Computers in Biology and Medicine 108 (2019) 42–48

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/compbiomed

# Independent component analysis based algorithms for high-density electromyogram decomposition: Experimental evaluation of upper extremity muscles

Chenyun Dai[a], Xiaogang Hu[a,*]

[a] Joint Department of Biomedical Engineering, University of North Carolina at Chapel Hill, North Carolina State University, United States

ARTICLE INFO

*Keywords:*
Biosignal processing
Independent component analysis
Upper extremity muscles

ABSTRACT

Motor unit firing activities can provide critical information regarding neural control of skeletal muscles. Extracting motor unit activities reliably from surface electromyogram (EMG) is still a challenge in signal processing. We quantified the performance of three different independent component analysis (ICA)-based decomposition algorithms (Infomax, FastICA and RobustICA) on high-density EMG signals, obtained from arm muscles (biceps brachii and extensor digitorum communis) at different contraction levels. The source separation outcomes were evaluated based on the degree of agreement in the discharge timings between different algorithms, and based on the number of common motor units identified concurrently by two algorithms. Two metrics, the separation index (silhouette distance or SIL) and the rate of agreement, were used to evaluate the decomposition accuracy. Our results revealed a high rate of agreement (80%–90%) between different algorithms, which was consistent across different contraction levels. The RobustICA tended to show a higher RoA with the other two algorithms (especially with Infomax), whereas FastICA and Infomax tended to yield a greater number of common MUs. Overall, through an experimental evaluation of the three algorithms, the outcomes provide information regarding the utility of these algorithms and the motor unit filter criteria involving EMG signals of upper extremity muscles.

## 1. Introduction

Electromyogram (EMG) signals represent a convoluted process of hundreds of motor unit (MU) discharge activities with the corresponding motor unit action potentials (MUAPs). Decomposition of the EMG signals involves the separation of the composite interference activities into the constituent MU discharge activities, which can provide clinical and scientific insights into the neuromuscular systems [1–4]. In addition, recent studies have shown that MU discharge timings could be used as a neural interface signal during human-machine interactions [5].

Earlier EMG decomposition mainly based on template-matching of MUAPs via manual expert editing or automated algorithms using intramuscular recordings [6–8]. With the development of algorithms and electrode hardware, MU activities can be extracted through the decomposition of high-density (HD) surface EMG signals using different blind source separation algorithms [9–12]. Despite these initial successes, the performance evaluation of the decomposition is still a challenging task. Previously, the decomposition performance has been evaluated through several methods. First, synthesized EMG signals can be simulated, and the accuracy of the decomposition can be evaluated by directly comparing with the ground truth. Although the model simulation may not fully reproduce the detailed features as in real EMG signals, this technique can directly measure the performance of decomposition [9,10]. Second, two source validation has been used to evaluate the decomposition accuracy of a small sample of MU firing activities [13–15]. Specifically, surface and intramuscular recordings are performed concurrently on the same muscle, and the two types of recordings at different sources are decomposed separately, with the intramuscular decomposition as the reference outcome. The rate of agreement (RoA) of the common MU activities are used as a measure of decomposition accuracy. However, the number of common MUs obtained from the two recording sources are typically small, and, therefore, only a small fraction of the decomposed MUs from the surface recordings can be assessed. Lastly, different metrics extracted from individual MUs (e.g. spike pulse to noise ratio [16], dissimilarities or amplitude of the MUAP [17]) have been used to predict the decomposition accuracy through a correlation analysis. Recent studies have

* Corresponding author. University of North Carolina at Chapel Hill, 144 MacNider Hall, Chapel Hill, NC, 27599, United States.
*E-mail address:* xiaogang@unc.edu (X. Hu).

https://doi.org/10.1016/j.compbiomed.2019.03.009
Received 5 December 2018; Received in revised form 8 March 2019; Accepted 9 March 2019

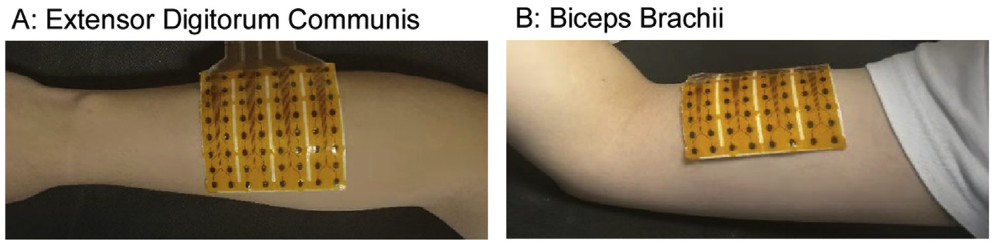


**Fig. 1.** Electromyogram recording setup. An 8 × 8 high-density electrode array is placed on the center of measured muscle. **A**: extensor digitorum communis (EDC) muscle. **B**: biceps brachii muscle.

also used a clustering index, the silhouette distance (SIL), as a measure of the degree of separation of the MUAP train from the background noise, including other potential source signals [18,19]. However, the association between the SIL and the decomposition performance has not been fully investigated.

Accordingly, the purpose of our current study was to evaluate the RoA of three ICA based EMG decomposition algorithms (FastICA [20], Infomax [21], and RobustICA [22]), based on EMG signals obtained from two arm muscles (biceps brachii and extensor digitorum communis) at different muscle contraction levels. The RoA between algorithms was evaluated based on the notion that the accuracy should be high if the same MUs can be separated repetitively from different algorithms with a high agreement. The decomposition yield of the algorithm was also compared based on the experimental data. Our results showed that the RoA of the decomposition from different algorithms was largely above 80% with the SIL > 0.85, although a number of MUs still showed high RoA (> 80%) with the SIL ranging from 0.50 to 0.85. Overall, the combination of RobustICA and Infomax showed a consistently higher RoA than other algorithm combinations. In contrast, the number of common motor units between Infomax and FastICA was the highest among the different algorithm combinations. These findings provided experimental evidence on selecting decomposition algorithms and performance assessment metrics for specific applications that have different accuracy and yield requirements.

## 2. Materials and methods

### 2.1. Subject

Eight healthy subjects (6 males, 2 females; aged 26.3 ± 4.9 years) without any known neuromuscular abnormality participated in the experiment. All subjects provided written informed consent. The experimental procedures were approved by the Institutional Review Board at the University of North Carolina at Chapel Hill.

### 2.2. Experimental setup and procedures

During the biceps EMG data acquisition, the subjects sat in a straight-back chair with their arm comfortably placing on a table, their shoulder abducted at approximately 30°, their elbow extended at approximately 120°, and their wrist supinated approximately 90°. During the experiment, the subjects were asked to isometrically flex their elbow against a horizontal board attached to their palm and wrist. We measured 64 channels of EMG signals of the biceps muscle, and selected one channel with the highest EMG amplitude from the high-density EMG grid, and the root-mean-square (RMS) value was calculated as an estimation of the muscle contraction level. During the maximum voluntary contraction (MVC) trial, the subjects were asked to perform their maximum contraction and maintain the effort for 3 s. The RMS value of the 3-s recordings from the selected channel was calculated as the MVC. We then determined the effort level based on the RMS values (very low: 5% MVC, low: 10% MVC, moderate: 30% MVC and high: 50% MVC). In each flexion effort, subjects produced 5 repetitions. The root mean square (RMS) of the EMG signals was displayed on the computer screen to guide their efforts.

During the EDC EMG acquisition, subject's wrist was secured with two stiff form pads, with the forearm in neutral position. The four fingers were naturally abducted, and each was secured with a velcro strap to a load cell (Interface, SM-100 N). During the experiment, the subjects were asked to isometrically extend their four fingers concurrently against the load cells. During the MVC trial, the subjects were asked to maintain the maximum isometric extension force for 3 s. The MVC value was determined by calculating the peak summed force of the four fingers during the 3 s recordings. Two extension efforts (moderate: 30% MVC and high: 50% MVC) were produced by the subjects with 5 repetitions at each level. The very low and low force levels were not performed, since the acquired EMG signals were essentially baseline noise. In each repetition, subjects took 3–5 s to ramp up to the target effort, maintained the effort for approximately 10 s, and took another 3–5 s to ramp down to the resting state. The order of the effort levels was randomized for both muscles.

### 2.3. EMG recordings

In both experiments, the EMG signals were obtains using an 8 × 8 channel HD EMG electrode grid with 10 mm inter-electrode distance (ELSCH064NM3, OT Bioelettronica, Torino, Italy), placed to the center of the muscle belly (Fig. 1). Before the electrode placement, the skin was cleaned with alcohol pads. Two water-based conductive belts were wrapped around the wrist as the ground electrode and the subject reference electrode. The EMG signals were recorded via EMG_USB2+ (OT Bioelettronica, Torino, Italy) with a gain of 1000, sampled at 2048 Hz, band-pass filtered from 10 to 900 Hz, and A/D converted with 12 bits resolution.

### 2.4. Methods of analysis

Individual MU discharge timings were extracted via the three ICA-based decomposition algorithms (FastICA [20], Infomax [21], and RobustICA [22]). A representative segment of the decomposition results is shown in Fig. 2. The details of the three decomposition algorithms can be found in the simulation Part 1 study. Here, the main steps of the decomposition were briefly described as follows:

(1) Extend the EMG signals by adding 8 delayed replicas to each original channel [9].
(2) Whiten the extended signals using the eigenvalue decomposition.
(3) Deconvolute the whitened signals using the three ICA-based algorithms: Infomax, FastICA and RobustICA.
(4) Identify discharge timings through peak detection and *k-means* clustering, and calculate silhouette distance values (SIL) for further analysis.
(5) Remove the duplicate MUs. The ICA-based algorithm may detect both the original MU and its delayed replicas. To remove the duplicate MUs, the percentage of synchronized firing events within ± 1 ms was calculated between any possible pairs of MU

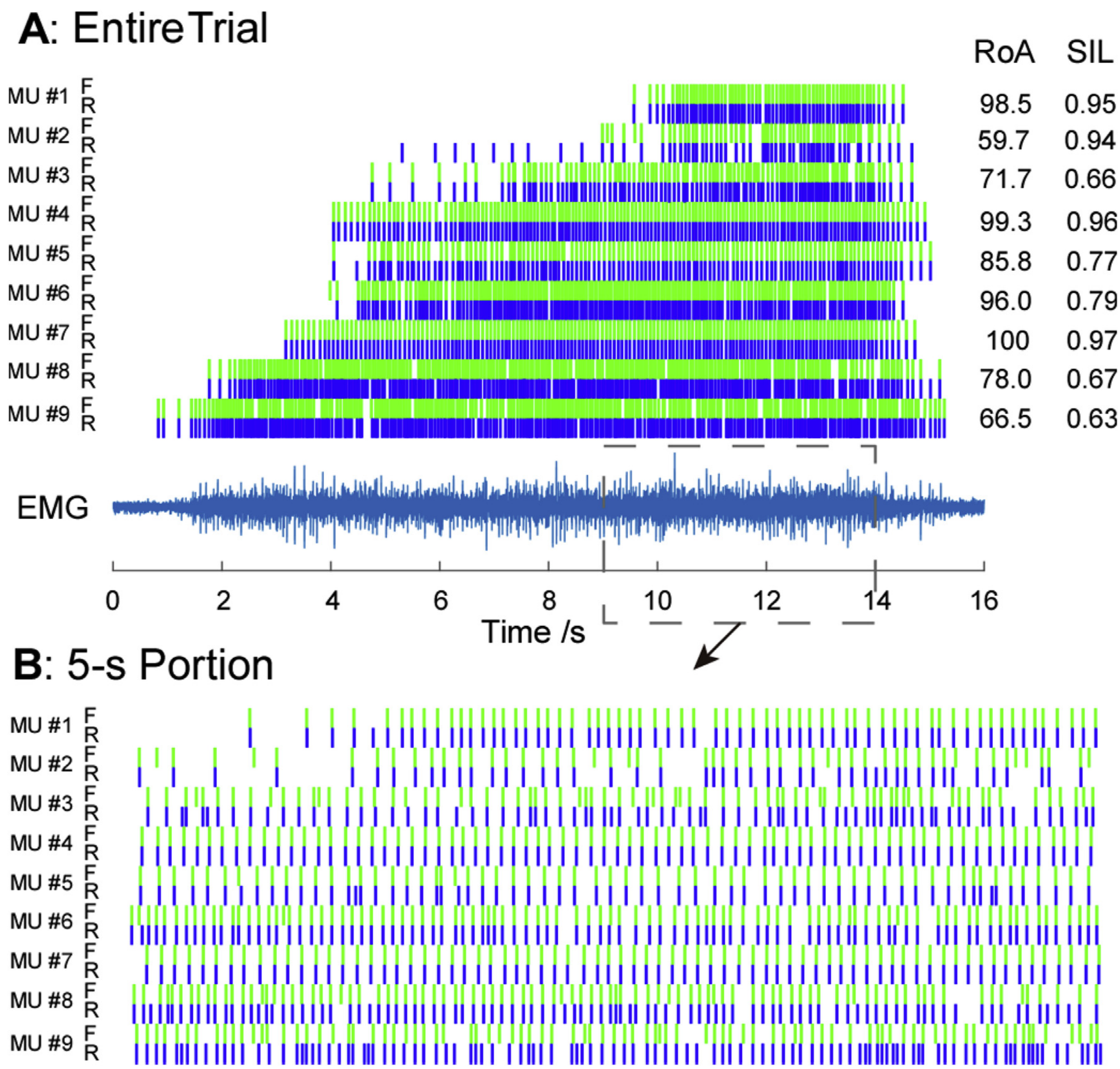


**Fig. 2.** Exemplar EMG decomposition results under high effort contraction of the extensor digitorum communis (EDC) muscle. The green and blue spikes represent the decomposition results of FastICA (F) and RobustICA (R), respectively. The rate of agreement (RoA) and mean silhouette (SIL) values of the entire 15-s trial are shown in the right. A: Entire trial with a representative EMG channel shown. B: Zoomed-in 5-s portion. Only nine common motor units are shown for clarity.

spike trains. If a pair of spike trains had > 50% synchronized firing events after adjusting the time delay, only the MU spike train with higher SIL value was reserved for further analysis.

(6) Detect the common MUs. A MU spike train was considered a "common MU", if a MU spike train detected by two algorithms had > 50% firing events discharging within ± 1 ms match window after compensating the time offset.

The algorithms were evaluated at different effort levels and with/without variations in the contraction level (i.e., the entire trapezoid contraction or just the steady contraction segment). With varying contraction level, the action potential amplitude may change due to small displacement between the muscle fibers and recording electrodes, which can pose challenge to the decomposition.

### 2.5. Evaluation of decomposition performance

First, the silhouette distance measurement was used as a metric to evaluate the performance. SIL measures the distance between the peaks of the extracted MUAP train and the baseline noise (including possible remaining MU activities) during *k-means* clustering. A higher SIL value typically means a better separation from the baseline. Since the SIL measure is embedded in the cluster analysis, it does not require extra computations. Second, the RoA of different algorithms was also used as a metric. A higher RoA value means that the same MU is extracted with consistent spike timings by different algorithms, which suggests that the decomposition accuracy is likely to be high. The RoA of the two algorithms was calculated as:

$$RoA = \frac{\#\ of\ matches}{\#\ of\ matches + NI}$$

where *# of matches* means the number of spike timings matches with each other within ± 1 ms window, and *NI* is the total number of firings not identified by either of the two algorithms.

### 2.6. Statistical comparisons

The performance was tested using a repeated measures analysis of variance (ANOVA) in SPSS 24 (IBM). The arcsine-square-root transformation was performed on the RoA values to satisfy the normal distribution assumption of the ANOVA and the regression analysis, since the agreement values were bounded at 1. *Post hoc* pair-wise multiple comparisons were conducted with Bonferroni correction when necessary. A significance level of $p < 0.05$ was used.

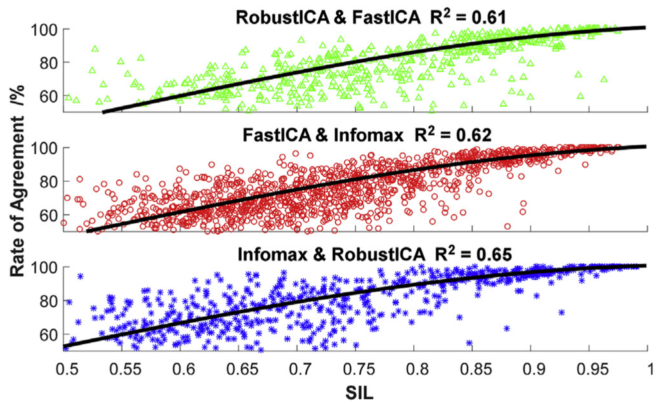


**Fig. 3.** The mean rate of agreement (RoA) vs mean silhouette (SIL) of each algorithm combination. Each point represents one motor unit.

## 3. Results

We first investigated the relation between the SIL and RoA values for each algorithm combination at a wide range of values. Individual MUs from all the conditions (including two muscles and all effort levels) were pooled and are shown in Fig. 3. Linear regression based on least squares fitting was performed. Note that only a single trial randomly selected from the five repetitions was used for the analysis to avoid potentially repeated count of the same MUs. The SIL and RoA showed a moderate correlation ($R^2$ ranged from 0.61 to 0.65) in different algorithm combinations. Our simulation study in Part 1 has investigated a broad range of SIL and RoA values in relation with the accuracy. Based on our simulated results, low RoA mostly indicated inaccurate decomposition results. Therefore, the MUs satisfying both thresholds (SIL ≥ 0.80 and RoA ≥ 70%) were further used for subsequent data analyses. The SIL criterion was still used to ensure that the decomposed spike activities are reliable. A lower RoA value was used here to ensure that MUs were not over-filtered.

The RoA of different algorithm combinations and the number of common MUs across algorithms are shown in Fig. 4 (EDC) and Fig. 5 (Biceps). The mean ± SD of the signal to noise ratio (SNR) values of the EMG signals across all 64 channels were also provided in the x-axis as a reference. The SNR was defined as the ratio between the power of the signals during steady muscle contraction and the power of the baseline noise. The SNR tended to show a moderate increase as the effort level increased. Overall, the RoA between FastICA and Infomax was the lowest among the different algorithm combinations, but the largest number of common MUs between these two algorithms was evident. Similar RoA and number of common MU trends were also observed in both muscles. However, the overall decomposition performance (both RoA and yield) of the EMG from the EDC muscle was slightly better than that of the biceps muscle with comparable effort levels. In addition, the decomposition performance also varied depending on the effort level. Specifically, the RoA tended to be higher at lower effort levels. However, a larger number of common MUs can be detected during moderate effort contractions, and a low or high effort contraction typically led to a smaller number of common MUs. Lastly, the decomposition performance showed a slight improvement when the entire trapezoid contraction was used for the MU decomposition, in comparison with the steady state contraction segment, which is indicated by a higher RoA (by approximately 2–5%) and a greater number of common MUs (by approximately 1–4 MUs). The detailed statistical outcomes of the three-way repeated measures ANOVAs (*contraction segment* × *effort level* × *algorithm combination*) and pairwise comparisons on both the RoA and the number of common MUs are summarized in Table 1.

## 4. Discussion

The purpose of this study was to evaluate the performance of three previously developed ICA-based source separation algorithms (Infomax, FastICA and RobustICA) on MU decomposition of EMG signals obtained from two arm muscles (biceps brachii and EDC). Two evaluation metrics, SIL and RoA between algorithms, were used to assess the decomposition performance. Our results revealed a high RoA between different algorithms across different muscle contraction levels. The RobustICA tended to show a higher RoA with the other two algorithms (especially Infomax), whereas FastICA and Infomax tended to yield a greater number of common MUs by these two algorithms. The experimental outcomes were also largely consistent with earlier simulation results in Part 1. These findings can provide guidance on selecting particular decomposition algorithms and particular performance assessment metrics for different applications that have different requirements on the decomposition accuracy and yield.

### 4.1. Decomposition performance

The SIL and RoA measurements were used to assess the algorithm performance. For the SIL measurement, although a majority of the SIL values of the MUs decomposed by the three algorithms were above 0.8,

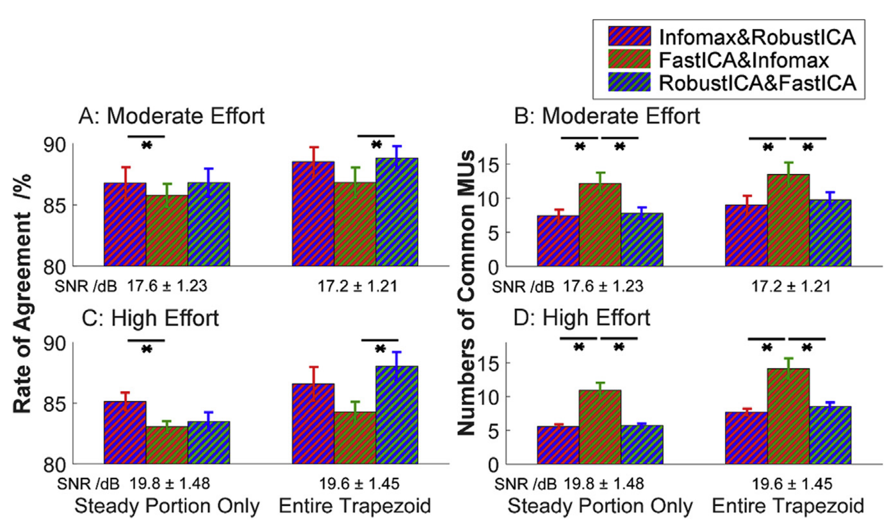


**Fig. 4.** The overall performance of the three algorithms of EDC data. Error bars represent the standard error. **A, C**: Rate of Agreement (RoA) between algorithm combinations from moderate to high efforts. **B, D**: Numbers of common motor units detected from moderate to high efforts.

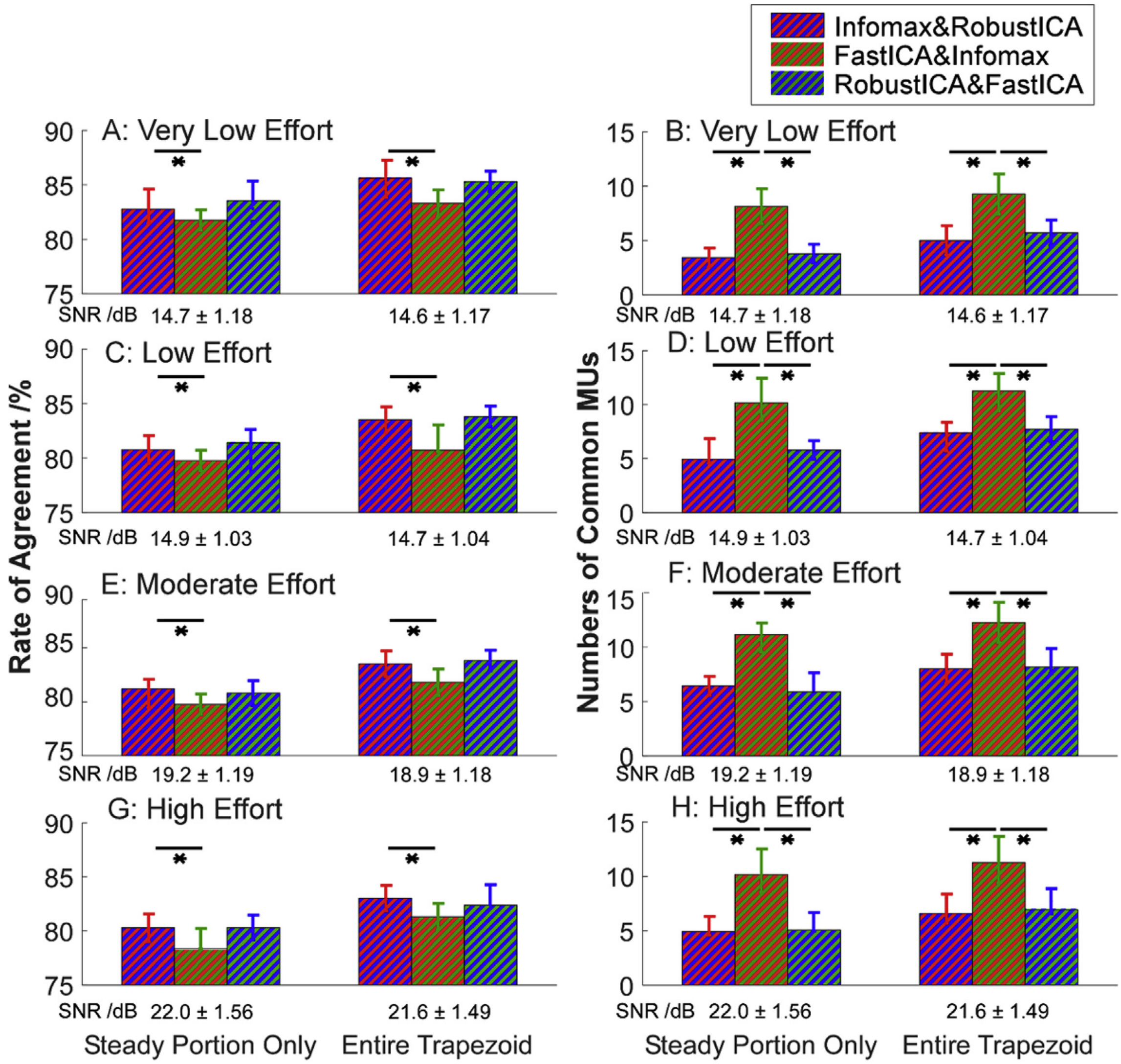


**Fig. 5.** The overall performance of the three algorithms of biceps data. Error bars represent the standard error. **A, C, E, G**: Rate of Agreement (RoA) between algorithm combinations from very low to high efforts. **B, D, F, H**: Numbers of common MUs detected from very low to high efforts.

**Table 1**
The three-way [*contraction type* × *effort level* × *algorithm combination*] repeated measures ANOVAs of the experimental data. **Trapezoid** and Steady represent the entire trapezoid contraction and the steady-only contraction segment, respectively. **RoA** and CNum represent the rate of agreement and the number of common MUs, respectively.

| Muscle | Significant Factors | | Main Outcomes |
|---|---|---|---|
| EDC | RoA | *interaction between contraction type × combination* | 1. RobustICA&FastICA > RobustICA&Infomax > FastICA&Infomax under Trapezoid.<br>2. RobustICA&Infomax = RobustICA&FastICA > FastICA&Infomax under Steady. |
| | CNum | *contraction type,*<br>*combination* | 1. FastICA&Infomax > RobustICA&FastICA = RobustICA&Infomax.<br>2. Trapezoid > Steady. |
| Biceps | RoA | *contraction type, effort level, combination* | 1. RobustICA&FastICA = RobustICA&Infomax > FastICA&Infomax.<br>2. Very Low effort level > the rest of effort levels.<br>3. Trapezoid > Steady. |
| | CNum | *contraction type, effort level, combination* | 1. FastICA&Infomax > RobustICA&FastICA = RobustICA&Infomax.<br>2. Medium effort level > the rest of effort levels.<br>3. Trapezoid > Steady. |

consistent with our simulated results, a large number of MUs with high RoA still showed SIL values ranging from 0.5 to 0.8. These results suggest that the SIL may not be a strong predictor of decomposition performance, and may over filter the decomposed MUs but could still retain the less accurate MU spike trains. In general, a high SIL indicates that the spike trains are well separated from the background noise and other source signals. But the well-separated spike trains can still have missed and spurious spikes, which would lead to low RoA and low accuracy.

For the RoA measurement, the agreement of RobustICA with

FastICA or with Infomax exhibited higher values than that of FastICA and Infomax. These differences can arise from the possibility that RobustICA tends to have a higher accuracy than the other two algorithms, and when two algorithms with low decomposition accuracy are compared with a more accurate algorithm, their RoA tends to be low. This possibility is further supported by the fact that the RoA between FastICA and Infomax is the lowest among the algorithm pairs. We also found that the RoA was at 86.67 ± 2.94% on the EDC muscle and 82.07 ± 3.18% on the biceps brachii muscle. The relatively low agreement shown in the biceps muscle can arise from the fact that the biceps brachii is more proximal and may have more fat tissue on top of the muscle. As a result, the low-pass filtering effect of the fat layer can widen the action potential duration, and make the action potential shapes less unique from the skin surface, which can lead to less accurate decomposition results and low RoA between algorithms.

Regarding the yield of the decomposition, approximately 5–15 MUs per contraction can be identified by RobustICA, and 6–25 MUs can be identified by FastICA or Infomax. Approximately 5–10 common MUs per contraction can be identified concurrently by RobustICA and FastICA (or Infomax), and 8–15 common MUs between Infomax and FastICA can be identified. The low yield of RobustICA can arise from the fact that the RobustICA calculates the optimal convergence step during each iteration of the separation vector. This step can increase the chance of converging to the same MUs or their replicas that are more distinguishable, which can lead to a smaller number of unique MUs being detected. In addition, we also observed an initial increase of the identified MU number from very low contraction level to moderate contraction level. However, at high contraction levels, the decomposition yield declined, potentially due to a high degree of superposition across a large number of concurrently active MUs. Lastly, we found that the number of common MUs with the entire trapezoid contraction was slightly higher than just with the steady state contraction segment. The changes in action potential amplitude and/or shape due to fiber shift beneath the electrodes had minimal impact on the decomposition performance. This effect could arise from the fact that more MU information was obtained from a prolonged recording time, which can help improve the known to unknown ratio in the source separation. In addition, a less degree of superposition during the ramp-up or ramp-down contractions can also help the separation of the different sources [23].

A potential source of interference to the surface EMG decomposition is the cross-talk among different muscles or different muscle compartments. The 8 × 8 high-density surface EMG grid (8 × 8 cm) placed at the center of the biceps or EDC muscle can record activities of nearby muscles [24]. For example, EDC is a multi-compartment muscle, and there are also multiple wrist muscles in close proximity [25]. The cross-talk from other muscle groups may be recorded by the HD EMG grid. The cross-talk can be manifested as MU activities with small MUAP amplitudes or activities only recorded by a small number of electrodes. The cross-talk can also distort the action potential features of the MUs in EDC. The cross-talk interference may have different effect on the decomposition performance of different algorithms. Since the RobustICA tended to detect MUs that are more distinguishable or have large amplitudes, the algorithm may be less affected by the cross-talk. However, Infomax and FastICA tended to detect more MUs with low amplitudes, which can reduce the RoA between algorithms.

### 4.2. Comparison with earlier decomposition results

Currently, different blind source separation methods have been used for EMG decomposition, including Convolution Kernel Compensation (CKC) [9], CKC combined with cluster analysis [12], peel-off FastICA [10], and FastICA combined with CKC [18]. A comparison between peel-off FastICA and CKC showed that the two algorithms tended to detect MUs with a high agreement [26]. Consistent with our experimental results, the different HD EMG decomposition studies showed that the decomposition accuracy and yield tended to become lower as the muscle activation level increased or the SNR of the signal decreased. The EMG signals obtained from biceps brachii and extensor digitorum communis showed that approximately 5–15 MUs per contraction can be identified by RobustICA, and 6–25 MUs can be identified by FastICA or Infomax. The decomposition yield was similar between these two muscles. However, an earlier study have reported that the decomposition yield varied between muscles, which ranged from 11 to 19 for abductor pollicis, and from 6 to 10 for vastus lateralis [27]. The differences largely arise from different muscle characteristics.

Methodologically, our study focused on three ICA-based algorithms with different objective functions: negentropy (FastICA [20]), mutual information (Infomax [21]), and kurtosis (RobustICA [22]). The FastICA calculation procedure used in this study differs from the peel-off FastICA or FastICA combined with CKC in several aspects. First, to increase the number of detected MUs, a peel-off step was performed in the peel-off FastICA [10], in which the decomposed source of each iteration was subtracted from the original signals. However, possible alignment errors or inevitable decomposition errors can distort the residual signals. To avoid the peel-off step, an alternative procedure with orthogonalization step [20] was performed in this study. Second, we did not perform the second convergence loop in the FastICA combined with CKC approach [18] based on the coefficient of variation (CoV) of the inter-spike intervals, because the CoV may change greatly during varying excitation levels. Lastly, existing EMG decomposition is typically performed in the time domain, transforming the signals to the frequency or time-frequency domains for decomposition requires further investigation.

### 4.3. Metric and algorithm selection for specific applications

Both the SIL and RoA could potentially be used to predict accuracy for the decomposition of the experimental data, with RoA being a more sensitive matric. The threshold selection of SIL and RoA could be varied depending on the study requirement. For example, studies of MU discharge behaviors rely on accurate decomposition results [28]. Our simulated results have shown that a MU with a high SIL may still contain erroneous spikes, and the error can be reduced largely by adding the threshold of RoA. More stringent criteria can help improve the decomposition accuracy of the retained MUs, but at a cost of low yield. Other studies (e.g. human-machine interaction) used the pooled spike trains as the control interface to predict the force/movement [5,29]. Having more MUs can better reflect the high-level neural control information of the entire motoneuron pool. In this case, less stringent criteria can be used to maintain a high yield.

The algorithm selection is similar to the threshold selection, which is also a ‘quantity vs. quality’ problem. Specifically, if the accuracy of the MU discharge timing is critical, for example, in estimating action potential shapes [30], RobustICA with a high decomposition accuracy may be preferred. However, if a large number of MUs are necessary to evaluate MU population behaviors, and the discharge accuracy is not critical (e.g., mean discharge rate over a long-time interval is of interests), FastICA or Infomax that can yield a large number of MUs may be preferred.

## 5. Conclusion

In general, we performed a systematic evaluation on the performance of different ICA-based algorithms for MU decomposition of EMG signals obtained from arm muscles. Specifically, RobustICA showed higher RoA with other algorithms, whereas FastICA and Infomax can decompose a greater number of common MUs, consistent with the simulation results in Part 1 [31]. The selection of specific algorithms or MU filtering metrics may depend on different applications with particular requirement. The outcomes can help us identify reliable MU activities at the population level that can be used to understand mechanistic and clinical aspects of the neural control of muscle activations.

## Conflict of interest

The authors have no financial relationships that may cause a conflict of interest.

## Acknowledgment

This work is supported the National Science Foundation, CBET1847319.

## References

[1] X. Hu, A.K. Suresh, W.Z. Rymer, N.L. Suresh, Altered motor unit discharge patterns in paretic muscles of stroke survivors assessed using surface electromyography, J. Neural Eng. 13 (2016), https://doi.org/10.1088/1741-2560/13/4/046025 046025.
[2] C. Dai, N.L. Suresh, A.K. Suresh, W.Z. Rymer, X. Hu, Altered motor unit discharge coherence in paretic muscles of stroke survivors, Front. Neurol. 8 (2017), https://doi.org/10.3389/fneur.2017.00202.
[3] C.J. De Luca, E.C. Hostage, Relationship between firing rate and recruitment threshold of motoneurons in voluntary isometric contractions, J. Neurophysiol. 104 (2010) 1034–1046 doi:jn.01018.2009 [pii]10.1152/jn.01018.2009.
[4] J. Duchateau, R.M. Enoka, Human motor unit recordings: origins and insight into the integrated motor system, Brain Res. 1409 (2011) 42–61, https://doi.org/10.1016/j.brainres.2011.06.011.
[5] D. Farina, I. Vujaklija, M. Sartori, T. Kapelner, F. Negro, N. Jiang, K. Bergmeister, A. Andalib, J. Principe, O.C. Aszmann, Manmachine interface based on the discharge timings of spinal motor neurons after targeted muscle reinnervation, Nat. Biomed. Eng. 1 (2017) 25.
[6] E.D. Adrian, D.W. Bronk, The discharge of impulses in motor nerve fibres, J. Physiol. 67 (1929) 9–151.
[7] K.C. McGill, Z.C. Lateva, H.R. Marateb, EMGLAB: an interactive EMG decomposition program, J. Neurosci. Methods 149 (2005) 121–133.
[8] R.S. LeFever, A.P. Xenakis, C.J. De Luca, A procedure for decomposing the myoelectric signal into its constituent action potentials-part II: execution and test for accuracy, IEEE Trans. Biomed. Eng. (1982) 158–164.
[9] A. Holobar, D. Zazula, Multichannel blind source separation using convolution kernel compensation, IEEE Trans. Signal Process. 55 (2007) 4487–4496.
[10] M. Chen, P. Zhou, A novel framework based on FastICA for high density surface EMG decomposition, IEEE Trans. Neural Syst. Rehabil. Eng. 24 (2016) 117–127.
[11] Y. Peng, J. He, B. Yao, S. Li, P. Zhou, Y. Zhang, Motor unit number estimation based on high-density surface electromyography decomposition, Clin. Neurophysiol. 127 (2016) 3059–3065.
[12] Y. Ning, X. Zhu, S. Zhu, Y. Zhang, Surface EMG decomposition based on K-means clustering and convolution kernel compensation, IEEE J. Biomed. Heal. Informatics (2015), https://doi.org/10.1109/JBHI.2014.2328497.
[13] B. Mambrito, C.J. De Luca, A technique for the detection, decomposition and analysis of the EMG signal, Electroencephalogr. Clin. Neurophysiol. 58 (1984) 175–188.
[14] X. Hu, W.Z. Rymer, N.L. Suresh, Accuracy assessment of a surface electromyogram decomposition system in human first dorsal interosseus muscle, J. Neural Eng. 11 (2014) 26007, https://doi.org/10.1088/1741-2560/11/2/026007.
[15] H.R. Marateb, K.C. McGill, A. Holobar, Z.C. Lateva, M. Mansourian, R. Merletti, Accuracy assessment of CKC high-density surface EMG decomposition in biceps femoris muscle, J. Neural Eng. 8 (2011) 66002, https://doi.org/10.1088/1741-2560/8/6/066002.
[16] A. Holobar, M.A. Minetto, D. Farina, Accurate identification of motor unit discharge patterns from high-density surface EMG and validation with a novel signal-based performance metric, J. Neural Eng. (2014), https://doi.org/10.1088/1741-2560/11/1/016008.
[17] J.R. Florestal, P.A. Mathieu, K.C. McGill, Automatic decomposition of multichannel intramuscular EMG signals, J. Electromyogr. Kinesiol. (2009), https://doi.org/10.1016/j.jelekin.2007.04.001.
[18] F. Negro, S. Muceli, A.M. Castronovo, A. Holobar, D. Farina, Multi-channel intramuscular and surface EMG decomposition by convolutive blind source separation, J. Neural Eng. 13 (2016) 26027.
[19] T. Kapelner, F. Negro, O.C. Aszmann, D. Farina, Decoding motor unit activity from forearm muscles: perspectives for myoelectric control, IEEE Trans. Neural Syst. Rehabil. Eng. 26 (2018) 244–251.
[20] A. Hyvärinen, E. Oja, Independent component analysis: algorithms and applications, Neural Network. 13 (2000) 411–430.
[21] A.J. Bell, T.J. Sejnowski, An information-maximization approach to blind separation and blind deconvolution, Neural Comput. 7 (1995) 1129–1159.
[22] V. Zarzoso, P. Comon, Robust independent component analysis by iterative maximization of the kurtosis contrast with algebraic optimal step size, IEEE Trans. Neural Netw. 21 (2010) 248–261.
[23] A.J. Fuglevand, D.A. Winter, A.E. Patla, Models of recruitment and rate coding organization in motor-unit pools, J. Neurophysiol. 70 (1993) 2470–2488.
[24] J.N. Leijnse, N.H. Campbell-Kyureghyan, D. Spektor, P.M. Quesada, Assessment of individual finger muscle activity in the extensor digitorum communis by surface EMG, J. Neurophysiol. 100 (2008) 3225–3235, https://doi.org/10.1152/jn.90570.2008.
[25] J.N. Leijnse, S. Carter, A. Gupta, S. McCabe, Anatomic basis for individuated surface EMG and homogeneous electrostimulation with neuroprostheses of the extensor digitorum communis, J. Neurophysiol. 100 (2008) 64–75, https://doi.org/10.1152/jn.00706.2007.
[26] M. Chen, A. Holobar, X. Zhang, P. Zhou, Progressive FastICA peel-off and convolution kernel compensation demonstrate high agreement for high density surface EMG decomposition, Neural Plast. 2016 (2016).
[27] A. Holobar, D. Farina, M. Gazzoni, R. Merletti, D. Zazula, Estimating motor unit discharge patterns from high-density surface electromyogram, Clin. Neurophysiol. 120 (2009) 551–562, https://doi.org/10.1016/j.clinph.2008.10.160.
[28] X. Hu, A.K. Suresh, W.Z. Rymer, N.L. Suresh, Altered motor unit discharge patterns in paretic muscles of stroke survivors assessed using surface electromyography, J. Neural Eng. 13 (2016), https://doi.org/10.1088/1741-2560/13/4/046025.
[29] C. Dai, Y. Cao, X. Hu, Prediction of individual finger forces based on decoded motoneuron activities, Ann. Biomed. Eng. (2019) 1–12, https://doi.org/10.1007/s10439-019-02240-1 in press.
[30] X. Hu, W.Z. Rymer, N.L. Suresh, Assessment of validity of a high-yield surface electromyogram decomposition, J. NeuroEng. Rehabil. 10 (2013) 99, https://doi.org/10.1186/1743-0003-10-99.
[31] C. Dai, X. Hu, Independent component analysis based algorithms for high-density electromyogram decomposition: systematic evaluation through simulation, Under review.