Methodological issues in the assessment of motor control during single-leg stance

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***Abstract*—In the study of muscle synergies during the maintenance of single-leg stance (SLS) there are methodological issues that must be taken into account before performing the synergy extraction. In particular, it is important to distinguish between epochs of surface electromyographic (sEMG) signals corresponding to a "good" balance control during the SLS test, from those characterized by an "excessive" body sway. The aim of this work is to assess the robustness in the segmentation and selection of sEMG signal epochs to be chosen as input for the synergy extraction algorithm. The robustness is evaluated in terms of: 1) consistency of the number of muscle synergies, and 2) weight vector correlation. Our results show that the same number of muscle synergies and similar weight vectors are obtained, independently from the threshold chosen to build the segmentation mask. The methodology proposed may help the interpretation of muscle synergies in SLS test.**

Keywords—muscle synergies, balance, unipedal stance, robustness.

I. INTRODUCTION

The postural sway analysis of human upright stance is applied to the study of various balance tasks (e.g. double-leg stance, semi-tandem, tandem, and single-leg stance), characterized by different motor control strategies and degrees of difficulty in the task performance [1]. In particular, the single-leg stance may be challenging in subjects affected by chronic ankle instability [2]. Considering a specific balance exercise, different conditions of visual and somatosensory integrations may be tested [3]. As an example, along with the eyes open (EO) condition, in which the subject exploits the visual feedback to maintain balance, a condition with eyes closed (EC) is also studied to assess the effect of visual deprivation on postural balance control [4].

Recently, there has been a growing interest in the use of muscle synergies to quantitatively assess motor control strategies in different motor tasks, including gait and postural balance [5]–[9]. This has a direct impact in clinics, sport science and robotics [10]. After recording surface electromyographic (sEMG) signals from several muscles involved in the actuation of a specific motor task, muscle synergies are extracted through algorithms for the dimensionality reduction of data, such as Non-Negative Matrix Factorization (NNMF) [11], [12].

In literature, the study of muscle synergies in upright stance is mainly focused on the evaluation of balance recovery after a perturbation [13]. In particular, it was demonstrated a high consistency of muscle synergies in different balance tasks [14]. This suggests that, increasing the task complexity, there are only slight modifications of the basic motor control strategies involved in postural balance control, evidence that supports the muscle synergy hypothesis. The extraction of muscle synergies has opened up new challenges in the field of postural balance analysis. To the best of our knowledge, there are no studies focusing on the muscle synergies adopted to maintain the single-leg stance. One possible reason may be the difficulty of selecting epochs of sEMG signals where the subject properly maintains the unipedal stance. Indeed, it is important to separate these sEMG epochs from those where a clear imbalance has occurred. The aim of this work is to define a robust procedure to segment and select epochs of sEMG signals, relative to a "well-balanced" single-leg stance, to be used as input for the muscle synergy extraction algorithm. This might help the interpretation of muscle synergies in single-leg stance.

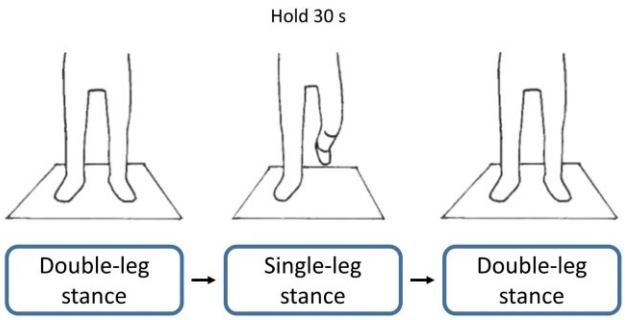

Fig. 1. Block diagram of the experimental protocol. Participants were asked to pass from a double-leg to a single-leg stance, mantaining the position for at least 30 seconds, and return to the double-leg stance.

II. Materials and Methods

A. Sample Population and Experimental Protocol

Twenty-two healthy subjects (age: 24 years ± 3 years, gender: 11 females and 11 males, height: 175.7 cm ± 9.6 cm, weight: 65.9 kg ± 12.2 kg) were enrolled in the study. None of the volunteers reported lower limb injuries or had neurological or musculoskeletal disorders that could compromise their single-leg stance performance. All the subjects were right-limb dominant, according to the preferred foot to start walking.

All subjects underwent the same experimental protocol consisting of a single-leg stance task. More specifically, they were asked to perform twice the single-leg stance (SLS) under two different conditions: eyes open (EO) and eyes closed (EC). Each task lasts at least 30 seconds and was performed on a firm surface. Arms were kept straight at the sides. Figure 1 represents the block diagram of the experimental protocol.

All participants signed a written informed consent for the experimental procedure and all the experiments were performed in accordance with the Declaration of Helsinki.

B. Data Acquisition

The following signals were simultaneously recorded during the experimental protocol:

i. sEMG signals by means of active probes (FREEEMG 1000, BTS Technology)

ii. Foot-switch signal to detect the onset/offset timing of the single-leg stance (FREEEMG 1000 – Footswitch Kit, BTS Technology)

iii. Ground reaction force by means of a force plate (Dynamic Walkway P6000, BTS Technology).

The sEMG active probes were positioned over the following 13 muscles of the trunk (bilaterally) and the lower limb (dominant side): right Longissimus Dorsii (LD_R), left Longissimus Dorsii (LD_L), Gluteus Medius (GMD), Rectus Femoris (RF), Lateral Hamstring (LH), Medial Hamstring (MH), Vastus Medialis (VM), Vastus Lateralis (VL), Lateral Gastrocnemius (LGS), Peroneus Longus (PL), Peroneus Brevis (PB), Soleus (SOL), and Tibialis Anterior (TA). sEMG signals were acquired with a sampling rate of 1000 kSa/s.

All the acquired signals were then imported into MATLAB® release R2019b (The MathWorks Inc., Natick, MA, USA) to be processed by means of custom routines.

Figure 2 represents a subject with sEMG probes placed over the observed dominant-side muscles. Foot-switch is also mounted on the contralateral side of the subject to detect the onset/offset timing of the single-leg stance.

C. Data Processing

Before muscle synergy extraction, the acquired sEMG signals were pre-processed to segment and select only the time-instants relative to a "well-balanced" single leg-stance, discarding those in which either double-leg stance or excessive unipedal-balance perturbations were detected (the quantitative definition is provided in the next Section).

Three different segmentation thresholds were applied to the acquired data to assess the robustness of the selection and segmentation approach and the consistency of the muscle synergy results.

D. Segmentation and Selection of Single-Leg Stance Epochs

The segmentation of the time-instants relative to a "well-balanced" SLS was performed considering the signals acquired from the foot-switch placed under the first metatarsal head of the non-dominant foot (left side) and the ground reaction forces acquired through the force plate.

The foot-switch signal was used to detect the time-instants after which the subjects moved from double- to single-leg stance and vice versa. The foot-switch signal was normalized in amplitude to obtain a signal in the range [0, 1], where 0 corresponds to an open foot-switch (foot raised from the floor), while 1 corresponds to a closed foot-switch (foot on the floor). The onset of the SLS was detected in correspondence of a 1-to-0 transition, while the offset was detected in correspondence of a 0-to-1 transition.

The ground reaction force was used to discard the possible excessive imbalances observed during single-leg stance. The ground reaction force acquired through the force plate is a tri-axial signal, where the x-axis is aligned to the antero-posterior direction, the y-axis is aligned to the down-top vertical direction, and the z-axis is aligned to the medio-lateral direction. As a first step, each component of the ground reaction force was pre-processed following an approach

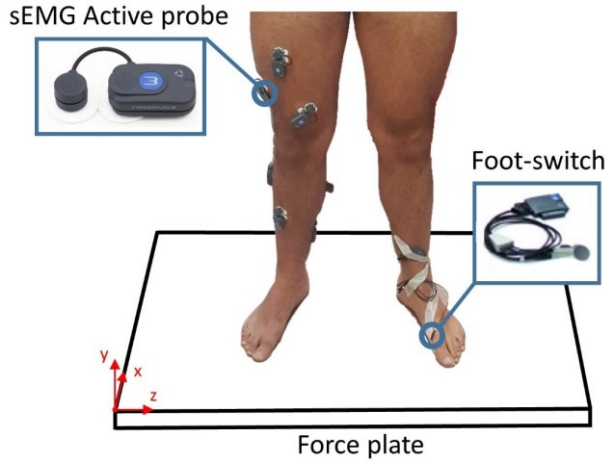

Fig. 2. Experimental set up. The sEMG probes are positioned over the main muscles of the dominant lower limb (sustaing the single-leg stance). A foot-switch is positioned under the first metatarsal head of the contralateral foot (raising from floor during the single-leg stance).

widely used in literature [15], [16]. More specifically, each component was low-pass filtered through a 5th order Butterworth digital filter with a cut-off frequency of 10 Hz.

Then, to detect excessive unipedal-balance perturbations, only the antero-posterior (AP) and the medio-lateral (ML) directions were considered. More specifically, the resultant of the antero-posterior and the medio-lateral components ($Fres$) was computed as described in (1):

$$Fres = \sqrt{F_{AP}^2 + F_{ML}^2} \quad (1)$$

where F_{AP} and F_{ML} represents the antero-posterior and the medio-lateral components of the ground reaction force, respectively.

The root-mean-square (rms) of the resultant reaction force ($Fres$) was computed by windowing the signals through 1-second epochs with no overlap, and was named $Fres_{rms}$. The time-instants relative to a "well-balanced" SLS were detected applying three different thresholds (Th_c) to $Fres_{rms}$, as described in (2):

$$Th_c = mean(Fres_{rms}) + c \cdot std(Fres_{rms}) \quad (2)$$

where c is a constant that was set equal to 1, 1.5, and 2, respectively. The values of the constant c have been chosen to be lower than 2 to achieve a sufficient length of the sEMG signals to be analyzed for the muscle synergy extraction.

The sEMG signals relative to a "well-balanced" SLS were segmented by windowing the filtered sEMG signals through a binary mask that was set equal to 1 in correspondence of the time-instants of the $Fres_{rms}$ below the threshold ("well-balanced" SLS condition) and to 0 in correspondence of the time-instants of the $Fres_{rms}$ above the threshold (excessive unipedal-balance perturbations). Figure 3 shows an example of the segmentation masks for a representative subject for each of the tested threshold (c = 1, 1.5, and 2).

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

Settings	NNMF function
Algorithm	Multiplicative update
Termination tolerance	$1e^{-6}$
Number of replicates	50
Number of iteration	1000

E. Muscle Synergy Extraction and Sorting

The segmented sEMG signals were high-pass filtered by means of an 8th order Butterworth digital filter with a cut-off frequency of 35 Hz, to remove motion artefacts, and full-cycle rectified to obtain a non-negative signal. Then, the sEMG envelopes were computed from the rectified signals through a low-pass 5th order Butterworth digital filter with a cut-off frequency of 12 Hz [17]. For each muscle, the sEMG envelopes were normalized in amplitude with respect to their global maximum to ensure that the activity in all the acquired muscle was equally weighted in the muscle synergy extraction process [17].

Muscle synergies were then extracted from the filtered sEMG signals by mean of the Non-Negative Matrix Factorization (NNMF) algorithm [11], [12]. The NNMF decomposes the original sEMG envelope matrix (M) as the linear combination of time-dependent activation coefficients

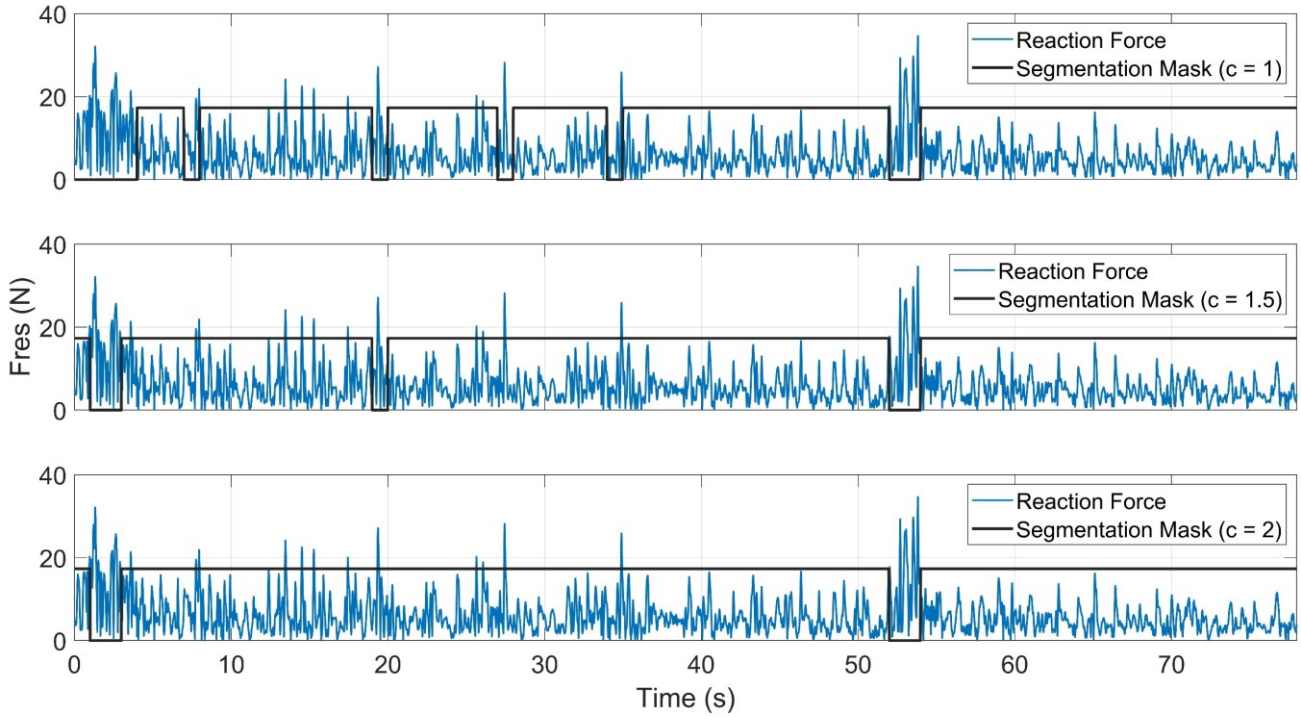

Fig. 3. Example of segmentation masks of "well-balanced" Single-Leg-Stance (SLS) for a representative subject, with eyes closed, for each of the tested thresholds (c = 1, 1.5, and 2). In blue it is represented the resultant reaction force ($Fres$) during a SLS test, while in black it is represented the segmentation mask computed considering the 3 different thresholds. The segmentation mask is set to 0 in correspondence of excessive unipedal balance perturbations ($Fres_{rms} > Th_c$), while is set to 1 in correspondence of "well-balanced" single-leg stance ($Fres_{rms} < Th_c$).

(C) and time-independent weight vectors (W) [18] as described in (3):

$$M(t) = \sum_{k=1}^{N} C(t)_k \cdot W_k + e \qquad (3)$$

where N represents the number of synergies needed to model the motor control and e is the reconstruction error. More specifically, the activation coefficient vector $C(t)_k$ represents the time modulation of the *k*-synergy, while the weight vector W_k describes the weighted contribution of each observed muscle to the *k*-synergy.

The MATLAB® function "*nnmf*" was used to apply the NNMF algorithm, setting the routine's input parameters as detailed in Table I. The input parameters used in this study were optimized in previous works focused on muscle synergy extraction during gait [9], [19].

To explore different solutions of the factorization algorithm, the *nnmf* function was run many times on the same sEMG data, changing the number of muscle synergies from 1 to 8. The accuracy in reconstruction of the original matrix (M) was computed for each number of muscle synergies by means of the total Variance Accounted For ($tVAF$), defined as in (4):

$$tVAF = \left(1 - \frac{\sum_{k=1}^{m}(M_k - M_k^R)^2}{\sum_{k=1}^{m}(M_k)^2}\right) \cdot 100 \qquad (4)$$

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

The optimal number of muscle synergies (N) necessary to properly reconstruct the original sEMG matrix was selected by choosing the least number of muscle synergies granting a $tVAF$ greater or equal to 90% [20]. Moreover, considering the number of synergies selected according to the previous criterion, the Variance Accounted For (VAF) was computed, for each muscle. If the VAF value was greater or equal to 75% for each of the 13 muscles, it was concluded that no additional muscle synergies were needed to properly reconstruct the original sEMG signals. Otherwise, the number of muscle synergies was incremented until all the muscles achieved a VAF value greater or equal to 75% [21].

A *k*-means algorithm was used to sort the muscle synergies extracted from each condition and each subject according to their weight vectors (W) [22]. The clustering algorithm was set considering N as number of *k*-means cluster, 1000 as maximum number of iterations, 15 as number of replicates, and cosine similarity as distance metric. The activation coefficients (C) were sorted consequently.

F. Muscle Synergy Analysis

The muscle synergies extracted considering the three different segmentation thresholds were quantitatively compared in terms of (*a*) consistency of the number of muscle synergies and (*b*) weight vector correlation obtained using the different thresholds.

a) Number of Muscle Synergies: As stated above, the optimal number of muscle synergies needed to properly reconstruct the original sEMG signals was selected by choosing the least number of synergies granting $tVAF \geq 90\%$ and $VAF \geq 75\%$ for each of the 13 muscles.

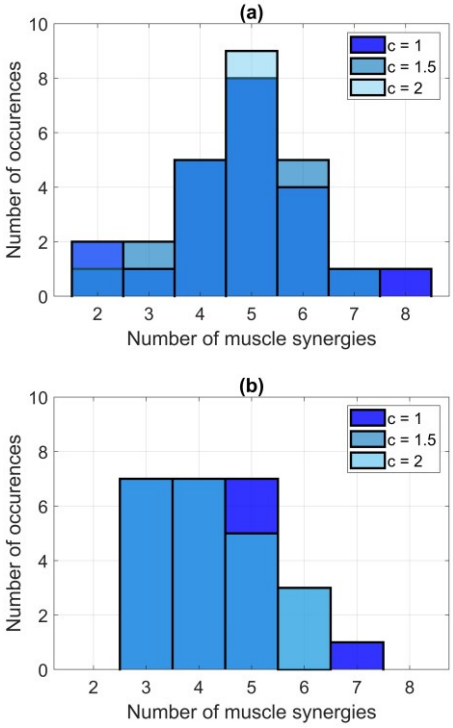

Fig. 4. Histograms of the number of muscle synergies extracted from all the subjects of the sample population during Single-Leg-Stanec (SLS) with (a) Eyes Open (EO) and (b) Eyes Closed (EC), considering the three segmentation thresholds (c = 1, 1.5, and 2).

b) Weight Vector Correlation: The similarity of the muscle synergies among the different segmentation conditions was assessed by computing the correlation coefficient of the previously sorted weight vectors (W_k). More specifically, the similarity was computed by means of the Pearson correlation coefficient (R) between each couple of weight vectors.

G. Statistical Analysis

To assess the robustness in the segmentation and selection of sEMG signal epochs as input for the synergy extraction algorithm, a two-way analysis of variance (ANOVA) was performed to assess the differences in the number of muscle synergies (N) and similarity of the synergy weights among the three different segmentation thresholds.

III. Results

In the following, results obtained with the three different segmentation thresholds were compared in terms of (A) consistency of the number of muscle synergies, and (B) similarity of synergy weights.

A. Number of Muscle Synergies

On average, all the tested segmentation thresholds required the same number of muscle synergies (N) to properly reconstruct the original sEMG signals with a $tVAF$ value higher than 90% and a VAF value for each observed muscle higher than 75%. More specifically, 4 muscle synergies for the EC condition and 5 muscle synergies for the EO condition were needed to properly reconstruct the original sEMG signals, for each of the three segmentation thresholds considered.

No statistically significant differences were found, in the number of muscle synergies, comparing the three segmentation thresholds (p-value = 0.95), while a significant increase of N was detected in the EO condition with respect to the EC condition (p-value = 0.005).

TABLE II. WEIGHT VECTOR CORRELATIONS (R) AVERAGED ON THE SAMPLE POPULATION

Condition	Pearson Correlation Coefficient (R) (mean ± standard deviation)		
	Th_1 vs $Th_{1.5}$	Th_1 vs Th_2	$Th_{1.5}$ vs Th_2
Eyes Open (EO)	0.98 ± 0.03	0.97 ± 0.06	0.99 ± 0.02
Eyes Closed (EC)	0.99 ± 0.01	1.00 ± 0.01	0.99 ± 0.02

Th_1: first threshold with c=1; $Th_{1.5}$: second threshold with c=1.5; Th_2: third threshold with c=2.

Figure 3 reports the histograms of the number of muscle synergies extracted during SLS from the sample population with (a) EO and (b) EC, considering the three segmentation thresholds. The histograms show a high consistency in the number of muscle synergies among the tested segmentation thresholds, both in EO and EC condition.

B. Muscle Synergy Similarity

Overall, results revealed high values ($R > 0.97$) of synergy weight correlations between each pair of segmentation thresholds chosen. No statistically significant differences in weight vector correlations were found comparing the three segmentation thresholds (p-value = 0.84), while a slightly significant decrease in the correlation was detected in the EO condition with respect to the EC condition (p-value = 0.048).

Table II shows the Pearson correlation coefficients (R), averaged on the sample population, between each pair of the tested segmentation thresholds. Results suggest a very high similarity among the muscle synergy weights extracted considering different segmentation thresholds, both in the EO and EC conditions.

IV. DISCUSSION AND CONCLUSIONS

The study of motor control in single-leg-stance can be challenging, due to the presence of out-of-balance epochs in sEMG signals. We demonstrated that a robust pre-processing can be applied to properly select the well-balanced periods during the SLS test. The procedure relies on a segmentation mask that allows for discarding periods when ground reaction forces exceed a certain threshold. Our results showed that the same number of muscle synergies and similar weights are obtained when extracting muscle synergies, independently from the threshold chosen to build the segmentation mask.

It should be noticed that, in the study of muscle synergies during locomotion, both weights and activation coefficients are usually analyzed [20], [23]–[26]. Conversely, when considering postural balance, the focus of the analysis is mainly on the synergy weights, rather than on the activation coefficients [6], [14]. This is somewhat not surprising since in locomotion there are cyclic patterns of activation, while there is nothing alike when considering postural balance motor control. The absence of typical cyclostationary processes in postural balance control prevents researchers from any direct interpretation of activation coefficients. Therefore, the main results in this field relate to the analysis of the muscle synergy weights, and this contribution is no exception.

In conclusion, we presented a methodology to pre-process sEMG signals, before muscle synergy extraction, that may help the interpretation of motor control strategies in single-leg-stance. Future developments will include the study of subjects affected by chronic ankle instability.

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