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Extraction of Muscle Synergies Using Temporal Segmentation of the record: a Preliminary Analysis

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Abstract — **Muscle synergies are considered as a potential strategy to reduce the computational workload undergoing the estimation of muscle activity during different motor tasks. They are usually extracted by means of algebraic factorization algorithms able to capture the greatest communality of a set of electromyographic (EMG) signals. Usually EMG signals are pooled across different sub-movements (e.g., going forward and backward during reaching) in order to increase the complexity of the data set and, consequently, capture the maximum communality. Despite of these, this preliminary study was designed to investigate how the communality of EMG signals can be explained looking at narrow subset of recorded signals. Results corroborate the hypothesis that using a suitable subset of the whole dataset can significantly modify the values of weight coefficients. In this regard, further methodological investigations of algorithms adopted for synergy extraction are still required.**

I. Introduction

One of the fundamental challenges of the Neuroscience is to understand how the Central Nervous System (CNS) organizes motor actions and movements. The brain is supposed to control complex movements through the adaptable combination of motor modules, often called muscle synergies, representing elements of the sensorimotor map that transform desired limb trajectories in motor instructions [1]. Commonly, muscle synergies are suggested as a strategy to manage the huge amount of degrees of freedom problem faced in motor control according to two concomitant hypothesis: *i.* instead of controlling many thousands of motor units or dozens of muscles, using muscle synergies, the CNS can achieve a motor task by controlling a much smaller number of variables [2-5]; *ii*. instead of calculating (i.e., high computational cost) the suitable muscle activity of a certain motor task, it results as the combination of some modules coming up from a sort of "lookup table" (i.e., low computational cost) [6, 7]. Evidence for the existence of muscle synergies has been provided by the experiments of several scientists [5, 8]. However, a number of unresolved issues pertaining to those studies still remain.

Previous authors provided a direct support for the hypothesis that the CNS organizes the motor output of the upper and lower limbs by the flexible combination of muscle synergies [6, 9]. On the whole, they are usually extracted by means of algebraic factorization algorithms able to capture the communality of a set of electromyographic (EMG) signals [10, 11], in order to highlight the modularity of the control of limb movements in several animal species and in several motor tasks [3, 12-16].

A common approach adopted in literature to extract muscle synergies consists in pooling EMG signals of different sub-movements (e.g., going forward and backward during reaching) in order to increase the complexity of the data set and, consequently, capture the greatest communality underlying a wide set of movements [12]. One of the potential limits of this approach is that, although similar motor tasks carried out by different individuals can involve a different relationship between the activities of several muscle groups, the factorization algorithms may not be able to capture the significant difference between them. For instance, it is well known that post-stroke patients use to carry out reaching movements by using a significant co-activation of flexor and extensor muscles with respect to healthy people [17]. The movement hence results jerky, lacks of precision, and is energy consuming. Nonetheless, the analysis of muscle synergy in post stroke patients does not seem to reveal discrepancies either between healthy and post-stroke patients, or with respect to the severity of the lesion [18].

We hypothesized that this surprising result may instead highlight that the adopted approaches cannot be able to completely capture the relationship between muscle groups. For instance, it is reasonable to believe that healthy people may achieve reaching movements by combining agonist and antagonist muscle groups in an anti-phase strategy, that is, the antagonist mainly brakes the end-effector when the movement is being terminated. Differently, due to the trauma, post-stroke patients cannot finely control the relationship between agonist and antagonist muscle groups such that the activity of these muscles is likely coupled along the whole movement. Consequently, according to the methodological issues described by previous authors [19], one would expect that the weight coefficients should have a different value and/or sign in order to reflect the different relationship between agonist and antagonist muscle groups in both groups of subjects.

In order to retain or reject this hypothesis, we designed a preliminary study aimed at verifying whether the communality of EMG signals can be widely explicated looking at a limited portion of the signal. In particular, we analyzed the similarity between muscle synergies extracted from both:

- the whole EMG data set corresponding to a complex motor task involving 16 planar reaching sub-movements;
- many subsets of the whole data set extracted by suitable moving time windows.

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II. Materials and Methods

A. Participant, procedures and technical apparatus

A neurologically intact young subject (male, age 27 years, right dominant arm) was involved in the present study. He did not show any evidence or known history of postural, skeletal or neurological diseases, and exhibited normal joint range of motion and muscle strength. The subject signed an informed consent before starting experimental sessions.

The subject was asked to move the upper arm while controlling the position of the end-effector of a robotic platform, the InMotion2 (Interactive Motion Technologies, Inc. Cambridge, Massachusetts), designed to enable subjects to accomplish planar reaching tasks. The robot can also move, guide, or perturb the movement of the upper limb of the subjects, and can record end-effector kinematics and applied force.

The subject was instructed to make a set of point-to-point (back and forth) movements of the handle from a central target to eight equidistant ones placed around a circumference with radius of 0.14 m. In order to allow comfortable positioning, before starting, participant was asked to check whether he was able to move his arm through its own full range of movement.

Exercises were carried out by the dominant limb in the horizontal plane, by combining elbow and shoulder movements. The exercises consisted of five experimental sessions, at different cadences, composed of a 10 minutes long warm-up period and 5 full turns. Trials were carried out without using robotic assistance or resistance but constrained by the beat of a metronome at the following frequencies: 30, 40, 60, 80 and 120 beats per minute (bpm).

B. EMG recording

EMG signals were recorded from ten upper arm and shoulder muscles (Biceps, BIC; brachialis, BRAC; brachioradialis, BRAD; anterior deltoid, DELA; medial deltoid, DELM; posterior deltoid, DELP; latissimus dorsi, LAT; pectoralis major, PECM; upper trapezius, TRAP; and triceps, TRI) by using dual Ag–AgCl snap electrodes with an inter-electrode spacing of 2 cm. A standard procedure, in accordance with surface electromyography for non-invasive assessment of muscles (SENIAM) guidelines, was used for skin preparation and electrode placement [20]. The reference electrode was placed over the electrically neutral lateral epicondyle where it interfered least with the movement and other electrode sites. EMG electrodes were connected to a hub and wirelessly transmitted to the Noraxon data acquisition system (NORAXON, Telemyo 2400T, V2), to enable unimpeded movements. Sample rate was set at 1500 Hz.

C. EMG pre-processing

Raw EMG signals were pass band filtered (Butterworth filter, 4th order) with lower and upper pass band cutoff frequencies at 6 and 500 Hz to remove artifacts. The signals were then rectified and normalized to those recorded during MVC and, finally, low pass filtered with cutoff at 3Hz (Butterworth filter, 4th order). The polished EMG data referring to second-fifth repetitions were resampled over 24000 samples and averaged. For this study, only the data related to the 60 bpm (confortable cadences) were used.

D. Muscle synergies extraction

Muscle synergies were extracted by using the Factor Analysis (FA) with "varimax" rotation. As well known, all factorization methods consist of decomposing a set of pre-processed EMG signals in order to express them as the product between primitive signals and weight coefficients. Each couple, primitive signals-related weightings, describes the weighted contribution of each primitive signal to the EMG activity of all recorded muscles. In this paper, with the term muscle synergy we explicitly refer to the weight coefficients representing muscle enrollment related to each synergy. The number of retained synergies was based on the *eigenvalue>1* criterion.

Three different procedures to extract muscle synergies were adopted. The first method consisted in extracting muscle synergies from the whole data set (**M1**) related to the complete task (i.e., pooled 16 forward and backward movements). The second method consisted in factorizing data for each of the 16 movements (**M2**). The third method of decomposition was based on a discrete time segmentation of the whole matrix of EMG signals (**M3**). Specifically, the whole data set was segmented by moving a time window of 24000/16=1500 samples, step by step. The FA was then performed for each of these subsets.

The degree of similarity between muscle synergies related to **M1** and **M2**, and those related to **M1** and **M3** was estimated by calculating the dot product between weight coefficient vectors extracted by the different methods.

Data were processed by using custom routines developed under Matlab environment (Mathworks Inc., Natick, MA, USA).

III. Results

According to the adopted criterion, the extracted synergies relating to **M1** accounted for about 70% of the cumulative variance of data sets. This value ranged between 70% and 85% with data referring to **M2** and **M3**.

The FA allowed to group muscle activity related to **M1** as follow:

- the first synergy (first column in Figure 1) functionally referred to the support of the arm achieved by DELM and DELP, and a lower contribution of TRI;
- the second synergy (second column in Figure 1) mainly accounted for the activity of DELA and DELM, and the lower contribution of BRAD and BRAC;
- the third synergy (third column in Figure 1) reflected the activity of LAT, PECM

Comparing muscle synergies extracted by **M1** and **M2** (Figure 2), it is possible to observe the modulation of weight coefficients ongoing the whole motor task accounting for 16

different sub-movements. In particular, it is possible to observe that, although some muscle groups load the same synergies, their weight coefficients can reflect either the modulation of their activity, or the modification of the phase relationship.

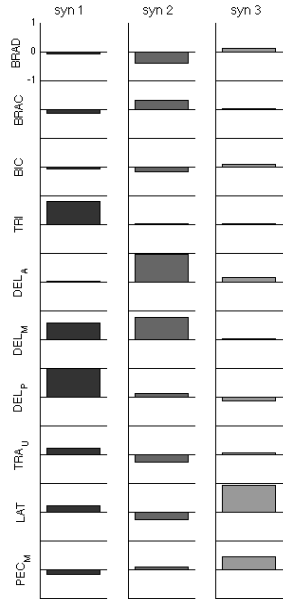

Figure 1. Weight coefficients referring to the three (columns) extracted synergies related to EMG signal record during whole data set related to the complete motor task, (**M1**).

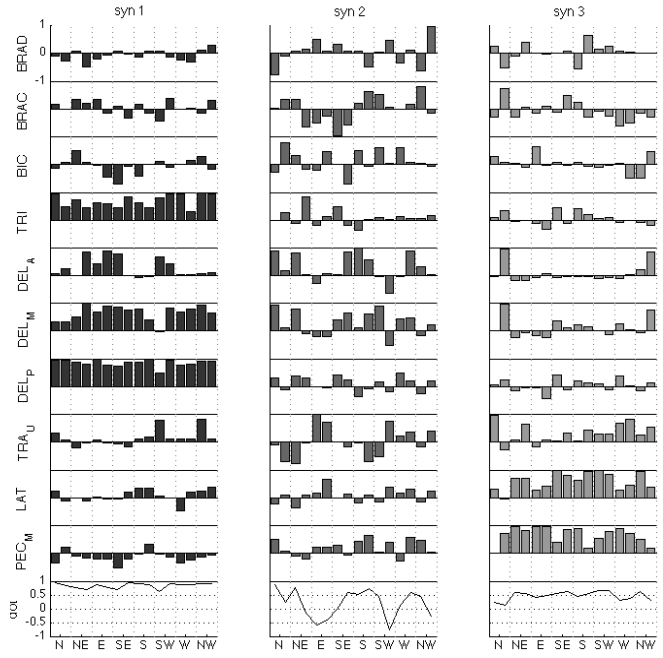

Figure 2. From first to tenth rows: weight coefficients referring to the three (columns) extracted synergies related to EMG signal related to each of the 16 movements included in time-segmentation (**M2**). For each direction of the movement (see labels on the x axis; N, North; NE, North-East; E, East; SE, South-East; S, South, SW, South-West; W, West; NW, North-West) weight coefficient refer respectively to forward and backward movements. Last row show, for each synergy, the degree of similarity (dot product) between muscle synergies to **M1** and **M2.**

For instance, the contribution of deltoids in the **M1** extraction is split in two synergies (Figure 1) and in particular the couples DEL_M – DEL_P and DEL_M – DEL_A, resulted always in phase (i.e., weight coefficients are all positive). Observing data extracted for each of the 16 sub-movements (**M2**; see Figure 2), it is possible to notice that the weight coefficient related to DEL_A is often (see East, South-East, and South-West in syn1, Figure 2) in disagreement with that found for **M1** data set.

The absence of agreement between muscle synergies related to **M1** and **M2** data sets is reflected in the degree of similarity reported on the bottom of Figure 2. Specifically, the second synergy was characterized by the widest trend ranging from 1 (i.e., maximum value of similarity, same phase) to -1 (i.e., maximum value of similarity, anti-phase), crossing 0 (i.e., no similarity).

A similar behavior was also observed when muscle synergies related to **M1** and **M3** data sets were compared (see Figure 1 and Figure 3). In particular, the weight coefficient related to each muscle oscillated significantly reflecting the modulation of both its activity and the phase relationship, which affected the degree of similarity between the data sets (see subplots on the bottom in Figure 3).

An interesting result concerned the high similarity observed in *syn1* and *syn3* in both coupled data sets (i.e., **M1** vs. **M2** and **M1** vs. **M3**). In particular, although the weight coefficients related to all muscle groups ranged from -1 to 1, the cosine of the angle between the coupled weighting vectors remained almost constant.

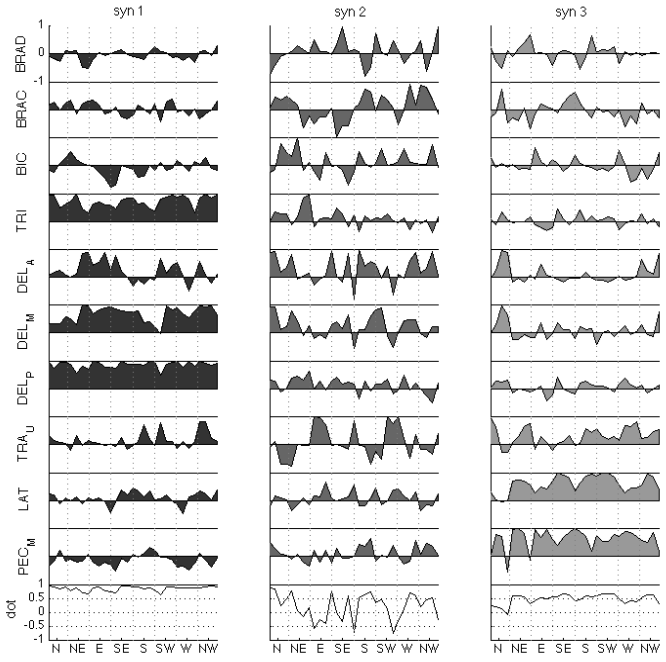

Figure 3. From first to tenth rows: weight coefficients referring to the three (columns) extracted synergies related to EMG signal record during whole data set, the area represent the trend weight value for each of the segmented movements (**M3**). Last row show, for each synergy the degree of similarity (dot product) between muscle synergies extracted with **M1** and **M3**. X-axis labels are the same of figure 2.

IV. Discussion

The aim of this study was to investigate the effect of the time segmentation on the extraction of muscle synergies in order to highlight whether the principal rules underlying muscle activity change along the whole movements.

Our results confirm that weight coefficients can be significantly modified by the observed time window, highlighting that it possible to achieve different results adopting different approaches. Indeed, this likely obvious observation shows that, on one hand, the analysis of muscle synergies needs a significant methodological effort to harmonize results across different authors, studies, and trials. On the other hand, it shows that the fundamental model underlying muscle activity, represented by the weight coefficient, may can change with the direction of the movement.

Actually, d'Avella and colleagues [21] already observed that the coefficient of a small number of their time-variant muscle synergies reflected the organization of the muscle patterns observed during movements in different directions. Our results support this evidence, highlighting that the factor "direction of the movement" can involve a specific relationship among different muscle groups, which may not come up when data are pooled across many records.

Reported results also showed that, although weight coefficient significantly change through the ongoing exercise (see Figures 2 and 3), the degree of similarity between synergies related to **M1** and those related to **M2** or **M3** can reach high values. We believe that two main reasons led this result. On one hand, the "dot product" takes into account for the load of all muscles, such that weighting coefficient vectors of two coupled datasets can really result almost aligned (i.e., the angle between them is small). On the other hand, we also have to acknowledge that the "dot product" is a non-linear function, which tends to overestimate the degree of similarity between two vectors diverging in a wide range of values (e.g., from 0 to 30 degrees). Therefore, we believe it is important to define a suitable threshold to characterize the relationship between two weight coefficients.

Actually, further deep investigations concerning many aspects may be needed in order to generalize these preliminary results and discuss inter-subject variability with respect to synergies identification. However, the showed results confirm that although muscle synergies are a valuable tool to investigate the principal roles adopted by the CNS to control the activity of many muscle groups, we must pay attention while using it in order to avoid unexpected artifacts.

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