

# Identifying the Muscle Synergy Pattern during Human Grasping

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## ABSTRACT

In this work, a methodology has been proposed and evaluated for identification the muscle synergy patterns during human grasping. The proposed approach is based on decomposition analysis of involved muscle activation profiles utilizing the Hierarchical Alternating Least Squares (HALS) algorithm. The surface EMG signals of Flexor Digital Superficialis and Flexor Pollicis Longus muscles were recorded during grasping a cylindrical object. EMG signals were full-wave rectified and smoothed through a low pass filter. Then the HALS algorithm was utilized for decomposition of muscle activation profiles. The HALS algorithm can be efficiently used instead of NNMF (non-negative matrix factorization) method. The HALS method not only provides a very good convergence property but also there is not the non-negativity constraint for the decomposed factors. The results of evaluations are interesting and promising.

**Key words:** Surface EMG, Hals algorithm, muscle synergy

## 1 Introduction

A functional muscle synergy means the pattern of co-activation of muscles recruited by a single neural command signal [2]. The central nervous system (CNS) uses multiple joints and muscles to perform the stable and flexible goal-directed movements. Existence of muscle synergies as a neural strategy has been proposed to justify how the CNS can solve the problem of redundancy and how it copes with complexity of control problem [1,7and13].

In recent years, many evidences have been presented proving modularity during the performance of different motor tasks in humans and other animals [3, 4]. According to modular control hypotheses, the motor primitives that are organized at the spinal level are modules that in a linear or non-linear manner can be combined to produce enormous collection of movements [2]. Muscle synergies are the possible candidates for motor primitives [10]. It is also has been shown that the decomposition of EMG envelope can be resulted in identifying a small number of muscle synergies [7, 14]. There are two main models for muscle synergies called synchronous muscle synergies and asynchronous muscle synergies [7, 8, and 9].

Recently, Castellini et al. [6], have presented the evidences of synchronous muscle synergies during human grasping using Principal Component Analysis (PCA). In this paper, we focused on human hand grasping while the wrist joint is at rest position. We analyzed the recorded SEMG signals of two muscles being involved in grasping a cylindrical object. We used NNMF method for EMG decomposition. Because it does not impose orthogonally and statistical independence (such as PCA and ICA respectively) [8,9]

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and it seems more suitable for extracting the entire muscle synergies[5]. Nevertheless, the standard NNMF applies non-negativity constraint for the decomposed factors. Since, smoothed full-rectified EMG are used for decomposition, the modified EMG may have the negative values for no ideality of smoothing filters. So, in this paper, the HALS algorithm has been used instead of NNMF method [12]. The HALS method does not apply such constraint. In addition, using The HALS results in achievement both better accuracy and repeatability [11].

The archived results show the acceptable performance of proposed methodology.

## 2 Method and Materials

### 2.1 Muscle synergy model

In the synchronous synergy model, the EMG can be decomposed as a linear combination of set of vectors capturing a specific balance of muscle activations [7], by a time-variant activation coefficient.

$$M(t) = \sum_{i=1}^k c_i(t) \cdot \vec{w}_i \quad (1)$$

$M$  Represent the time-varying muscle activation pattern of  $d$  involved muscles.  $\vec{w}_i$  is the  $i$ th  $d$ -dimensional basis vector.  $c_i(t)$ , is the scalar activation coefficient for the  $i$ th basis vector.

In fact, each  $\vec{w}_i$  represents a muscle synergy related to the synaptic weights from premotor neurons to different motor neuronal pools, each  $c_i$  represents the synergy activation coefficient or firing frequency recruiting a synergy.

#### 2.1.1 Non-Negative Matrix Factorization

Most non-negative matrix decomposition methods are attributed to researchers such as Lee and Seung in which is the observation matrix [13]. Let's suppose:

$$M = C W + E \quad (2)$$

$$W = [w_1, w_2, \dots, w_j] \in R_+^{I \times T} \quad (3)$$

$$C = [c_1, c_2, \dots, c_j] \in R_+^{I \times T} \quad (4)$$

Where  $W$  and  $C$  are matrices containing the basis vectors and activation coefficients and  $E$  represents estimation error.

Let's define a cost function for a  $w_j$  and its corresponding coefficient  $c_j$  using the Frobenius norm as follows:

$$D_F^j(M^j | c_j w_j) = \frac{1}{2} \|M^j - c_j w_j\|_F^2 \quad (5)$$

### 2.2 HALS Algorithm

In this manner we will have a bank of local cost functions. By minimizing the cost functions consecutively, based on the optimality conditions (KKT) [12], the stationary points of local cost function can be estimated using the gradient of local cost functions as follows:

$$\nabla_{c_j} D_F^j(M^j) ||c_j w_j^T \geq 0 \tag{6}$$

$$\nabla_{w_j} D_F^j(M^j) ||c_j w_j^T \geq 0 \tag{7}$$

Where the gradient of the local cost function can be estimated as follows:

$$\nabla_{c_j} D_F^j(M^j ||c_j w_j) = \frac{\partial D_F^j(M^j ||c_j w_j)}{\partial c_j} = c_j w_j^T c_j - M^j w_j \tag{8}$$

$$\nabla_{w_j} D_F^j(M^j ||c_j w_j) = \frac{\partial D_F^j(M^j ||c_j w_j)}{\partial w_j} = c_j^T c_j w_j - M^j c_j \tag{9}$$

If it is assumed the  $c_j$  and  $w_j$  are positive number then the stationary points can be estimated using the update laws as follows:

$$w_j \leftarrow \frac{1}{c_j^T c_j} \left[ M^j{}^T a_j \right] + = \frac{1}{c_j^T c_j} \max\{\varepsilon, M^j w_j\} \tag{10}$$

$$c_j \leftarrow \frac{1}{c_j^T c_j} \left[ M^j{}^T a_j \right] + = \frac{1}{c_j^T c_j} \max\{\varepsilon, M^j w_j\} \tag{11}$$

Where  $\varepsilon$  is a small positive number, above update rules are known as the HALS algorithm was proposed by Chikoki et al. [14].

### 2.3 Data Collection and Preprocessing

Ten healthy participants, men and women, are asked to hold a one-kilogram cylinder in their hands for 10 seconds and then drop it, and repeated it again for five times. During the experiments the wrist joint of the participants were at the rest posture. The recorded EMG signals was rectified and passed through a low-pass filter with 20 Hz cut-off frequency. Then, the obtained signals were normalized.

## 3 Results

One of most prevalent methods being used to determine the number of synergies is based on R2 criterion. R2 represents the fraction of total variation accounted for by the synergy reconstruction (Eq. 12), [15].

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_s \sum_{k=1}^{k_j} ||m^j(t_k) - \sum_i c_i^j w_i(t_k - t_i^j)||^2}{\sum_s \sum_{k=1}^{k_j} ||m^s(t_k) - \bar{m}||^2} \tag{12}$$

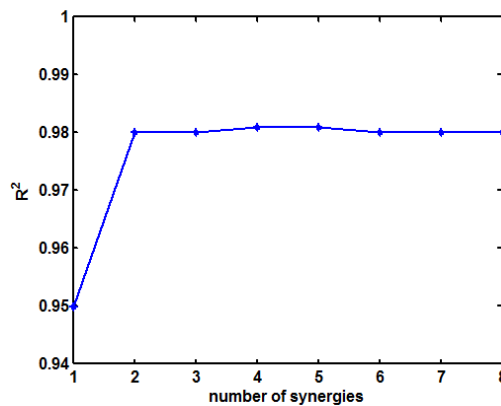
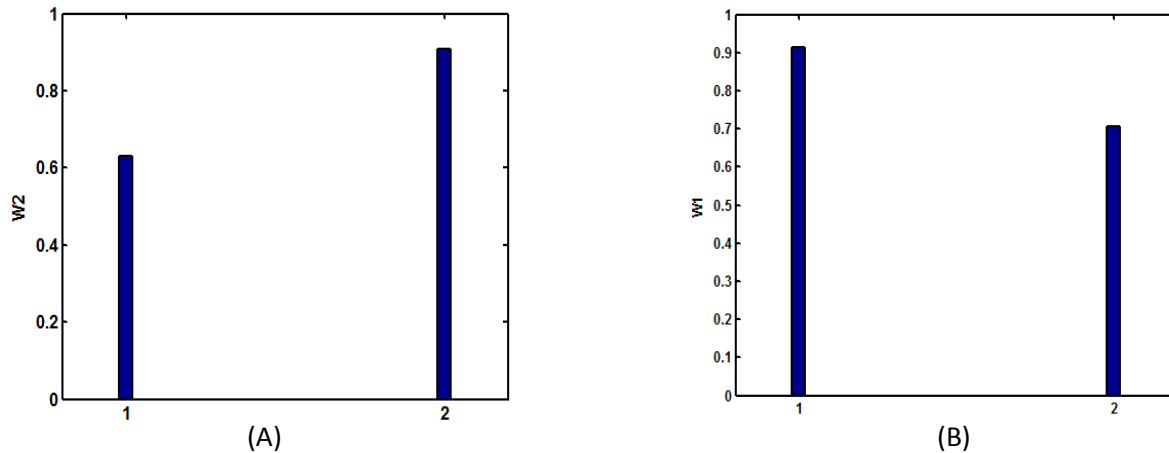


Figure 1: R2 changes versus the number of synergies.

Where  $SSE$  is the sum of the squared residuals,  $SST$  is the sum of the squared residual from the mean activation vector ( $\bar{m}$ ). As the Fig.1 indicates, the slope of  $R^2$  changes has been decreased considerably at 2. So, in this work the number of selected synergies is 2.



**Figure 2: Shows the activation level of the two involved muscles corresponding to each synergy pattern**

In the next step, basis vectors and activation coefficients were estimated using HALS algorithm described in the previous section. Figure 2, shows the activation level of the two involved muscles corresponding to each synergy pattern.

#### 4 Discussion

In figure 3, the muscle synergy pattern during object grasping was extracted using analyses of computed muscle activation profiles relating to two involved muscles. In this research, HALS algorithm and NMF were utilized for identifying the synergy vectors.

HALS algorithm is known as a fast convergent approach without non-negativity constraint for the decomposed factors [11, 14]. In the other hand, the main purpose of the present study was to achieve the proper muscle synergy patterns by solving the problem of nonnegative matrix analysis. For quantitative evaluation of the propose approach, the root mean square (RMS) of the error signal, the difference between the reconstructed muscle activation profiles and actual activation profiles, were calculated [Table 1]. The calculations show the low difference between the actual and reconstructed signals. This can be due to the efficiency of HALS algorithm; however there is difference between actual signal and reconstructed signal by NMF algorithm.

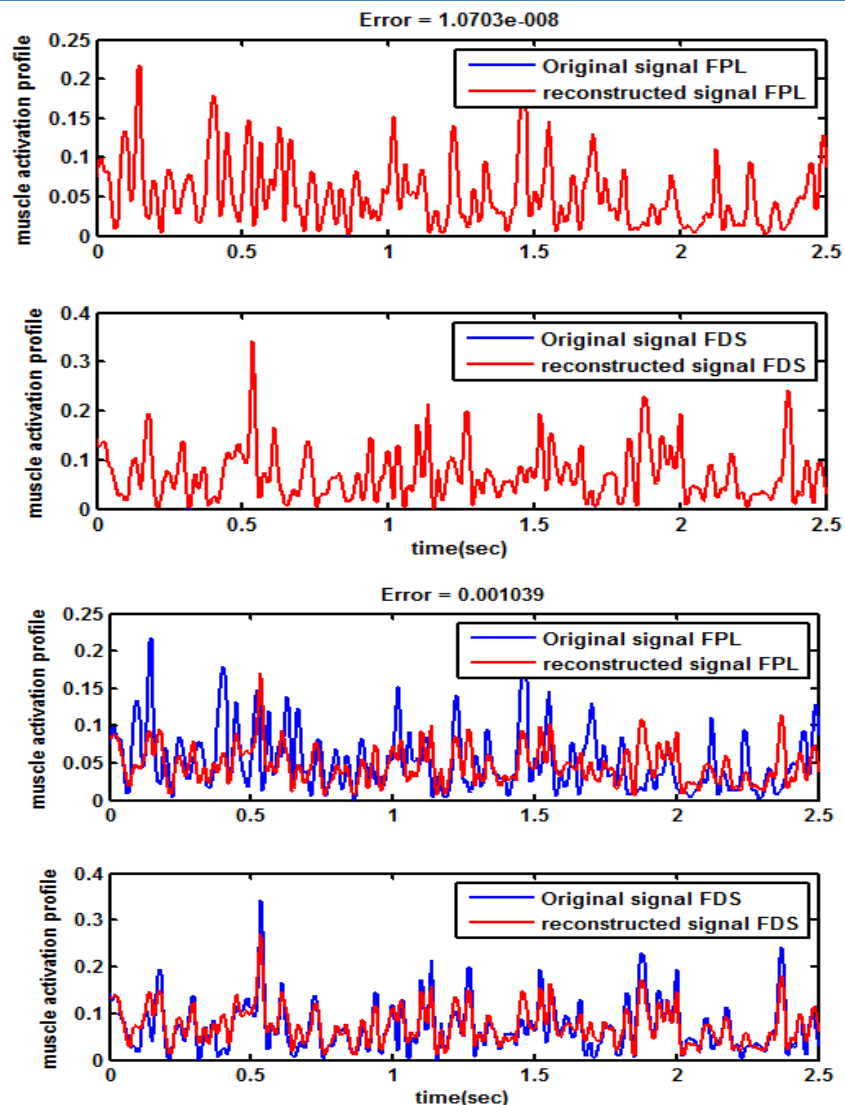
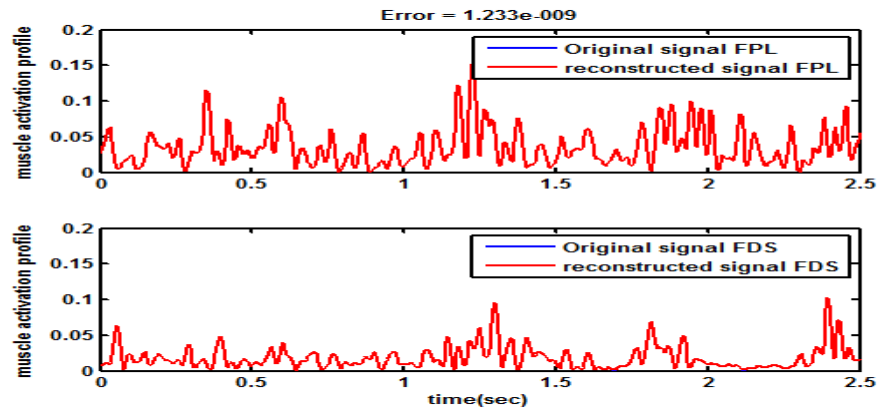


Figure 3: Comparing the reconstructed muscle activation with the original signals by 3 numbers of synergy, (A) demonstrate HALS algorithm and (B) demonstrate NNMF. FDS: demonstrates signals of Flexor Digital Superficialis, FPL: demonstrates signals of Flexor Pollicis Longus

Table 1: Demonstrate RMS of both algorithm (Hals, NNMF) for Flexor Digital Superficialis, Flexor Pollicis Longus

Subject	Rms(Hals) FDS× 10 <sup>-8</sup>	Rms(Hals) FPL× 10 <sup>-8</sup>	Rms(NNMF) FDS× 10 <sup>-4</sup>	Rms(NNMF) FPL× 10 <sup>-4</sup>
Male1	1.1511	1.2334	2.3647	2.2103
Male2	1.4567	1.9712	2.1999	2.3614
Male3	1.8835	1.3451	3.8041	3.1200
Male4	1.3260	1.0241	2.3330	2.3212
Male5	1.1249	1.7503	3.0100	3.0144
Female1	1.0241	1.0021	2.4851	2.4851
Female2	1.7503	2.0144	3.3541	3.3541
Female3	1.0021	1.0222	3.0144	1.0039
Female4	2.0006	2.0314	1.4729	3.1533
Female5	1.0703	1.3766	2.0342	2.0342



**Figure 4: Comparing the reconstructed muscle activation with the original signals by 2 numbers of synergy, HALS algorithm**

If number of synergies over estimated, we are going to compare the performance of reconstruction method base on HALS algorithm.

In figure.4, showed that when the number of synergies are over estimated (more than 2 synergies), there was not seen any difference between the actual signal and reconstructed signal. After identifying the synergy vectors, the activation profile of two involved muscles were reconstructed using the estimated basis vectors and coefficients. The reconstructed profiles were compared to the actual activation profiles. Figure 3, 4 and table 1, show reconstructed muscle activation profiles, computed, accompanied by actual computed muscle activation profiles. This research illustrated for the first time, it could be reconstructed signals by the minimizing of the number of synergies like 2 synergies.

Identifying the muscle synergy patterns, quantifying the modular organization of motor control, can provide insights on novel diagnostic and rehabilitation tools [11]. The achieved results prove the presented method has potential application to the neuron- rehabilitation.

## 5 Result

Difference between the reconstructed muscle activation profiles and actual activation profiles, were calculated for ten participants in hand grasping. The calculations showed the low difference between the actual and reconstructed signals. This can be due to the efficiency of HALS algorithm.

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## REFERENCES

- [1] M. C. Tresch and A. Jarc., "The case for and against muscle synergies". *Current Opinion in Neurobiology*".19, 601-607, 2009.

- [2] Bernstein, N. "The coordination and regulation of movements". Pergamon Press, Oxford.1967.
- [3] Lacquaniti, F., Ivanenko, Y.P., Zago, M. "Patterned control of human locomotion". J. Physiol. 590, 2189–2199 .2012.
- [4] Bizzi, E., Cheung, V.C., d'Avella, A., Saltiel, P., Tresch, M. "Combining modules for movement". Brain Res. Rev. 57, 125–133. 2008.
- [5] D. Ioannis, B. Bastien, P. Thierry and P. Stefano, "A methodology for assessing the effect of correlations among muscle synergy activations on task-discriminating information", *Frontiers in Computational Neuroscience*, 7, 2013, Article 54.
- [6] Castellini, C., van der Smagt, P. "Preliminary evidence of dynamic muscular synergies in human grasping". In: *Proceedings of ICAR -International Conference on Advanced Robotics*, 28-33 (2011).
- [7] A. d'Avella, P. Saltiel and E. Bizzi, "Combinations of muscle synergies in the construction of a natural motor behavior", *Nat Neurosci*, 6, 300–308. 2003.
- [8] L. Omlor and M. A. Giese, "Anechoic blind source separation using wigner marginal" *J. Mach. Learn.Res.*, 12, 2011, 1111–1148.2011
- [9] A. d'Avella, L. Fernandez, A. Portone and F. Lacquaniti, "Modulation of phasic and tonic muscle synergies with reaching direction and speed", *J. Neurophysiol*, 100, 1433–1454, 2008.
- [10] E. Bizzi, A. D'Veila, P. Saltiel and M. Tresch, "Modular organization of spinal motor systems", *Neuroscientist*, 8,437–442, 2002.
- [11] A. H. Phan and A. Cichocki, "Multi-way nonnegative tensor factorization using fast hierarchical alternating least squares algorithm (HALS)", In *Proc. of the 2008 International Symposium on Nonlinear Theory and its Applications*, Budapest, Hungary, 2008.
- [12] Cichocki, A., Zdunek, R., & Amari, S. I., "Hierarchical ALS Algorithms for Nonnegative Matrix and 3D Tensor Factorization", in *ICA07*, London, UK, September 9-12, *Lecture Notes in Computer Science*, 2007,4666, pp. 169-176.2007.
- [13] Lee, D. D., & Seung, H. S., "Algorithms for Nonnegative Matrix Factorization", *Advances in neural information processing systems*, 13, 556-562,2001.
- [14] A. Cichocki, R. Zdunek, A. H. Phan and S. Amari, "Nonnegative Matrix and Tensor Factorizations", John Wiley & Sons Ltd: Chichester, UK, 2009.
- [15] Andrea d'Avella, Alessandro Portone, Laure Fernandez and Francesco Lacquaniti, "Control of fast-reaching Movements by Muscle synergy combinations. *J.Neuroscience*, 26,77917810, 200