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Modulation of Phasic and Tonic Muscle Synergies during Hand Movement

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ABSTRACT

Hand movement is done in such a way that data is transferred to motor cortex through brain Broca. The motor cortex receives a fixed motion from cerebellum. In the next stage, synergic patterns are sent to muscles in the form of motor orders. In some researches, it has been indicated that muscle movement patterns involved in motor function are linear combination of basic vectors with varying coefficients each of which are capable of producing different time-space activating patterns of arm muscles when hand movement occur. In order for basic vectors to be estimated, an HALS algorithm and PCA were used as being efficient at extracting muscle synergic patterns. Three synergies have been extracted from healthy people and compared with each other. In this method, in order to extract synergy pattern, the sEMG signals of Biceps-brachii, Flexor Digital Superfacialis, Flexor pollicis longus, and Brachio radialis muscles have been used.

INTRODUCTION

Applying electrical stimulation externally leads to nerve stimulating pulses being generated on the wall of nerve fibers. Generated through nerve fibers, stimulating pulses move towards motor unites and contracts the muscles. Muscle contraction results in generating torque around joints, which might be followed by a motion in disabled or handicapped organ (Marsolais, E.B., R. Kobetic, 1988). Therefore, by generating different motions in different organs, it is possible for motion-disordered people to perform some particular functions such as picking up and dropping an object or raising hand. There is a limited range of muscle synergies for each person, which is able to create different time-space activating patterns. The pattern of each synergy will determine to what extent each muscle contrebutes to the function of that particular muscle. Every muscle activation patterns is a linear combination of synergy patterns with different coefficients (Marsolais, E.B., R. Kobetic, 1988).This model is compatible with the idea of rule based, feed-forward control of dynamic joint torque (D'avella, A., E. Bizzi, 2005) As a result, the output of commands that are produced creates a proper combination of the synergy vectors on the contribution of which the overall pattern is created. (D'Avella, A., 2003) In studies with non-negative matrix decomposition method (Cichocki, A., 2009; Berry, M.W., 2007; Cichocki, A., 2007) the classical method and fundamental component analysis methods (Cichocki, A., 2009) and reduced gradient (D'Avella, A., 2006) have been considered given the fact that the mentioned methods encounter problems such as non-repeatable analysis and provide non-unique synergies. In this paper, the HALS algorithm (Tresch, M.C., 2006) was used because it does not have these shortcomings. Also, given the fact that the electromyogram signals are composed of two phasic and tonic parts, by removing tonic components, the remained EMG signal obtain negative values.

II. Method and materials:

In this paper, firstly, 8 healthy people were asked to contract and extend their hands for 10 seconds, which was repeated for 5 times. Ultimately, resulting signal was rectified and passed through a low-pass filter with 20 Hz cut-off frequency. Then, the obtained signal was normalized. In order to remove the tonic component

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(synergies counteracting gravity and stabilize posture during movement) by fitting a linear ramp and earn the phasic component (synergies responsible for accelerating and decelerating the arm during the movement), the method used in the article was used (D'Avella, A., 2006). In order to estimate the activity of each muscle in the initial and final positions, the EMG signals were averaged from time to time in order to prepare the motion to 200 milliseconds before taking the object and 200 milliseconds after taking the object completed and to make sure that estimated tonic component is subtracted from SEMG signal.

RESULT AND DISCUSSION

3.1. Synergy pattern:

We first tested the performance of each algorithm on data sets with- Known statistical properties. In all cases, each data set was constrained to contain only nonnegative data. Simulated data were generated as a weighted combination of basis vectors:

$$\vec{d} = g\left(\sum_{i=1}^{k} c_i \vec{w}_i + \vec{\varepsilon}\right) \quad (3.1)$$

Coefficient for the ith basis vector, $\vec{\varepsilon}$ is an M-dimensional noise vector, and $\vec{y}=\overrightarrow{g(x)}$is a thresholding function such that yi = 0 for xi < 0 and yi = xi for xi ≥ 0. This thresholding function $g(\vec{x})$ enforces the nonnegative constraint. Each basis vector was scaled to have a vector norm of 1.In a physiological context, $\vec{d}$ represents the observed EMG activity for M recorded muscles, each $\vec{w}$i represents a muscle synergy related to the synaptic weights from pre- motor neurons to different motoneuronal pools, each ci represents the synergy activation coefficient or firing frequency recruiting a synergy, and $g(\vec{x})$ is roughly related to the thresholding function of motor neurons. In the context of principal component analysis, $\vec{d}$ represents the data to be decomposed, the $\vec{w}$i values constitute the principal components, and the ci values are the component scores. Here, we will refer to the ci as activation coefficients and the $\vec{w}$i values as synergies or basis vectors. Each of these variables was manipulated within the simulated data sets to examine the performance of different algorithms. Although many different types of data sets could be examined, we focus only on those that are relevant to experimental data sets.

3.2. Extraction of synergy:

One of methods used for extracting a number of synergies is R2 criterion. *R*2 represents the fraction of total variation accounted for by the synergy reconstruction.

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_s \sum_{k=1}^{k_j} ||m^j(t_k) - \sum_i c_i^j w_i\left(t_k - t_i^j\right)||^2}{\sum_s \sum_{k=1}^{k_j} ||m^s(t_k) - \bar{m}||^2} \quad (3.2)$$

Where *SSE* is the sum of the squared residuals, *SST* is the sum of the squared residual from the mean activation vector ($\bar{m}$). Firstly, the number of phasic muscle synergies required to adequately reconstruct the muscle patterns for the movements must be determined. For these movements, the tonic waveform of each muscle was estimated by fitting a linear ramp and was subtracted from its total waveform to obtain a phasic wave form. EMG signals have negative values after tonic waves have been removed from it. For each subject, sets of one to 4 muscle synergies are identified from the postural muscle patterns averaged over trials in the same direction by using HALS algorithm and PCA algorithm. Three postural muscle synergies were selected for each subject. Then, we extracted sets of one to three time-varying synergies from the phasic waveforms for movements in the group of trials with the shortest duration in all 4 directions ($0^0, 30^0, 45^0, 90^0$) time-normalized to unit movement duration and averaged over trials in the same direction**.** Sets with three synergies are selected in all subjects like the number of synergies at which the curve of reconstruction R^2 had a clear change in slope. Therefore, the three synergies were extracted. The R^2 value for three synergies ranged from 0.88 to 0.93 among subjects. Generally, the median of the distribution of the R^2 values of all the regressions were around 0.87. (fig.1)

3.3. Hals algorithm (Hierarchical algorithm least square:

Most non-negative matrix decomposition methods are attributed to researchers such as Lee an Seung in which is the observation matrix.

$$Y = A_{\pm} X_{\pm} + E \quad (3.3)$$

$$X = B^T = [b1, b2, \ldots bj] \in R_+^{I\times T} \quad (3.4)$$

$$A = [a1, a2, \ldots, aj] \in R_+^{I\times T}$$

Y= is a known input data matrix
A = is an unkown Basis matrix with non-negative vectors
X=is a matrix representing unknown nonnegative components
E = represents error or noise
Y vectors must be normalized to unit length.
HALS algorithm can be described in five stages.

1. Initializing a randomly or using the recursive application of Perron-Frobenius theory to SVD.
2. Estimating $\boldsymbol{X}$ from the matrix equation$A^T AX = A^T Y$ by solving.

$$\min_X D_F(Y = AX) \frac{1}{2} \|Y - AX\|_F^2 \tag{3.5}$$

3. Setting all negative elements of $\boldsymbol{X}$ to zero or a small positive value.
4. Estimating $\boldsymbol{A}$ from the matrix equation $X X^T A = XY^T$

$$\min_A D_F(Y = AX) \frac{1}{2} \|Y^T - A^T X^T\|_F^2 \tag{3.5}$$

5. Setting all negative elements of $\boldsymbol{A}$ to zero or a small positive value ε.

Y is a constructed signal with different rows and columns. There are several methods to reduce the number of rows and columns from matrix Y. One way is selecting the first or second row or column or averages them. Another approach is to cluster all rows and columns.

Minimizing the cost function based on the optimality conditions (KTT) and calculating the gradient of local cost function

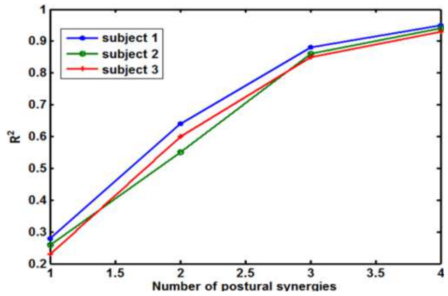


Fig. 1: The number of synergies which is selected by R^2.

3.4. PCA (Principle Component Analysis):

PCA was invented in 1901 by Pearson (Abdi, H., L.J. Williams, 2010). It was later independently developed independently (and named) by Hotelling in the 1930s. (Pearson, K., 1901). PCA is mostly used as a tool in exploratory data analysis and for making predictive models. PCA can be done through by eigenvalue decomposition of a data covariance or singular value decomposition of a data matrix, usually after mean centering and normalizing the data matrix for each attribute. The results of a PCA are usually discussed in terms of component scores, sometimes called factor scores.

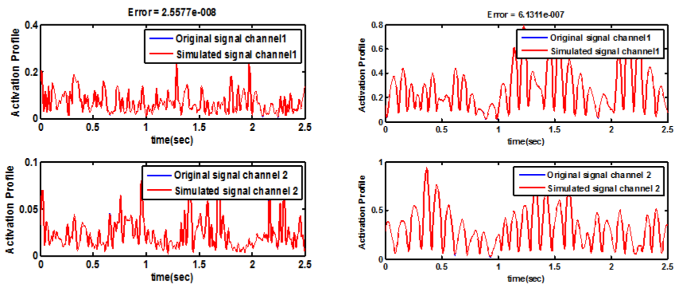
$$Q\left(PC_{(j)}, PC_{(k)}\right) \propto \left(Xw_{(j)}\right).\left(Xw_{(k)}\right) \tag{3.6}$$

X= data matrix and W=weigh matrix

To study the organization of the phasic muscle patterns across subjects, in figures (2,3), we first normalized in time the integrated EMG waveforms to equal movement duration. The waveform of each muscle in each trial was aligned to the time of movement onset and re-sampled, using linear interpolation with 25 samples per movement duration. They showed the variations of the postural muscle patterns after movement end across the experimental conditions were characterized by identifying muscle synergies from the mean postural EMG activity averaged over repetitions in each direction. Thus, for each subject, we computed a set of 20 vectors, each representing the average activity of all recorded muscles in one condition. Then, HALS and PCA algorithms were used to decompose each one of these muscle activity vectors. These muscle synergies capture the coordinated synchronous recruitment of groups of muscles with specific amplitude balances. Each postural synergy expressed a specific balance in the activation of the muscles and was modulated in amplitude across movement conditions. After decomposing signals, reconstructed signals could be done from the sum of vectors which have been extracted by HALS and PCA algorithms. By comparing the reconstructed signals with the original signals in figures 2 and 3, it is determined that Hals algorithm compared to PCA algorithms has the minimum error so that the reconstructed signal is able to follow the original signal very well. To reduce the discrepancy between the data matrix and reconstructed matrix, the noise distribution criteria, the data structure and components estimation was used. In this paper, HALS algorithm is used for two reasons: the first reason is that this method is used in the analysis of matrix that only have positive values and the second reason is that for every iteration in the generated responses program, they are converging to a single value.

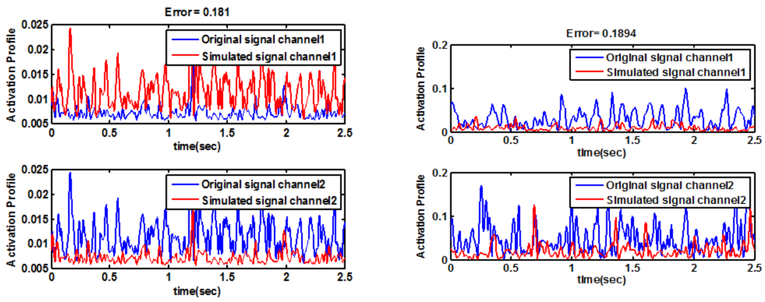
In figure(2.A) : Channel 1: demonstrates signals of Flexor Digital Superfacialis,Channel 2: demonstrates signals of Flexor pollicis longus

In figure(2.B) : Channel 1: demonstrates signals of Biceps brachii Channel 2: demonstrates signals of Brachioradial



(A) (B)

Fig. 2: comparing the reconstructed signals with the original signals in HALS algorithm.



(a) **(b)**

Fig. 3: Comparing the reconstructed signals with the original signals in PCA algorithm.

Three postural muscle synergies were selected in all 8 subjects as the number of synergies which contained the curve of the reconstruction *R*2. Each postural synergy expressed a specific balance in the activation of the muscles and was modulated in amplitude across movement conditions. For example, distinctive features of the first and third postural synergy (W1, W2) identified in 8 subjects were the strong activations of the biceps brachii and Flexor Digital Superfacialis. The structure of the second synergy (W2) was characterized by a strong activation of the Brachio radialis and Flexor pollicis longus. The results which had been collected from various directions of the postural synergies were similar for each subject. Therefore, the variations of the postural EMG activity in many shoulder and arm muscles at the end of point-to-point hand movements with different directions were well captured by the combinations of three postural muscle synergies.
(see Fig.4)

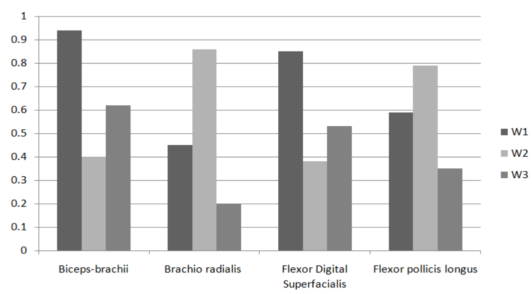


Fig. 4: Express the feature of each synergy base on the types of muscles.

Hand movement is a vital process in human life, but some nerve disorders and spinal disorders diseases can lead to the malfunction this ability (Marsolais, E.B., R. Kobetic, 1988). Many researchers have conducted synergy pattern extraction during hand movement through functional electrical stimulation. Analysis of the muscle patterns have been done with hand movements in (n) directions, which has led to a number of finding parameters that control the hand movement. First, the pattern of muscle synergy must be considered as scaling in time, scaling in amplitude, and shifting in time a few time-varying muscle synergies. Second, the muscle patterns for movement are generated by modulating two different types of time-varying synergies: phasic and tonic and the tonic must be removed. Third, the muscle activity recorded after the movement, responsible for maintaining a stable posture at the target location, is generated by the combination of a few postural time invariant synergies. Time invariant synergy means that it is not necessary to rely on time and also, it is used in muscle patterns during the maintenance of a static hand posture while a time variant synergy is used for muscle activation which is included by both synchronous and asynchronous muscle and can be different across muscle. As a matter of fact, phasic and tonic parameters can be distinguished much better via time variant synergy compared to time invariant synergy. The decomposition of muscle patterns into time invariant synergy vectors and time-varying combinations of coefficients is related, which in many cases are similar (Basilevsky, A.T., 2009) to that obtained with other algorithms such as principal component analysis (PCA), factor analysis and independent component analysis. Many research studies have been conducted on synergy extracting through main component analysis method (Lee, D.D., H.S. Seung, 2001), gradient reduction and non-negative matrix analysis (classic method) (Cichocki, A., 2007) whose goal was extraction of muscle synergy pattern in many species and behavior whose reconstructed signal are able to follow main signal with the minimum error. Synergy models not only describe functions of the controller but also provide organization and convey it to the output of a system. It must be mentioned that the number of sampling must be sufficient and provided based on central neural system. Three phasic time varying muscle synergies are extracted from the curve of R^2 . In other words, these synergies were chosen while the slope of the R^2 remained constant. In this study, the first and the third synergies have the same approach; however, the second synergy is different. As mentioned in previous sections, EMG data have been time-normalized to equal movement time and amplitude scaling of the phasic synergies in which these synergies are involved in order to generate the appropriate dynamic torques for controlling movement trajectories (Cichocki, A., 2009).

In this paper, for the first time, the muscle synergy pattern in hand movement is extracted using HALS and PCA algorithms (Tresch, M.C., 2006; Gottlieb, G.L., 1997). In general, the purpose of the present study is to achieve a proper and quick pattern in order to solve the problem of non-negative matrix analysis. This algorithm is highly resistant to noise and includes different potential functions. Also, these algorithms are useful for estimating a large number of data using local learning rules. It has been accepted that obtaining unique responses makes HALS algorithm to be the first priority when non-negative matrix needs to be analyzed because in this method, the existence of non-negative signal creates no limitation and obtains unique responses whose rate of error during signal reconstruction is lower than other methods.

IV. Conclusion:

The combination of muscle synergies could help the CNS to provide and transfer information to the different organs of body in order to move them. Three synergies are selected by R^2 and represent a wide range of muscle behavior. HALS and PCA algorithms are used in this paper in order to extract muscle synergy. The HALS algorithm is robust to noisy data and also suitable to large scale dataset due to their local learning rules and fast processing speed.

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