Evaluation of muscle synergies stability in human locomotion: A comparison between normal and fast walking speed

Evaluation of Muscle Synergies Stability in Human Locomotion:

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***Abstract*—Motor control strategies can be described by muscle synergies, a model of functional muscle recruitment to perform a movement. However, stability of muscle synergies during locomotion has not yet been investigated. The objective of this work was the evaluation of the stability of muscle synergies while walking at normal (NS) and fast (FS) speed. Each walking condition was tested during a prolonged session lasting 5 minutes on five healthy subjects. After data processing with statistical gait analysis, 168±29 valid strides in NS and 181±48 in FS were obtained. They were aggregated in subgroups, with 10 strides each. Muscle synergies were extracted for all subgroups with non-negative matrix factorization. On the average, 6 synergies were suitable to reconstruct the original electromyographic signal. They were functionally correlated to the activities of propulsion, trunk stability, limb deceleration at the end of swing, forefoot control, and limb stiffening for initial contact stability. To compare muscle synergy stability over time, a similarity measurement was carried out. This showed that from 1 to 3 synergies were unstable in NS. As for the FS condition, only one subject showed unstable synergies, corresponding to the hip stabilizing synergy.**

Keywords—muscle synergies; statistical gait analysis; electromyography; walking; fast speed

I. INTRODUCTION

Human walking is characterized by a large adaptability to different conditions. In this sense, one important element influencing gait patterns is walking speed, whose biomechanical effects emerged in previous studies, particularly on dynamics [1][2], kinematics [3], and stability [4]. Furthermore, speed has been proved to supply relevant elements for comparing gait function between pre- and post-therapy or surgical intervention [5],[6]. Muscle synergies refer to a model of modular recruitment of muscles as functional subunits applied by Central Nervous System (CNS): each synergy is activated by a single neural command with the objective of simplifying motor control and executing effectively complex movements such as locomotion, posture control, or grasping [7]. Several studies revealed that human locomotion can be expressed by simple and well defined muscle activation patterns [8], finding that different strategies could be expressed in terms of synergies [9].

Factorization is the most used method to extract muscle synergies: the neural modularity is inferred from common features extracted from electrical muscle activity [10]. Nevertheless, limitations have been highlighted since factorization does not allow researchers to fully understand the neurophysiological basis of the control scheme, and further measures of neural function are required [11]. Moreover, works commonly focused on the analysis of a limited set of gait cycles, but this could be reductive and misleading. In fact, human walking may be influenced by environmental or other factors, even pathological conditions [12], which may lead to a change in typical patterns. Therefore, it is reasonable to hypothesize that CNS strategies commonly expressed by muscle synergies vary to adapt the muscle recruitment for performing the most effective movement. To overcome the above limitations, "statistical gait analysis" (SGA) could be integrated with muscle synergy extraction. Indeed, SGA is designed to study prolonged gait signal recordings and to provide, automatically and user-independently, gait parameters for over than 100 consecutive strides [13][14][15]. When many strides are recorded, previous studies revealed that gait pattern may vary from stride-to-stride, showing both a different recruitment of lower limb muscles and foot contact [13], [15]. Many studies use treadmill walking at a fixed pace instead of level walking at a preferred speed. However, this may alter natural stride variability [16], leading to different biomechanical behaviors and, hence, different underlying motor control strategies.

The present work is aimed to compare the stability (in time) of muscle synergies between normal and fast walking. Each walking condition was tested during a prolonged session lasting 5 minutes on five healthy subjects. Firstly, gait data were pre-processed with SGA to remove atypical and outlier strides. Secondly, muscle synergies were extracted with non-negative matrix factorization for gait cycles arranged in subgroups of 10 strides. Finally, multiple comparisons between subgroups were performed by calculating cosine similarity.

II. Material and Methods

A. Experimental protocol

Five healthy females (24.8±2.2 years old) were recruited to perform two walking tasks at normal (NS) and fast speed (FS). First they were instructed to walk barefoot, at normal self-selected pace, back and forth along a 10-meter walkway for 5 minutes. Afterwards, maintaining the same probe positioning and instruments configuration, the task was repeated, instructing the subjects to walk at a quicker pace (again self-selected).

B. Data Acquisition and Processing

Processing phases are summarized in Fig. 1. Signals were acquired at a sample frequency of 2000 Hz by means of a multichannel recording system for statistical gait analysis (STEP 32, Medical Technology, Italy) equipped with foot-switches, knee goniometer, and surface electromyographic (EMG) probes. Three foot-switches (size 10 × 10 × 0.5 mm; activation force: 3 N) were placed beneath the heel, the first and the fifth metatarsal heads of each foot. A goniometer (accuracy 0.5°) was attached to the lateral side of knee joints for measuring the articular angle in the sagittal plane. EMG probes with the following characteristics were used: size 7 × 17 × 19 mm, single differential, 4-mm diameter AgCl disks, inter-electrode distance 12 mm. An overall gain ranging from 1000 to 50000, could be chosen to suit the need of the specific muscle observed (input referred noise ≤1 μV_{rms}). EMG probes were attached on 11 muscles (right side): vastus medialis (VM), tensor fasciae latae (TFF), gluteus medius (GMD), medial hamstring (MH), longissimus dorsii (LD), tibialis anterior (TA), lateral gastrocnemius (LGS), peroneus longus (PL), soleus (SOL), rectus femoris (RF), and lateral hamstring (LH). Sensors were attached to the shaved skin with bi-adhesive tape (see Fig. 2).

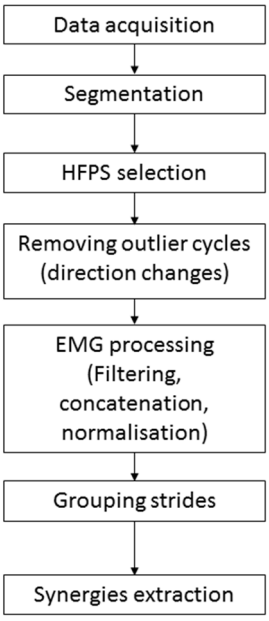

Fig. 1. Data processing scheme

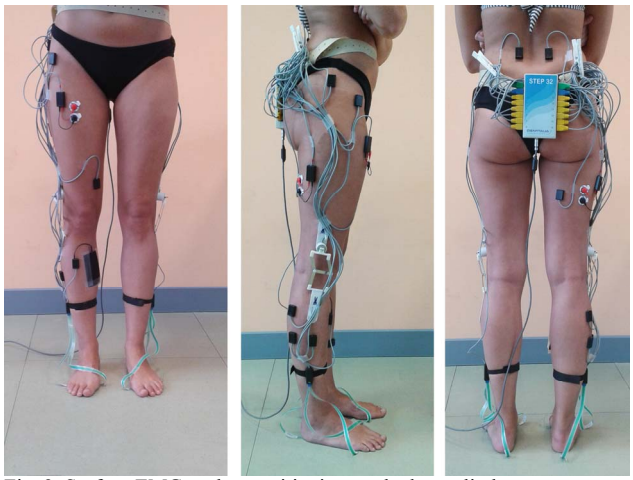

Fig. 2. Surface EMG probes positioning on the lower limb.

Acquired signals were imported into Matlab (TheMathWorks Inc., Natick, MA, USA) to be processed by custom routines. The two tasks were processed separately and overall data included: EMG signal to extract muscle synergies, basographic signal for timing the strides, and knee goniometry to remove outlier cycles. A double-threshold algorithm was used to count the number of muscle activation during a stride. Since muscles may activate a variable number of times within a stride, the most recurrent activation modality was selected for the LGS muscle to increase homogeneity in selected strides [17]. The input parameters of the algorithm (background noise, signal-to-noise ratio and duty cycle of the EMG) were estimated by the algorithm described in [18]. First, data were segmented according to the type of stride as described in [19]: a typical gait cycle consists of the sequence of Heel contact, Foot flat, Push-off, and Swing (HFPS). An algorithm automatically recognized with high accuracy which cycles corresponded to the HFPS sequence and discarded the others [20]. Then, gait cycles corresponding to direction changes were removed by recognizing abnormally lower knee range of motion and alterations in gait phase's durations. After having removed anomalous strides, the number of LGS activations within each stride was determined, and the most recurrent activation pattern was selected: strides with 2 LGS activations were included for analysis and concatenated. Then, EMG was processed: it was highpass filtered at 35 Hz, demeaned, full-cycle rectified, and then lowpass filtered at 12 Hz with a 5^{th} order Butterworth filter. Eventually, EMG signals were normalized in amplitude to the maximum activation for each muscle, and time-interpolated over single gait cycles to fit a 1000-point time base.

C. Muscle Synergies Extraction and Sorting

Before extracting synergies, EMG signals were separated in smaller subgroups of time intervals, each corresponding to 10 strides. In this way, synergies were extracted from an equal number of strides, allowing comparing them over time. In summary, for each original matrix consisting of concatenated EMGs of each task (NS and FS), we extracted *n* subgroups matrixes of dimension *number of muscles* × *number of gait*

cycles. Final strides were excluded in order to have the same size (10 strides) in all subgroups.

Muscle synergies were extracted from EMG matrixes previously computed by using non-negative matrix factorization, as introduced by [21] and applied to EMG by [22] and [23]. By this methodology, an EMG pattern is decomposed as a linear combination of fixed weights, and a vector of time-dependent coefficients, representing the neural command of CNS. The overall variance accounted for (VAF, uncentered Pearson Coefficient), adopted to quantify the goodness of the matching between measured and reconstructed EMG, was set to 90% to choose the suitable number of synergies gathering all information needed.

Afterwards, to enable comparison of synergies between subgroups, it was necessary to maintain the correspondence between similar synergies. To this purpose, K-means method was used. K was set equal to the number of extracted synergies, and clustering was repeated 5 times with different random initial clusters. The solution with the lowest within-cluster sums of point-to-centroid distance was selected. For a given 10-cycle subgroup *i*, synergies were permutated until the minimum distance of synergy W_i, with respect to the centroid of the synergies of the other subgroups, was reached.

D. Similarity Measurement

Cosine distance between synergies was adopted to quantify synergy similarity in different 10-cycle subgroups. For a given synergy W, a square matrix of cosine distances **Tw** (dimension *n* x *n*, with *n* subgroups) was calculated. For K synergies, K matrixes of similarity **Tw** were computed. For each element of **Tw**, we tested the synergies similarity among subgroups. More specifically, the null-hypothesis of the distance $t_{i,j}$ being equal to zero was tested. For each synergy, a matrix of p-values **Pw**, with the same size of **Tw**, was calculated. For the K-synergy, the *i*-th and *j*-th subgroups were considered similar if $p_{i,j}<0.05$. Finally, **Pw** matrixes were converted to a colour-coded map, to easily recognize subgroups of cycles with similar synergies.

III. Results

After signal segmentation and processing, 168±29 and 181±48 strides were included in the analysis, for NS and FS condition, respectively. Mean walking velocity was equal to 1.1 ± 0.11 m/s in NS and 1.48 ± 0.17 m/s in FS. A 1-way ANOVA revealed a significant difference of velocities between the two conditions ($p<0.01$). From 5 to 7 synergies satisfied the VAF > 90% condition for both velocities (mean VAF across subgroups and subjects: 91.2 ± 1.2% for NS, 90.0 ± 1.2% for FS). First, we report the results of the stability analysis on a representative subject; secondly, we summarize the results obtained on the sample of 5 subjects.

A. Representative subject

Fig. 3 shows weights and coefficients for NS (3-A) and FS (3-B) conditions for a representative subject. Comparing the weights over the subgroups (left panels), three behaviours were observed. First, some synergies were highly stable across different subgroups: it was the case of W1, both in NS and FS condition, where LGS, PL, and SOL weights assumed nearly the same value in all subgroups. Second, the same muscles were recruited in all the subgroups, but with different weights. Considering W4, this was the case of GMD and MH muscles in NS condition, and TFF and GMD muscles in FS condition.

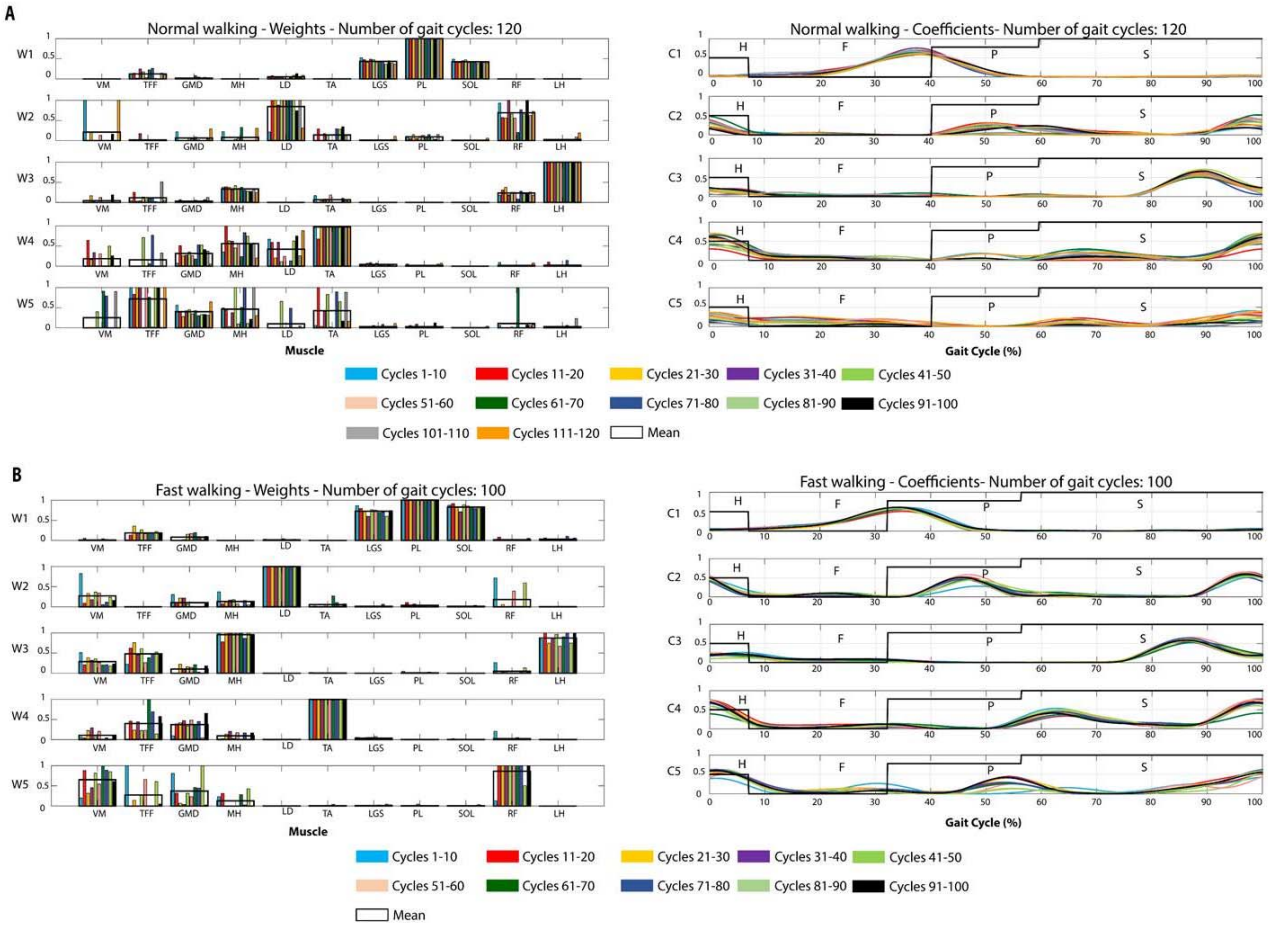

Fig. 3 Muscle synergies for (A) normal walking and (B) fast walking on a representative subject: weights (left plot) and coefficients (right plot). Synergies of different 10-cycle subgroups are represented in the same subplot differently colour coded. A thick black line indicates mean weights over the subgroups. In coefficients' plot the mean basographic signal with the levels of Heel-contact (H), Foot flat (F), Push-off (P), and Swing (S) is drawn superimposed.

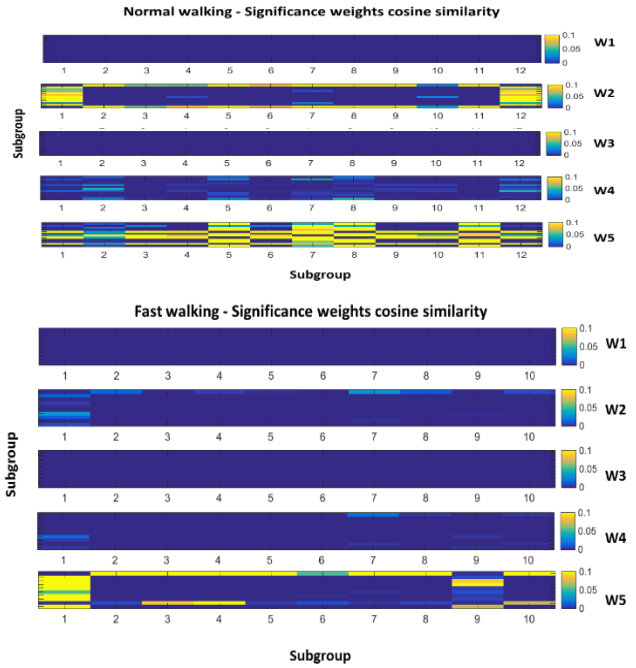

Fig. 4 Colour map representation of significance matrix of similarity of synergies across subgroups for normal (top) and fast (bottom) walking. Colour code ranges from high (dark blue), weak (light blue) and absence (yellow) of similarity.

Third, some synergies greatly varied among subgroups, being active in some subgroups and 0-weight in others. For example, in W5 of the FS condition, TFF muscle was not recruited in the subgroups 2 (strides 11-20), 4 (31-40), 7 (61-70), and 8 (71-80), being different from 0 in the remaining subgroups.

Synergies coefficients and mean gait phases are reported in the left panels of Fig. 3. Coefficients curves maintained the same shape over the subgroups. Some differences were observed between NS and FS coefficients: indeed, C5 amplitude was lower in NS than FS during swing (S-level) and at the beginning of heel contact (H-level). FS condition was characterized by a shorter F-phase with respect to NS. Furthermore, there was a good agreement between the beginning of the P-phase and the C1 peak, both in NS and FS.

In Fig. 4, the statistical significance of similarity measurements for NS (top) and FS (bottom) are reported. Subgroups are enumerated from 1 (cycles 1-10) to 12 (cycles 111-120) for NS, and, similarly, from 1 to 10 for FS. For each synergy, the color code represents the level of significance between pairs of subgroups. A dark blue indicates a high similarity between subgroups (p value < 0.05). Conversely, yellow represents a significant difference between subgroups. Similarity among subgroups was higher in FS than NS condition.

In NS condition, W1, W3, and W4 were very stable among subgroups, with all the similarity measurements lower than significance level. By contrast, W2 and W5 greatly varied among subgroups. In particular, in W2, subgroups 1 and 12 were very different from all the other subgroups. In fact, it was characterized by a high activation of VM (see Fig. 3A). W5 greatly varied in some subgroups, particularly subgroups 5, 7, 8, and 11.

In FS condition, measures of similarity for synergies from W1 to W4 were definitively below the level of significance. Only in W5, subgroup 1 was not similar to the others.

B. *Sample population*

Table I summarizes the analysis of muscle synergy stability in the sample population, for NS and FS conditions. The number of muscle synergies extracted is the same between conditions, except for one subject (S3). The number of unstable synergies is reduced in 3 out of 5 subjects (S2, S4, S5) in FS with respect to NS condition, while it remaines unaltered in the remaining 2 subjects (S1, S3).

TABLE I. SUMMARY OF THE ANALYSIS OF MUSCLE SYNERGIES STABILITY ON THE SAMPLE POPULATION.

Subjects	**Normal speed (NS)**	**Fast speed (FS)**
	Num. of synergies (Num. of unstable synergies) [a]	***Num. of synergies (Num. of unstable synergies)*** [a]
S1	6(1)	6(1)
S2	5(2)	5(1)
S3	6(0)	7(0)
S4	7(2)	7(0)
S5	6(1)	6(0)

[a] For each subject, the number of unstable synergies is reported in parentheses, next to the total number of synergies extracted.

IV. DISCUSSION

Our work investigated the stability of muscle synergies during normal and fast walking. We considered a synergy stable if its weights were statistically correlated among different 10-cycle subgroups.

We found substantially the same synergies in NS and FS conditions. Synergy W1 was constituted by LGS, SOL, and PL, 3 plantarflexors of the foot, and they were activated in correspondence of the propulsive phase of the gait cycle. Synergy W2 was mainly constituted by LD: it was activated in the transition phase from swing to stance to maintain the trunk stability. Synergy W3 was composed by MH, LH: these muscles were enrolled to decrease the knee extension velocity at the end of the swing phase (S-level), with the objective of decelerating the leg before the heel strike of the subsequent cycle. W4 was mainly represented by TA, whose contraction causes the dorsiflexion of the foot, most probably to control forefoot drop. Finally, W5 was a synergy aimed at stabilizing the hip and knee joints and it was constituted by VM, TFF, GMD, and MH.

Overall, more stable synergies were found in fast walking with respect to normal walking. In both conditions, W5 was the most varying synergy across subgroups.

A limitation of this work is that we analysed only five subjects. Nevertheless, we focused on developing the method to investigate hundreds of strides, which is a condition that allows for studying the subject's walking performance in a

manner closer to reality. On the other hand, similarity measurements were centred on weights, rather than coefficients curves. However, coefficient curves agreed with weights sorting, and, hence, they did not appear a discriminating element of similarity.

V. Conclusion

In conclusion, we presented a method to integrate the extraction of muscle synergies with statistical gait analysis for the study of a prolonged walking session. By the integration of the two methods, the stability of motor strategies in time was evaluated. We were able to bring out differences in stability of motor strategies for different walking speeds. Future works should verify the repeatability of results in a wider sample of subjects, by including both healthy and pathological individuals. Additionally, a deeper investigation of varying synergies, atypical gait patterns and the effect of different muscle activation patterns are required to figure out their physiological basis and the role of CNS in determining walking activity.

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