the Department of Clinical and Experimental Sciences, University of Brescia, Italy.

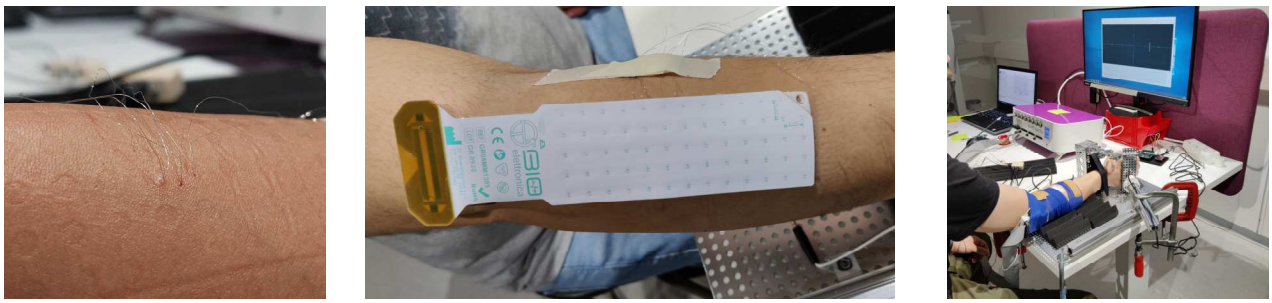

Figure 1: (Left) Three fine-wire electrode pairs inserted into the subject's ECRB. (Middle) A 64-channel high-density electrode matrix placed on top of the subject's ECRB and centered above the fine-wire insertion points. (Right) Experimental setup: rig for measurement of isometric wrist extension forces and a display for force feedback and experimental prompting.

B. *Experimental setup*

Subjects were seated for the duration of the experiment with their dominant arm placed on a tabletop and secured by a specialized rig constraining the wrist at various joint angles (Fig. 1). A load cell (TAS606, HT Sensor Technology, China) was used to measure isometric extension force at a sampling rate of 100 Hz. The subject's maximum voluntary contraction (MVC) forces were first measured at wrist joint angles corresponding to 0%, 12.5%, and 25% of their maximal extension, with 0% relating to a neutral position.

The insertion of three iEMG electrode pairs was then conducted. The insertion points were centered at the bulk of the ECRB and aligned along the muscle axis at approximately 4 mm intervals (Fig. 1). Location of the subject's ECRB was guided by [12] and palpation during wrist extension and radial deviation movements. Fine-wire stainless steel/silver (SS/Ag) electrode pairs with Teflon insulation (DIMW1105030102, Spes Medica s.r.l., Italy) were used. The wires had a diameter of 0.11 mm with the final 3-5 mm of the recording tip stripped of insulation. The fine-wire pairs were inserted using 25G cannulae to a depth targeting MUs proximal to the surface of the ECRB. Signal inspection was conducted after each individual insertion. If the signal was invalid (short circuited, excessive noise, low selectivity or no viable units detected) and could not be remedied by light manipulation of the fine-wires, the wires were removed and another insertion was made slightly lateral to the original insertion point. The maximum number of insertion attempts was bounded to five for the sake of subject comfort, at which point the experiment proceeded so long as at least one valid iEMG channel was attained. Each electrode pair was connected to an adapter (ADx5JN, OT Bioelettronica, Italy) which preamplified the differential signal with a gain of 5. These were then sampled by a benchtop bioamplifier (Quattrocento, OT Bioelettronica, Italy) at 10240 Hz with 10-4400 Hz hardware bandpass filtering. The acquired iEMG signals were then high-pass filtered [13] using a zero-phase shift 1st order Butterworth filter with a cut-off of 250 Hz to lower baseline noise while narrowing action potentials.

Placement of the overlaying HD-sEMG matrix was performed 8 minutes after fine-wire insertions to allow for sufficient coagulation. This minimized the leakage of blood and plasma to the surface recording site which otherwise may cause signal shunting. A 64-channel rectangular electrode matrix (GR08MM1305, OT Bioelettronica, Italy) was placed on the ECRB, centered above the fine-wire insertion sites (Fig. 1). The signals were buffered by a preamplifier (AD64F, OT Bioelettronica, Italy) with a gain of 150 and simultaneously acquired using the same hardware and filter settings as iEMG. Two reference electrodes (Neuroline 720, Ambu A/S, Denmark), one for the preamplifier and one for the bioamplifier, were placed at the medial epicondyle and olecranon process. Preprocessing of the HD-sEMG signal for subsequent automatic decomposition included downsampling to 2048 Hz and 5th order Butterworth bandpass filtering with 10-900 Hz cut-offs.

Prior to the commencement of recordings, subjects were asked to perform slow dynamic wrist extension movements, up to 25% of the maximum range of movement, to allow the settling-in of fine-wire electrodes. The recording and cueing of trials were facilitated by a custom Matlab R2021b (MathWorks Inc., USA) framework. All subject cues along with the real-time force feedback were displayed on a computer screen (Fig. 1).

C. *Experimental protocol*

Isometric contractions with trapezoidal force profiles (5 s ramp, 20 s plateau) were recorded at different conditions of wrist extension angle and contraction intensity. For subjects A and B, contractions at 5%, 10%, and 15% of MVC were recorded at 0% and 25% of maximum wrist extension. For subjects C, D and E, contractions at 5%, 7.5%, and 10% of MVC were recorded at 0%, 12.5%, and 25% of maximum wrist extension. Three trials were recorded for each contraction condition with periodic breaks taken to prevent subject fatigue. In total, this protocol yielded 117 trials. All subsequent analysis was performed on the central 12 s section of the 20 s plateau.

D. *Semi-automated method for extraction of MU activity concurrent in iEMG and HD-sEMG*

To efficiently identify MUs present in both surface and intramuscular signals, we leveraged established surface decomposition techniques. For each trial, a set of MUSTs were first extracted via the batch decomposition method presented in [6]. For each of these spike trains, intramuscular MUAPs

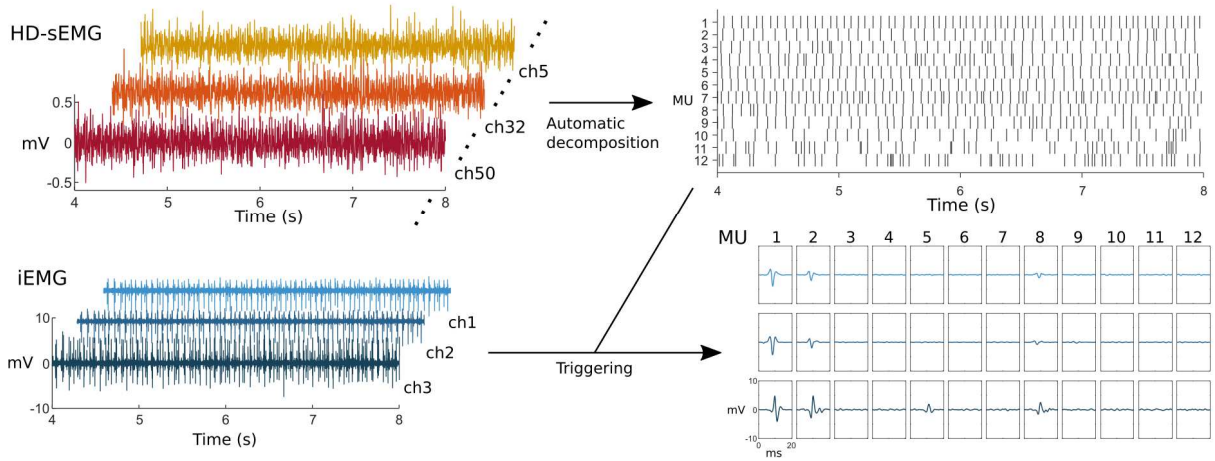

Figure 2: Process flow for identification of MUs that are extractable by HD-sEMG decomposition and are also present in concurrently recorded iEMG signals. Spike intervals extracted from decomposition of HD-sEMG are use as triggers for calculation of MUAPs in the iEMG signal. MUs that are also captured in the iEMG signal will trigger stereotypical action potentials while those that are not proximal to the iEMG insertion points will trigger flat action potentials. In this example, MUs 1,2 5 and 8 qualify as the former and their MUSTs will proceed to be manually inspected in EMGLAB.

(iMUAPs) were then computed via spike-triggered averaging with 20 ms windows. MUs detectable in concurrently recorded HD-sEMG and iEMG, will thus trigger viable iMUAPs. Specifically, these are stereotypical monophasic and multiphasic action potentials with amplitudes well above the baseline noise [4]. Meanwhile, MUs not detectable in the iEMG channels will trigger flat action potentials. This process is illustrated in Fig. 2. The spike-trains of MUs exhibiting viable iMUAPs were then imported to EMGLAB [13], a Matlab-based spike annotation software, for manual correction by an experienced operator, similar to past studies [14], such that a high-confidence decomposition may be achieved.

E. Source verification

To verify that the identified MUs correspond to genuine sources in iEMG, their contribution to the signal power was quantified. Specifically, we calculated the reduction ratio in signal power when iMUAP trains were removed from the iEMG signals. Each iMUAP train was formed through convolution of the iMUAP and its respective MUST. For comparison, the power reduction ratio with a perturbed source signal was also calculated. Here, a jitter modelled by a normal distribution with a standard deviation of 1 ms was added to the intervals used for triggering iMUAPs.

F. Rates of Agreement

The accuracies of the initial HD-sEMG decompositions were quantified by means of calculating the Rate-of-Agreement (RoA) between the MUSTs before and after operator inspection [6]:

$$RoA = \frac{c}{c + A + B} \times 100\%$$

where c is the number of spikes identified in both the pre- and post-inspection state of the decomposition, A is the number of spikes identified only from the initial HD-sEMG decomposition, and B is the number of spikes identified only by the operator.

III. Results

At least two viable iEMG channels were established in all subjects. From the 117 trials, 1753 sources were extracted via automatic HD-sEMG decomposition, of which, 367 had distinct enough iMUAPs to facilitate operator inspection against the iEMG signals. Note, this includes potential repeat identification of MUs that were present across trials. On average, HD-sEMG decomposition of each trial yielded 15±5 MUs of which 4±2 were concurrently detectable in iEMG and resulted in a high-confidence decomposition (Fig. 3). When the iMUAP trains of such sources were subtracted from the iEMG signals, an average reduction ratio of 0.52±0.23 in signal power was observed. In the case of perturbed iMUAPs, the corresponding signal power reduction ratio was only 0.92±0.04. The average RoA between pre- and post-inspection decomposition results was 95±5% across all subjects, and 95±3%, 91±7%, 96±6%, 95±5%, 96±5% for subjects A-E, respectively (Fig 3.).

IV. Discussions

We have demonstrated a method for efficient extraction of MUs that are concurrently decomposable in HD-sEMG and iEMG. Specifically, these MUs are extractable by surface decomposition algorithms and are also identifiable by distinct iMUAPS (Fig. 2). This facilitates a semi-automated process in which MUSTs are initially extracted by a surface decomposition algorithm and then passed for operator inspection against the iEMG signal. In past studies involving concurrently recorded surface and intramuscular signals, manually decomposed spike trains from iEMG are utilized as 'gold-standard' benchmarks from which the accuracies of automatic decomposition algorithms can be gauged [6], [7], [15]–[17]. However, manual decomposition is a labor-

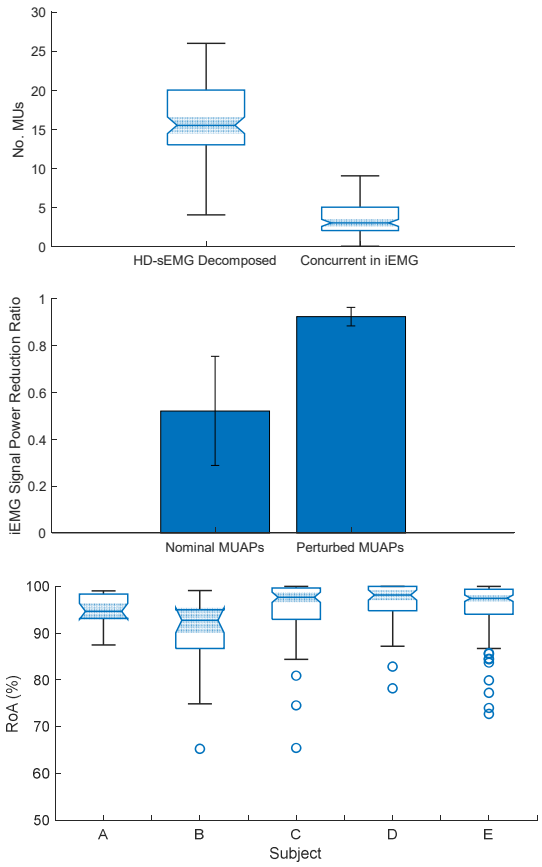

Figure 3: (Top) The average number of MUs automatically decomposed each trial from HD-sEMG and the subset of MUs with activities that were reliably verified in iEMG by an operator. (Middle) The reduction in signal power when iMUAP trains were subtracted from iEMG signals compared to reduction in signal power when using perturbed iMUAP trains. Error bars indicate standard deviation. (Bottom) The RoA between pre- and post-inspection decomposition for each subject.

intensive task that can only be reliably performed by experienced operators [4], [7]. Furthermore, only a subset of MUs decomposed from iEMG are extractable by surface decomposition algorithms [7]. The method presented here thus minimizes unnecessary labor as the spike trains from MUs that are extractable by the automatic surface decomposition algorithms are focused on and initialized for subsequent operator inspection.

By using the surface decomposed MUSTs to trigger iMUAPs, any resultant waveform can suggest that the surface-identified source was also a legitimate source in the iEMG signal. The validity of decompositions obtained via this method was thus demonstrated by the observable reduction in signal power when iMUAP trains were subtracted from the original iEMG signals. In other words, the sources extracted via decomposition of HD-sEMG, and subsequently selected by their iMUAP waveforms, were also sources of the iEMG signals.

While this study includes trials with different contraction intensities and joint angles, future work will still need to entail the tracking of MUs between trials. Only then, can an appropriate benchmark for advanced decomposition algorithms be achieved, where algorithms are required to account for changes in the sMUAP profiles that occur naturally across contraction conditions.

V. Conclusion

Recently, there has been an increasing focus on extending the automated surface EMG decomposition algorithms to operate under non-stationary conditions [2], [8], [9]. To assess their accuracies rigorously and robustly, benchmarks derived from iEMG will need to be considered. However, this can quickly become an overwhelmingly laborsome task as it will require manual decomposition across multiple contraction conditions. As such, our semi-automated approach effectively alleviates this overhead as it efficiently produces high-confidence decompositions under different conditions.

Acknowledgment

We acknowledge the computational resources provided by the Aalto Science-IT project.

References

[1] D. Farina, F. Negro, S. Muceli, and R. M. Enoka, "Principles of motor unit physiology evolve with advances in technology," *Physiology*, vol. 31, no. 2, pp. 83–94, Feb. 2016.

[2] A. Holobar and D. Farina, "Noninvasive Neural Interfacing with Wearable Muscle Sensors: Combining Convolutive Blind Source Separation Methods and Deep Learning Techniques for Neural Decoding," *IEEE Signal Process. Mag.*, vol. 38, no. 4, pp. 103–118, Jul. 2021.

[3] J. L. Dideriksen and D. Farina, "Amplitude cancellation influences the association between frequency components in the neural drive to muscle and the rectified EMG signal," *PLoS Comput. Biol.*, vol. 15, no. 5, May 2019.

[4] R. Merletti and D. Farina, "Analysis of intramuscular electromyogram signals," *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.*, vol. 367, no. 1887, pp. 357–368, Nov. 2008.

[5] A. Holobar and D. Zazula, "Gradient Convolution Kernel Compensation Applied to Surface Electromyograms," in *Independent Component Analysis and Signal Separation*, Berlin, Heidelberg: Springer Berlin Heidelberg, 2007, pp. 617–624.

[6] F. Negro, S. Muceli, A. M. Castronovo, A. Holobar, and D. Farina, "Multi-channel intramuscular and surface EMG decomposition by convolutive blind source separation," *J. Neural Eng.*, vol. 13, no. 2, p. 026027, Apr. 2016.

[7] A. Holobar, M. A. Minetto, A. Botter, F. Negro, and D. Farina, "Experimental Analysis of Accuracy in the Identification of Motor Unit Spike Trains From High-Density Surface EMG," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 3, pp. 221–229, Jun. 2010.

[8] C. Chen, S. Ma, X. Sheng, D. Farina, and X. Zhu, "Adaptive Real-Time Identification of Motor Unit Discharges from Non-Stationary High-Density Surface Electromyographic Signals," *IEEE Trans. Biomed. Eng.*, vol. 67, no. 12, pp. 3501–3509, Dec. 2020.

[9] V. Glaser and A. Holobar, "Motor Unit Identification From High-Density Surface Electromyograms in Repeated Dynamic Muscle Contractions," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 1, pp. 66–75, Jan. 2019.

[10] J. R. Florestal, P. A. Mathieu, and K. C. McGill, "Automatic decomposition of multichannel intramuscular EMG signals," *J. Electromyogr. Kinesiol.*, vol. 19, no. 1, pp. 1–9, Feb. 2009.

[11] C. D. Katsis, T. P. Exarchos, C. Papaloukas, Y. Goletsis, D. I. Fotiadis, and I. Sarmas, "A two-stage method for MUAP classification based on EMG decomposition," *Comput. Biol.*

Med., vol. 37, no. 9, pp. 1232–1240, Sep. 2007.

[12] A. A. Leis and V. C. Trapani, *Atlas of electromyography*. Oxford University Press, 2000.

[13] K. C. McGill, Z. C. Lateva, and H. R. Marateb, "EMGLAB: An interactive EMG decomposition program," *J. Neurosci. Methods*, vol. 149, no. 2, pp. 121–133, Dec. 2005.

[14] F. Negro, A. Holobar, and D. Farina, "Fluctuations in isometric muscle force can be described by one linear projection of low-frequency components of motor unit discharge rates," *J. Physiol.*, vol. 587, no. 24, pp. 5925–5938, Dec. 2009.

[15] A. Holobar, D. Farina, M. Gazzoni, R. Merletti, and D. Zazula, "Estimating motor unit discharge patterns from high-density surface electromyogram," *Clin. Neurophysiol.*, vol. 120, no. 3, pp. 551–562, Mar. 2009.

[16] A. K. Clarke *et al.*, "Deep Learning for Robust Decomposition of High-Density Surface EMG Signals," *IEEE Trans. Biomed. Eng.*, vol. 68, no. 2, pp. 526–534, Feb. 2021.

[17] D. Y. Barsakcioglu and D. Farina, "A real-time surface EMG decomposition system for non-invasive human-machine interfaces," *2018 IEEE Biomed. Circuits Syst. Conf. BioCAS 2018 - Proc.*, Dec. 2018.