Muscle Synergy Stability across multiple Blind Source Separation algorithms in transradial EMG data

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1 Introduction

In this report, we apply Blind Source Separation (BSS) algorithms—Non-negative Matrix Factorization (NMF), Principal Component Analysis (PCA), and Independent Component Analysis (ICA)—to EMG signals to isolate motor unit potentials, aiding in the study of muscle coordination for advanced prosthetic development. We assess muscle synergy stability across these algorithms and various EMG data preparations, using a data set from a 64-channel electrode array on three subjects performing five repetitions of 30 isometric movements.

2 Methods

Preprocessing

To pre-process our raw EMG signals sampled at 2kHz, we first applied a band-pass Butterworth filter between 5-500 Hz. The lower bound frequency removes mainly motion artefacts while the upper bound removes high-frequency noise. For computational purposes, we then sub-sampled the data by a factor of 2, so our new sampling frequency was 1024Hz. After sub-sampling, we rectified the signal by squaring it in order to better quantify the muscular activation and lastly, we computed the envelop of the signal by applying a moving average filter of with a kernel size of around 200 time points.

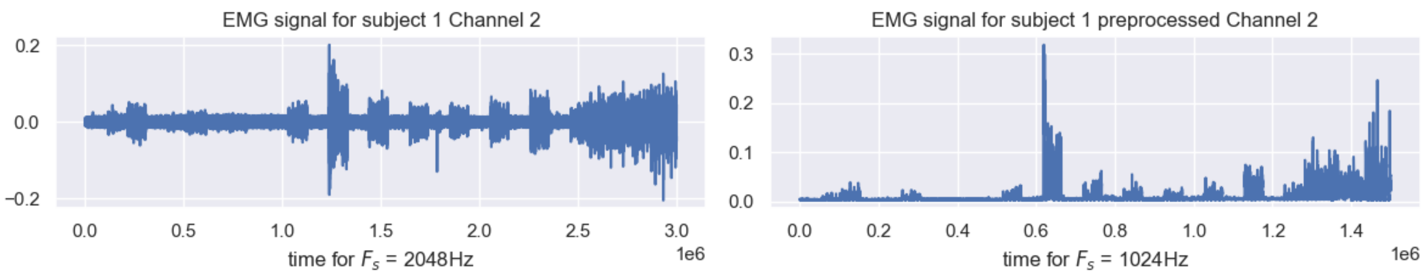

Figure 1: Raw EMG signal (left) and pre-processed EMG signal (right)

Choice for number of components

In order to choose the number of components for the BSS algorithms, we first calculated the reconstruction error of our signal varying the number of components per algorithm and then identified our optimal number of components K^* using the elbow method (as shown in the report code). From this figure we can clearly see that $K^* = 5$ for all BSS algorithms. However, in the literature (Tytus Wojtara (2014)), we also saw that the 90% thresholding of the Variance Accounted For (VAF) is the classical way of selecting the number of muscle synergies expressed during a motor task.

This metric quantifies the reconstruction accuracy of the blind source separation factorization (Tytus Wojtara (2014)), it is defined as:

$$VAF = 1 - \frac{\|(\boldsymbol{x} - \tilde{\boldsymbol{x}})\|^2}{\|\boldsymbol{x}\|^2}$$

Where $\boldsymbol{x}$ is the original EMG signal and $\widetilde{\boldsymbol{x}}$ is the reconstruction using one of the factorisation methods. The VAF was calculated for a number of synergies (components) K between 2 and 9 for each of our 3 selected BSS algorithms. Due to the simplicity of the dataset, we obtained very high VAF values even for low values of K. To facilitate visualization and reduce computational cost we choose $K = 3$ for the rest of our study which achieved a VAF of 99%.

Stability criterion

In order to quantitatively evaluate the stability of the computed muscle synergies of our different BSS algorithms, we introduce the Synergy Stability Index (SSI) Tytus Wojtara (2014) represented as:

$$\mathrm{SSI} = \frac{1}{k} \sum_{i=1}^{k} \left[\frac{2}{p(p-1)} \sum_{l \neq q}^{p} \mid r\left(w_l(i), w_q(i)\right) \mid \right]$$

where r is the Pearson's correlation coefficient, p is the number of trials, k is the number of synergies, and $w_l(i)$ and $w_q(i)$ are the i-th normalized synergy vectors of the l-th and q-th trials, respectively.

Varied Parameters in Spatial Synergy Analysis

We initiated our analysis by comparing the muscle synergies across various BSS algorithms on the entire dataset and assessed the stability. The results are shown in Figure 2.

Subsequently, we computed the spatial synergies to distinct subsets of the dataset. In the first subset division, we conducted comparisons of different repetitions of all movements concatenated. The BSS process decomposed all movements into K = 3 distinct components. We then replicated this subset division but focused on the repetitions of a single movement. In this case, the BSS algorithm decomposed a single movement into our 3 distinct components. We finally extracted one last subset, and compared the synergies of all repetitions across different hand movements. The results of these comparisons are presented in Table 1.

Additionally, we modified the band-pass Butterworth filter frequency range utilized in the preprocessing step. We used the following frequencies ranges: $[(5-1000),(5-750),(5-500),(5-250),(5-100)]$ Hz. The results are illustrated in Figure 4. Lastly, we computed spatial synergies and their stability for three distinct subjects, and the results are shown in Table 1.

3 Results

3.1 Spatial Synergies across different BSS algorithms

As previously detailed, we computed the spatial synergies employing different BSS methods. Upon examination of the resulting plots, we can see that the synergy patterns are stable across different BSS algorithms (SSI = 0.62).

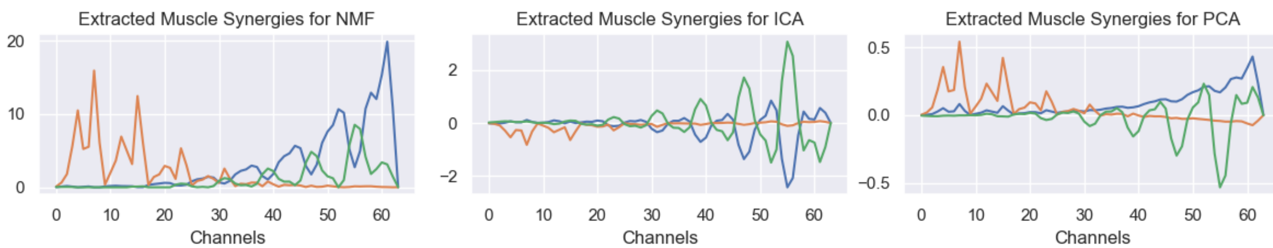

Figure 2: Spatial Synergies across different BSS algorithms. Each color represents a muscle synergy (MS). Consistently across the report we will use Blue representing MS1, Orange MS2 and Green MS3.

3.2 Spatial Synergies across Trial Repetition

For this part, the stability of our synergies across the repetitions of all hand movements are pretty stable across all algorithms with NMF being the most stable (Set Avg. > 0.5). Plots are shown in the report code.

3.3 Spatial Synergies across Repetitions for a Single Movement

In this part, we chose the hand movement of label 1 and the stability of our BSS methods were surprisingly poor for PCA and ICA (plots shown in the code) but NMF was once again stable across the repetitions of a same movement as illsutrated here:

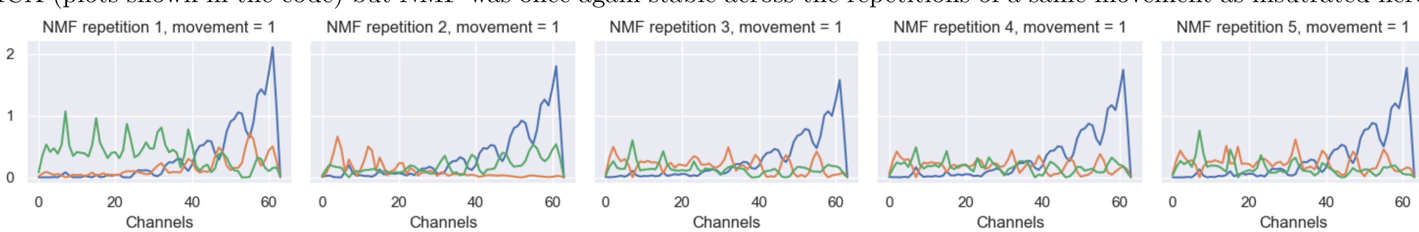

Figure 3: Spatial Synergies across repetitions for 1 hand movement using NMF

3.4 Spatial Synergies across Hand Movements

In this particular subset, it was reasonably anticipated and shown that the results would be less stable. Set Avg < 0.5, since these are hand movements. Plots are shown in the report code.

3.5 Spatial Synergies across band-pass frequency ranges

From the results, the spatial synergies across different preprocessing frequency seem stable when the lower frequencies are kept but aren't stable as we reach higher frequencies ranges.

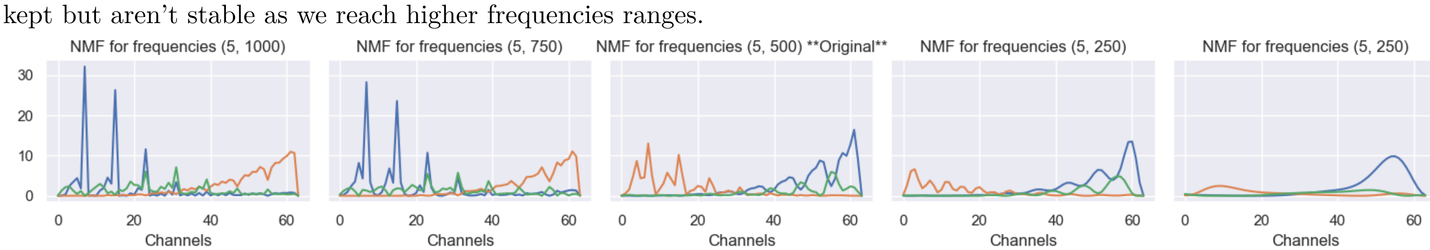

Figure 4: Spatial Synergies across bandpass frequencies using NMF

3.6 Spatial Synergies across subjects

Once again the plots are shown in the code and we can see that the synergies are not stable across subjects but NMF seems to yield the most stable results. The SSI Set Average is of 0.33, which is quite unstable for our metric.

3.7 Synergy Stability Index (SSI) Results

	PCA	**ICA**	**NMF**	**Set Avg**	**Set Std**
Across Trial Repetition	0.74	0.63	0.78	0.72	0.04
Across Repetitions for a Single Movement	0.34	0.27	0.60	0.40	0.14
Across Hand Movements	0.44	0.38	0.54	0.45	0.06
Across Bandpass Frequencies	0.59	0.47	0.64	0.54	0.07
Across Subjects	0.31	0.31	0.38	0.33	0.03
BSS Method SSI Average	0.484	0.412	0.588	/	/

Table 1: Synergy Stability indexes

4 Discussion

4.1 Muscle Synergy Stability across BSS Methods

Our study evaluated muscle synergies (MS) stability using different BSS algorithms. We found a consistent MS pattern across methods, as evidenced by a Similarity Index (SSI) of 0.62 and visual analysis. This implies that the exact choice of BSS algorithm is less crucial. Interestingly, each MS dominated different channel ranges. For instance, MS1 is predominantly active in the last 40-60 channels, while MS2 is active in the initial 20 channels.

BSS algorithms effectively reduced the complexity of hand movement data, aligning with theories of the central nervous system's efficiency in motor control. Exploring MS stability with varied data structures and preprocessing could yield further insights.

4.2 Muscle Synergy Stability across Data Structures, Pre-processing and Subjects

Our analysis showed consistent muscle synergy stability across trial repetitions (SSI > 0.5), confirming the reliability of BSS algorithms. However, single hand movement trials had varying stability, with NMF outperforming PCA and ICA. PCA and ICA showed low stability, each with an SSI of 0.31, while NMF displayed slightly better stability at an SSI of 0.54, just above the threshold of 0.5. These findings suggest that fewer muscle groups are involved in single movements, and sometimes only one component is necessary for accurate muscle activity representation.

The study also revealed that frequency filtering impacts MS stability. Altering the lower limit of the Butterworth filter led to signal loss and poor BSS performance. Stability improved in narrower, lower frequency ranges, which is consistent with the importance of these frequencies in sEMG. Conversely, increasing the upper frequency limit introduced too much high-frequency noise, destabilizing muscle synergies. The overall SSI scores were satisfactory, averaging at 0.54.

For the stability of muscle synergies across subjects, we initially expected consistent results, assuming uniform electrode placement and comparable performance among subjects. However, our findings showed lower-than-expected average stability (below 0.5), indicating inconsistency in muscle synergies across different individuals. This outcome is not overly surprising, considering the stringent assumptions required for inter-subject muscle synergy stability, such as identical arm lengths, electrode placement, movement comprehension, and uniformity in hand movement speed and amplitude.

In summary, this part of the study highlights that different data structures (like single movement trials or concatenated EMG signals) and preprocessing approaches significantly impact the identified muscle synergies.

4.3 Best and Worst Performing Algorithms

Our findings suggest that a limited set of three generator muscle synergies suffices for representing 30 distinct hand movements. NMF performed best due to its additive feature learning, while ICA was less effective across our experiments.

4.4 Combining Two Algorithms: PCA + ICA

Besides evaluating the performance of each individual BSS algorithms, we also attempted to combine different algorithms together in order to achieve better results. Specifically, we tried to combine PCA with ICA, i.e. applying PCA as a noise reduction step before ICA. Interestingly, compared to standard ICA, this approach could occasionally reduce the variability of muscle synergies measured by SSI (across different hand movements and subjects), but in some other cases it tends to generate more unstable synergies. (Details in the code) In conclusion, combining different BSS algorithms involves considering the trade-off between different optimization objective (since PCA minimizes L2 matrix norm whereas ICA maximize non-Gaussianity), and the best practice should be determined on a case-by-case basis.

References

Shingo Shimoda Hidenori Kimura Tytus Wojtara, Fady Alnajjar. Muscle synergy stability and human balance maintenance. *Journal of NeuroEngineering and Rehabilitation*, 2014. doi: https://doi.org/10.1186/1743-0003-11-129.