European Journal of Applied Physiology
https://doi.org/10.1007/s00421-021-04762-w

ORIGINAL ARTICLE

Effects of body weight support and guidance force settings on muscle synergy during Lokomat walking

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Received: 17 December 2020 / Accepted: 29 June 2021

Abstract

Background The Lokomat is a robotic device that has been suggested to make gait therapy easier, more comfortable, and more efficient. In this study, we asked whether the Lokomat promotes physiological muscle activation patterns, a fundamental question when considering motor learning and adaptation.

Methods We investigated lower limb muscles coordination in terms of muscle activity level, muscle activity pattern similarity, and muscle synergy in 15 healthy participants walking at 3 km/h on either a treadmill or in a Lokomat at various guidance forces (GF: 30, 50 or 70%) and body weight supports (BWS: 30, 50 or 70% of participant's body weight).

Results Walking in the Lokomat was associated with a greater activation level of the rectus femoris and vastus medialis (×2–3) compared to treadmill walking. The level of activity tended to be diminished in gastrocnemius and semi-tendinosus, which particularly affected the similarity with treadmill walking (normalized scalar product NSP = 0.7–0.8). GF and BWS independently altered the muscle activation pattern in terms of amplitude and shape. Increasing BWS decreased the level of activity in all but one muscle (the soleus). Increasing GF slightly improved the similarity with treadmill walking for the tibialis anterior and vastus medialis muscles. The muscle synergies ($N = 4$) were similar (NSP = 0.93–0.97), but a cross-validation procedure revealed an alteration by the Lokomat. The activation of these synergies differed (NSP = 0.74–0.82).

Conclusion The effects of GF and BWS are modest compared to the effect of the Lokomat itself, suggesting that Lokomat design should be improved to promote more typical muscle activity patterns.

Keywords Robotic-rehabilitation · Muscle synergy · Electromyography · Locomotor coordination

Communicated by Andrew Cresswell.

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Abbreviations

ANOVA	Analysis of variance
BWS	Body weight support
C	Synergy activation matrix
E	EMG matrix
GF	Guidance force
IMVC	Isometric maximal voluntary contraction
M	Number of muscles
GM	Gastrocnemius medialis
NNMF	Nonnegative matrix factorization
NSP	Normalized scalar products
RF	Rectus femoris
S	Number of synergies
SENIAM	Surface EMG for non-invasive assessment of muscles
SO	Soleus
SSE	Sum of squared errors
SST	Total sum of squares
ST	Semitendinosus
T	Number of time points

Published online: 04 July 2021

TA	Tibialis anterior
VAF	Variation accounted for
VM	Vastus medialis
W	Synergy weightings matrix

Introduction

In the past two decades, neurorehabilitation has been complemented with modern robotic devices, such as the Lokomat for gait training, to improve the care of patients with movements disorders. The Lokomat offers a locomotor training environment that is suggested to make gait therapy easier, more comfortable, and more efficient (Riener et al. 2006). Indeed, the Lokomat is adjustable in terms of assistance (guidance force GF), body weight support (BWS), and gait velocity, allowing to personalize training intensity to the severity of the patients' impairments (Lünenburger et al. 2005; Riener et al. 2006). Therefore, it provides a safe and simplified environment for gait pattern generation, including postural control, limb coordination, and forward propulsion (Gottschall and Kram 2003). It also allows following the basic sensorimotor learning principles such as the practice of the complete task or the principle of progression in task difficulty (Kleim and Jones 2008; Wolpert et al. 2011). Previous studies have shown positive benefits of Lokomat training on balance (Uçar et al. 2014; Wallard et al. 2015), walking speed (Cherni et al. 2020), endurance (Chisari et al. 2015; Cherni et al. 2020), or lower limb muscle strength (Cherni et al. 2017). However, improving these aspects may not necessarily promote typical muscle activation patterns (Kim and Lim 2018), which are required to navigate in a natural walking environment comprising obstacles and other complexities.

These aspects are fundamental when considering motor learning and adaptation. Firstly it is important to ensure that a transfer between what has been trained and real life environment is feasible (Kleim and Jones 2008). Secondly, previous studies suggested that learning can be easier when what is learned conforms with the intrinsic structure of the motor command (Sing et al. 2009; Berger et al. 2013). Therefore, favoring typical muscle activation patterns during Lokomat training or simply understand in what sense the Lokomat alters the natural patterns may contribute to improving rehabilitation interventions.

The locomotor pattern is characterized at the temporal level by the presence of stereotyped sequences of multiple muscles activation, called modules or motor primitives (Ivanenko 2005; Dominici et al. 2011; Lacquaniti et al. 2012). Indeed, movements and particularly locomotion are thought to be generated by the combination of various classes of primitives, such as muscle synergies (Bizzi and Cheung 2013). Previous studies additionally suggested that these primitives may impose structural constraints on learning (Wolpert et al. 2011), meaning that the production of behavior requiring non-physiological primitives would be difficult to learn (Berger et al. 2013). Therefore, one potential limitation of using the Lokomat may come from the coordination imposed by the robotic assistance—because this assistance might alter the patterns of muscle recruitment compared to physiological walk (Hidler and Wall 2005). In this context, the synergies analysis can be a proper approach to examine the potential differences in motor control strategies during Lokomat training. These analyses identify weighted groups of muscles that are commonly activated together, known as synergies or modules, which are calculated from electromyography data (Chvatal and Ting 2012; Turpin et al. 2021).

Previous studies have reported contradictory conclusions concerning this issue [e.g., Hidler et al. (2005) and Van Kammen et al. (2016) vs. Gizzi et. al. (2012) and Moreno et al. (2013)]. For example, Hidler et al. (2005), highlighted that walking with the assistance of the Lokomat leads to changes in muscle activation patterns. In this study, the subject weight was not supported and the kinematic was fully prescribed (position-control mode) by the device. In these conditions, the authors reported higher activity for the quadriceps and hamstring during the swing phase of Lokomat walking compared to treadmill walking, but lower activity in the ankle flexor and extensor muscles. Likewise, Van Kammen et al. (2016) reported that the Lokomat could alter the muscle activity patterns in healthy subjects and that increasing GF (set to 0%, 50% and 100%) could make these patterns different to physiological walk, although no direct comparison with the "typical" patterns was provided in this study. Conversely, Moreno et al. (2013) showed that GF, varied between 20 and 100%, and walking speed, varied between 1.5 and 2.5 m/s, during Lokomat walking in eight healthy subjects did not alter the basic locomotor control and timing—in this study BWS was set to 30%. They also mentioned that walking with the aid of the Lokomat was achieved by similar motor modules and activation signals as treadmill walking. Based on previous studies it is still, however, uncertain whether Lokomat walking and Treadmill walking are similar in terms of motor control strategies. Moreover, to our knowledge, the interacting effect of GF and BWS settings on muscle coordination is still to be investigated. This interaction must be understood to guide clinical decisions during therapy. Therefore, additional studies are needed to investigate these issues.

The aims of this study were (1) to assess the effects of Lokomat settings—GF and BWS—on the level of muscles activation as well as on muscle coordination in comparison to regular treadmill walking and (2) to investigate the interaction between these settings. Previous studies showed that motor adaptation can be very fast in terms of muscle activations level—suggested to be linked to feedback-driven adaptations (Lam et al. 2006). Therefore, we hypothesized that the level of muscles and synergies activation might decrease when increasing BWS and GF because BWS would naturally decrease the amount of muscle activation needed to remain standing and GF would provide assistance to the movement. On the other hand, as per previous studies (Tresch et al. 2006; Steele et al. 2017), muscle coordination was analyzed using a synergy analysis and more precisely using nonnegative matrix factorization (NNMF), which allows for the characterization of the locomotor modules in terms of their spatial and temporal structures. We hypothesized that neural control of walking would be robust enough in terms of modular organization not to be altered by the different biomechanical constraints imposed by the Lokomat. Consequently, we expected similar muscle synergies with a similar sequence of activation of the synergies between Lokomat and treadmill walking.

Materials and methods

Participants

Fifteen healthy participants (eight females and seven males; age = 27.3 ± 4.7 years; mass = 64.7 ± 11.4 kg; height = 171.9 ± 10.0 cm) with no neurological or gait disorders volunteered in the study. The participants were right-foot dominant [based on the inventory for foot preference (Chapman et al. 1987)] and had no previous experience with robotic-assisted walking. Exclusion criteria were the presence of current or previous lower-limb and back injuries or orthopaedic surgeries during the last 12 months. This study was approved by the Research Ethics Board of UHC Sainte-Justine (2016-831, 4049).

Protocol

The Lokomat exoskeleton Pro (Hocoma AG, Volketswil, Switzerland) was used for this experiment. The Lokomat is a robotic gait trainer including a treadmill, a body-weight support system, and two robotic actuators attached and adjusted to the participant's legs. The robotic actuators of the Lokomat assist the hip and knee movement in the sagittal plane, while the ankle joint kinematics is supported by a spring system. The actuators generate torques that forces—to adjusted degrees—the joints to follow a reference joint trajectory. During the protocol, an experienced experimenter adjusted the hip and knee range of motion of the Lokomat actuators as well as the synchronisation between the speed of the treadmill and the feet to mimic physiological gait. The session started with a 15-min familiarization with the Lokomat gait. Then, each participant was asked to walk as normally as possible, following the movements generated by the Lokomat in nine different conditions that combined different settings of BWS (30%, 50%, 70%) and GF (30%, 50%, 70%). These levels of BWS and guidance match with the ranges that are usually reported during therapy (Mazzoleni et al. 2011; Chang et al. 2012; Niu et al. 2014; Chisari et al. 2015; Cherni et al. 2017). Walking speed was set to 3 km/h for each participant. The order of the nine Lokomat conditions was randomized between participants. A reference condition, consisting of treadmill walking with no assistance of the Lokomat was additionally recorded after the completion of the nine previous Lokomat conditions. The duration of measurements was 60 s for each condition including the reference condition. Participants were provided with a 1–2-min familiarization period before the recording of each condition to ensure a stable gait pattern (Lam et al. 2005). For the treadmill condition, in order to limit possible after-effects due to the Lokomat walking conditions, each participant was asked to walk for 5-min on the treadmill and only the 5th min was recorded.

Electromyography

Six EMG electrodes (Trigno™; Delsys Inc., Boston, MA) were placed on the right leg to record the activity of the following muscles: rectus femoris (RF), vastus medialis (VM), semitendinosus (ST), gastrocnemius medialis (GM), Soleus (SO), and tibialis anterior (TA). Prior to electrode placement, the skin was shaved and cleaned with 70% isopropyl alcohol pads to minimize the impedance between the skin and the electrode. Each electrode location was determined according to the recommendations of Surface EMG for Non-Invasive Assessment of Muscles (SENIAM) (Hermens et al. 2000). Prior to the recordings, three trials of isometric maximal voluntary contraction (IMVC) were performed for each muscle to normalize and compare EMG between different conditions. IMVCs were performed: (1) in a seated position with the knee bent at 90 degrees to determine the maximum activation of the flexors (ST) and extensors (RF, VM) of the knee, (2) in a seated position with the foot on the ground and the ankle in the neutral position to measure the maximum activation of the ankle flexors (TA), and (3) in a prone position with the ankle in the neutral position to measure the maximum activation of the ankle extensors (GM).

Data processing

Data were analyzed using customized Matlab programs (Matlab R2018a, MathWorks Inc., USA). All filters mentioned thereafter are zero-lag 4th-order Butterworth filters. Raw EMGs were band-pass filtered between 15 and 450 Hz (Cj et al. 2010). Electrical noise was removed using a notch filter at 60 ± 0.3 Hz. Thereafter, filtered EMG signals were full-wave rectified and envelopes were obtained using a low-pass filter with a cut-off frequency of 10 Hz (Shiavi et al. 1998). Then, the resulting envelopes were normalized by the highest EMG envelope magnitude obtained during the IMVC trials (overall peak activation). Gait events were determined measured by a Vicon motion capture system (Vicon, Oxford, UK), based on the trajectory of a marker positioned on the right heel (for heel contact). Finally, the EMG patterns for each cycle were interpolated on 500 points (spline method). For each subject and each walking condition ($n = 10$: 1 Treadmill + 9 Lokomat), nine cycles were used for the analysis. The averaged EMG corresponded to the average across all cycles of a given condition. For visualization, the ratio between the averaged EMG of the treadmill and each Lokomat condition was computed ($EMG_{Lokomat}$/$EMG_{Treadmill}$).

Synergy extraction

The muscle synergy analysis based on NNMF was conducted to assess the temporal and spatial structure of the muscles' coordination (Hug et al. 2011). NNMF iteratively factorizes the EMG matrix E (of dimension $t \times m$) into the synergy activation matrix C ($t \times s$) and the synergy weightings matrix W ($s \times m$)—i.e., E = W × C + residuals—until the Frobenius norm of the residuals was minimized. Dimensions t, m and s were the number of time points, the number of muscles, and the number of synergies, respectively (see Hug et al. 2011 for detail). The matrix E corresponded to the concatenated EMG patterns (normalized in time and amplitude) from each condition and was of dimensions $(N \times t) \times$ m, with N the being number of cycles ($N = 9$), t the number of time bins ($t = 500$) and m the number of muscles ($m = 6$). Not all the muscle channels could be analyzed for all the participants and only 14 (out-of-15) participants—with at least four channels available—were included in this analysis (see Table 1).

The synergy activation profiles—the time-varying activations of the synergies—corresponded to the columns of C and the synergy vectors—the muscle weightings in each synergy—to the rows of W. To hasten convergence, matrices C and W were initialized using the scores and loadings obtained from a principal component analysis extracted from the correlation matrix of E, negative values being replaced by positive random values (Zheng et al. 2007). At each iteration of the NNMF algorithm, the synergy vectors were normalized by their norm. The reconstruction quality was assessed by means of the variation accounted for (VAF) index defined as:

$$\mathrm{VAF} = 1 - \frac{\mathrm{SSE}}{\mathrm{SST}}$$

where SSE (sum of squared errors) is the unexplained variation and SST (total sum of squares in the residual matrix, i.e., residual = E − W × C) is the total variation (sum of squares in E). In order to compute the 95%-confidence interval of the VAF, we implemented a bootstrapping procedure in which the matrix **E** was resampled 100 times with replacement.

Table 1 Muscle included in the analysis in the function of the subject

Subject#	RF	VM	ST	GM	SOL	TA	Total
1	×	×	×	×	×	×	6
2	×	×	×	×	×	×	6
3	×	×	×	×	∅	×	5
4	×	×	×	×	∅	×	5
5	×	×	×	∅	×	×	5
6	×	×	×	∅	×	×	5
7	×	×	×	×	∅	×	5
8	×	×	×	∅	×	×	5
9	×	∅	×	×	∅	×	4
10	∅	×	×	∅	×	×	4
11	∅	×	×	∅	×	×	4
12	∅	×	×	×	∅	×	4
13	×	×	×	∅	×	∅	4
14	×	∅	×	×	∅	×	4
15	∅	×	∅	∅	×	×	3
Total	11	13	14	8	9	14	

The crosses indicate the channels included in the analysis (judged of good quality), and the ∅ signs indicate the non-included channels

RF rectus femoris, *VM* vastus medialis, *ST* semi-tendinosus, *GM* gastrocnemius medialis, *SOL* soleus, *TA* tibialis anterior

The synergies were extracted at each time. This procedure was performed with the number of synergies s varying from 1 to 6. The number of synergies was defined as the minimal value of s for which the lower bound of 95%-confidence interval of the total VAF was greater than 90% and the VAF for each muscle was greater than 75% (Allen et al. 2017). Synergies were extracted separately for each walking condition. The first VAF value, i.e., the VAF corresponding to the extraction of one synergy ($s = 1$), was used to quantify the complexity of the modular coordination between different conditions. The first VAF values appears to be more discriminative than the number of synergies itself to quantify motor coordination complexity (Klein Breteler et al. 2007; Clark et al. 2010; Steele et al. 2015).

Cross-validation procedure

The spatial structure extracted from the treadmill walking condition ($W_{reference}$) was compared to the structure of the different Lokomat conditions using cross-validation, as this method may be more sensitive than correlations (i.e., NSP) (Oliveira et al. 2014). In this procedure the synergy vectors from the treadmill condition ($\mathbf{W}_{treadmill}$) was extracted from a randomly selected part of the treadmill dataset, corresponding to 75% of the data, and used to extract the activation coefficients in the remaining 25% of the data in the treadmill dataset (auto cross-validation) and in 25% of the data from the different Lokomat conditions. The activation coefficients ($\mathbf{C}$) were extracted using the update rule (Lee and Seung 2001):

$$C_{i,j} \leftarrow C_{i,j} \times \left(E \times W^{T}_{treadmill}\right)_{i,j} \Big/ \left(C \times W_{treadmill} \times W^{T}_{treadmill}\right)_{i,j}$$

With $\mathbf{E}$ the EMG matrix of the treadmill or Lokomat conditions and $\mathbf{C}$ the activation coefficient matrix, initialized with positive pseudo-random numbers. The VAF (named cross-VAF for this procedure) was then computed using $\mathbf{E}$, $\mathbf{W}_{treadmill}$ and the extracted $\mathbf{C}$.

Statistical analyses

Repeated measures ANOVAs were used to assess the effect of the "device" (Lokomat or Treadmill), body-weight support (BWS = 30, 50 or 70%) and guidance force (GF = 30–50 or 70%) on average muscle activity, VAF-1 and cross-VAF. The model included an interaction term between BWS and GF (see model specification in appendix). Post-hoc analysis was performed using paired t tests where p values were adjusted for multiple comparisons using Holm-Bonferroni's method. The similarity of muscle activation profiles, synergy activation profiles, and synergy vectors between Treadmill and each Lokomat conditions was assessed using normalized scalar products (NSP), computed as the inner product of the two vectors normalized by the product of their norms (Oliveira et al. 2013, 2016). NSP values range from 0 to 1, corresponding to no and perfect similarity between the two vectors, respectively. NSP values, VAF1 and cross-VAF were Fisher-Z transformed before statistical analysis. Student's t tests for single means were used to compare the averaged NSPs—obtained for all comparisons between treadmill and the nine Lokomat conditions—with the $NSP_{threshold}$ (0.8 or 0.95). By generating 10,000 pairs of random vectors of dimension 6 from a uniform distribution (between 0 and 1) we determined that the upper limits of the 95% CI of the resulting NSPs were 0.94 for vectors of dimension 6 and 0.77 for vectors of dimension 500. Therefore, the thresholds of 0.95 (synergy vectors comparison) and 0.8 (synergy activation comparisons) were taken as the criteria for the similarity between two vectors (Oliveira et al. 2013). A Holm-Bonferroni correction was applied to account for multiple comparisons. Two-way repeated-measures ANOVAs were used to assess the effect of GF (30%, 50%, and 70%) and BWS (30%, 50%, and 70%) and their interaction on NSP values.

Results

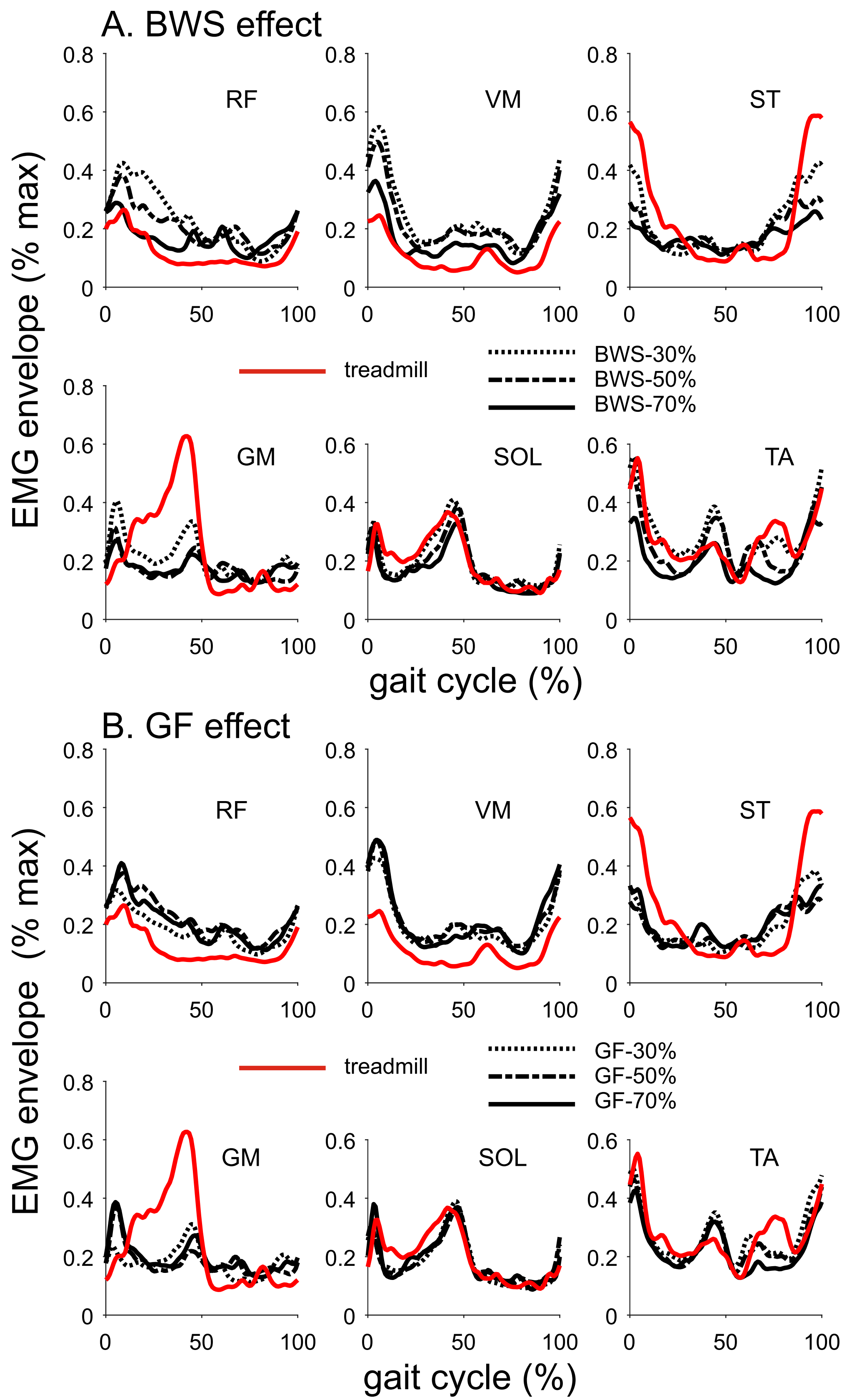
Muscle activation magnitude

Averaged patterns of muscle activity are displayed in Fig. 1. The ANOVAs revealed a large effect of the device (treadmill vs. Lokomat) on the averaged muscle activation for RF, VM and ST ($p \leq 0.024$, $\eta^2 \geq 0.33$; Table S1). Post-hoc analysis revealed higher RF (+ 136.8%) and VM (+ 191.2%) averaged muscle activations during Lokomat walking conditions compared to treadmill walking (Fig. 2). For ST, activation level was significantly lower during Lokomat than during treadmill walking (i.e., − 8.3%).

The ANOVAs revealed no interaction between BWS and GF (Table S1; $p \geq 0.052$) on average muscle activation. GF had an effect on the averaged muscle activation for RF and TA only ($p = 0.017$ and $p = 0.049$, respectively; $\eta^2 \geq 0.21$). For RF, averaged muscle activation was + 34.1% higher during GF-50% compared to GF-30% ($p = 0.042$). For TA, average muscle activation decreased with GF and significant differences were found between GF-30% and GF-70% (− 15.0%; $p = 0.026$). Muscle activation level significantly decreased with BWS increase in all muscles ($p \leq 0.021$; $\eta^2 > 0.30$) except SOL ($p = 0.129$).

Muscle activation similarity

The similarity index between the muscle activation profiles during treadmill and Lokomat walking are shown in


A. BWS effect
EMG envelope (% max)
RF
VM
ST
GM
SOL
TA
treadmill
BWS-30%
BWS-50%
BWS-70%
gait cycle (%)
B. GF effect
EMG envelope (% max)
RF
VM
ST
GM
SOL
TA
treadmill
GF-30%
GF-50%
GF-70%
gait cycle (%)

◂**Fig. 1** EMG patterns. Muscle activation patterns for the different GF and BWS conditions compared to treadmill walking (red line). The muscle activation patterns were normalized by their IMVCs and averaged over all subjects. *RF* rectus femoris, *VM* vastus medialis, *ST* semi-tendinosus, *GM* gastrocnemius medialis, *SOL* soleus, *TA* tibialis anterior, *BWS* body weight support, *GF* guidance force. The gait cycle starts from initial contact (IC 0% of gait cycle) of the foot to the successive IC of the same foot (100% of gait cycle)

Fig. 3. By testing the NSP values against the $NSP_{threshold}$ (=0.8), *t* tests for single mean revealed that the muscle activation profiles were similar for the TA (NSP = 0.86 ± 0.07) and the SOL (NSP = 0.89 ± 0.06; $p \leq 0.033$). NSP was not different from 0.8 for the RF (NSP = 0.84 ± 0.11), the VM (NSP = 0.83 ± 0.07), the ST (NSP = 0.78 ± 0.08) and the GM (NSP = 0.78 ± 0.08; $p \geq 0.037$; Table S3). The two-way ANOVAs revealed no interaction between GF and BWS on the NSP values for all the muscles ($p \geq 0.140$; Table S4). NSP significantly increased with GF for VM and TA (main effect: $p = 0.010$ and $p = 0.008$, respectively; $\eta^2 > 0.31$). Conversely, NSP decreased with BWS for VM (Fig. 3; main effect: $p = 0.021$; $\eta^2 = 0.21$).

Motor modules

The synergies vectors and activation profiles are depicted in Fig. 4. Four synergies were required to reconstruct the EMG envelopes in all conditions, including treadmill walking. Total VAF was greater than 95% in all conditions, i.e., 96.7 ± 2.3% on average overall conditions. VAF-1 ranged between 68.7 ± 10.8 and 73.9 ± 8.8%. VAF-1 was similar between the different Lokomat conditions and treadmill walking ($p \geq 0.08$, Table S5). We found no effects of the device (Lokomat or treadmill), GF or BWS, nor the interaction between GF and BWS on VAF-1 ($p \geq 0.345$; Table S6).

Synergy #1 activated mainly the knee flexor (ST), synergy #2 activated mainly knee extensors (VM, RF), synergy #3 activated ankle plantar flexors (GM and SOL) and synergy #4 co-activated mainly ankle dorsi- and plantar- flexors (TA and SOL). Concerning synergy vectors, the NSP values between Treadmill and Lokomat conditions were 0.97 ± 0.06, 0.93 ± 0.09, 0.95 ± 0.09 and 0.96 ± 0.07, for synergy #1, #2, #3, and #4, respectively. Similarity for synergy vectors #1, #3 and #4 were significantly higher than the 0.95 similarity threshold ($p < 0.001$). As for synergy activations, the NSP values between Treadmill and Lokomat conditions were 0.74 ± 0.14, 0.82 ± 0.13, 0.79 ± 0.13, and 0.82 ± 0.12 on average for synergy #1, #2, #3 and #4, respectively. These values were not different than the 0.8 similarity threshold ($p \geq 0.069$, Table S8).

Only the subjects for which more than four muscles were available were included in the cross-VAF analysis, i.e., $N = 8$ (Table 1), to obtain representative reconstruction values using four basis vectors. The cross-VAFs for the Lokomat conditions ranged between 88.2 ± 10.3% (GF-50%-BWS-50%) and 97.4 ± 3.4% (GF-30%-BWS-30%), and were significantly lower than treadmill cross-VAF at the highest GF, i.e., at GF-50% associated with BWS-30% and BWS-70%, and at GF-70% associated with BWS-30% and BWS-50%; $p < 0.002$; Cohen's $|d| > 1.38$; Table S9, suggesting that the structure of the synergies has been altered by the Lokomat conditions. Indeed, the ANOVA revealed significant large effects of the Lokomat (device), BWS, GF and a significant interaction between BWS and GF on cross-VAF ($p \leq 0.046$; $\eta^2 \geq 0.36$), and post-hoc analysis showed that increasing both BWS and GF decreased cross-VAF (Figure S1).

Discussion

The present study investigated: (1) the effects of Lokomat settings—GF and BWS—on the level of muscles activation as well as on muscle coordination in comparison to regular treadmill walking and (2) the interaction between these settings. The results were only partly consistent with our hypotheses, i.e., muscle activation decreased when increasing BWS as expected but the effects of GF were non-trivial. The structure and complexity of the motor output were conserved to a great extent, but we found evidence of alterations of the synergies during Lokomat walking.

Influence of Lokomat walking on EMG activity

Although the Lokomat has been considered effective for improving walking abilities in adults with neuromotor diseases (Swinnen et al. 2014), the effects of training settings on neuromuscular control remain unclear. By studying the effect of these settings on muscle activity in healthy adults, we observed that muscle activations were altered in terms of intensity (magnitude) and temporal profile during Lokomat walking. There was typically higher muscle activation in the quadriceps muscles (e.g., RF and VM) during Lokomat walking than during treadmill walking, which is in agreement with previous reports (Hidler and Wall 2005; Sylos-Labini et al. 2014). This increase was observed during all Lokomat walking conditions. The increase in the knee extensors is probably not linked to greater co-activation with the hamstrings (e.g., ST), as these muscles showed decreased activity in the present study. A likely explanation is that this extra activation is due to a discrepancy between the physiological walking kinematics and the kinematics imposed by the device (i.e., the GF). This interpretation has been suggested by previous authors by observing that EMG activity in the Lokomat can be reduced when the participants were asked to match the kinematic trajectories of the device (Israel et al. 2006). This interpretation is also consistent with

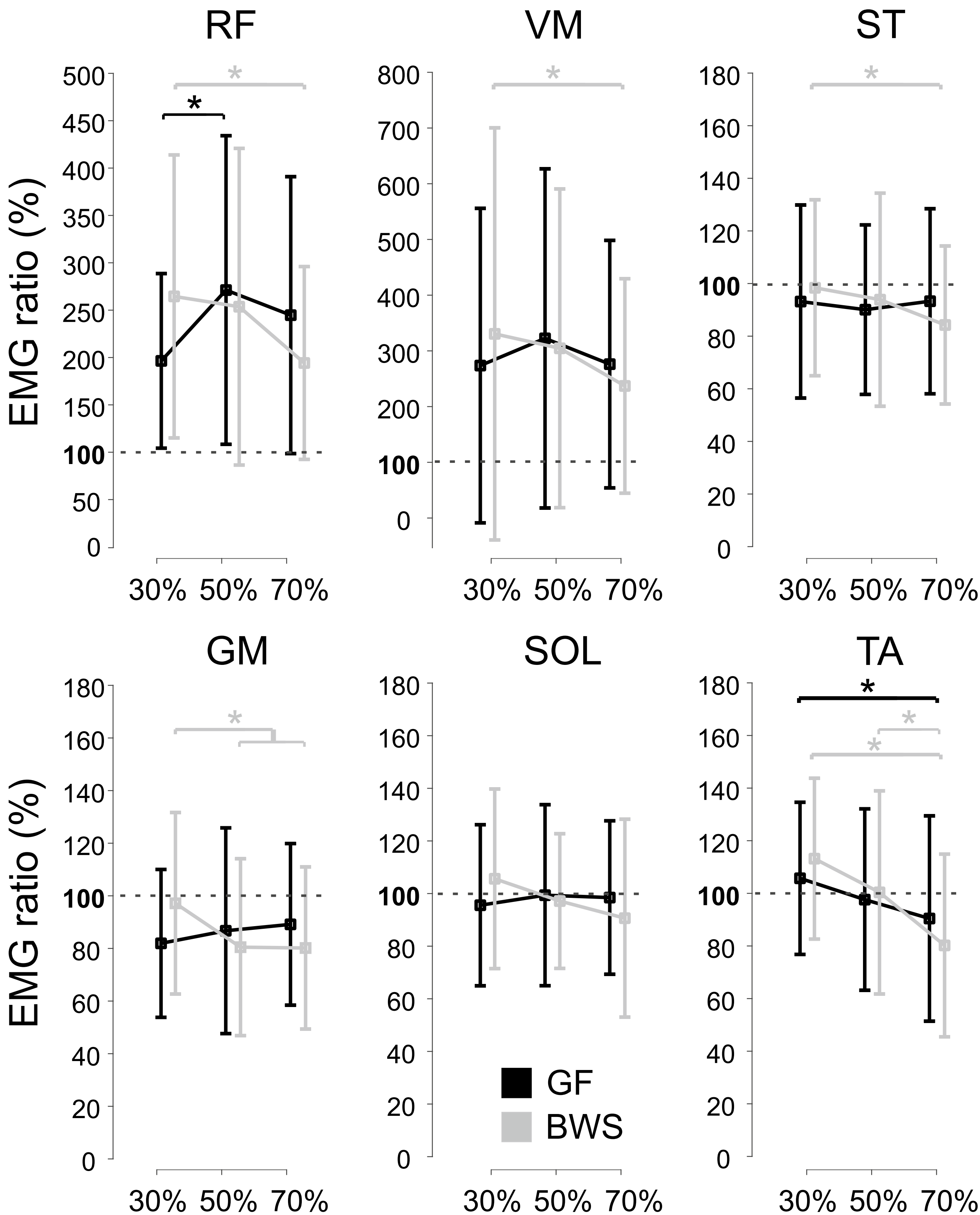


Fig. 2 Effect of BW and GF on EMG activation levels. The figures indicate the ratio (in percentage) between Lokomat and treadmill walking activations. Ratios > 100 indicates greater EMG activation levels during Lokomat than Treadmill walking. No interaction between guidance force (GF) and body-weight support (BWS) was present in any muscle. Therefore, only the main effects of GF and BWS are illustrated. *In black and gray indicate a significant effect of GF and BWS, respectively. Data are presented as mean ± 1SD

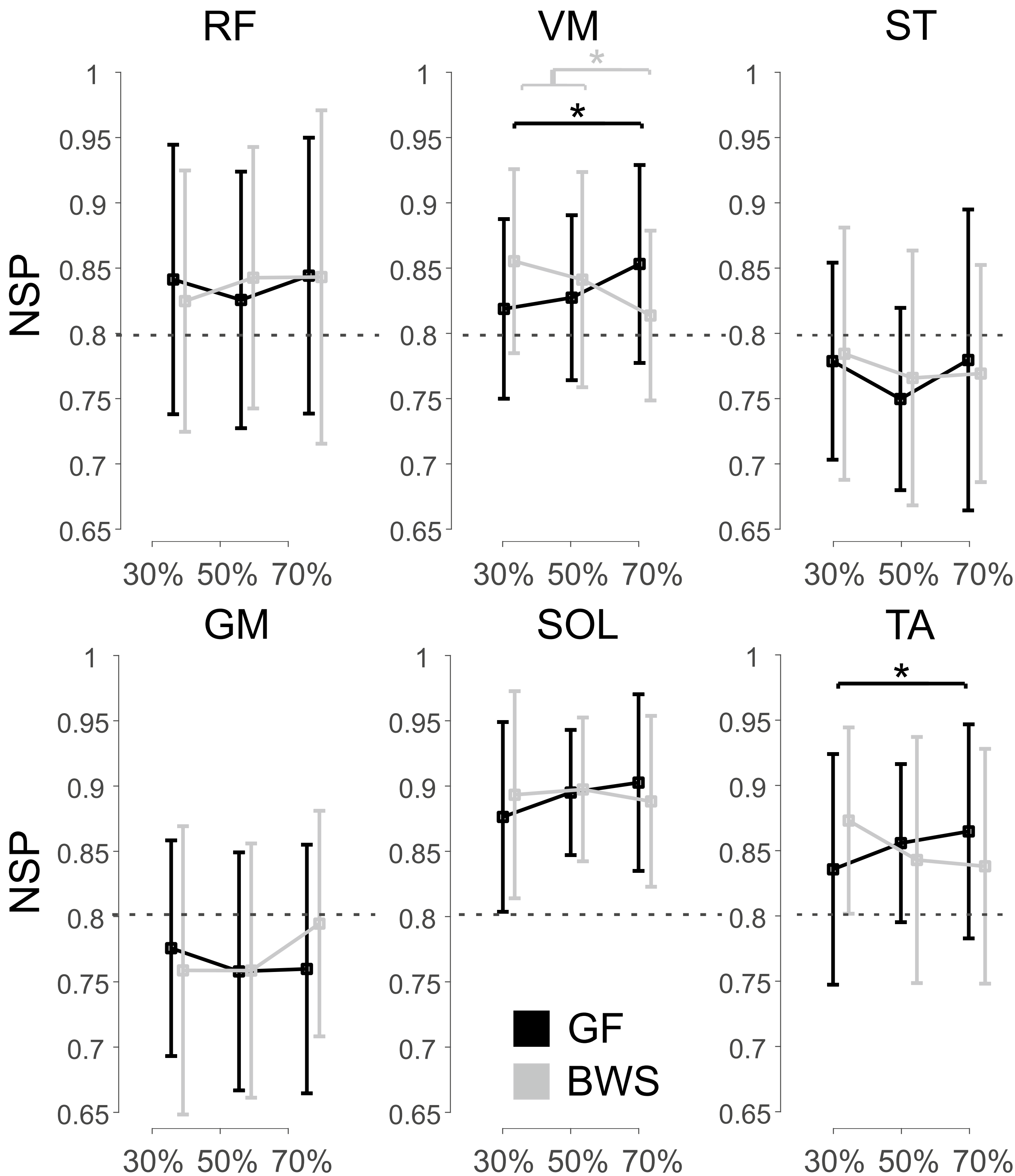


Fig. 3 Effect of BW and GF on the similarity of the muscle activation patterns between Lokomat and Treadmill walking. The similarity was computed using normalized scalar products (NSP). Data represent the average (± 1SD) overall participants

the referent control hypothesis (Levin et al. 1992; Feldman et al. 2007). The referent control hypothesis predicts that muscle activity increases when the intended position does not correspond to the actual position, i.e., the one imposed by the device, and therefore, muscle activity would be observed only if the subject's intended position—or more

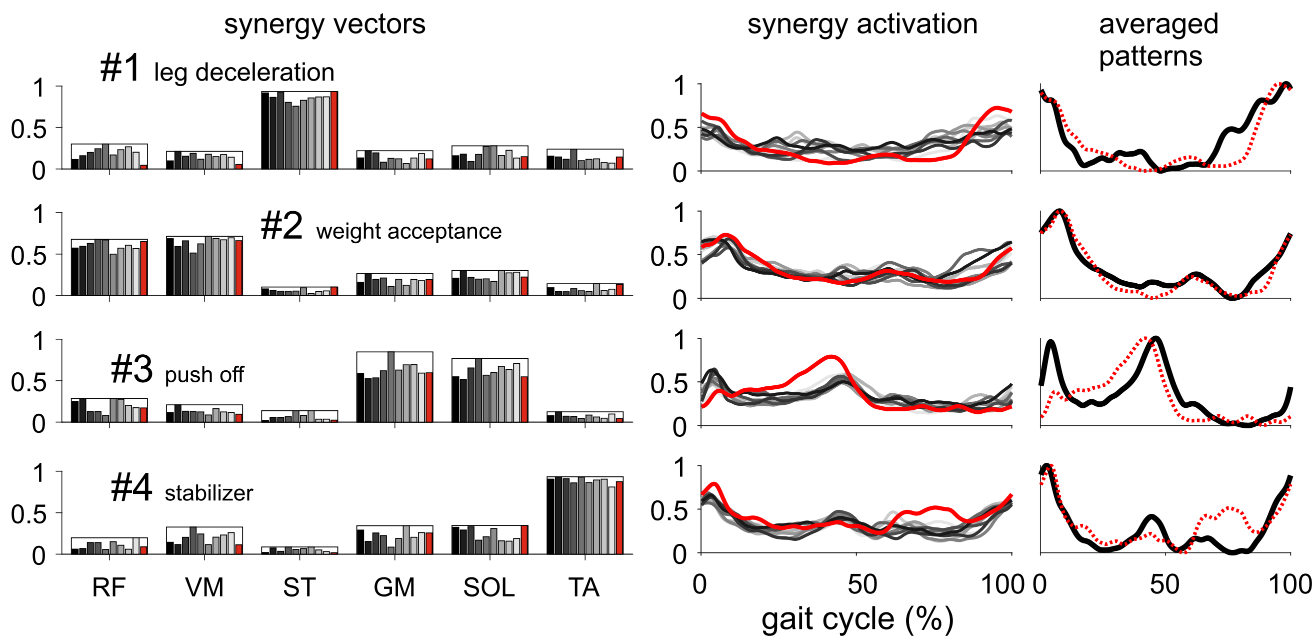


Fig. 4 Motor modules. The figure depicts the synergy vectors (left) and the synergy activations (right). The averaged patterns panel shows the average overall Lokomat conditions in black and the treadmill condition in red. The waveforms have been normalized by their maximum after the minimum value was subtracted to illustrate only their shapes. The various GF and BWS conditions are displayed in different gray levels. The modules obtained during treadmill walking are in red. The data are the average over all subjects and in arbitrary units

precisely its referent body configuration—precedes or lags that imposed by the kinematics of the device. This might explain why the changes in muscle activity differ from one study to another. Actually, if the participant is able to follow perfectly the device movement (and if not forced to sustain its own body weight), it can be predicted that no muscle activity would be observed (Israel et al. 2006). Indeed, the intention of the participant is fundamental to be considered, as individuals can voluntary increase (Aurich Schuler et al. 2013) or decrease muscle activity in the Lokomat (Israel et al. 2006).

We found that the effects of BWS and GF were independent to each other regarding the level of muscle activation and their shape. As expected, increasing BWS decreased the average muscle activity in most muscles (Fig. 2), but BWS had little effect on the shape of the muscle activation in general, except for VM (Fig. 3). The similarity of the activation profiles was commonly lower for the ST and the GM (Fig. 3). Qualitatively, the TA also shows some differences in the late swing phase (~70–80% of cycle). These differences in GM and TA can also be appreciated in the activation profiles of synergies #3 and #4 (Fig. 4). The similarity decreased by increasing BWS for VM but increased with increased GF for VM and TA. However, the effect of GF appears quite small (Fig. 1).

Overall, the idea that GF should be kept at a minimum due to these effects (Israel et al. 2006) might need careful considerations. As previously observed, the movement imposed by the device may elicit a more symmetrical pattern of leg muscle activity (Coenen et al. 2012). Finally, a general observation is that the effects of GF and BWS on muscle activity are relatively modest compared to the effect of the Lokomat itself.

Motor complexity in the Lokomat

Our results showed that the locomotor pattern was structured within 4 synergies during both Treadmill and Lokomat walking. This result is in agreement with previous studies (Neptune et al. 2009; Gizzi et al. 2012; Escalona et al. 2020) and suggests that walking in the Lokomat does not require a more complex coordination pattern compared to treadmill walking. The finding could be transferable to overground walking, since it has been pointed out that treadmill and overground walking share similar motor modules and timing (Oliveira et al. 2016). The composition of the synergies vectors found in the present study were robust across the different BWS and GF conditions, with very high NSP values, and very similar to those reported in previous studies (Chia Bejarano et al. 2017; Boccia et al. 2018). Consequently, similar functional roles were hypothesized (Fig. 4). More precisely, the 1st synergy consisted of the knee flexor activation (ST) and was active during late swing and the initial contact phase. This synergy was assumed to decelerate the leg. The 2nd synergy activated the knee extensors (VM, RF) and was assumed to be responsible for weight acceptance and single-leg support. The 3rd synergy mainly activated plantar flexors (SOL and GM) and was associated with the push-off phase. Regarding the 4th synergy, it mainly co-activated flexors and extensors of the ankle and we inferred that it would help support and stabilize the body during the mid-stance (weight-bearing and phase of double support). A previous study assumed that this synergy ensures trunk balance or leg or foot clearance (Chia Bejarano et al. 2017). The composition of this synergy is particularly variable across studies and its activation profile possesses at least two peaks, one after the push-off, and the other during the stance together with the activation of the weight acceptance synergy (3rd synergy) (Clark et al. 2010; Barroso et al. 2014; Chia Bejarano et al. 2017). However, the cross-validation procedure suggested that the Lokomat significantly altered the structure of the synergies.

The analysis revealed that the synergy activations were similar to those observed during treadmill walking (i.e., not different from 0.8). These results are in agreement with those of Moreno et al. (2013) and Gizzi et al. (2012) who found similar synergy activation between Lokomat and treadmill walking (Moreno et al. 2013) as well as overground walking (Gizzi et al. 2012). However, in previous studies (Gizzi et al. 2012; Moreno et al. 2013), the participants received visual biofeedback displayed step-by-step in line graphs representing the walking performance. Adding biofeedback might help to decrease the discrepancy between intended and actual body movement and generate more physiological EMG patterns in those previous studies.

Clinical implications

The results of our study suggest that therapists should be aware that alterations in muscle control may occur when certain combinations of settings are provided during training. Combining high levels of BWS ($\leq 50\%$) and very low GF may result in typically low muscle activation and may therefore not be desirable during training. Moreover, GF around 50% seems to increase muscle activity of knee extensors which can be particularly interesting during locomotor training in patients such as those with cerebral palsy and who walk in crouch gait (Cherni et al. 2019). In general, this feature of Lokomat training is considered as an important aspect of its clinical implication because voluntary contraction of muscles plays a key role in motor relearning (Coenen et al. 2012).

In terms of muscle coordination, our results showed that the locomotor pattern was structured within four synergies during both Treadmill and Lokomat walking. This observation could be different in individuals with neuromotor disorders. In fact, individuals with neuromotor disorders (i.e., cerebral palsy (Steele et al. 2015), stroke (Clark et al. 2010), spinal cord injury (Hayes et al. 2014), Parkinson's Disease (Roemmich et al. 2014)) have altered synergies during gait compared to typically developing peers. Fewer synergies are required for locomotor tasks in these populations, which is thought to contribute to the impaired movement (symptoms of spasticity Steele et al. 2015; Barroso et al. 2016), selective motor control (Steele et al. 2015), muscle strength (Steele et al. 2015). Furthermore, a study in post-stroke survivors showed that individuals with synergies more similar to healthy individuals had greater improvements in walking after a treadmill training program (Routson et al. 2013). Finally, although synergy complexity and weights are challenging to change in individuals with neuromotor disorders (Shuman et al. 2019), synergy activations may provide a target for gait rehabilitation with the Lokomat.

Study limitations

There are some limitations of this present study that need to be acknowledged. Firstly, this study only included healthy participants although the purpose of the Lokomat is to be used with people with impaired motor control abilities. However, this choice allowed an easier exploration of Lokomat settings in a relatively homogeneous population and patients with gait disorders would have not been able to perform physiological gait without any support during the Treadmill condition. Healthy subjects are also likely to more rapidly adapt to the constraints imposed by the Lokomat. However, although adaptations can be faster, notable differences could be evidenced between Lokomat and treadmill walking even though a familiarization period was imposed. This suggests that Lokomat may affect the typical muscle patterns to a greater extent in patients, for example in children with cerebral palsy or post-stroke subjects, which have slower adaptation rates. We might also add that we analyzed only the dominant leg of each participant. It may be asked whether the alterations observed in the present study would be greater if the non-dominant was investigated. Secondly, the treadmill condition was performed after the Lokomat conditions, which does not allow us to completely exclude an aftereffect of Lokomat. Thirdly, due to the straps of the Lokomat to secure the participants into the device (Kammen et al. 2014), the number of recorded muscles was limited in the present study and this may have affected the structure of synergies or lead to the over-estimation of VAF (Steele et al. 2013). Fourthly, the muscles available were not the same for all subjects which may have weakened the conclusions about the synergy analysis too, although the number of muscles recorded in previous clinical studies was quite similar to the present study (e.g., ≤ 6 Steele et al. 2015; Krogt et al. 2016)). Finally, although the mechanical constraints seem to be relatively similar between the treadmill *vs.* overground walking (van Ingen Schenau 1980; Lee and Hidler 2008), the differences observed between the Lokomat walking and treadmill walking maybe not fully transferable to overground walking. Other some factors might affect the physiological determinants of locomotion on a treadmill vs overground: the compliance of the surface, the fixed rather than moving visual feedback, the degree of habituation, etc.

Conclusions

Based on our results, Lokomat walking does not necessitate a more complex coordination structure than normal treadmill walking, and similar muscle synergies were found in both walking conditions. Moreover, we observed that the GF and BWS parameters had some effects on muscle activations, while these effects appear small compared to the effect of the Lokomat itself. The Lokomat clearly alters the physiological muscle coordination patterns in terms of shapes and amplitudes. The present results suggest that the Lokomat design should be improved to promote more physiological movements.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00421-021-04762-w.

Acknowledgements The authors would like to acknowledge the participation of all subjects in this study.

Author contributions YC: responsible for the study design, data analysis, and interpretation as well as the manuscript writing. MH: responsible for data analysis and interpretation, as well as major revisions of the manuscript. FDM: responsible for the study design, EMG expertise, as well as major revisions of the manuscript. NT: responsible for the study design, supervision of the project, EMG expertise, validation of the main decisions during the study, validation of data interpretation as well as major revisions of the manuscript.

Funding None.

Declarations

Conflict of interest The authors have no conflict of interest.

Ethics approval and consent to participate This study was approved by the Research Ethics Board of UHC Sainte-Justine (2016–831, 4049). All subjects signed informed and written consent before any procedure of the experiments.

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