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Identification of spatial-temporal muscle synergies from EMG epochs of various durations: a time-warped tensor decomposition

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Abstract— Extraction of muscle synergies from electromyography (EMG) recordings relies on the analysis of multi-trial muscle activation data. To identify the underlying modular structure, dimensionality reduction algorithms are usually applied to the EMG signals. This process requires a rigid alignment of muscle activity across trials that is typically achieved by the normalization of the length of each trial. However, this time-normalization ignores important temporal variability that is present on single trials as result of neuromechanical processes or task demands. To overcome this limitation, we propose a novel method that simultaneously aligns muscle activity data and extracts spatial and temporal muscle synergies. This approach relies on an unsupervised learning algorithm that extends our previously developed space-by-time decomposition to incorporate the identification of linear time warps for individual trials. We apply the proposed method to high-dimensional spatiotemporal EMG data recorded during performance of whole-body reaching movements and show that it identifies meaningful spatial and temporal structure in muscle activity despite differences in trial lengths. We suggest that this algorithm is a useful tool to identify muscle synergies in a variety of natural self-paced motor behaviors.

I. Introduction

Muscle synergies have been hypothesized to be the building blocks of movement generation [1]. In human motor control studies, muscle synergies have been typically inferred by EMG recordings using dimensionality reduction techniques. The synergies identified by such approaches represent patterns of muscle activity that are shared across trials/tasks and their linear combinations approximate the recorded EMG signals. An important practical limitation of the above approach is that natural motor behaviors are self-paced, thus different trials have different durations and the corresponding EMG signals have different lengths. In particular, muscle activity on a single trial may be shifted and stretched in time due to differences in neural and biomechanical processes or task parameters (e.g. speed or distance) and sensory feedback. This temporal variability can inflate the apparent dimensionality of data and obscure our ability to recover inherently simple, low-dimensional structure. Specifically, in the context of muscle synergy extraction, such temporal variability cannot be dealt with by dimensionality reduction algorithms, hence researchers typically assume trials of equal lengths and achieve this either by cutting the EMG recordings into segments of equal durations or by normalizing the duration of each trial.

Here we propose a new approach for the extraction of muscle synergies from EMG signals of variable lengths. The novel algorithm jointly learns a low-dimensional representation of the EMG data together with trial-specific time warpings for alignment [2]. Specifically, this method extends our previously developed space-by-time representation of muscle activity [3] to incorporate a linear transformation of the time axis that allows the decomposition of variable-length EMG recordings, thus making it readily applicable to muscle activations measured during natural motor behaviors. To illustrate the methodology and its output modular representation, we apply it to a high-dimensional EMG dataset recorded during performance of several whole-body reaching movements that varied in amplitude and speed.

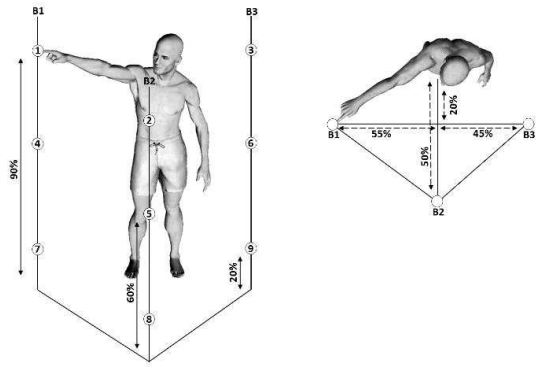

Fig. 1. Experimental design. The experimental protocol specified nine targets on three supporting bars (B1, B2, B3, three targets on each vertical bar. Subjects performed point-to-point movements between all pairs of targets (a total of 72 movements) and repeated each movement 30 times.

II. Material and Methods

A. Experimental Procedures

Human participants executed whole-body point-to-point movements in various directions at a self-selected pace. In brief, the experimental protocol (Fig. 1) specified 9 targets on 3 vertical bars. Each bar had 3 targets on different heights determined based on the participant's height. Participants performed pointing movements between all pairs of targets (i.e. a total of 72 different pointing movements or "tasks")

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using the index fingertip of their dominant right arm.

We recorded the activity of 30 muscles on both sides of the body by means of an Aurion (Milan, Italy) wireless surface EMG system. We defined movement onset t_0 and end t_{end} times as the times between which the fingertip velocity (computed from the analysis of motion capture signals) superseded 5% of its maximum and restricted our analysis to the interval (t_0-100ms, t_{end}) of EMG activity. These movement-related EMGs for each trial were digitally full-wave rectified, low-pass filtered (Butterworth filter, cut-off frequency of 5Hz, zero-phase distortion). The EMG signal of each muscle was then normalized in amplitude by dividing each single-trial muscle signal by its maximal value attained throughout the experiment. For each subject, we finally formed an EMG matrix consisting of all the movement-related EMG activity of the 30 muscles for all recorded trials.

B. Data Analysis

We used a tensor decomposition with non-negative constraints to decompose the single-trial EMG signals into spatial and temporal synergies [3]. This modularity model represents muscle activity as a linear combination of separate but concurrent spatial and temporal synergies combined in single trials by scalar coefficients. This method has been shown to reliably extract the spatial and temporal structure of "ground-truth" data. To incorporate trial-by-trial temporal variations in the form of shifts and stretches, we employed a recently developed method for the time-warping of individual trials [2]. To make this algorithm consistent with the space-by-time decomposition, we imposed non-negativity to all the outputs and also introduced a core tensor carrying the single-trial coefficients that combine each temporal synergy with each spatial synergy to reconstruct single-trial muscle activity. Ultimately, according to this model, a single-trial muscle pattern M^l can be written as a three-factor multiplication:

$$M^l \simeq W^{tem}_{(\tau^l,:)} A^l W^{sp}, \quad \forall l \in [1, L] \quad (1)$$

where W^{tem} is a matrix whose columns are the temporal synergies, W^{sp} is a matrix whose rows are the spatial synergies, the matrix A^l includes all activation coefficients for trial l and

$$\tau^l = ct + \delta, \quad \forall l \in [1, L] \quad (2)$$

is a linear temporal warping function that stretches and shifts time on trial l by c and δ respectively. Hence, the algorithm aims to identify the three above matrices as well as the single-trial time-warping functions in order to approximate the single-trial muscle activity M^l as accurately as possible.

III. Results

By applying the new algorithm to the EMG data recorded during various whole-body reaching movement, we were able to characterize the spatial and temporal structure of muscle activity and identify two temporal parameters for each trial that account for the different trial durations. We extracted 4 temporal and 5 spatial synergies because prior work showed that these dimensions provide a reliable and task-discriminative description of muscle activity in this dataset.

We found that the four temporal synergies consisted mainly of consecutive bursts of muscle activity that spanned the whole movement (Fig. 2A) and that each of the five spatial synergies activated multiple muscles from different body locations (Fig. 2B). Finally, our algorithm identified the linear time-warping functions that stretched or squeezed time (and shifted time to a lesser extent) to align trials taking into account the different durations (i.e. speeds and amplitudes).

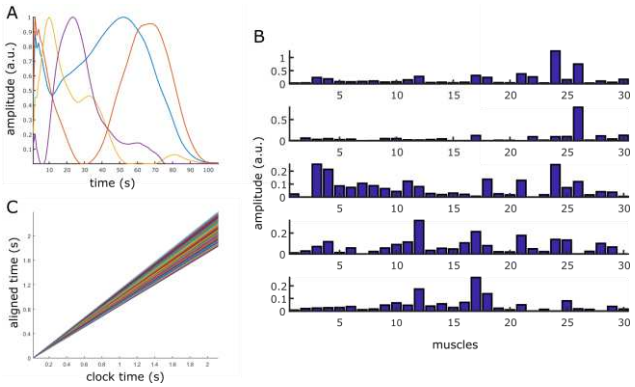

Fig. 2. Output of the algorithm when applied to whole-body EMG recordings. A. The four temporal synergies describing the data B. The five spatial synergies. C. The single-trial linear time-warping functions.

IV. Discussion

In this study, we proposed an algorithm for the simultaneous a) alignment of EMG recordings of different durations using linear time-warping and b) extraction of muscle synergies using a tensor decomposition. Alignment of trials of different durations (or movement speeds or amplitudes) has been an unresolved problem in muscle synergy studies. Our approach addresses this challenge and performs both dimensionality reduction and temporal warping in a data-driven, unsupervised manner, removing the need for explicit alignment with external variables.

The proposed method has two important advantages. First, it approximates the recorded muscle activity compactly using only two more single-trial parameters compared to the standard space-by-time model. Second, it provides a plausible mechanistic representation of how modular structures can be recruited in single trials to produce self-paced movements varying in speed, amplitude etc. Therefore, it constitutes a more naturalistic modularity model that can be tested in future studies to understand if the CNS may be using such a scheme.

References

[1] Bizzi E, Cheung VCK, d'Avella A, Saltiel P and Tresch M (2008), "Combining modules for movement.", Brain Res Rev 57, 1, 125--133.

[2] Poole B, Williams A, Maheswaranathan N, Yu B, Santhanam G, Ryu S, Baccus S, Shenoy K, Ganguli S (2017), "Time-warped PCA: simultaneous alignment and dimensionality reduction of neural data". Computational Systems Neuroscience (COSYNE).

[3] Delis I, Panzeri S, Pozzo T & Berret B (2014), "A unifying model of concurrent spatial and temporal modularity in muscle activity". Journal of Neurophysiology 111:675-693.