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How to Improve Robustness in Muscle Synergy Extraction

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***Abstract*— The muscle synergy theory was widely used in literature to assess the modular organization of the central nervous system (CNS) during human locomotion. The extraction of muscle synergies may be strongly influenced by the pre-processing techniques applied to surface electromyographic (sEMG) signals. The aim of this contribution is to assess the robustness improvement in muscle synergy extraction obtained using an innovative pre-processing technique with respect to the standard procedure. The new pre-processing technique that we propose is based on the extraction of principal muscle activation intervals (necessary to accomplish a specific biomechanical task during gait) from the original sEMG signals, discarding the secondary muscle activation intervals (activations that occur only in some strides with auxiliary functions). Results suggest that the extraction of the principal activation intervals from sEMG provide a more consistent and stable description of the modular organization of the CNS with respect to the standard pre-processing procedure.**

I. Introduction

In the last years, the muscle synergy concept was proposed for the assessment of the modular organization of the central nervous system (CNS) during different motor tasks and was applied in several research fields, such as clinics, robotics, and sports [1]. According to the theory of muscle synergies, the CNS controls a small number of muscles rather than coordinating each single muscle involved in a specific motor task [2], [3].

Muscle synergies are extracted from surface electromyography (sEMG) signals by applying different factorization techniques, such as Non-Negative Matrix Factorization (NNMF) [4], [5]. Before applying these algorithms, the acquired sEMG signals must be properly processed. These procedures may strongly influence the accuracy of muscle synergy reconstruction in the assessment of the modular organization of the CNS. In literature, several algorithms were proposed for the extraction of muscle synergies during cyclic movements [2], [4]–[7]. However, these techniques may not be sufficient to fully understand motor control mechanisms due to the high intra-cycle variability of the sEMG activation intervals. Innovative techniques, such as Statistical Gait Analysis [8], [9] and CIMAP [10], [11], have been introduced to deal with this issue by selecting only the representative gait patterns. The aim of this study is to show how the application of Statistical Gait Analysis and CIMAP algorithms may influence muscle synergy extraction increasing the robustness of results.

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II. Materials and Methods

A. Data Acquisition

The sEMG signals were recorded by means of a multichannel system for gait analysis (STEP32, Medical Technology, Italy) from one healthy female volunteer (age: 25 years, height: 160 cm and weight: 61 kg). The subject walked for 5 minutes at self-selected speed, back and forth a 10-m straight walkway. The active probes were positioned over 12 muscles of the right lower limb and trunk: right Longissimus Dorsii (LD_R), left Longissimus Dorsii (LD_L), Tensor Fasciae Latae (TFL), Gluteus Medius (GMD), Rectus Femoris (RF), Lateral Hamstring (LH), Medial Hamstring (MH), Vastus Medialis (VM), Lateral Gastrocnemius (LGS), Peroneus Longus (PL), Soleus (SOL) and Tibialis Anterior (TA). Foot-switches, placed bilaterally under the foot-soles, were used to segment gait cycles and extract only gait cycles showing the typical gait phases, discarding those with atypical sequences (e.g. turning and acceleration/deceleration in correspondence of direction changes) [12].

B. Identification of Muscle Activation Intervals

The Clustering for Identification of Muscle Activation Patterns (CIMAP) algorithm was used to select the principal and secondary muscle activations intervals over all the representative gait cycles [10].

The muscle activation intervals were computed by means of a double-threshold detector, specifically developed for gait analysis [13]. These activation intervals were extracted from the original sEMG signals windowing each gait cycle by means of a binary mask that was set to 1 in correspondence of a muscle activation and to 0 where no muscle activation was present.

The principal activations were defined as the muscle activations that are necessary to accomplish a specific biomechanical task and occur in each gait cycle. By contrast, the secondary activations occur only in some strides with auxiliary functions (e.g. to provide corrections to the main muscle activations for better controlling possible subject distractions or extemporaneous external disturbances).

An example of application of CIMAP algorithm is shown in Fig. 1 for PL and GMD muscles.

C. sEMG signal pre-processing

Before muscle synergy extraction, the acquired sEMG signals were pre-processed considering a) all the muscle activations, b) only the principal activations, and c) only the secondary activations.

First, gait data were segmented into typical gait cycles selecting only strides with a typical sequence of the gait

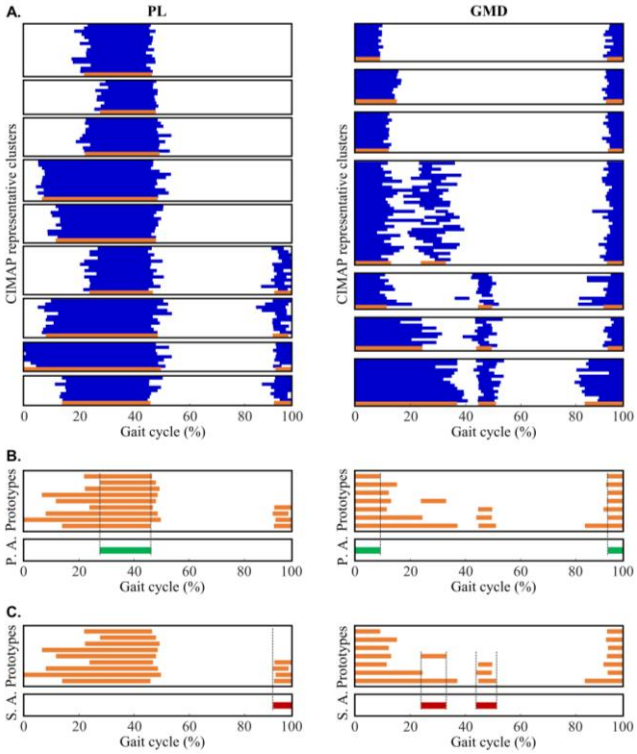

Figure 1. Example of clustering of muscle activation intervals using the CIMAP algorithm. (A) Blue intervals represents the cluster elements (sEMG activation intervals) normalized with respect to the gait cycle duration for PL (left) and GMD (right) muscles, while orange intervals represent the cluster prototypes. (B) Principal activation (P. A.) are highlighted in green and are defined as the intersection of all the clusters' prototypes extracted through CIMAP. (C) Secondary activation (S. A.) are highlighted in red and are modeled as the union of all the auxilliary activation of the clusters' prototypes discarding principal activations.

phases. Then, each segmented gait cycle was time-normalized into 1000 time points [14] and concatenated into a single vector [15]. Depending on the pre-processing procedure, the selection of the muscle activation intervals was performed windowing each normalized gait cycle by means of a different binary mask. After the removal of outlier strides and the selection of the muscle activation intervals, sEMG signals were high-pass filtered (8th-order Butterworth filter with a cutoff frequency of 35 Hz), full-cycle rectified to obtain a non-negative signal and low-pass filtered (5th-order Butterworth filter with a cutoff frequency of 12 Hz) to obtain the envelopes of the sEMG signals. Then the envelopes were normalized in amplitude with respect to the global maximum of each muscle. Before the muscle synergy extraction, the envelopes were divided into subgroups of 10 concatenated gait cycles (i.e. subgroup 1 contains gait cycles from 1 to 10, subgroup 2 contains gait cycles from 11 to 20, etc.) allowing for muscle synergy assessment over the 5-minute walk [16].

C. Muscle Synergy Extraction and Sorting

Muscle synergies were extracted for each subgroup from the pre-processed sEMG signals by means of the NNMF algorithm [4], [5]. This factorization algorithm decomposes the original sEMG-envelope matrix (M) as the linear combination of time-independent muscle synergy weights (W) and time-dependent activation coefficients (C) [17] as described in (1):

$$M(t) = \sum_{k=1}^{N} C(t)_k \cdot W_k + e \qquad (1)$$

where N represents the number of synergies needed to describe the motor control strategy. The weight vector W_k represents the weighted contribution of each specific muscle to the *k*-synergy, the activation coefficients vector $C(t)_k$ represents the time-dependent neural commands that activate the recruitment of the synergistic muscles in the *k*-synergy and e represents the prediction error of the factorization algorithm.

The MATLAB® function "*nnmf*" was used to apply the NNMF algorithm setting the routine parameters as detailed in TABLE I.

The first algorithm initialization was performed differently for the weights vector W_k and the activation coefficients vector C_k. The C_k vector was initialized with values randomly chosen from a uniform distribution in the range [0, 1]. To improve the performance of the factorization algorithm and the accuracy in the reconstruction of the original sEMG matrix, a sparseness constraint was imposed in the initialization of the weights matrix [18]. The W matrix was firstly initialized with values randomly chosen from a uniform distribution between 0 and 0.05, then one random element of each weight vector W_k was set to a value randomly selected from a uniform distribution in the range [0.7, 0.8].

The goodness of the sEMG matrix reconstruction with respect to the original matrix was computed by means of the total Variance Accounted For ($tVAF$), defined as the uncentered Pearson's correlation coefficient expressed in percentage (2):

$$tVAF = \left(1 - \frac{\sum_{k=1}^{m}(M_k - M_k^R)^2}{\sum_{k=1}^{m}(M_k)^2}\right) \cdot 100 \qquad (2)$$

where m represents the number of muscles observed, while M_k and M_k^R describe the original and the reconstructed sEMG envelopes of the *k-th* muscle, respectively.

The optimal number of muscle synergies needed to properly model the sEMG signals of the *i-th* subgroup (N_i) was selected by choosing the least number of synergies granting a $tVAF$ value greater than 90% [14]. Since each 10-gait-cycle subgroup could be described by a different number of synergies, the final number of synergies (N) was defined as the mode of the number of synergies computed on each subgroup.

The *k*-means algorithm was used to sort the muscle synergies extracted from each subgroup according to their muscle synergy weights W [19]. The clustering was performed using the following parameters: N number of *k*-means clusters, 10000 maximum iterations, 15 replicates and cosine distance

TABLE I. SETTINGS OF THE MATLAB® ROUTINE "NNMF" USED FOR MUSCLE SYNERGY EXTRACTION

Settings	NNMF routine
Algorithm	multiplicative update
Function tolerance	1e^{-6}
Search tolerance	1e^{-6}
Factorization replicates	50
Factorization iterations	1000

metric. The activation coefficients C were ordered consequently. To investigate changes in the robustness of the muscle synergies extracted using different pre-processing techniques, muscle synergies were extracted three times from the same original data considering: a) all the muscle activation intervals (standard procedure), b) only the principal activation intervals, and c) only the secondary activation intervals.

D. Muscle Synergy Robustness

The robustness of the muscle synergy extraction algorithm across different subgroups of gait cycles was assessed by means of the Cross-Variance Accounted For [15] defined as follows:

$$CrossVAF^{i,j} = \left(1 - \frac{\sum_{k=1}^{m}\left(M_k^i - M_k^{R,j}\right)^2}{\sum_{k=1}^{m}\left(M_k^i\right)^2}\right) \cdot 100 \qquad (3)$$

where M_k^i and $M_k^{R,j}$ represent the original and the reconstructed sEMG signals of the *k-th* muscle for the *i-* and *j-th* subgroup, respectively. Then, the average CrossVAF value was computed over all the subgroups for each pre-processing technique.

III. Results and Discussion

Using all the muscle activation intervals as well as using the principal activation intervals only, 5 muscle synergies were necessary to accurately reconstruct the original sEMG signals with an average $tVAF$ value of 93.2 ± 0.6% and 94.5 ± 0.5%, respectively. Considering only the secondary muscle activations, 6 muscle synergies were necessary to accurately describe the original sEMG signals with an average $tVAF$ value of 93.5 ± 3.7%.

Fig. 3 reports the muscle synergies extracted using the three different pre-processing procedures. Considering the muscle synergies extracted from all the muscle activation intervals (Fig. 3 (A)) and from the principal activation intervals only (Fig. 3 (B)), it can be noticed that muscle synergies are not significantly modified both in the number and in the shapes of C_k and W_k. However, the selection of the principal activation intervals increased the consistency of muscle synergies among subgroups, as it can be noticed by the reduced dispersion of both C_k and W_k.

The C_k and W_k computed using the secondary activation intervals discarding the principal activation (Fig. 3 (C)) were significantly different with respect to the ones represented in Fig. 3 (A, B) in terms of number of synergies, shapes and biomechanical function. The activation coefficients represented in Fig. 3 (C) were characterized by a lower amplitude and a significantly higher dispersion of the neural commands among the subgroups with respect to the activation coefficients computed using the first two pre-processing procedures.

Fig. 4 shows the colour maps of CrossVAF values for each couple of subgroups using (A) all the muscle activation intervals, (B) the principal muscle activation intervals only,

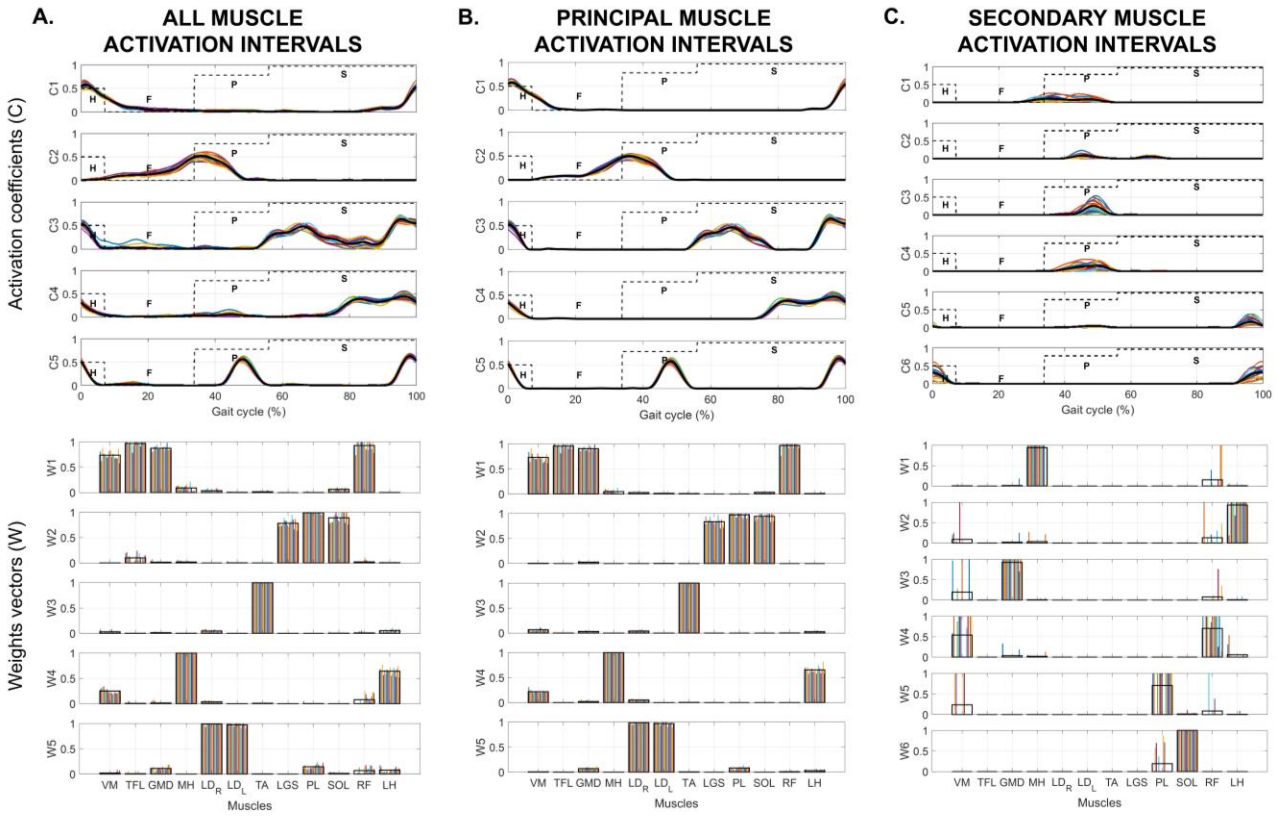

Figure 3. Activation coefficients $C_k$and weights W_k obtained with three different pre-processing techniques: (A) selection of all muscle activation intervals, (B) principal activation intervals discarding secondary activations , and (C) secondary activation intervals discarding principal activations. Each colored line represents the activation coefficients and weights extracted from a single subgroup, while the black lines represent the average activation coefficients and weights among subgroups. The dotted lines in the activation coefficients plots represent the mean foot-switch signal with the levels of Heel contact (H), Flat foot contact (F), Push off (P) and Swing (S).

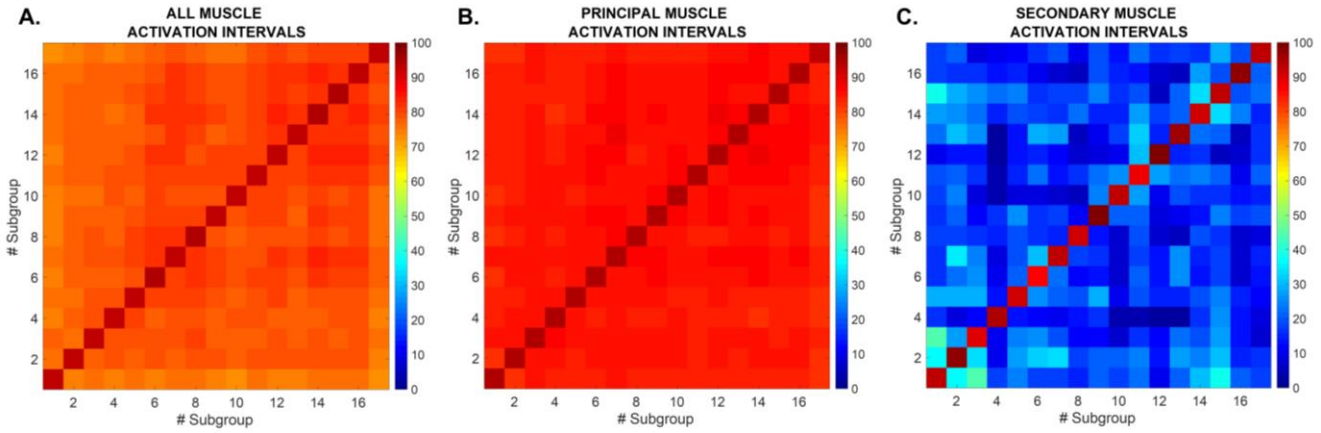

Figure 4. Colour map representation of muscle synergy robustness (CrossVAF) across subgroups of gait cycles considering: (A) all the muscle activation intervals, (B) the principal muscle activation intervals discarding the secondary activations, and (C) the secondary muscle activation intervals discarding the principal activations. Colour code ranges from 0% (blue) to 100% (red).

and (C) the secondary muscle activation intervals discarding the principal activations. CrossVAF values range from 0% (blue) to 100% (red) suggesting low and high correlation between the reconstructed and original sEMG signals, respectively. Considering all the muscle activation intervals, an average CrossVAF value of 79.5 ± 1.5% was obtained. Using the principal activations only, an average CrossVAF value of 85.3 ± 0.8% was obtained, while selecting only the secondary activations an averaged value of 22.2 ± 3.8% was obtained.

Hence, applying the CIMAP algorithm for the selection of principal activation intervals from sEMG signals, it was observed that the same number of synergies is needed to describe the motor task and the robustness of muscle synergies across subgroups significantly increased with respect to the standard pre-processing procedure (all muscle activation intervals).

IV. Conclusions

The present study analyzed the impact of the selection of principal and secondary muscle activation intervals from sEMG signals on the robustness of the muscle synergies extracted during a walking task in a healthy volunteer. Results suggest that the extraction of the principal activation intervals provide more consistent and more stable activation coefficients and weights vectors.

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