

Extracting Time-Varying Muscle Synergy with Imposing Interchannel Correlation Constraints

Janghyeon Kim¹ and Han Ul Yoon²

¹Division of Computer and Telecommunication Engineering, Yonsei University (Mirae)
Wonju 26493, Korea
²Division of Software, Yonsei University (Mirae)
Wonju 26493, Korea
{janghyeonk, huyoon}@yonsei.ac.kr

Abstract. Central nervous system sends a command signal to modularized muscle combinations, which are called muscle synergies, via neuromuscular pathway to control muscles while performing a specific task. Conventional synergy extraction approach often generates problematic issue; specifically, the extracted synergy shows biomechanical discrepancy against a correlation among muscle activities due to the nature of a linear matrix decomposition. To mitigate this issue, in this paper, we propose a novel approach to extract muscle synergies. The key idea of the proposed approach is to impose a relationship among muscle activities as constraints for the numerical optimization problem of synergy extraction. To validate the proposed approach, we present time-varying muscle synergies which are extracted from surface EMG data set for bicep-brachii workout. The result shows that the relationship matrix has a feasibility to represent a relationship among muscles and can be compensated by employing various time-series similarity metrics.

Keywords: Muscle Synergy, Time-Varying Muscle Synergy, Non-negative Matrix factorization, Muscle Relationship Matrix

1 Introduction

In 1967, Bernstein found that a human motor control system consists of modularized muscle groups, which are called muscle synergies, instead of controlling individual muscles [1]. For each specific task, the muscle synergies are predetermined and central nervous system(CNS) controls their activation level to perform a motion [2]. By employing muscle synergies, CNS can control muscles with the reduced number of command signal, which in turn helps the human motor control to be performed in more efficient way.

For muscle synergy studies, existing findings there have introduced two different muscle synergy types on a basis of time-invariant/-variant characteristics. Time-invarying

muscle synergy is assumed to be a vector of which elements stand for the contribution of each muscle to perform a specific motor task; namely, the synergy itself will be sustained along a time, and a muscle activation is represented by the combinations of muscle synergies and corresponding activation curves [3]. In contrast, time-varying muscle synergy is depicted by two dimensional matrix in which the activation of muscles along a time can be represented by row and column [4]. Even though the two muscle synergy types have been broadly studied for various motor tasks by extracting the muscle synergy as a result of numerical optimization process, a relationship among muscles have not been considered during the process. This aspect often causes a problematic issue, i.e., the extracted synergy does not make sense in biomechanical perspective. Therefore, if the relationship among muscles can be considered while muscle synergies is being extracted, the aforementioned issue might be prevented or at least mitigated.

To solve the above issue, this paper proposes a novel approach to extract muscle synergies. To reflect the muscle relationship, the proposed approach imposes interchannel correlations among time series multi-channel surface EMG (sEMG) data as constrains in numerical optimization process to extract muscle synergies. First, we introduce time-varying muscle synergy by recapitulate its mathematical definitions. We then discuss a method to construct a relationship matrix which will be eventually utilized as constrains to extract muscle synergies throughout a numerical optimization process. The experiment is also introduced in order of measuring sEMG data, data processing, and synergy extraction. Finally, the extracted synergies are presented to validate the proposed approach and discussion will be followed.

2 Methods

2.1 Time-varying muscle synergy W_i

Let $M \in \mathbb{R}^{m \times k}$ be the time series sEMG data where m and k are the number of channels and the number of time steps, respectively. Time-varying muscle synergy is defined as matrix $W_i \in \mathbb{R}^{m \times u}$ where u is a horizon size and positive constant less than k , typically $u \leq \frac{k}{2}$; correspondingly, an activation coefficient and a time delay are expressed by $c_i \in \mathbb{R}^+$ and $\tau_i \in \mathbb{R}^+$, respectively. Now M can be represented as below

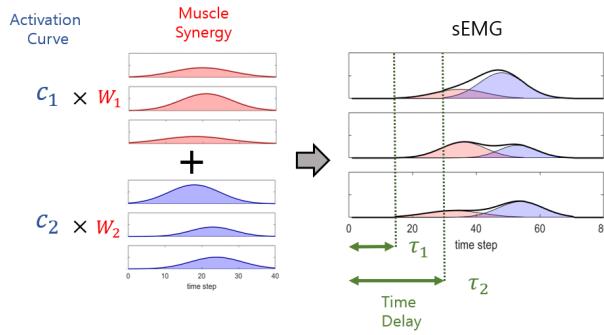


Fig. 1. An illustrative example of time-varying muscle synergy in case of the numbers of channels and synergies are $m = 3$ and $n = 2$, respectively.

$$M(m, k) = \sum_{i=1}^n c_i W_i(m, k - \tau_i). \quad (1)$$

where n is the number of synergies and can be typically predetermined by investigating a variance accounted for (VAF).

Fig. 1 shows an illustrative example of time-varying muscle synergy in case of the numbers of channels and synergies are $m = 3$ and $n = 2$, respectively. The time-varying muscle synergy as well as the activation coefficient can be extracted by employing iterative non-negative matrix factorization(NMF) [5]. The time delay can be selected by investigating a time-shift yielding the highest cross-correlation [4].

2.2 Constructing a tensor-type data T

Fig. 2(left) shows the accumulated $M(m, k)$ for r repetitions; consequently, we have $M(m, k, r)$ of which data type is three dimensional tensor. The $M(m, k, r)$ is transposed with respect to k and r , and the resulting tensor-type data is represented as $X(m, r, k)$ as shown in Fig. 2(right). Note that, after the transposition, we have matrix $X(m, r)$ for a fixed time step k .

Fig. 3 depicts our procedure to construct a tensor-type data T . Given $X(m, r)$ for a fixed time step k , we first calculate correlation coefficients

$$r_{X_i, X_j} = \frac{\text{cov}(X_i, X_j)}{\sigma_{X_i} \sigma_{X_j}} \quad \text{for } 1 \leq i, j \leq m. \quad (2)$$

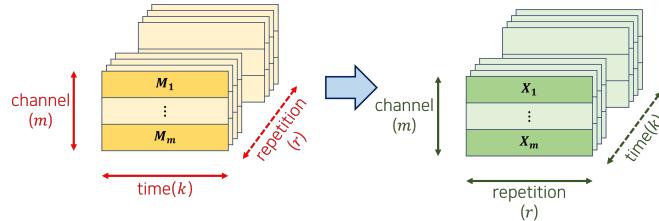


Fig. 2. A procedure to transpose $M(m, k, r)$ (left) and the transposed $X(m, r, k)$ (right).

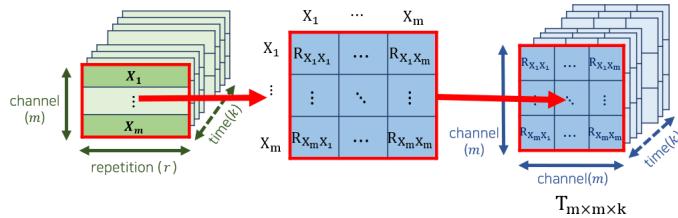


Fig. 3. A procedure to construct tensor-type data $T_{m \times m \times k}$ from $X(m, r, k)$ by using Eq. (3).

where X_i is a shorthand notation for $X(i, k)$ as shown in the leftmost of Fig. 3. From Eq. (2), we know that r_{X_i, X_j} will have a value ranging from -1 to 1. Since we are mainly interested in the coactivation of two muscles (either positive or negative correlation), we modify the Eq. (2) to represent a relationship between two muscles as follow:

$$R_{X_i, X_j} = \text{MAX}(0, r_{X_i, X_j}). \quad (3)$$

The $m \times m$ matrix in the midst of Fig. 3 is obtained by calculating the relationship using Eq. (3). Finally, as shown in the rightmost of Fig. 3, we can construct a tensor-type data by completing the calculation of R_{X_i, X_j} for all time step k . Throughout this paper, the constructed tensor-type data will be referred to as $T(m, m, k)$ and $T_{m \times m \times k}$ in shorthand notation.

2.3 Extracting time-varying muscle synergy with imposing an interchannel muscle relationship constraint

Our approach to extract time-varying muscle synergies with imposing an interchannel muscle relationship constraint consists of two step procedures as follows: decomposing the interchannel muscle relationship constraint matrix and formulate the time-varying muscle synergy extraction as a numerical constrained optimization problem.

Let $S_i \in \mathbb{R}^{m \times m}$ and $\alpha_i \in \mathbb{R}^{1 \times k}$ denote a muscle relationship matrix and a corresponding activation curve, respectively. Now we assume that the tensor-type data $T_{m \times m \times k}$ can be represented as

$$T_{m \times m \times k} = \sum_{i=1}^n \alpha_i S_i. \quad (4)$$

This assumption holds without a loss of generality since $T_{m \times m \times k}$ has been constructed based on the co-activaiton of muscles. Namely, what we want to do is to decompose $T_{m \times m \times k}$ into multiple muscle relationship matrices S_i s to utilize them as constraints for time-varying synergy extraction. Accordingly, n is set to the same as the number of synergies. S_i and α_i can be also found by applying the iterative NMF [5].

Recall that $M(m, k)$ is the measured m -channel sEMG data for time step k which can be represented by Eq. (1). Let \widehat{W}_i , \widehat{c}_i , and $\widehat{\tau}_i$ denote the estimated time-varying muscle synergy, the corresponding activation coefficient, and the time delay, respectively. Now our muscle synergy extraction with imposing interchannel muscle relationship can be achieved by solving the following optimization problem:

$$\begin{aligned} & \min_{\widehat{W}_i, \widehat{c}_i, \widehat{\tau}_i} && \|M(k) - \widehat{M}(k)\| \\ & \text{sub to.} && \widehat{M}(k) = \sum_{i=1}^n \widehat{c}_i \widehat{W}_i(m, k - \widehat{\tau}_i) \\ & && |S_i - \widehat{S}_i| < \epsilon \end{aligned} \quad (5)$$

where \widehat{S}_i denotes a muscle relationship matrix obtained from \widehat{W}_i by using Eq. (3) and ϵ is a small positive constant. The extracted time-varying muscle synergies will be presented in Sec. 4.2.

3 Experiment

3.1 Measuring sEMG data

Time series sEMG data was measured by using multi-channel armband-type sEMG sensor(MyoArmband, Thalmic Labs, Brooklyn, NY) while the demonstration of bicep brachii workout was being performed by a professional trainer. For sEMG channels, Ch 1, 2, 3 were deployed at bicep brachii and Ch 5, 6, 7 were positioned at tricep brachii. Ch 4, 8 were located at boundaries between biceps and triceps. The professional trainer was instructed to demonstrate dumbbell-curl at the rate of one attempt per 1.6 seconds; one session consists of 20 attempts; an experiment was organized with three sessions. The sampling rate of the armband-type sEMG sensor was set to 20ms; hence, 80 samples were collected during the one attempt. By completing the experiment, consequently, the 60 sEMG data (each $M \in \mathbb{R}^{8 \times 80}$) were collected.

3.2 Data processing

The measured sEMG data were processed by following steps. First, the sEMG data was moving average filtered and then integrated over a window size of 2 time steps. Next, for time-varying synergy extraction, intra-channel normalization was performed; in contrast, while finding a muscle relationship matrix, inter-channel normalization was applied. Finally, $M_{8 \times 40}^{\text{intra}}$ and $M_{8 \times 40}^{\text{inter}}$ were prepared according to the normalization types. We here note that shorthand notations $M_{8 \times 40}$ was used for a better clarity instead of $M(8, 40)$

3.3 Synergy extraction

As illustrated in Fig. 2 and Fig. 3, a tensor-type data $T_{8 \times 8 \times 40}$ was constructed by accumulating 60 $M_{8 \times 40}^{\text{inter}}$ s. Time-varying synergies were extracted by using $M_{8 \times 40}^{\text{intra}}$ for the numerical optimization problem formulated in Eq. (5) under two different conditions – S_i were imposed as constraints or not – to compare the outcomes. Two different synergy numbers $n = 5, 6$ were tested and the horizon size u was set to 11 after investigating VAF.

4 Results

4.1 Result for finding muscle relationship matrices

Fig. 4 shows muscle relationship matrices S_i and activation curves α_i that were found under $n = 6$ and $u = 11$. S_i presents correlation among sEMG channel number 1 through 8. The colormap setting in MATLAB was jet; therefore, blue and red represent 0 and 1, respectively. α_i represents the activation level of S_i along time step k . From S_1 and S_5 , we can see that there exists correlation among sEMG channel 5, 6, 7, 8 corresponding to tricep brachii muscles. Also, correlation among sEMG channel 1, 2, 3, 4 corresponding to bicep brachii muscles was shown in S_2 and S_4 . The activation curve of S_6 is 0 for all time steps which implies that this muscle relationship matrix is redundant one. Therefore, we can determine the number of synergy n to be 5.

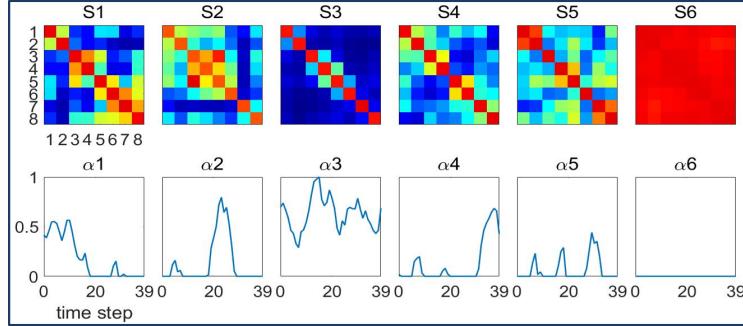


Fig. 4. Muscle relationship matrices S_i and activation curves α_i that were found under $n = 6$ and $u = 11$.

4.2 Result for extracting time-varying muscle synergy

Fig. 5 presents extracted time-varying muscle synergies W_i under $n = 5$ and $u = 11$. For each W_i , row and column represents sEMG channel m and time step k , respectively. The synergies in a top row are extracted without any constraints whereas the ones in a bottom row are outcomes with imposing muscle relationship matrices S_i as constraints.

Considering the sEMG data were collected while performing dumbbell curl (which uses bicep brachii muscles), from the five synergies in the top row, we can explicitly see that W_3 and W_5 show the activation of sEMG channel 1, 2, 3 corresponding to the bicep brachii muscles. However, the mixture of bicep and tricep brachii muscles can also be found in W_1 , W_2 , and W_4 , which are problematic issues.

Among the five synergies in the bottom row, W_1 , W_3 , and W_4 depict the activation of bicep brachii related channels, but W_2 and W_5 still show the tendency of having the mixed activation pattern throughout all sEMG channels. This results shows a feasibility of the proposed approach, because we were able to extract synergies satisfying desired constraints which describe inter-muscular relationship, but it is still needs to be compensated; for instance, we need to employ more elaborated muscle relationship as constraints.

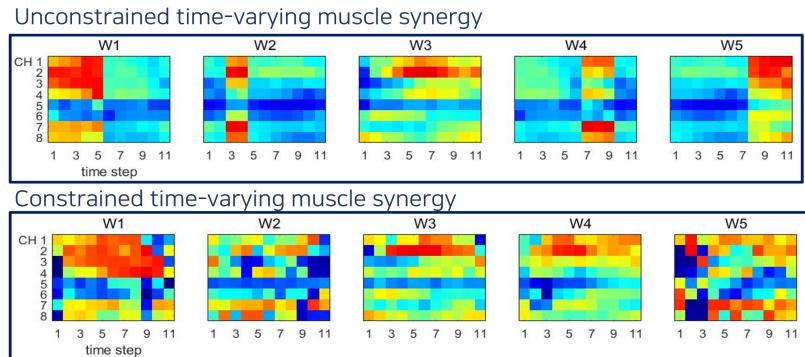


Fig. 5. Extracted time-varying muscle synergies W_i under $n = 5$ and $u = 11$.

5 Conclusion

This paper proposed a novel numerical optimization approach to extract time-varying synergies with imposing muscle relationship as constraints. To validate the proposed approach, the experiment was performed to collect the sEMG data of bicep brachii muscles, and time-varying synergies were extracted. The result showed a feasibility of the proposed approach; however, it also remained few drawbacks needed to be concerned. This study should be proceeded to the design of more elaborated or sensitive muscle relationship which will eventually be utilized as constraints to extract muscle synergies.

Acknowledgments

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