Constrained ALS for Estimation of Human Upper Limb Synergies

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Abstract: Human body movement is a complex task that requires the control of multiple joints via a network of muscles. The biological signals, particularly electromyography (EMG), are correlated by nature. The brain transmits these signals through the neuromuscular transmission system of the body. The combination of muscular activation for each particular movement presents a set of weights known as synergies. The traditional alternating least square (ALS) based non-negative matrix factorization (NMF) gets trapped in local minima for co-linear data. Therefore, it is not a suitable method for extracting muscle synergies. This paper advocate using *l2-norm* as an additional constraint for ALS-based NMF. The addition of *l2-norm* decorrelates the data, resulting in a better estimation of synergistic weights. For our results, we acquired EMG signals from six healthy subjects. Both plain and regularized NMF were used to extract the synergies. The synergies acquired via plain NMF have a higher cross-correlation within and indicate the triggering of the same muscles irrespective of the targeted isometric contraction. In contrast, the regularized NMF synergies targeted the correct muscular set for a particular isometric contraction. Our results show that the synergies acquired via regularized NMF are also more correlated with the physiologically inspired synergies.

1 INTRODUCTION

Human body movement is a complex task requiring multiple joint control via a network of muscles. The human hand movement is performed by a pair of agonist/antagonist muscles in coordination with assistance from adjacent muscles(Ayhan and Ayhan, 2020). The agonist muscle is a prime mover, while the antagonist is a sleeping partner in that direction. For the opposite direction of the same joint, the role of the agonist and antagonist are switched. The participation of muscles in any movement varies between 0 to 1 on a normalized scale. Where 0 refers to relax state of a muscle while 1 refers to maximum contraction. The action of these muscles is controlled via the neuromuscular translational system of the human body. It is a hierarchical process; initiated by the motor neurons in the brain, ending up at synergistic level activation (Bahadur and Rahman, 2018). Synergies describe the level of muscle activation involved in a particular movement. The concept of muscular synergies reduces the dimensionality of complex human neuromuscular coordination systems.

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Finding the muscle synergies can be challenging as the only available data is a matrix of recorded electromyographic (EMG) signals. Separating muscle synergies from time-variant motor unit action potentials using surface EMG is a blind source separation problem(Bahadur R. and Khan, 2021). There exist several algorithms in literature for the estimation of muscle synergies, among which the most prominent are principal component analysis (PCA), independent component analysis (ICA), and non-negative matrix factorization (NMF) (Rodrigues et al., 2022; Rasool et al., 2016; Ma et al., 2021). PCA requires the sources to be uncorrelated, while ICA requires independence of the sources (Naik and Nguyen, 2015; Zhao et al., 2022). For biological systems, such assumptions about the sources cannot be established; therefore, the literature is more focused on NMF and its variants (Roh J. and Bee, 2015; Naik and Nguyen, 2015; Lin C. and Farina, 2018; Bahadur R. and Khan, 2021). NMF is a non-convex optimization problem; the implementation of the problem via an iterative multiplicative update was a revival of this technique (Lee and Seung, 2000). However, the convergence of this algorithm is not guaranteed (Lin, 2007); therefore, several algorithms are adopted to implement

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NMF. One very famous approach is the alternating least square (ALS) method. The solution is faster and convergent; however, it gets trapped in local minima, especially becoming very slow for co-linear data (Cichocki and Zdunek, 2007).

Biological signals in general and EMG data, in particular, are naturally co-linear; traditional ALS lacks to provide an optimal solution. Therefore, this paper advocates using constrained ALS-based NMF for synergy estimation from EMG signals. The paper is organized in the following manner, section 2 presents the mathematical details, while the experimental setup is presented in section 3. The 4^{th} module describes synergies for elbow & shoulder based on the physiological studies. The methodology is provided in section 5. Results and discussion are presented in section 6, followed by a conclusion at the end.

2 MATHEMATICAL MODEL

In the initial part of this section, we will introduce the plain NMF, followed by the recommended regularization function.

2.1 NMF and Traditional ALS

A standard NMF problem is defined by eq(1).

$$\mathbf{Y} = \mathbf{S}\Phi(t) + \mathbf{E}, \qquad \mathbf{S}, \Phi(t) \geq 0 \tag{1}$$

Where $\mathbf{Y} \in R^{[N\times M]}$ is the root mean square (RMS) of the recorded EMG signal for a length of $'T_a'$, N is the total number of channels, and M is the total number of RMS values, $\mathbf{S} \in R^{[N\times P]}$ is the synergy matrix and P is the estimated rank of matrix $\mathbf{Y}$. $\Phi(t) \in R^{[P\times M]}$ is a matrix of P time variant signals (motor units) and $\mathbf{E} \in R^{[N\times M]}$ is the additive noise. For error minimization, consider calculating the Euclidean norm.

$$D(\mathbf{Y}|\mathbf{S}\Phi(t)) = ||\mathbf{Y} - \mathbf{S}\Phi(t)||^2, \qquad \mathbf{S}, \Phi(t) \geq 0 \tag{2}$$

Since both the motor signals and synergies are unknown, the overall problem is non-convex. ALS proposes the use of an alternating procedure for estimation of $\mathbf{S}$ and $\Phi(t)$, converting the non-convex problem into convex (eq. (3)).

$$\Phi^k(t) = \arg\min_{\phi(t)} ||\mathbf{Y} - \mathbf{S}^{k-1}\Phi(t)||^2, \qquad \Phi(t) \geq 0 \tag{3a}$$

$$\mathbf{S^k} = \arg\min_{S} ||\mathbf{Y} - \mathbf{S}\Phi^{k-1}(t)||^2, \qquad \mathbf{S} \geq 0 \tag{3b}$$

S^0 and $\Phi^0(t)$ are initialized randomly. S^k and $\Phi^k(t)$ are the k^{th} estimates while S^{k-1} and $\Phi^{k-1}(t)$ are the estimates from the previous iteration. Gradient descent is adopted to attain minimum error. For pNMF, there is only one essential constraint: elements of all decomposed matrices should be positive; there is no additional constraint in the traditional ALS. The problem can quickly get caught in the local minimum; simultaneously, the algorithm can become much slower to converge for co-linear data such as EMG signals (Cichocki and Zdunek, 2007). Therefore, additional penalty functions are required to address these issues.

2.2 Constrained ALS for Synergy Estimation

Stochastic theory's two famous optimization constraints are the $l_1 - norm$ and the $l_2 - norm$. $l_1 - norm$ is used for sparse data while $l_2 - norm$ (also known as regularization) has the inherited property of decorrelating the channels(Cichocki and Zdunek, 2007). Physiological signals, especially multiple channel EMG from a specific limb, are correlated with each other (Ma et al., 2021). Therefore, this paper uses regularization as an additional penalty function to accelerate and obtain an optimal solution for synergy extraction from EMG signals using the ALS-based NMF algorithm. It is a kind of regression that restricts the error towards zero; thus, the modified version of eq.(3) would be:

$$\Phi^k(t) = \arg\min_{\phi(t)} ||\mathbf{Y} - \mathbf{S}^{k-1}\Phi(t)||^2 + \alpha_\phi ||\Phi^k(t) - \Phi^{k-1}(t)||^2, \qquad \Phi(t), \alpha_\phi \geq 0 \tag{4a}$$

$$\mathbf{S^k} = \arg\min_{S} ||\mathbf{Y} - \mathbf{S}\Phi^{k-1}(t)||^2 + \alpha_S ||\mathbf{S^k} - \mathbf{S^{k-1}}||^2, \qquad \mathbf{S}, \alpha_S \geq 0 \tag{4b}$$

The regularization parameters $\alpha_\phi$and α_S are non-negative values that compel the variation in the decomposed matrices towards zero. The values of these parameters are based on error variance. The system's noise variance (σ_n^2) is calculated from the initial state where the muscles are at rest. The regularization values are iteratively updated using the formula $\alpha^k = c\alpha^{k-1}; 0 < c < 1$,. The smaller values of the regularization constraint result in the imposition of a full rank matrix providing the possible optimal solution. For the given problem, the iterations stop when an optimal value is achieved, i.e., $\alpha^k \approx \sigma_n^2$.

3 EXPERIMENTAL SETUP

3.1 Consent & Declarations

Arms + Hands SRA Labs provided a database for carrying out this study. The experiment was conducted with the consent of participants following the Declaration of Helsinki under the approval of the Northwestern University Institutional Review Board.

3.2 Participants

Six healthy subjects' data is selected for this study. The database comprised EMG signals using isometric contractions collected from two females and four males aged 55 to 71. All subjects were right-hand dominant with no neuromuscular impairment in the upper limbs.

3.3 Setup

The participants were comfortably seated in a chair, and the arm and hand movement was restricted using a brace and strap mechanism; the setup is provided in fig. (1a). Isometric contractions were applied in a 3D space, and forces generated were recorded using the multi-axis cartesian-based arm rehabilitation machine (MARCARM). The subject grasped the MARCARM's handle to exert isometric contraction informally in a 3D space. Setup details can be further explored in (Roh J. and Bee, 2015) paper.

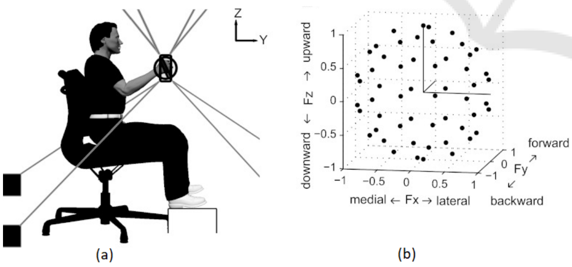

Figure 1: (a) Experimental brace and strap setup followed using MARCARM. (b) Target force contractions applied in multiple directions matching the exemplary target in 3D.

3.4 EMG Acquisition

EMG signals are recorded using the Delsys Bagnoli EMG acquisition unit at a sampling frequency of 1850 Hz. The signals are filtered via a built-in zero-lag 20-450 Hz bandpass filter. Eight channel surface EMG data are recorded from both arms while performing isometric force contractions in multiple directions, presented in fig. (1b). The targeted muscles of the upper arm are bicep brachii (BI), brachioradialis (BRD), tricep longus (TI_{long}), tricep lateral (TI_{lat}), deltoid anterior (DA), deltoid medial (DM), and pectoralis major (PM). The recording duration is 9 sec for each contraction with a 2 sec initial baseline period. A successful trial would mean maintaining the target force at the sphere's center for 0.8 sec. A total of 10 trials were performed for each target sphere in a 3D space. To avoid fatigue, a break of 1 min is given between each trial.

4 SYNERGY & HUMAN PHYSIOLOGY

Synergy is the interrelated actuation of several muscles using a smaller number of activation patterns. The human upper arm works by activating the shoulder and elbow joints. The two joints are controlled by employing multiple muscles working as antagonistic pairs with assistive secondary muscles (Ayhan and Ayhan, 2020). Each shoulder and elbow joint requires two dedicated synergies activating the flexion and extension of each joint (Inouye and Cuevas, 2016). Thus, four synergies (i.e., 2^2) are required to analyze the movement of the upper arm. The four synergies of the human upper limb based on the two joints (elbow and shoulder) can be categorized as elbow flexor-pronator/extensor-supinator and shoulder abduction/adduction. Based on our study of the kinesiology of elbow and shoulder complex (Yesilyaprak, 2020; Ayhan and Ayhan, 2020) fig. (2) presents the physiologically inspired synergistic weights presenting the involvement of the targeted eight muscles in the movement of elbow and shoulder joints. The muscles on x-axis are organized in such a manner that the left most muscles start with the elbow activation while the right most is pectoralis major of the shoulder.

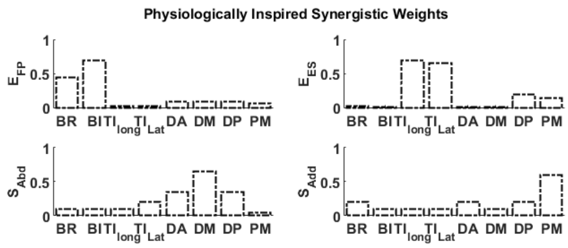

Figure 2: Synergistic distribution involved in upper limb movements according to human physiology. E_{FP}: Elbow Flexion-Pronation; E_{ES}: Elbow Extension-Supination; S_{Add}: Shoulder Adduction; S_{Abd}: Shoulder Abduction.

To understand the statistical behavior of the physiologically inspired synergies, table (1) presents the auto-correlation of the synergies. Elbow flexion and

Table 1: Auto-correlation matrix of synergies based on human physiology. E_F: Elbow Flexion; E_E: Elbow Extension; S_{Add}: Shoulder Adduction; S_{Abd}: Shoulder Abduction.

Movements	E_{FP}	E_{ES}	S_{Abd}	S_{Add}
E_{FP}	1	-0.629	-0.380	-0.220
E_{ES}	-0.629	1	-0.111	-0.131
S_{Abd}	-0.380	-0.111	1	-0.350
S_{Add}	-0.220	-0.131	-0.350	1

extension result from the bicep-triceps muscles working as agonist/antagonist pair. Therefore, a minimum correlation is observed between the two synergies. The correlation among other cross synergies is negative or close to zero because the assistive muscles in all movements are the same with variation in intensities, while prime movers are the exact opposite.

5 METHODOLOGY

5.1 Pre-processing

Matlab R2020a is used to analyze the data. The respective mean value is subtracted from each surface EMG signal for pre-processing, and the baseline was removed. The active areas are selected based on signal segmentation and recorded timings. RMS of the segmented surface EMG was calculated with a window length of 0.1 sec ($T_a = 180$ samples) and an overlapping window, $T_{ol} = 10$ samples. EMG signals from multiple trials for each subject were concatenated to acquire the synergies.

5.2 Variance Accounted For Test

We infer from eq. (1 & 2) that the pseudo rank ‘P’ of the matrix $\mathbf{Y}$ is substantial for effectively decomposing the EMG signals into motor signals and intended synergistic weights. To determine the minimum number of synergies (P) using NMF, we use the Variance Accounted For (VAF) test, eq. (5). The traditional and regularized NMF were used to perform VAF; from fig. (3) it can be observed that the knee-curve is attained near 4 synergies with an average accuracy of 96.5%. The findings of number of synergies ‘P’ is in accordance with the physiological study as mentioned in section (4). Therefore, the dimension of the synergy matrix $\mathbf{S}$ would be $[8 \times 4]$, where $N = 8$ presents the number of channels and $P = 4$ is the minimum number of synergies to effectively reconstruct the database.

$$VAF = \left(1 - \frac{var(\mathbf{Y} - \hat{\mathbf{Y}})}{var(\mathbf{Y})}\right) \times 100 \tag{5}$$

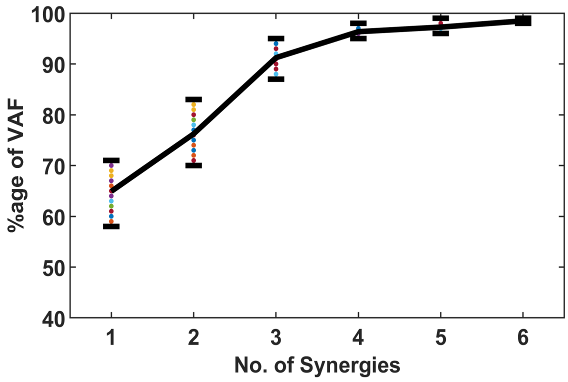

Figure 3: VAF test to determine the number of minimum synergies required. Each dotted color presents percentage the VAF score for the reconstructed EMG signal from its decomposed matrices using NMF.

5.3 Synergy Alignment

As per our findings, the knee curve is obtained around four synergies with an accuracy of 96.5% using the VAF test. Therefore, four synergies were acquired using plain NMF and regularized NMF. As synergistic weights are the coefficients associated with the temporal motor signals; therefore, temporal motor signals acquired via the NMF are used to align the muscle synergies. For this purpose, a pivot signal is randomly selected from an arbitrary subject. The correlation between estimated motor signals across different subjects is calculated. Maximum correlated value is used in a nested procedure to align the four synergistic weight patterns for the entire database.

6 RESULT & DISCUSSION

6.1 Synergy Estimation Via Traditional ALS

This section provides a detailed discussion on the synergy estimation using the plain NMF, i.e., ALS without additional constraints. The traditional ALS is an iterative procedure; the estimations stop when a count limit is reached. For this study, the count limit is set to 300. Synergistic muscle activation involves identifying specific muscles engaged in a particular contraction. However, in fig. (4), we do not observe such unique muscle activation patterns; in fact, different synergies indicates the activation of similar muscles. For example, on average same pattern is observed in synergy 1 and 2 (with a correlation coefficient, r = 0.6), while synergy 2 and 3 are also closely correlated (r = 0.647). Table (2) presents the auto-correlation matrix for the four synergistic weights estimated via plain NMF. It can also be inferred that the estimated synergies lack the recognition of specific antagonistic muscular pairs. Synergy 2 (fig.(4)-top right) refers to the activation of BI and TI muscles simultaneously, which is not feasible in case of a healthy subject. The behavior observed in the cross-correlation of synergies using plain NMF is very opposite to that assessed by actual human physiology. These observations refer to the inaccurate or non-optimal synergy estimation of traditional ALS.

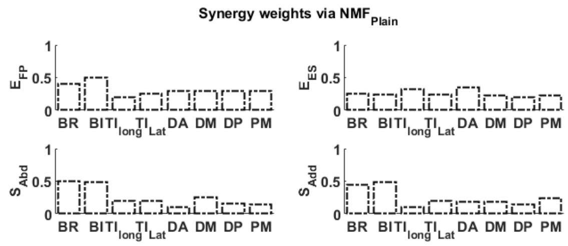

Figure 4: Synergistic estimated via traditional ALS-based NMF. E_{FP}: Elbow Flexion-Pronation; E_{ES}: Elbow Extension-Supination; S_{Add}: Shoulder Adduction; S_{Abd}: Shoulder Abduction.

Table 2: Correlation matrix of synergies estimated using plain NMF. E_F: Elbow Flexion-Pronation; E_E: Elbow Extension-Supination; S_{Add}: Shoulder Adduction; S_{Abd}: Shoulder Abduction.

Movements	E_{FP}	E_{ES}	S_{Abd}	S_{Add}
E_{FP}	1	0.6	0.298	-0.414
E_{ES}	0.6	1	0.647	-0.4336
S_{Abd}	0.298	0.647	1	0.136
S_{Add}	-0.414	-0.4336	0.136	1

6.2 Synergy Estimation via Regularized ALS

Regularized NMF refers to the adaptation of the ALS algorithm with additional Tikhonov constraint. The mathematical details are already discussed in section(2.2). The algorithm converges when regularization parameter reaches its optimal value $\alpha^* \approx \sigma_n^2$. Synergies extracted via regularized NMF are presented in fig. (5), and the correlation table is presented in table (3;). The first synergy indicates activation of bicep BI and BR, referring to elbow flexion. In comparison, the second synergy identifies elbow extension with the tricep (TI_{lat} and TI_{long}) as the most active identified muscle, followed by PM and BR. Synergy 3 presents a low composite activation of BR, BI, and shoulder muscles, referring to shoulder abduction. Finally, synergy 4 with dominant deltoid anterior followed up by PM, TI_{long}, and the BR as shoulder adduction. The behavior of synergies estimated via the proposed algorithm and human-inspired physiological synergies are closely related, *p=0.753*. The cross-correlation among the synergies is negative in the majority of cases (table(3)); a correlation of 0.38 is observed in the case of elbow flexion and extension due to the secondary muscles involved. Unlike plain NMF, regularized NMF does not simultaneously provide multiple antagonistic pair activation in a single synergy.

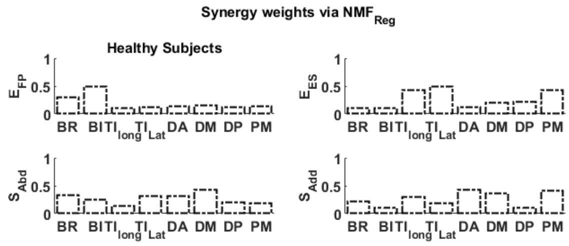

Figure 5: Synergistic estimated via regularized NMF.E_{FP}: Elbow Flexion-Pronation; E_{ES}: Elbow Extension-Supination; S_{Add}: Shoulder Adduction; S_{Abd}: Shoulder Abduction.

For better evaluation of synergies estimated via plain and regularized NMF, this paper investigates the cross-correlation of estimated weights with physiological synergies, presented in fig.(6). Correlation between estimated synergy and physiologically-inspired synergy is called 'auto' if they belong from the same order. Correlation between different orders will be referred to as 'cross'. In majority cases regularized NMF provides maximum auto correlation with physiologically-inspired synergy as compared to plain NMF. Secondly, the synergies estimated via plain NMF indicates a higher cross correlation; shoulder abduction synergy is comprised on the activation of BR and BI as opposed to the actual deltoid muscles. This synergy estimated via regularized NMF is also having a consideraly low correlation *(r = 0.6637)*, yet it is able to detect the correct activation of deltoid muscles. Also in case of elbow extension-supination synergy a very low correlation factor *(r = 0.1848* was observed when comparing physiologically inspired synergy to plain NMF. In this particular case, the synergy estimated via plain NMF shows an almost uniform activation of all muscles. In contrast, regularized NMF targets the activation of tricep muscles in assistance with PM *(r = 0.8321)*.

It can be overall concluded that the synergy estimated via regularized NMF are rigorous and provides much similarity to the actual physiological data. Therefore, this paper recommends using the proposed regularized NMF compared to plain NMF.

Table 3: Correlation matrix of synergies estimated using regularized NMF. E_F: Elbow Flexion; E_E: Elbow Extension; S_{Add}: Shoulder Adduction; S_{Abd}: Shoulder Abduction.

Movements	E_{FP}	E_{ES}	S_{Abd}	S_{Add}
E_{FP}	1	0.380	-0.353	0.388
E_{ES}	0.380	1	-0.633	-0.136
S_{Abd}	-0.353	-0.633	1	0.079
S_{Add}	0.388	-0.136	0.079	1

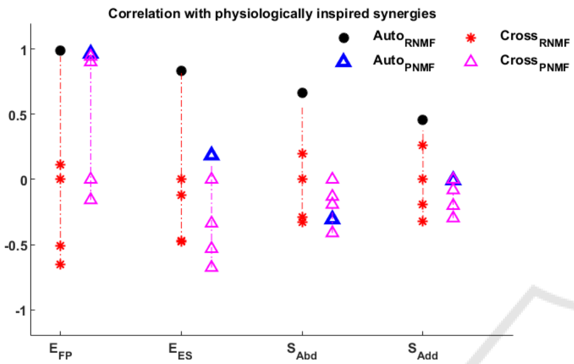

Figure 6: A comparison of synergies estimated for healthy subjects with Synergistic activation based on human physiology. The red '*' refers to cross correlation of regularized NMF based synergistic weight with physiologically inspired synergies; the black dots present auto correlation for similar order synergies. The purple 'Δ' refers to the one estimated via plain NMF and the blue 'Δ' are the correlation between similar order synergies E_{FP}: Elbow Flexion-Pronation; E_{ES}: Elbow Extension-Supination; S_{Add}: Shoulder Adduction; S_{Abd}: Shoulder Abduction.

7 CONCLUSION

Human body movements are based on the synergistic activation of muscles. This paper investigates the number of synergies and the approriate muscular activation involved in isometric contraction of the human upper arm. According to our findings four synergies are sufficient for upper limb movement identification. Plain ALS-based NMF algorithm is insufficient for synergy estimations as the method fails to provide optimal solution for co-linear data. Therefore, this paper proposes using a constrained ALS-based NMF; the regularization constraint decorrelates the EMG signals to attain the synergies behind the particular contractions, thus, resolving the issue. Our statement is supported by the results presented in section (6). In the future, we look forward to analyzing the pathological disorder in the upper limbs of post-stroke subjects using muscle synergies.

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