E3S Web of Conferences **271**, 03019 (2021) https://doi.org/10.1051/e3sconf/202127103019
ICEPE 2021

A Reliable Muscle Synergy Extraction Method based on Multivariate Curve Resolution-Alternating Least Squares

Yehao Ma[1,2,*], Changcheng Shi[1,2], Dazheng Zhao[1], Sijia Ye[1], Guokun Zuo[1,2]

[1]Cixi Institute of Biomedical Engineering, Ningbo Institute of Materials Technology and Engineering, Chinese Academy of Sciences, Ningbo, China
[2]Zhejiang Engineering Research Center for Biomedical Materials, Ningbo Institute of Materials Technology and Engineering, Chinese Academy of Sciences, Ningbo, China

Abstract. Muscle synergy is an important approach to evaluate motor function for patients with neurological diseases. Nonnegative matrix factorization (NMF) is the most widely used muscle synergy extraction method from electromyography (EMG) data. However, NMF usually falls into local optimum and is susceptible to noise, which significantly limit the promotion of muscle synergy. In this paper, a reliable synergy extraction method based on multivariate curve resolution-alternating least squares (MCR-ALS) was put forward. Its performance was compared with NMF through analyzing the EMG data of upper limb motor. The repeatability and intra-subject consistency were used to evaluate the two methods. As a result, MCR-ALS provided unique resolution result and better repeatability and consistency in contrast to NMF. Thus, the results of this study are of significance for the expansion and application of muscle synergy in medicine.

1 Introduction

Muscle synergy was proposed to answer how the central nervous system (CNS) to accomplish complex motor. CNS coordinately activate these synergies to overcome the complexity of limb dynamics for musculoskeletal system[1,2]. Despite the physiological origin and meaning of muscle synergies are still debated [3], it is certain that motor task execution can be described by the coordination of a limited number of muscle synergies. A muscle synergy is the activation of a group of muscles contributing to a particular movement, reducing the dimensionality of muscle control. A single muscle can be part of multiple muscle synergies, and a single muscle synergy can be made up of multiple muscles. Muscle synergy provides an important approach to quantify the covariation of the muscle during a task, and its is used to evaluate the motor function of the patients with stroke[4], spinal cord injury[5] and cerebral palsy[6].

Various matrix factorization algorithms have been used to extract muscle synergy from electromyography (EMG) data. Nonnegative matrix factorization (NMF) [4-6], principal component analysis (PCA) [7], factor analysis (FA) [8] and independent component analysis (ICA) [9] are four common muscle synergy extraction algorithms. PCA extracts the muscle synergies that best describe the EMG data's variance. ICA makes the data statistically independent through transforming it orthogonally and extract synergies that maximize the absolute value of the fourth moment of the data. FA extracts muscle synergy weights through calculating the eigenvectors of the data's covariance matrix. In contrast to PCA, ICA and FA, NMF, owning simple principle, can provide positive factorization result through imposing nonnegative constraint. Thus, NMF is the most widely used algorithm for muscle synergy analysis[4-6]. However, NMF is easy to fall into local optimum and susceptible to noise[10,11], which seriously restrict the promotion of muscle synergy in motor function evaluation.

To deal with the problem, a novel muscle synergy extraction method based on multivariate curve resolution-alternating least squares (MCR-ALS) was proposed, which was used to analyze the electromyography (EMG) data of upper limb motor. Its performance was compared with the conventional synergy extraction method (NMF). The repeatability and intra-subject consistency of muscle synergy estimated by the two methods were analyzed.

2 Theory and Experiment

2.1 Muscle synergy pattern model

In the muscle synergy theory, the EMG signals are weighted summation of activation coefficients containing the activation time information of several muscle groups. the weights, reflecting relative activation strengths of multiple muscles, make up synergy matrix. Thus, the muscle synergies can be estimated through resolving EMG data as the following bilinear model [4]:

$$D = CS + E \quad (1)$$

* Corresponding author: mayehao@nimte.ac.cn

where D is the $m \times n$ matrix consisting a set of m preprocessed EMG signals and n data points for each EMG signal correspondingly; C is the $m \times r$ matrix of muscle synergy reflecting relative activation strengths of multiple muscles; r is the number of muscle synergies; S is the activation matrix with the size of $r \times n$; E is residual matrix with the size of $m \times n$.

2.2 Experimental data

Twenty-one healthy subjects (age range 25-37 yr, mean age 26.1 yr) volunteered to participate in this study. The healthy subjects had no neurological disorder history. The experimental protocol conformed to the Declaration of Helsinki. Written informed consents were obtained from all subjects according to the procedures of the Ethics Committee of Cixi Institute of Biomedical Engineering.

The EMG data used in this study were collected from upper limb movement based on an rehabilitation robot. Subjects sat on a chair with their back straight. The resistance of robot was adjusted to a uniform and comfortable level for each subject. Each subject performed upper limb movements with the trajectory of circle (Fig. 1). In the experiment, subjects sat on the side of upper limb rehabilitation robot, and operated a shot stick by their evaluated upper limb (dominant hand of healthy subject) to accomplish the task repeatedly (six trials for each subject). The consuming time of each trial was about 3 s.

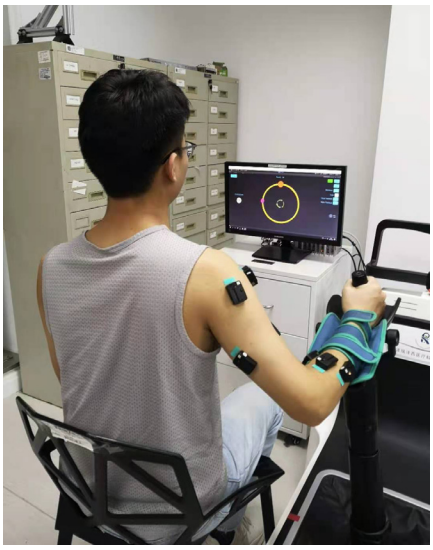

Fig. 1. The upper limb movement experiment based on rehabilitation robot.

The EMG data of seven muscles, including anterior deltoid (DA), posterior deltoid (DP), triceps brachii (TI), biceps brachii (BI), extensor carpi radialis (ECR), flexor carpi radialis (FCR), brachioradialis (BIO), were recorded using a 16-channels EMG system (Delsys Inc., Boston, MA) with sampling frequency 1926 Hz. Before place the EMG sensors, the excessive hair was shaved from skin. The alcohol was applied to wipe the skin to remove oils and surface residues. The raw EMG signals were banded-pass filtered between 40 and 400 Hz (3th order zero-lag Butterworth) to remove the noise and drifts. The filtered EMG signals were full-wave rectified and low-pass filtered at 5 Hz (3th order zero-lag Butterworth) to calculate the envelopes of EMG signals [12,13]. Before muscle synergy calculation, each envelope was normalized with the maximum amplitude of the envelope itself [14].

3 Methodology

3.1 NMF

NMF, firstly proposed by Lee and Seung [16], is the most widely used muscle synergy extraction method [4-6,12]. Muscle synergies are resolved through iterative optimization (multiplicative update rules) after random initial matrices (C and S) creation. The iteration is to minimize the Frobenius norm of residual matrix (preprocessed EMG matrix D minus multiplication of the matrix S and C) illustrated by Equation (2). The stop criterion was set based on the parameter Q, the percentage of change in the lack of fit between two iterations (f_l(S,C) and f_{l+1}(S,C)), which was calculated by Equation (3). The stop criterion was: 1) Q equaled to 0.01%; 2) max number of iterations equaled to 1000.

$$f(S,C) = \frac{1}{2}\left\|D - CS\right\|_F^2 \tag{2}$$

$$Q = 100 \cdot \left(\frac{f_{l+1}(S,C) - f_l(S,C)}{f_l(S,C)} \right) \tag{3}$$

3.2 MCR-ALS

MCR-ALS is a popular matrix factorization algorithm used to resolve component information from mixture system [17]. In this study, the initial matrices of MCR-ALS were obtained from self-modeling mixture analysis (SMMA). In addition, alternating least squares (ALS) was used to optimize the initial resolution according to Equation (4) and Equation (5). In the iterative process, nonnegative constraint was imposed. The stop criterion of MCR-ALS was the same as NMF (Q equaled to 0.01%; max number of iteration equaled to 1000).

$$C = (DS^T)(SS^T)^{-1} \tag{4}$$

$$S = (C^T C)^{-1} C^T D \tag{5}$$

3.3 Algorithm Evaluation

The repeatability of different algorithms was evaluated through analyzing the variation of repeated estimated synergies (25 times) utilizing Pearson's correlation coefficient. The evaluation was based on the similarity between matched synergies extracted from any two repeated performances. The analysis was to match the synergies extracted from two performances for the same dateset (trial). The pair of synergies with the highest correlation were matched together. The correlation

coefficients of all possible combinations of full matched synergies extracted from 25 repeated performances were used to assess the repeatability of the two algorithms.

The intra-subject consistency of synergies across multiple trials of each subject was applied to evaluate the robustness of the two synergy extraction algorithms. The intra-subject consistency was calculated through analyzing Pearson's correlation coefficient between each pair of trials for each subject. The correlation coefficients of all possible combinations of full matched synergies from the two trial data sets were calculated respectively. For each subject, the average correlation coefficient of all trial combinations was considered as intra-subject consistency.

4 Results

In this study, variance account for (VAF), reflecting similar degree between the reconstruction data and original data, was used to determine the number of muscle synergies. The number of muscle synergies was the minimum when VAF exceeded 80%[18]. For each subject, 3 muscle synergies were enough to reconstruct the EMG data accurately. Muscle synergies were extracted with average VAF values of 87.82±4.80% and 88.05±4.65% for NMF and MCR-ALS, respectively. Thus the two methods had close reconstruction performances.

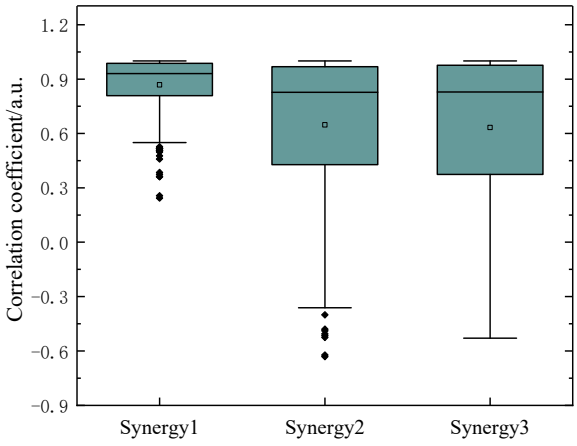

Fig. 2. The boxplots of the correlation coefficients of muscle synergies extracted from one typical trial data using NMF.

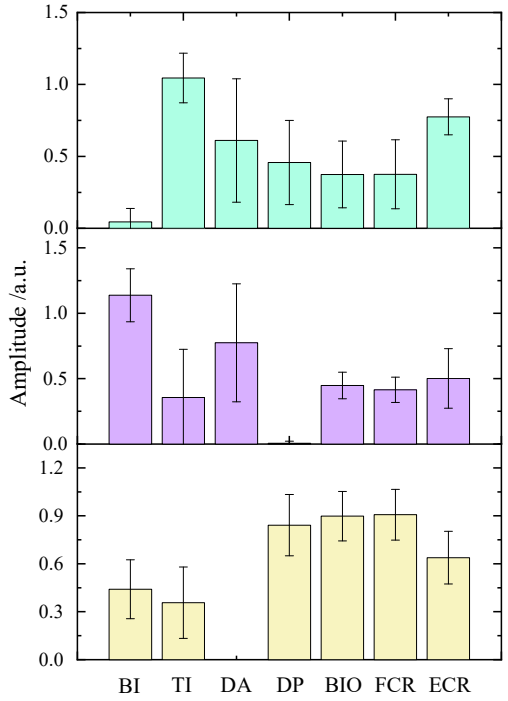

Fig. 3. The statistical chart of synergies extracted from one typical trial data by NMF.

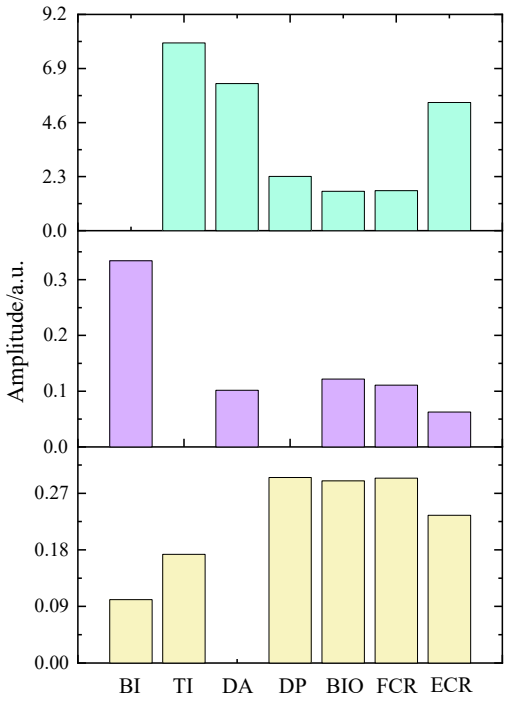

Fig. 4. The statistical chart of synergies extracted from one typical trial data by MCR-ALS.

To compare the repeatability of MCR-ALS and NMF, we analyzed 25 repeated resolution results for each trial dateset. For all subjects, the average repeatability of NMF was 0.87±0.10. Thus, NMF had a large volatility in repeatable performances. Fig. 2 shows the boxplots of the correlation coefficients of muscle synergies extracted from one typical trial EMG data. As seen in Fig. 2, the average correlation coefficients of three synergies were 0.87, 0.65, 0.63, respectively, with their box lengths 0.19, 0.54 and

0.61. Obviously, NMF presented inferior repeatability for the upper limb movement data. However, MCR-ALS could provide unique resolving result through pure variables extraction in initialization phase, thus its repeatability was 1 [19]. Fig. 3 and Fig. 4 show the muscle synergies estimated by NMF and MCR-ALS from one typical trial data. The synergies identified by NMF had large standard deviations, especially for the synergy 1. However, MCR-ALS provided unique resolution results. Fig. 5 shows the statistical results of intra-subject consistency of the synergies resolved by the two methods. The consistencies of NMF and MCR-ALS were equal to 0.93±0.04 and 0.84±0.08, respectively. Obviously, NMF had inferior consistency in contrast to MCR-ALS. The main reason might be that NMF is easy to fall into local optimum in estimating muscle synergy.

From the study, NMF could not supply satisfactory performance. In contrast, MCR-ALS could provide more reliable synergy identification, which had great significance for the promotion of muscle synergy in medicine.

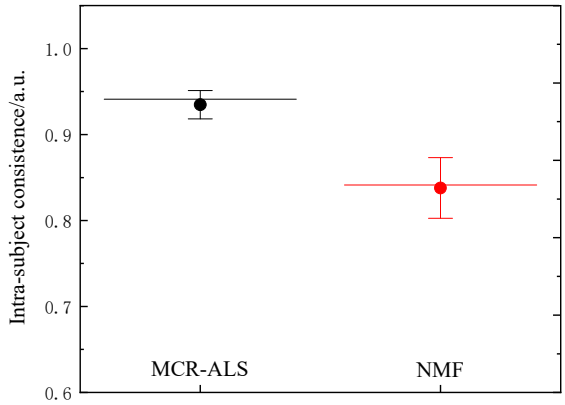

Fig. 5. Average (±SE) values of consistency computed to compare the standard method (NMF) and the novel method (MCR-ALS).

5 Conclusion

In this study, a novel muscle synergy extraction method called MCR-ALS was proposed. Its performance was compared with NMF through analyzing EMG data of upper limb movement. The results show that 1) The problem of non-unique decomposition of NMF was worked out by MCR-ALS; 2) In contrast to NMF, MCR-ALS presented greater reliability in synergy identification, In addition, MCR-ALS produced positive decomposition results through imposing nonnegative constraint. Therefore, MCR-ALS is a promising muscle synergy extraction method. The results of this study are of great significance for promoting the application of muscle synergy to motor function evaluation.

Acknowledgments

This work was supported by the Chinese Postdoctoral Science Foundation (2019M662128), the Major Scientific and Technological Projects in Ningbo City (2018B10073, 2019B10034), the Key Research and Development Program of Zhejiang Province (2019C03090), the Zhejiang Provincial Natural Science Foundation of China (LQ20F030003), the Ningbo Natural Science Foundation (2019A610089).

References

1. M.C. Tresch, P. Saltiel, A. d'Avella, E. Bizzi, Brain Res. Rev. **39**, 66 (2002)
2. L.H. Ting, H.J. Chiel, R.D. Trumbower, J.L. Allen, J.L. McKay, M.E. Hackney, T.M. Kesar, Neuron **86**, 38 (2015)
3. M.C. Tresch, A. Jarc, Curr. Opin. Neurobiol. **19**, 601 (2009)
4. V.C.K. Cheung, A. Turolla, M. Agostini, S. Silvoni, et al, PANS **109**, 14652 (2012)
5. H. B. Hayes, S. A. Chvatal, M. A. French, L. H. Ting, R. D. Trumbower, Clin. Neurophysiol. **125**, 2024 (2014)
6. L. Tang, X. Chen, S. Cao, D. Wu, G. Zhao, X. Zhang, Front. Hum. Neurosci. **11**, 130 (2017)
7. L. H. Ting, J. M. Macpherson, J. Neurophysiol. **93**, 609 (2005)
8. P. Kieliba, P. Tropea, E. Pirondini, M. Coscia, S. Micera, F. Artoni, IEEE Trans. Neural Syst. Rehabilit. Eng. **26**, 882 (2018)
9. W. J. Kargo, D. A. Nitz, J. Neurosci. **23**, 11255 (2003)
10. Y. Ma, X. Li, P. Huang, et al, Spectrochim. Acta A **177**, 49 (2017).
11. M. W. Berrya, M. Browne , A. N. Langville , V. P. Pauca, R. J. Plemmons, Comput. Stat. Data An. **52**, 155 (2007)
12. M. Baniasad, F. Farahmand, M. Arazpour, H. Zohoor, Hum. Movement Sci. **62**, 184 (2018)
13. N. Yang, Q. An, H. Kogami, H. Yamakawa, Y. Tamura, et al, IEEE Trans. Neural Syst. Rehabilit. Eng. **27**, 2118 (2019)
14. F. O. Barroso, D. Torricelli, J. C. Moreno, J. Taylor, et al. J. Neurophysiol. **112**, 1984 (2014)
15. D. J. Clark, L. H. Ting, F. E. Zajac, R. R. Neptune, S. A. Kautz, J. Neurophysiol. **103**, 844 (2009)
16. D. D. Lee, H. S .Seung, *14th Annual Neural Information Processing Systems Conference*, (Denver, 2000)
17. S. Horii, M. Ando, A. Z. Samuel, et al, J. Nat. Prod. **83**, 3223 (2020)
18. S. Li, C. Zhuang, C. M. Niu, Y. Bao, Q. Xie, N. Lan, Front. Neurol. **8**, 337 (2017)
19. W. Windig, J. Guilment, Anal. Chem. **63**, 1425 (1991)