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A novel method of identifying motor primitives using wavelet decomposition*

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Abstract

This study reports a new technique for extracting muscle synergies using continuous wavelet transform. The method allows to quantify coincident activation of muscle groups caused by the physiological processes of fixed duration, thus enabling the extraction of wavelet modules of arbitrary groups of muscles. Hierarchical clustering and identification of the repeating wavelet modules across subjects and across movements, was used to identify consistent muscle synergies. Results indicate that the most frequently repeated wavelet modules comprised combinations of two muscles that are not traditional agonists and span different joints. We have also found that these wavelet modules were flexibly combined across different movement directions in a pattern resembling directional tuning. This method is extendable to multiple frequency domains and signal modalities.

I. Introduction

Neural control of movement is thought to follow the principle of modularity. Anatomical evidence for neural control units can be found in the structural organization of cortical columns and segmental organization of spinal circuitry involved in the control of locomotion and reaching [1]. Functional evidence comes from studies identifying neural synergies that control different phases of movement [2]. This modularity principle is thought to also be

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evident in the final output of the motor system, muscle activation, in the form of muscle primitives or synergies.

Muscle primitives are usually defined as common variance in electromyographic (EMG) recordings across multiple muscles and multiple movements. Arguably, the most advanced linear approach to obtain muscle primitives from EMG relies on optimization to find shared variance through components that are shifted in time [3], [4]. This method is physiologically relevant, because it enables the identification of the same hypothetical control modules being used at different phases of movement. Here we sought to simplify this identification using wavelet decomposition. Wavelet decomposition is the representation of nonstationary signal as a sum of components with compact support. These components originate from scaling and translating over time a single mother wavelet function, which has desired properties with respect to the duration and shape. Thus, this method measures the strength of the common unit of predefined duration between EMG of two or more muscles at different times during a given movement [5]. In this study, we used the mother wavelet function as a hypothetical neural module of control that provides a common signal to the muscles. With this approach, we obtained wavelet modules to characterize muscle primitives during a reaching task performed by healthy human subjects.

II. Methods

A. Experimental procedure

The data obtained during experiments reported elsewhere were used to test the proposed method [6]. Briefly, 10 healthy human subjects performed pointing movements in virtual reality (VR) toward visual targets (Vizard software, Worldviz). Targets were arranged on a sphere to mimic a common center-out task. Movements to each target location were repeated 15 times and performed in a randomized order. The study was approved by the institutional review board.

Motion of the arm and trunk was recorded with an active motion capture system (PhaseSpace, Impulse) at 480 frames per second. The light emitting diodes of the motion capture system were placed on anatomical landmarks according to best practice guidelines [7]. Surface EMG was recorded using MA400-28 EMG system (MotionLab Systems, Inc) at a rate of 2000 Hz. Muscles recorded during the experiment included the pectoralis major (PM), anterior deltoid (AD), posterior deltoid (PD), long and lateral heads of the triceps (TLo and TLa respectively), short and long heads of the biceps (BS and BL respectively), brachioradialis (BR), flexor carpi radialis (FCR), extensor carpi radialis (ECR), teres major (TM), and flexor carpi ulnaris (FCU); also numbered 1–12 respectively in figures. The recorded signals were synchronized through a common trigger generated by VR software and a custom circuit [8]. All data analysis of recorded signals was done in MATLAB (Mathworks, Inc).

EMG signals were high-pass filtered at 20 Hz to remove motion artefact, then rectified, and low-pass filtered at 10 Hz. The activation profiles for decomposition were obtained by averaging processed EMG across trials for each of 14 outward and 14 return (inward) movements per subject. The duration of the mean EMG was normalized to the average

duration across trials per subject. The magnitude of the mean EMG was normalized to the maximal magnitude across all trials of a given movement per subject.

B. Synergy Extraction

We used the 1st order Gaussian mother wavelet function [5]. The function was scaled in time to between 0.45 and 0.55 of normalized movement duration. Then continuous wavelet transform [9] of EMG from each muscle was calculated, and wavelet decomposition coefficients were added for each time shift, to obtain a wavelet activation trend.

Continuous wavelet transform W_Ψ of EMG signal is the function of two variables:

$$W_\Psi(\alpha,\tau)=\int x^k(t)\Psi^*_{\alpha,\tau}(t)dt, \quad (1)$$

where $\breve{x}^k(t)$ is EMG signal of k-th muscle, and $\Psi^*_{\alpha,\tau}(t)$ is the complex conjugate to the scaled and translated versions of mother wavelet function $\Psi(t)$ as follows:

$$\Psi_{\alpha,\tau}(t)=\frac{1}{\sqrt{\alpha}}\Psi\left(\frac{t-\tau}{\alpha}\right), \quad (2)$$

were α is the scaling factor greater than zero, and τ is an arbitrary time translation.

A set of scaled and translated versions of mother wavelet was used to obtain the decomposition coefficients $W_\Psi(\alpha, \tau)$, which indicate the degree of similarity between the analyzed signal and the corresponding component $\Psi_{(\alpha, \tau)}(t)$ (with particular duration and position on the time axes). Scaling factors in wavelet signal representation control the duration of the scaled mother wavelets to be used for decomposition of the signal of interest. They are related to the duration of the components extracted from the initial signal, thus enabling the study of the signal contents at different time scales. The effective duration of the wavelet is inversely proportional to the scaling factor, so it is possible to identify the scales α, which result in the scaled wavelet with required duration. Therefore, the values of the CWT coefficients $W_\psi(\alpha,\tau)$ are associated with the intensity of a given component of known duration and position in the entire signal [10].

To extract the EMG components for further analysis of synergetic activation, we selected the component durations which are meaningful from the physiological point of view, and then selected the appropriate range of scaling coefficients $\Delta\alpha=[\alpha_1,\alpha_2]$. The coefficients $W_\psi(\Delta\alpha,\tau)$ for every time shift τ show the time-varying presence of the corresponding component in the EMG signal, which we term muscle activation profile (MAP):

$$MAP_{\Delta\alpha}(\tau)=\int_{\alpha_1}^{\alpha_2} W_\Psi(\alpha,\tau)da \quad (3)$$

MAPs were calculated for each muscle based on the corresponding EMG channel. Wavelet modules (WM) were obtained by multiplying the activation profiles of individual muscles:

$$WM_{\Delta\alpha,K}(\tau) = \Pi_{k=1}^{K} MAP_{\Delta\alpha,k}(\tau), \quad (4)$$

where K is the number of muscles k included in a synergy.

The wavelet modules were calculated for groups of 2, 3 and 4 muscles in every possible permutation without repetitions. Wavelet modules containing 2-muscle combinations (K=2) are referred to below as 2-muscle modules and so on for 3- and 4-muscle modules.

This analysis was repeated using the same 1st order Gaussian mother wavelet function, but of shorter durations. The durations of scaled wavelets included in the analysis were between 0.2 and 0.3, and between 0.05 and 0.15 of normalized movement duration. Only results of the analysis using the wavelet mother function of 0.45 – 0.55 movement duration are illustrated in figures. Summaries of the analyses with shorter mother wavelet functions are included in the Results section.

C. Hierarchal Clustering

The hierarchical clustering was used to quantify the agonistic and antagonistic relationships between the identified representative wavelet modules. First a correlation matrix of all synergy activation profiles was constructed. The correlation matrix was then transformed into the heterogeneous variance explained (HVE) as reported elsewhere [11]. Briefly, the transformation ensured that wavelet modules whose temporal profiles were positively correlated grouped together, i.e. had small distance values approaching 0, whereas wavelet modules whose temporal profiles were negatively correlated appeared relatively far apart, i.e. had larger distance values approaching 2. Wavelet modules that were insignificantly correlated were defined by intermediate distances close to 1. Hierarchical clustering was applied to the HVE matrix using the linkage function with unweighted average distance method to identify clusters for each movement per subject. The goodness of fit of hierarchal clustering was quantified using cophenetic correlation coefficient, which measures how faithfully the hierarchal distance tree represents the dissimilarities among observations. The repeating wavelet modules were defined as those that repeat in the majority of subjects (N > 4) within each of the same cluster identified by hierarchical clustering. The directional tuning of identified clusters was determined by calculating projections of the number of repeating modules per movement direction onto the Cartesian axes of corresponding virtual targets.

Statistical analysis of the hierarchal clustering was done using one-way analysis of variance (ANOVA) on cluster assignments for each number of clusters separately, e.g. a single ANOVA on 2-cluster breakdown of the different wavelet modules and F-statistic and p-values are reported.

III. Results

Subjects performed the reaching movements consistently with low variability in kinematics and consistent, but somewhat higher variability in EMG patterns, the details of which were reported elsewhere [6]. We identified muscle wavelet modules that were variable between movements of each subject and between subjects for the same movements (Fig. 1).

To evaluate the consistency of wavelet modules across subjects, we have counted the number of repeating wavelet modules as defined in Methods for every movement direction and cluster subdivision. We found that when the wavelet modules were divided into two clusters, the number of repeating modules was the highest (Fig. 2A). However, with increasing number of clusters, the number of repeating wavelet modules in each cluster declined. Across movements there were ten 2-muscle modules (Fig. 2B) and none 3-muscle or 4-muscle modules that repeated at least once across movements in the majority of subjects. The number of repeating modules within a cluster also declined with the increasing number of clusters, so that at a 12-cluster grouping none of the modules repeated more than 5 times (Fig. 2B). It is worth noting that shortening the duration of the mother wavelet function to ¼ or $\frac{1}{8}$ of movement duration also shows no repeating 3-muscle and 4-muscle modules and an increase in the number of repeating 2-muscle modules. Therefore, the following analysis was conducted only on repeating 2-muscle modules.

Hierarchical clustering based on HVE represented the grouping of 2-muscle wavelet modules with high consistency. This was measured by cophenetic correlation coefficient, which quantified how faithfully the hierarchal distance tree represents the dissimilarities among observations (Fig. 3, top plot). However, the high cophenetic correlation coefficient corresponded to the division of wavelet modules into 28 ± 1 clusters (mean ± standard deviation) across all movement directions (Fig. 3, bottom plot). Note, that at this number of clusters there were no repeating modules across movements nor subjects (Fig. 2).

Hierarchical clustering has also shown that the identified consistent clusters of 2-muscle modules are directionally tuned (Fig. 4). The orientation of population vectors covered the whole task workspace, but the number of modules that repeated across movement directions varied between clusters. ANOVAs have rejected a null hypothesis that wavelet modules constitute a single population (Table 1). Interaction terms were significant across all cluster subdivisions, which shows that the grouping of wavelet modules differed across different movements. This grouping of wavelet modules is similar to the directional tuning of muscle synergies found with traditional decomposition methods, where muscle synergies are recruited with larger scaling factors for a particular “preferred” movement direction [4].

IV. Discussion

In this study, we have used continuous wavelet transform to characterize synchronous activation of muscles during pointing movements by human subjects. The wavelet modules obtained with this method detected co-activation between two or more muscles that occurred at a selected biomimetic temporal scale determined by the wavelet mother function scaled to movement duration. Results have shown that multiple wavelet modules repeat in multiple

individuals across pointing movements. Surprisingly, the most frequently repeated wavelet modules comprised combinations of two muscles that are not traditional agonists and span different joints (Fig. 2). We have also found that these wavelet modules were flexibly combined across different movement directions in a pattern resembling directional tuning (Fig. 3). This is consistent with previous results obtained with other decomposition methods [3], [4]. The combinations of wavelet modules were most repeatable across subjects at a gross 2- or 3-cluster grouping. Altogether, these results suggest that muscles may be activated by task-specific neural control modules that are organized hierarchically.

The primary limitation of this study is common to all decomposition methods. The complex anatomy of the nervous and musculoskeletal systems can be explored with multiple types of motion-related signals, such as endpoint kinematics or joint torques, many of which are not independent or orthogonal. Therefore, the shared variance captured by the decomposition methods, including wavelet transform, may simply be a reflection of that complex anatomy rather than neural control. However, the advantage of using continuous wavelet transform for EMG decomposition is that the temporal dynamics represented by the mother wavelet function can be a-priory defined. Moreover, flexible signal combinations can be explored, such as two or more muscles. This constrains the types of physiological processes that can contribute to the obtained wavelet modules. The scaling of the mother wavelet function to the movement duration ensured that, in this study, only signals or processes with similar phase durations, e.g. forces or fast cortical feedback loops, can contribute to the observed wavelet modules. At the same time, signals or processes on the slower temporal scale, such as motion kinematics or cognitive feedback loops with larger delays, are excluded from this analysis. To further develop this technique, in future studies we will examine the possible relationships between the wavelet modules extracted from EMG and those obtained from electrical activity of the brain measured with electroencephalography.

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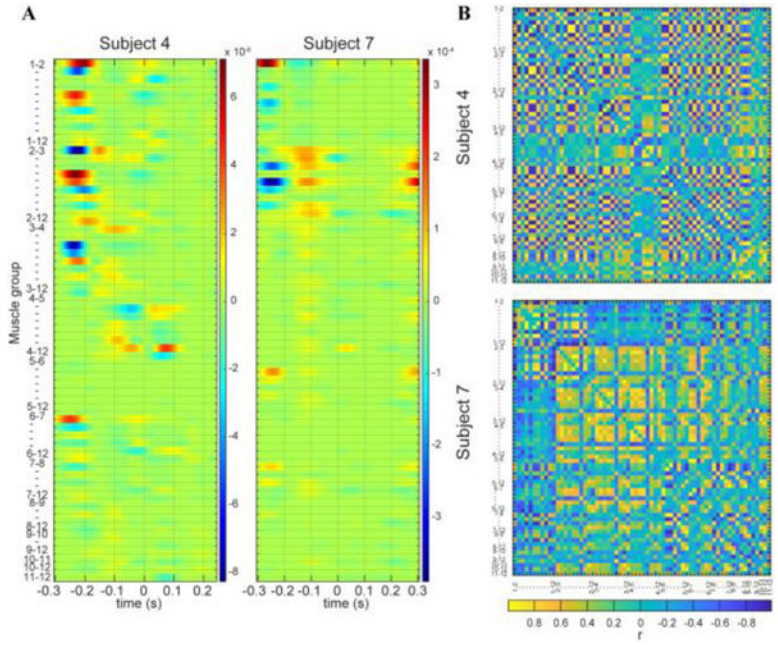

Figure 1.

Examples of synergy activation profiles and their correlations for one of the movements in two subjects. **A.** 2-muscle modules are identified by muscle group labels, numbered as described in Methods. The color bars indicate the scale of the magnitude of synergy activation profiles in arbitrary units. **B.** Correlation matrices between signals in A. Same axes labels as in A for vertical axes. Color bar shows the scale of Pearson correlation coefficients.

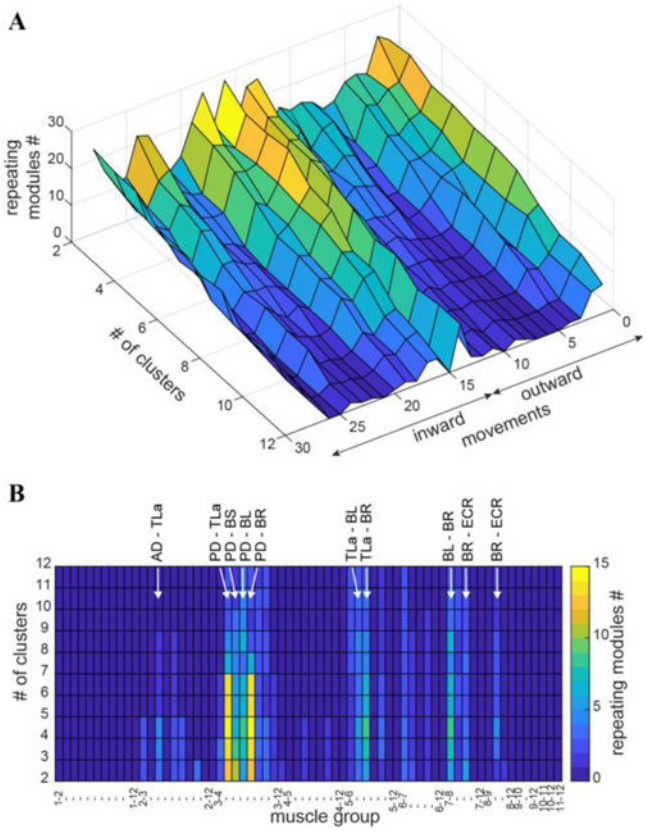

Figure 2.

The number of repeating wavelet modules based on 2-muscle combinations across subjects. **A**. Repeating wavelet modules across subjects per movement and cluster number. **B.** Repeating wavelet modules from A that also repeat across movements.

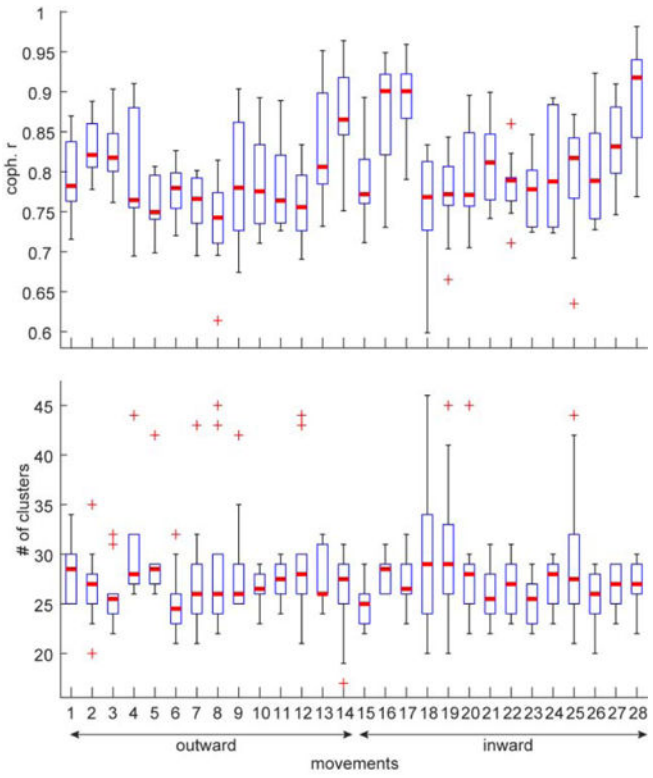

Figure 3.

The quality of representation of the relationships between wavelet modules by hierarchal clustering. Medians are plotted in thick red lines; the bottom and top edges of the blue box indicate the 25th and 75th percentiles, respectively; the whiskers extend to the most extreme data points not considered outliers, the outliers are plotted as red crosses; coph.r is cophenetic correlation coefficient.

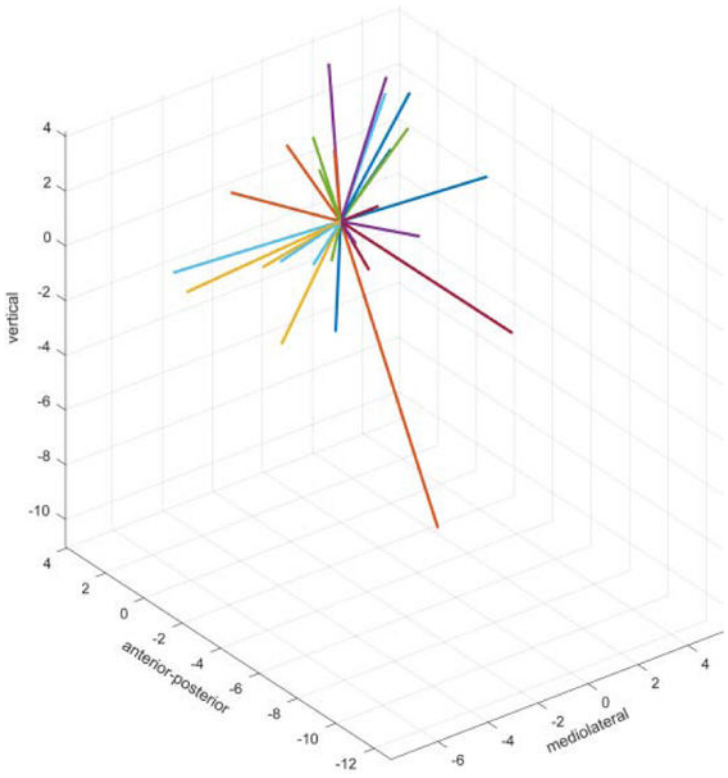

Figure 4.

Directional tuning of clusters of wavelet modules. Cartesian coordinates for each vector are based on VR target locations. Colors indicate 28 consistent clusters. The length of each population vector reflects the number of comprising wavelet modules across all movement directions.

TABLE I

Statistical analysis of hierarchal clustering

ANOVA factors[a]		Clusters					
		2	*3*	*4*	*5*	*6*	*7*
Wavelet modules	F	2.28	1.12	1.79	3.4	1.88	15.6
	p	**0.001**[c]	0.322	**0.015**	**< 0.001**	**0.009**	**< 0.001**
Move[b]	F	50.11	37.8	25.29	35.99	26.08	7.3
	p	**< 0.001**	**< 0.001**	**< 0.001**	**< 0.001**	**< 0.001**	**< 0.001**
Wavelet × Move.	F	1.55	1.88	2.05	2.48	3.61	7.2
	p	**< 0.001**	**< 0.001**	**< 0.001**	**< 0.001**	**< 0.001**	**< 0.001**

[a] ANOVAs were done on consistent wavelet modules based on 2-muscle combinations.

[b] Move. is an abbreviation of movement direction.

[c] bold p-values indicate significance