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„Inter-subject variability of muscle synergies while walking with progressive constraints“

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Abstract

Muscle synergies are coordinated patterns of muscle activation used to perform specific movements or tasks. The central nervous system simplifies the motor control by activating a limited set of vectors rather than each muscle, thereby reducing the dimensionality of skeletal muscle activation. The aim of this study was to get an insight of the inter-subject variability of muscle synergies while walking with increasing constraints. Gait patterns were constraint through changes in cadence and stride length. Our first task involved walking without any limitations. In the second task, participants walked to the rhythm of a metronome, while the third task combined the constrained cadence of the second task with a restricted stride length, requiring participants to step on markers placed on the ground while walking in the rhythm. The activity of ten lower limb muscles were recorded using surface electromyographic electrodes. To record the kinematics, a three-dimensional motion capture analysis system was used. We discovered shared muscle synergies among participants facing similar walking constraints. Furthermore, the inter-subject variability of muscle synergies increased, the more walking became constrained. The kinematics exhibited distinct behaviour and increased variability when only the cadence was constrained. We concluded that with increasing constraints, leading to unnatural gait, participants solved their problem in different ways and variability increased. Kinematic variability is influenced by step length and walking speed and not in relation to muscle synergies when movements are unfamiliar.

Zusammenfassung

Muskelsynergien sind gemeinsam angesteuerte Muskeln, also Muster, welche vom zentralen Nervensystem aktiviert werden, um spezifische Bewegungen auszuführen. Dies dient als Vereinfachung, um Muskeln nicht separat, sondern als Gruppierungen aktivieren zu können. Um die motorische Kontrolle besser zu verstehen, ist es sinnvoll, Alltagsbewegungen wie das Gehen zu untersuchen. Das Ziel dieser Studie war es, mehr Informationen über Muskelsynergien während des Gehens mit Einschränkungen zu erhalten und herauszufinden, ob sich die Veränderungen der Muskelsynergien zwischen den Probanden ähnlich verhalten, wenn das Gehen schrittweise erschwert wird. Die Probanden bekamen drei verschiedene Gang-Aufgaben. Zuerst einen normalen Gang mit selbst ausgewählter Geschwindigkeit, danach einen Gang, bei welchem die Schrittfrequenz mittels Metronoms vorgegeben wurde, und zuletzt wurden zusätzlich zum Metronom Bodenmarkierungen geklebt, auf welche die Probanden steigen mussten, wodurch die Schrittlänge bestimmt wurde. Elektromyographie-

Signale von zehn Muskeln der unteren Extremitäten wurden gemessen und eine dreidimensionale-Bewegungsanalyse durchgeführt. Wir stellten fest, dass die Muskelsynergie-Muster zwischen den Probanden während des Gehens mit Einschränkungen zwar ähnlich waren, aber die Variabilität signifikant zunahm, je stärker der Gang eingeschränkt wurde. Die Kinematik verhielt sich jedoch anders und die Variabilität war lediglich erhöht, als der Gang mit Metronom eingeschränkt wurde. Daraus lässt sich schließen, dass das Problem eines unnatürlichen Ganges von verschiedenen Personen auf unterschiedlicher Art gelöst wird und die Variabilität zwischen ihnen zunimmt. Die Kinematik hängt von der Schrittlänge und Ganggeschwindigkeit ab und verhält sich anders als Muskelsynergie-Vektoren, wenn Bewegungen ungewohnt sind.

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1 Introduction

In the human body, each lower limb consists of more than fifty muscles controlled by the central nervous system (CNS). Scientists often refer to the redundancy issue when dealing with the control of multiple degrees of freedom within the musculoskeletal system (Zelik et al., 2014; Barroso et al., 2014). Muscle synergies were first discovered by Bernstein (1967) and became very popular in the field of neuroscience. It is said that the CNS reduces the dimensionality of muscle activation for specific and well-known motor tasks with developing certain patterns of muscle activations (Cheung et al., 2009; d'Avella and Bizzi, 2005). Each synergy defines a consistent pattern of activation for the motoneurons that innervates a specific group of muscles (Pale et al., 2020; Zelik et al., 2014). Instead of individually activating each muscle, groups of co-active muscles (known as motor synergy vectors) are activated by activation coefficients to streamline the complex coordination of the large number of muscles (Bizzi and Cheung, 2013; Bernstein, 1967; DAVIES, 1968).

Through many studies people were working on getting a better understanding of these muscle activation patterns, how the CNS generates movements and activates and coordinates thousands of motor units simultaneously (Bizzi and Cheung, 2013). Various studies showed that similar synergy vectors are engaged in different movements, reinforcing the idea of spatially consistent synergy vectors. The concept of 'shared synergies' refers to comparable movement components that align with specific mechanical objectives (Barroso et al., 2014; d'Avella et al., 2003; Nazifi et al., 2017). For exemple, Hug et al. (2010) discovered in their study that two of three extracted synergies during cycling are shared with two of four extracted synergies during walking (Neptune et al., 2009). Frère and Hug (2012) concluded that muscle synergies are consistent across participants, even during a skilled motor task requiring learning. Nine experienced gymnasts were assessed while performing backward giant swings on the high bar. Through calculations of three synergies, the study revealed an average correlation coefficient (CC) value of 0.83 for muscle synergy vectors among participants. When comparing experts and untrained participants during bench press exercises, experts demonstrate less variability in muscle synergy vectors compared to untrained participants. However, there was larger variability observed in the activation coefficients among the expert participants (Kristiansen et al., 2016). Expert dancers exhibited a greater amount of shared synergies between overground walking and balancing tasks compared to individuals with no dancing experience (Allen et al., 2020; Sawers et al., 2015).

Hug et al. (2011) constrained pedalling in torque-velocity and body posture and were looking at the consistency of muscle synergies. They concluded strong robust consistency specifically within the muscle synergy vectors. This high similarity in the composition of the three extracted synergies was accompanied by subtle adjustments in their activation coefficients when faced with substantial alterations in torque and posture.

Different studies show that fundamental muscle synergy structures, such as synergy weights or vectors, exhibit minimal variation even when external environmental changes occur during walking (Ivanenko et al., 2004; Gonzalez-Vargas et al., 2015; Sawers et al., 2015). For example, Kim et al. (2022) identified muscle synergy variability in walking with constraints, examining the differences between children with typical development and those with cerebral palsy. Constraints were imposed in two manners: one by altering walking speed and the other by narrowing the walking path. They observed relatively consistent patterns between strides among healthy subjects. In contrast, children with cerebral palsy exhibited more affected and less consistent muscle activation patterns. In a study by Singh et al. (2020) the comparison of muscle synergies between walking and slacklining revealed that both synergies 1 and 2 were associated with balance and control. However, notable variations in their muscle weights were observed between these two tasks. Most of the synergies were more similar during walking than slacklining. Furthermore, inter-subject analyses indicated that most synergies during walking were consistent across participants. Other researchers examined muscle synergy variation across six different postural configurations: one-leg, narrow, wide, very wide, crouched, and normal stance. Their findings revealed that the muscle synergies employed during normal stance remained consistent across all stance conditions. However, in tasks that significantly differed from the normal stance, such as one-legged or crouched stances, additional task-specific synergies were recruited to the existing ones (Torres-Oviedo and Ting, 2010). Other researchers investigated the relation between kinematics and muscle synergies. For example, d'Avella et al. (2003) studied the behavior of muscle synergies when changing kinematics and proved their direct relation. They investigated muscle synergies of frogs during kicking in different directions. The researchers found out that the utilization of two of these synergies varied across different kicks, and these variations correspond to consistent alterations in the kick's movement patterns. They concluded that synergy activation correlated with movement kinematics. Furthermore, a gait-study of Bonnard et al. (2000) indicated that as movement frequency rises, joint stiffness needs to be increased. Yet, reducing frequency doesn't inherently mandate a reduction in stiffness. Their study also highlighted that walking with non-preferred frequency-to-amplitude relationships leads to alterations in the EMG pattern and that gait constraints impact both the swing and stance phases during walking. In a study where muscle synergies were calculated for three different gait velocities, group low- and medium-speed shared synergies whereas in group high speed variability was higher and two muscle synergy patterns where replaced (Liang et al., 2023). A study of Kibushi et al. (2022) investigated the variability of muscle synergy numbers when changing stride time and stride length combinations (stride time-length). It was observed that the number of synergies noticeably rose as the stride time-length increased. However, synergy numbers remained stable at the preferred walking speeds (1, 1.3, and 1.7 m/s). Yet, the synergy numbers exhibited inconsistency during very slow and fast walking speeds (0.6 and 2.2 m/s).

To the best of our knowledge, no study has yet examined the inter-subject variability of muscle synergies when walking gets constraint increasingly. Therefore, the present study addresses this research gap. This study aimed to investigate the influence of external modifications to gait on muscle synergies by comparing normal walking with restricted walking. Following the normal, unrestricted walk, two distinct levels of restrictions were imposed, and to induce an unnatural gait, we made alterations to both stride length and gait rhythm. As far as gait with restrictions could be considered as different and unnatural, our hypothesis was that constraints lead to an increase in similarity of muscle synergy vectors between subjects. The second hypothesis was that variability of the kinematics correlates with the variability of muscle activation patterns.

2 Method

2.1 Participants

Gait data from ten healthy and young participants (age: 25.9 ± 3.21 years; bodyweight: 72.4 ± 14.74 kg; height: 176.2 ± 11.07 cm; body mass index: 23.37 ± 1.23; 6 men and 4 women) were analysed. It was ensured that the subjects had no neurological, orthopaedic diseases, injuries, or other conditions affecting motor performance. The participants engaged in physical activity at least twice a week. The study received approval from the ethics committee of the University of Vienna (reference number: 00820), participants were informed of the experimental procedure and provided written informed consent.

2.2 Experimental Setup and Data Collection

After arrival at the laboratory, demographic and anthropometric data were recorded. All participants were equipped with surface electromyography (sEMG) electrodes (eleven Pico-EMG and two Mini Wave Infinity, Wave Plus wireless EMG system, Cometa, Milan, Italy) and retro-reflective markers, for assessing muscle activations and three-dimensional (3D) joint kinematics, respectively. SEMG is a commonly used non-invasive method known for the lack of discomfort or pain during movement (Di Nardo et al., 2017). Myoelectrical signals were recorded from 10 superficial muscles at 1000Hz. Electrodes were placed following the SENIAM guidelines (seniam.org). Myoelectrical activity signals of the tibialis anterior (L/R_tib_ant), soleus (L/R_sol), gastrocnemius medialis (L/R_gast_med), vastus lateralis (L/R_vast_lat), and semitendinosus (L/R_semitend) in both legs were recorded.

3D marker coordinates of 22 markers were recorded using a 12-camera motion capture system (Vicon Oxford, UK) at 200Hz. The standard Vicon Plug-in-Gait marker set was utilized, complemented by additional markers on the fifth metatarsal, thigh, and shank clusters. Ground reaction forces (GRF) were recorded using ground embedded force plates (Kistler Instrumente, Winterthur, Switzerland) at 1000Hz to record foot contacts and marker data.

A tape measure was positioned on the ground alongside and right next to the force plates without touching them, spanning the measured area where participants walked barefoot. Subjects placed their right foot on the right side of the tape measure, directly on the force plates, and their left foot on the left side hence on the floor.

Participants were asked to walk under three conditions. For each condition, ten repetitions were recorded, while synchronized sEMG, GRF and marker data were recorded.

1. ‘Norm’: The first task was walking at a self-selected pace without any constraints. This condition is referred to as ‘Norm’.
2. ‘Met’: For the second condition, labelled as 'Met' for Metronome, the average individual cadence from the natural gait in the initial task was decreased by twenty percent. A metronome application played beats per minute, prompting the subjects to synchronize their walking pace accordingly.
3. ‘MetMark’: The third condition is called ‘MetMark’ and combined the conditions of the second task with a constraint on step length. The calculation for the step length involved dividing the stride length from Vicon Quick Report by two and then subtracting twenty percent. Participants had to walk on adhesive tapes with their individual step length calculated from the 'Norm' condition, again reduced by twenty percent, resulting in an unnatural and shorter step length. The adhesive tape strips, each measuring approximately ten centimetres in length, were positioned over the tape measure directly adjacent to the force plates, without contacting them.

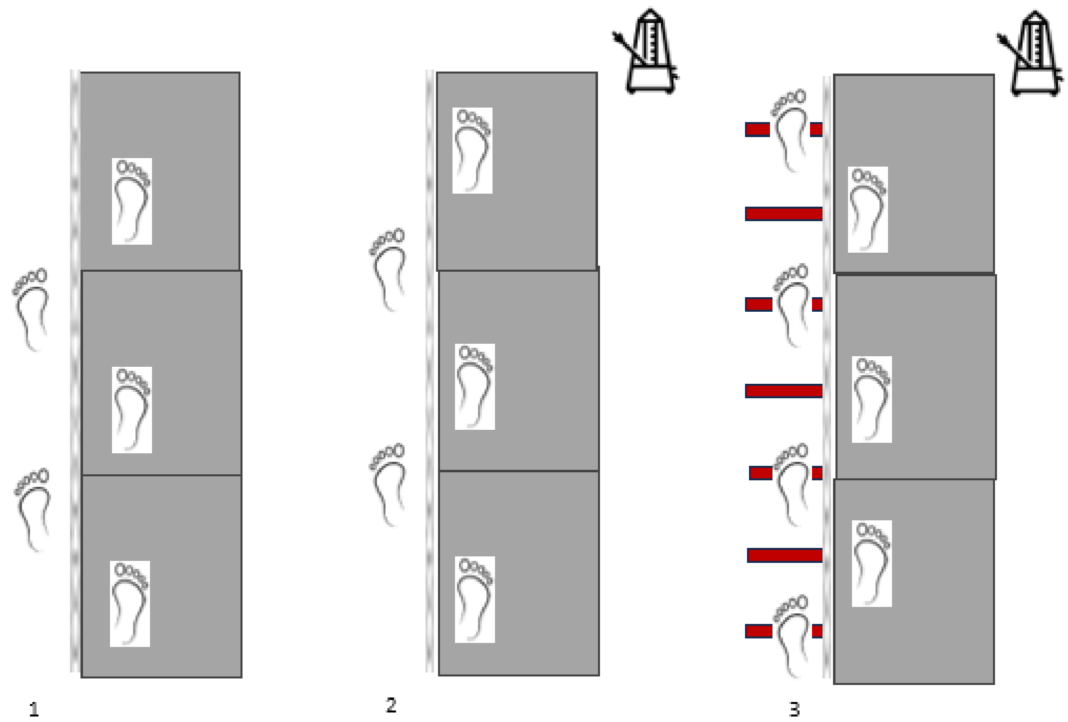

Figure 1: The schematic illustration showcases the three conditions. The right foot traversed over the force plates (gray), while the left foot moved along the left side of the tape measure on the ground. The first condition involved a normal, unconstraint walk. The second condition constrained the cadence using a metronome. The third condition incorporated ground markers (red) in addition to the previous constraints.

For all gait conditions, mean stride length and cadence were calculated via Vicon Quick Report. All data were recorded using Vicon Workstation v4.5 and Vicon Nexus CC.

Participants were instructed to place both feet at the height of the tape, with only their right foot crossing over the force plates. The data recorded between two consecutive right-leg heel strike is a gait cycle.

2.3 EMG processing

SEMG Data were exported in c3d format for offline analyses using Octave 6.2.0. Raw EMG signals were filtered using a 4^{th}-order high-pass filter with a cut-off frequency of 20 Hz. The signal was demeaned, and full wave rectified by taking absolute value. The rectified signal was further filtered using a 4^{th}-order low-pass filter with a cut-off frequency of 9 Hz. Mean resting EMG-signals was subtracted from the filtered signal to correct the baseline. EMG signals were amplitude- and time-normalized to 101 time points to ensure consistent temporal information (Bianco et al., 2018). Filtered and raw EMG-signals of every step and muscle were carefully examined for artefacts (i.e., movement artefacts) and sorted out. Ultimately ten to thirteen trials per condition per subject were used for the following synergies and kinematics calculations.

2.4 Synergy extraction and analyses

A non-negative matrix factorization (NNMF) was performed to extract the muscle synergies providing two components: muscle synergy vectors and synergy activation coefficients. Therefore we used the “nmf_bpas” octave function (Kim and Park, 2008), an advanced algorithm of the classic NNMF (Lee and Seung 1999; Paatero and Tapper 1994) and the random initialization for identification of correlated synergies (Turpin et al., 2021). K-means clustering was repeated fifty times to identify the most akin vectors within conditions across all participants (Cheung et al., 2020; Kim et al., 2016; Scano et al., 2019; Sylos-Labini et al., 2022). We computed the average silhouette value (Rousseeuw, 1987) for every iteration and cluster count. The optimal cluster number was identified at the point where the maximum silhouette values levelled off, signifying minimal distances within clusters and significant distances between clusters (Cheung et al., 2020).

Muscle synergies were extracted over all conditions and the number of synergies was determined through the knee-point (v) of the total variance accounted for (tVAF) curve (Ballarini et al., 2021; Ghislieri et al., 2023; Tresch et al., 2006; Turpin et al., 2021). The knee-point on the tVAF curve was used to define the point, where the curve changes significantly. This method presumes that past the knee-point, any further data or noise that is accounted for is only attributed to unstructured information or noise by additional synergy vectors (Tresch et al., 2006).

The calculated number of synergies varied from three to seven, with the most frequently being 4 and 5. In other studies within this field, such as (Taborri et al., 2017), they utilized three, four, or five synergies and concluded that there is no statistically significant difference for these three examined synergies, neither for global data nor for each muscle. Artoni et al. (2013), who examined lower-extremity muscles during walking to ascertain the ideal number of synergies, found that 4 synergies accounted for 100% of their unfiltered EMG data, making it the most favourable option. Hagedoorn et al. (2022) came to the same conclusion. We opted to conduct all further tests using 4 synergies. For comparing subjects among each other, we used the CCs of fixed spatial synergy vectors as well as time-varying activation coefficients (Profeta and Turvey, 2018; Turpin et al., 2021). The averaged value per condition represents the overall inter-subject similarity for synergy activation coefficients and synergy vectors. These parameters are widely used to quantify variabilities in synergy, EMG and kinematic waveforms (Banks et al., 2017; Barroso et al., 2014; Frère and Hug, 2012). The CC values were interpreted using previously proposed categories, where an CC ranging from 0.00 to 0.20 is considered poor, 0.21 to 0.40 as fair, 0.41 to 0.60 as moderate, 0.61 to 0.80 as substantial, and 0.81 to 1.00 as almost perfect (Landis and Koch, 1977). High values of CC of activation coefficients indicate a similarity in timing and a substantial amount of overlapping in synergy activations. A high correlation coefficient between two muscle synergy vectors suggests they play a similar role in coordinating movements or specific movement patterns (Clark et al., 2010; Soomro et al., 2018). We calculated muscle synergy vectors as well as activations coefficients for all synergies averaged and separately (Figure 3,4,5, & 6).

2.5 Kinematic analyses

For the kinematic analyses, we first calculated the knee axis using SARA (Symmetrical Axis of Rotation Analysis) operation on Vicon Nexus. According to the maximal range of motion trials of the knee joint, SARA defines the knee axis (Keizer and Otten, 2020). Sagittal plane joint angles of the ankle-, knee- and hip flexions of both feet were then calculated with the Plug-in gait model in Vicon Nexus and used for all further analyses (Duffell et al., 2014). The computed joint angles were smoothened using a 6 Hz low-pass filter (4th-order Butterworth zero lag filter) and time normalized to 101 datapoints. The joint angles were compared by calculating the inter-subject correlation coefficients for all joints and subsequently averaging them per condition. We also calculated the mean walking speed and step length as well as mean inter-subject variability of walking speed and step length across conditions.

2.5 Statistical analyses

Statistical analyses were conducted with Jasp 0.18.0.0 (Amsterdam, Netherlands). All data were tested for normality using the Shapiro-wilk. Repeated measurements ANOVA tests with Bonferroni correction were used for comparing the CC of the conditions. For calculating inter-subject variability, all Participants were compared within each condition, resulting in 45 correlation coefficients (CC) that were averaged. A p-value lower than 0.05 was considered statistically significant ($p<0.05$).

3 Results

3.1 Synergy analyses

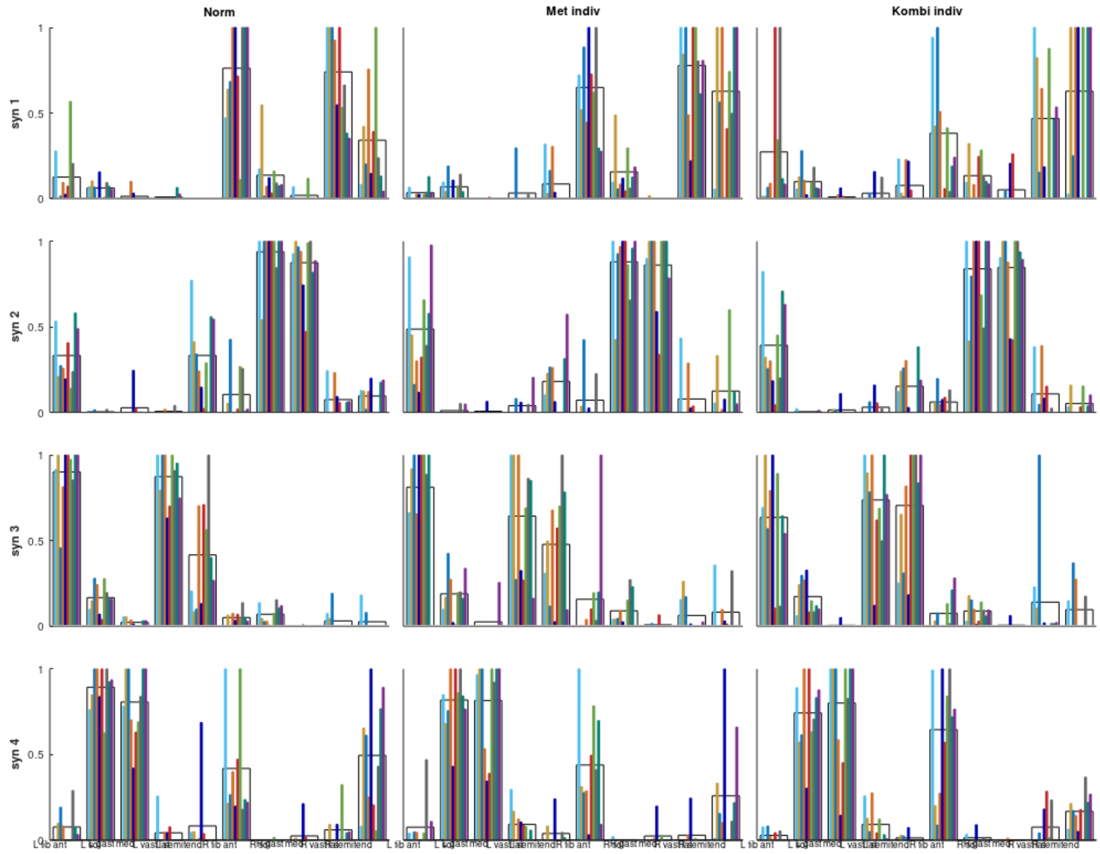

Figure 2: The muscle synergy weightings of all participants per synergies. Each colour describes one participant, and each bar represents one muscle. The higher the bar, the higher the muscle activation. Synergy 1 - 4 (lines) are shown per condition (columns). 10 muscles are represented as black bars. From left to right, the following muscles are listed: left tibialis anterior, left soleus, left gastrocnemius medialis, left vastus lateralis, left semitendinosus, right tibialis anterior, right soleus, right gastrocnemius medialis, right vastus lateralis, right semitendinosus. Each participant is assigned a specific colour.

The averaged CC of all synergy vectors together in mean calculated per condition showed significant differences between all conditions (p=0.004). Yet, all CC were higher than 0.63 which indicates shared synergies. Inter-individual variability in muscle synergy vectors was greatest during step length constraint ‘MetMark’ with a CC of 0.64, followed by cadence constraint walking 'Met' with 0.71 and the lowest variability was observed during unconstraint walking ‘Norm’, where the CC was 0.81 (Figure 3).

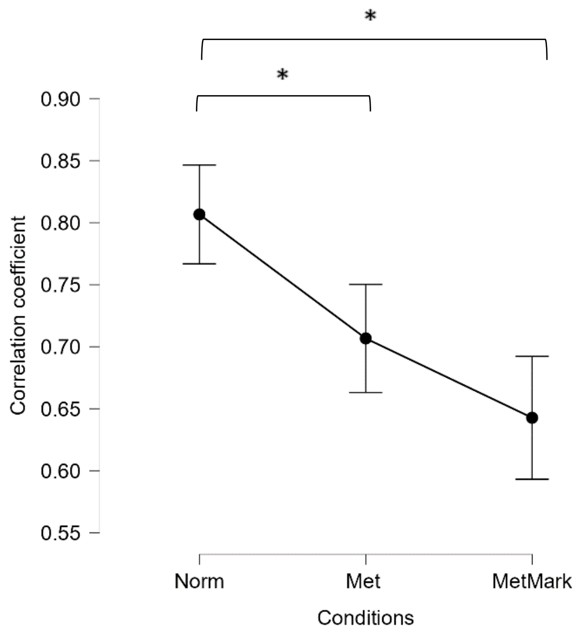

*Figure 3: The inter participant comparison of the synergy vectors per condition. The four synergies were combined and averaged. On the x-axis, the three conditions can be seen. The y-axis represents the correlation coefficient averaged across all participants. Error bars show a confidence interval of 95 percent. Significant differences are indicated by *.*

The CC for mean activation coefficients in Synergy 1 was 0.71 in the 'Norm' condition, 0.71 in 'Met', and 0.32 in 'MetMark'. Synergy 2 displayed CCs of 0.88 in 'Norm', 0.81 in 'Met', and 0.84 in 'MetMark'. In Synergy 3, 'Norm' had a CC of 0.89, 'Met' had 0.59, and 'MetMark' had 0.65. Lastly, Synergy 4 showed CCs of 0.75 in 'Norm', 0.72 in 'Met', and 0.77 in 'MetMark'. Synergy two and three were responsible for the relation of 'Norm' and 'Met'. Synergy 2, 3 and 4 showed a non-significant difference between 'Met' and 'MetMark' whereas Synergy 1 seemed to be responsible for the decreasing trend of 'MetMark' in the aggregate (Figure 2). While in figure 2 all CC were above 0.63, some of them were significantly below that threshold. The CC for synergy 1 within the 'MetMark' condition was 0.32, while for synergy 3 within the 'Met' condition 0.59, indicating they are not shared synergies.

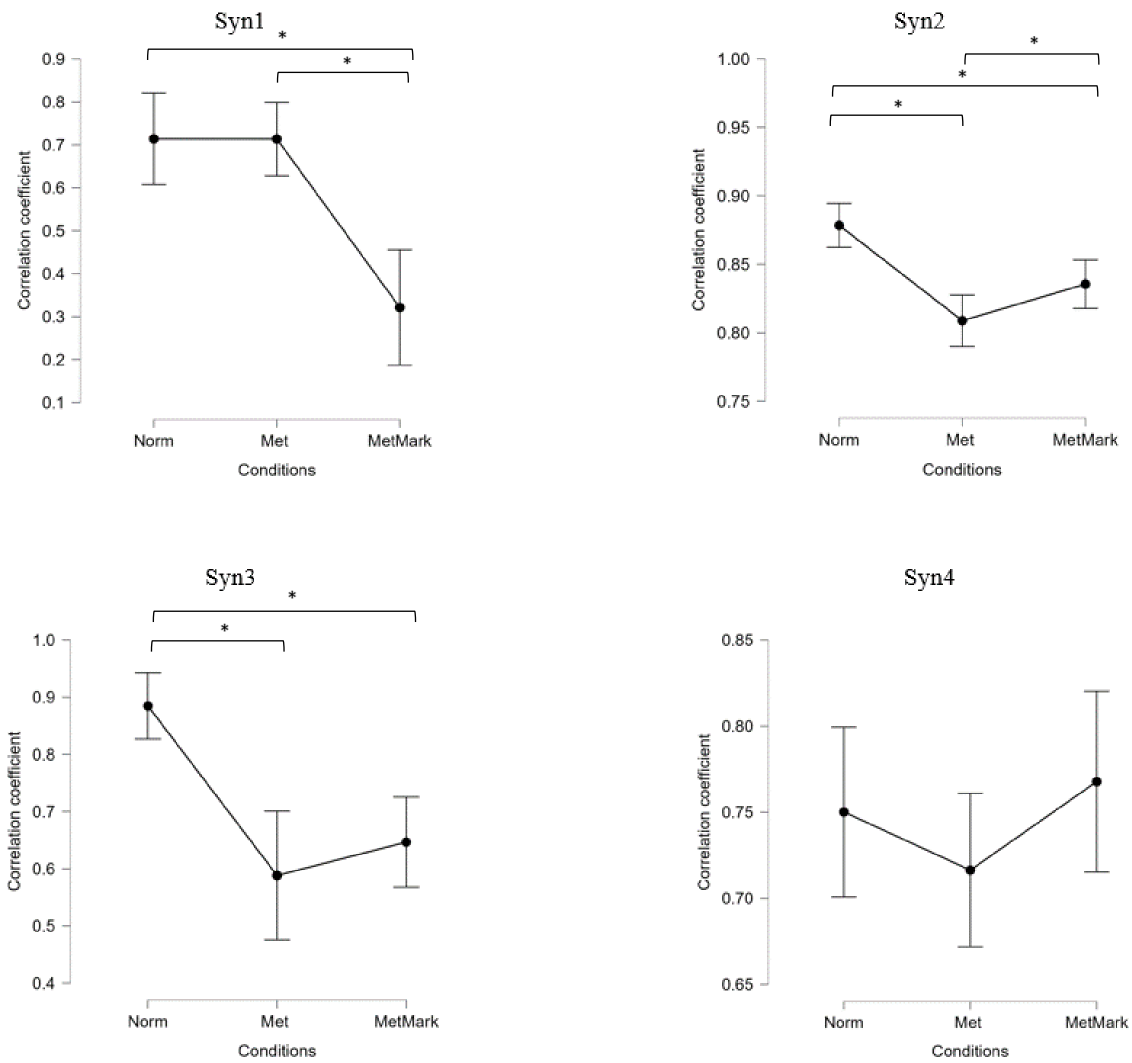

*Figure 4: The inter-subject comparison of the correlation coefficients of synergy vectors per condition synergy wise. On the x-axis, the three conditions can be seen. The y-axis represents the correlation coefficient averaged across all participants. Error bars show a confidence interval of 95 percent. Significant differences are indicated by *.*

Significant differences in variability within activation coefficients were noted between the 'Norm' and 'MetMark' conditions (p=0.013). The 'Norm' condition exhibited the lowest variability (indicating the highest similarity) in activation coefficients with a correlation coefficient of 0.7. 'Met' exhibited a CC of 0.66 and 'MetMark' of 0.63.

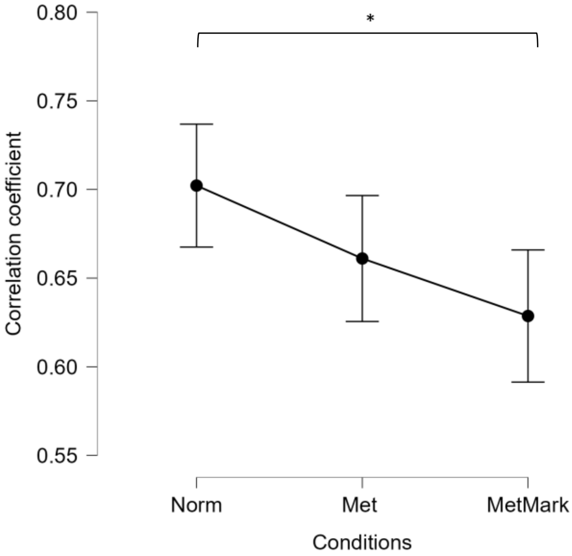

*Figure 5: The inter-subject comparison of the correlation coefficients of synergy activation coefficients per condition. The four synergies were combined and averaged. On the x-axis, the three conditions can be seen. The y-axis represents the correlation coefficient averaged across all participants. Error bars show a confidence interval of 95 percent. Significant differences are indicated by *.*

The CC for mean activation coefficients in Synergy 1 were 0.55 in the 'Norm' condition, 0.7 in 'Met', and 0.28 in 'MetMark'. Synergy 2 displayed CCs of 0.8 in 'Norm', 0.77 in 'Met', and 0.8 in 'MetMark'. In Synergy 3, 'Norm' had a CC of 0.7, 'Met' had 0.47, and 'MetMark' had 0.64. Lastly, Synergy 4 showed CCs of 0.75 in 'Norm', 0.71 in 'Met', and 0.8 in 'MetMark'. Synergy 2, 3 and 4 strengthened the relationship between ‘Norm’ and ‘Met’. Synergy 1 seemed to have a strong impact on the difference of ‘Met’ and ‘MetMark’ (Figure 6).

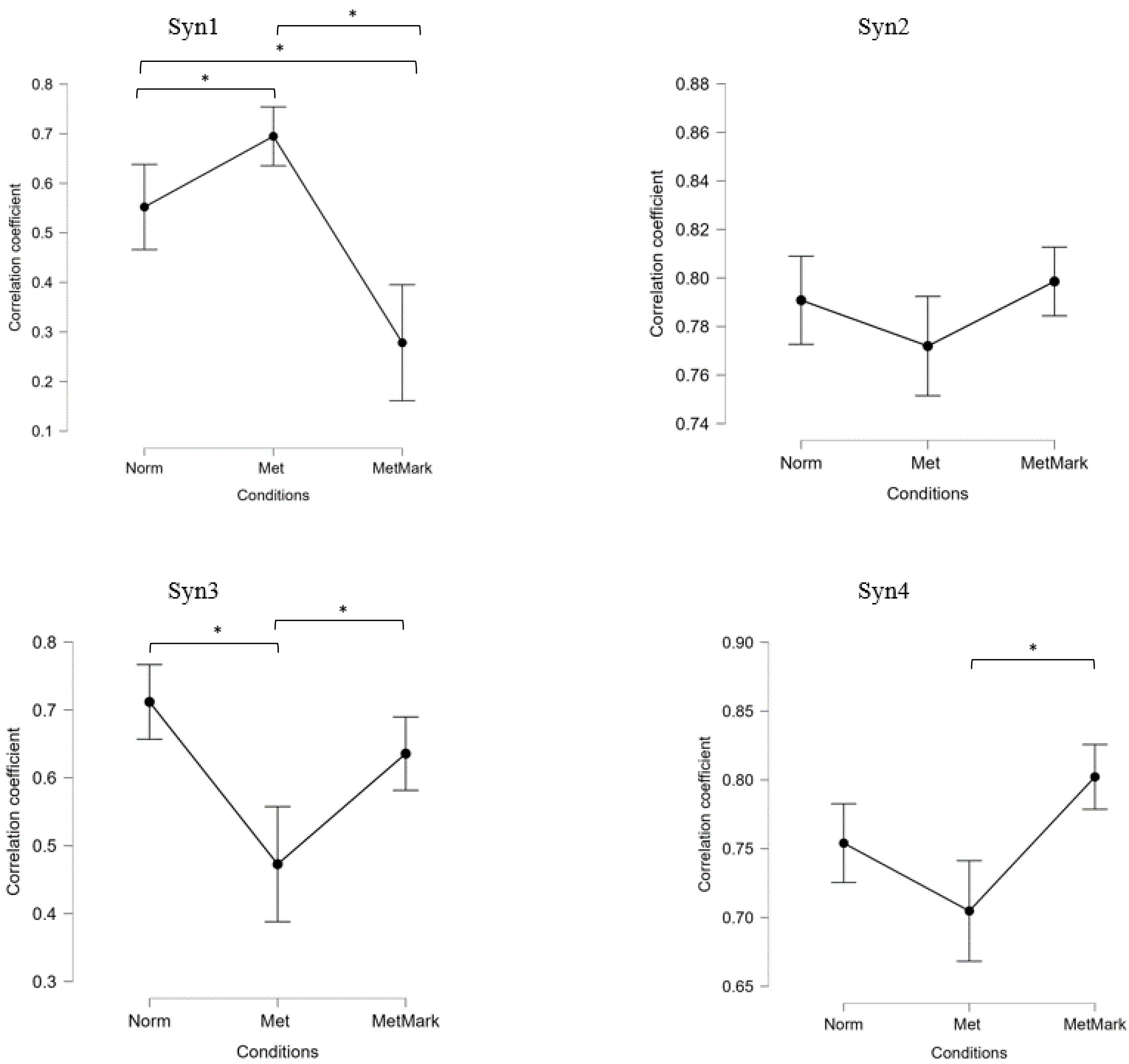

*Figure 6: Inter-subject comparison of the correlation coefficients of synergy activation coefficients per condition synergy wise. On the y-axis the correlation coefficient can be seen. On the x-axis the three conditions. The error bars are calculated with a 95 percent confidence interval. Significant differences are indicated by *.*

3.3 Kinematic analyses

The 'Norm' and 'Met' conditions ($p<0.001$), as well as the 'Met' and 'MetMark' conditions ($p=0.002$), demonstrated significant differences in kinematics. The inter-subject similarity of kinematics for all three joints was very high with a CC of 0.9 in condition ‘Norm’, 0.85 in ‘Met’ and 0.89 in ‘MetMark’. Nevertheless, results showed significantly greater movement variability during cadence constraint walking 'Met' compared with unconstraint ‘Norm’ and step length constraint ‘MetMark’ conditions (Figure 7).

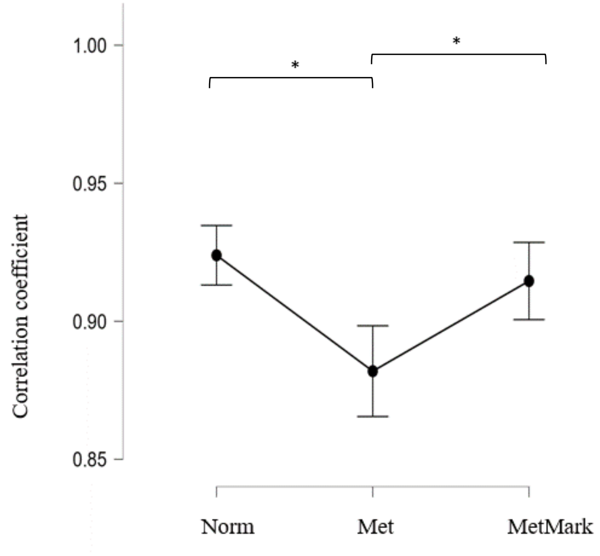

*Figure 7: The inter-subject comparison of the mean correlation coefficients of kinematics per condition. The y-axis represents the correlation coefficient, the x-axis the three conditions. Error bars are calculated with a 95 percent confidence interval. Significant differences are indicated by *.*

3.4 Gait parameters

Step mean velocity indicated significant differences between all conditions ($p<0.001$). During self-selected walking without any constraints ('Norm'), participants maintained a mean velocity of 1.28 m/s. However, in the 'Met' condition, where the cadence was reduced by twenty percent, their walking speed dropped by almost thirty percent to 0.93 m/s, which means that participants automatically reduced their stride length by almost ten percent. In the 'MetMark' condition, where stride length was additionally restricted, participants walked at a specified velocity of 0.83 m/s (Figure 8).

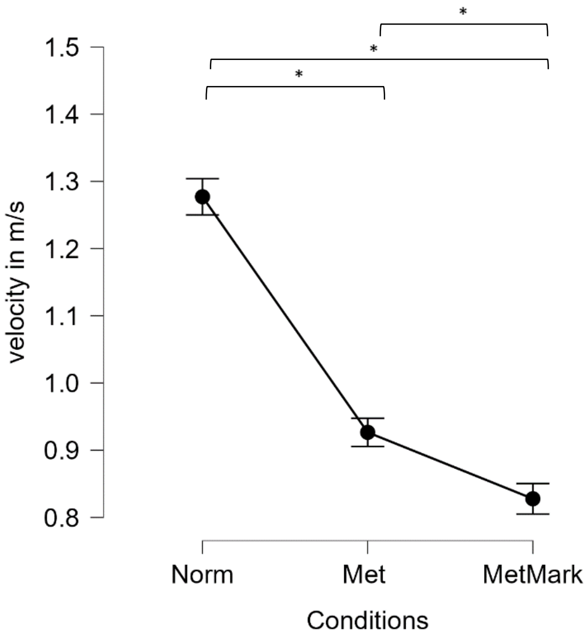

*Figure 8: The comparison of the mean gait velocity in meters per second per condition. The y-axis represents the correlation coefficient, the x-axis the three conditions. Error bars are calculated with a 95 percent confidence interval. Significant differences are indicated by *.*

The variability in gait speed among participants was notably low. Conditions ‘Norm’ and ‘MetMark’ as well as ‘Met’ and ‘MetMark’ were significantly different (p<0.001) concerning inter-subject variability of gait velocity. Both 'Norm' and 'Met' conditions exhibit almost identical inter-subject differences with 0.10 and 0.11 m/s (p=0.83). However, in the 'MetMark' condition, the variability significantly decreased, with an inter-subject difference of only 0.08 (Figure 9).

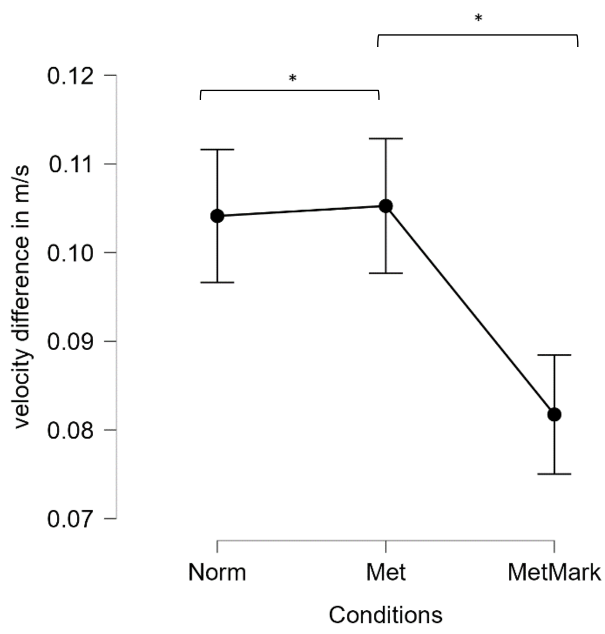

*Figure 9: The inter-subject comparison of the mean velocity difference per condition in meters per second. The y-axis represents the velocity difference in meters per second, the x-axis the three conditions. Error bars are calculated with a 95 percent confidence interval. Significant differences are indicated by *.*

The mean step lengths were significantly different for all conditions (p<0.001). The average step length of participants in the unconstrained walking condition ('Norm') was 1.38 m. However, in the 'Met' condition, it was significantly shorter at 1.24 m, and in the 'MetMark' condition, it reduced further to 1.1 m (Figure 10).

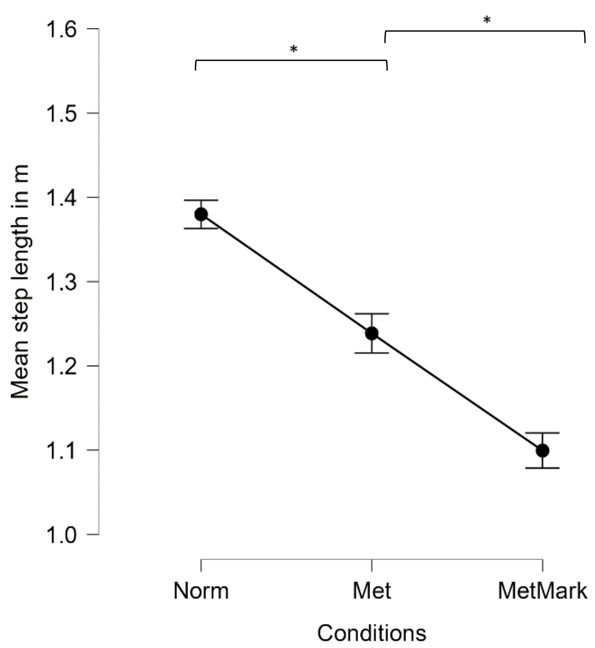

*Figure 10: The comparison of the mean step length per condition in meter. The y-axis represents the correlation coefficient, the x-axis the three conditions. Error bars are calculated with a 95 percent confidence interval. Significant differences are indicated by *.*

The mean step length variability between participants were significantly different for all conditions (p<0.001). Yet, very low with 0.12 m in condition 'Norm', 0.15 m in condition 'Met' and 0.1 m in condition 'MetMark' (Figure 11).

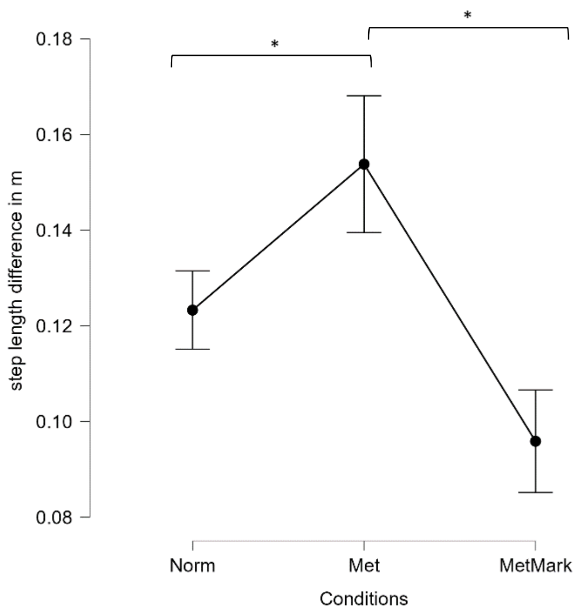

*Figure 11: The inter-subject comparison of the mean step length difference per condition in meter. The y-axis represents the velocity difference in meters per second, the x-axis the three conditions. Error bars are calculated with a 95 percent confidence interval. Significant differences are indicated by *.*

4 Discussion

The aim of this study was to determine if external walking manipulations influence inter-subject variability of lower-limb muscle synergies. We investigated muscle synergies in gait with constraints and compared 10 participants among each other. We found that muscle synergies are shared between participants despite affecting cadence and stride length and that consistency of kinematics persists between participants. However, the results did not support the hypothesis that the inter-subject variability of muscle synergies would decrease due to gait constraints. Additionally, the behaviour of kinematics differed from that of EMG patterns.

When examining individual synergies, it becomes evident that they follow distinct patterns (Nazifi et al., 2017). Several studies have explored task-specific patterns in more complex movements, such as standing on one leg or balancing on a slackline, which were found to be shared among participants (Allen et al., 2020). Shared muscle synergies can be identified across various movements, particularly in familiar tasks like walking or pedalling (Gonzalez-Vargas et al., 2015; Ivanenko et al., 2004; Sawers et al., 2015; Scano et al., 2019; Singh et al., 2020; Torres-Oviedo and Ting, 2010; Kim et al., 2022) . Sylos-Labini et al. (2022) compared muscle activity data from stepping neonates, infants, preschoolers, and adults. They concluded that the complexity of modularity escalates from the neonatal stage to adulthood. The low complexity and heightened variability of neuromuscular signals indicate neonatal immaturity. It seems that variability during the learning process increases the likelihood of finding the optimal motor command (Wu et al., 2014). It can be inferred that as a result of a learning process, regular walking under these constraints by participants would likely lead to a decrease in variability.

In this present study, all averaged synergy vectors where shared among participants whereas variability increased with increasing constraints. Various studies indicate that as movement complexity rises, the variability of muscle synergies also increases (Kristiansen et al., 2016; Allen et al., 2020; Sawers et al., 2015). Comparing experts to untrained participants during bench press exercises, experts display reduced variability in muscle synergy vectors compared to untrained individuals (Kristiansen et al., 2016). Expert dancers exhibit more shared synergies between overground walking and balancing tasks compared to individuals without dancing experience (Allen et al., 2020; Sawers et al., 2015). This also indicates that with learning new movements, muscle synergies get more consistent and specific. In our current study, the constraints did not involve balancing, but rather maintaining an unfamiliar rhythm and walking with a specific stride length. As far as walking with restrictions in cadence and stride length can be seen as more complex than normal gait, our study supports the theory of increased variability in unfamiliar movements.

Furthermore, several studies investigated the influence of walking speed on the activation of muscle synergies (Kibushi et al., 2018; Yokoyama et al., 2016; Hagedoorn et al., 2022; Liang et al., 2023). Yokohama et al. (2016) concluded in their study that the number of muscle synergies differed depending on walking and running speed. Specifically, the number of modules in slow walking (0.3-1.0 m/s) was significantly lower than that in moderate run, fast run, and whole speed (0.64-4.4 m/s). Furthermore, Liang et al. (2023) showed that the muscle synergy similarity among participants is higher in low- and medium-speed gait than in high-speed gait. In contrast Hagedoorn et al. (2022) found out that the muscle synergies exhibited similarity between unperturbed and perturbed walking at a high walking speed (0.8 m/s). Nevertheless, there was a notably lower count of similar muscle synergies between perturbed and unperturbed walking at lower walking speeds (0.4 and 0.6 m/s). This aligns with the findings of the current study. Muscle synergy similarity among participants decreased as the walking speed decreased. Participants were walking with a mean speed of 1.28 m/s in the first condition, 0.93 m/s in the second condition, and decreased again to 0.83 m/s in the third condition. While the variability in gait speed between subjects was minimal, comparing different conditions revealed that the normal unconstrained walk was significantly faster and the synergy similarity higher. Kibushi et al. (2022) examined changes in gait speed and concluded that synergy numbers remained stable at the preferred walking speeds (1, 1.3, and 1.7 m/s). Yet, the number of synergies exhibited inconsistency during slow and fast walking speeds (0.6–8 m/s). According to these results, gait speed of condition ‘Met’ and ‘MetMark’ where unnaturally low hence variability increased.

d'Avella et al. (2003) investigated that the recruitment of muscle synergies depends on kinematics. In their study they analysed muscle pattern of frogs during kicking and concluded that muscle synergies varied with changes in kick direction. Kibushi et al. (2022) investigated muscle synergies during five different stride time and stride length combinations with a fixed gait speed and concluded that muscle synergy numbers were highly similar across preferred (1.36 ± 0.06 m), short (1.06 ± 0.01 m), and long (1.56 ± 0.03 m) stride length while the number of synergies was inconsistent in the very short (0.60 ± 0.13 m) and very long (2.03 ± 0.24 m) conditions (extreme combinations). In this present study, kinematic analyses revealed a discrepancy in the behaviour of joint angles compared to muscle synergies. Joint

angles showed the most similarity among participants during normal gait and the highest variability during walking with only one constraint (‘Met’). Interestingly, the normal walk (‘Norm’) and the two-constraint walk (‘MetMark’) demonstrated no significant difference, appearing nearly identical in this context. This could be associated with the relatively similar step length observed in the 'Norm' and 'MetMark' conditions. In the 'Norm' condition, individuals walked at their natural frequency and step length (with an average step length of 1.38 m). In the 'MetMark' condition, both frequency and step length were stipulated, resulting in a reduced step length of 1.1 m (twenty percent reduction), thus contributing to this similarity. However, in the 'Met' condition, only cadence was specified, allowing participants to determine step length independently. Moreover, the average step length of this condition was 1.24 m, which is ten percent less that their natural gait. Hak et al. (2012) investigated that rather than simply reducing walking speed, individuals adopt a strategy involving a combination of decreased step length, increased step frequency, and widened step width to manage challenges encountered during walking. Stokes et al. (2017) concluded from their study that when faced with perturbations, participants widened their steps, took shorter and more variable strides, and exhibited increased variability in postural sway compared to their normal walking pattern. In this current study, participants were required to maintain a specific rhythm, limiting their ability to walk naturally, yet they had the freedom to choose their step length. This combination of constraints, which lead to an unnatural gait, and individual step-length choices resulted in the higher variability among participants in condition ‘Met’.
Our study included a few notable Limitations. Firstly, the limited number of participants likely restricted the spectrum of muscle synergies observed within specific walking conditions. Therefore, acquiring larger datasets across multiple sites would be advantageous to comprehensively explore a wider range of diverse muscle synergies. Another limitation lies in the fact that our findings stem from a single session. The theory that variability is higher in unnatural movements could be supported when repeating these tasks, considering that prolonged training can modify muscle synergies (Sawers et al., 2015). The third limitation would be that we only had three conditions and only two different parameters to change the gait, which may not reflect a real increase in constraints. Moreover, the evaluation of kinematics was limited to the sagittal plane, and the assessment involved averaging all joint movements without examining them separately.

In summary, our study aimed to increase our insights in inter-subject muscle synergy variability in gait. We found that synergies are shared among participant consistently despite constraints in gait. Furthermore, with increasing constraints, inter-subject similarity of muscle synergy vectors as well as activation coefficients decrease. Our results support the notion that unnatural or unfamiliar movements accompany with higher muscle synergy variability. Additionally, the behaviour of kinematic variability differed from that of EMG patterns. This divergence appears to stem from the liberty permitted in step length when only cadence is constrained.

5 Conclusion

The findings of this study suggest that despite constraints on participants' gait, there is a shared presence of muscle synergies while the consistency of kinematics persists among subjects. However, modifying cadence and stride length during walking impacts both muscle synergies and the participants' kinematics significantly. We infer that as walking becomes constrained by stride length and cadence, gait becomes unnatural and the variability of muscle synergy vectors and activation coefficients among subjects increases. The variability in kinematics increased solely when cadence was constrained, emphasizing the influence of step length freedom.

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Explanation

„I declare that I have composed this work independently and only used the indicated aids. This work has not been submitted elsewhere (e.g. for other courses) or presented by other individuals (e.g. works by other people from the internet)."

Julia Seidl

St. Pölten, am 21.12.2023