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# Synergy in motion: Exploring the similarity and variability of muscle synergy patterns in healthy individuals

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ABSTRACT

*Background:* Recent studies suggest that muscle synergy patterns can be a guide for diagnosis and rehabilitation.
*Research question:* Does human's lower limb synergy pattern significantly change with changes in walking speed? Are there large differences in synergy patterns among different healthy individuals?
*Methods:* 22 healthy subjects from an open-source datasets were included. Non-negative matrix factorization was applied to identify the module composition of surface electromyography(sEMG) data, and the similarity index was adopted to quantify the overall similarity between synergy patterns.
*Results:* Results demonstrated that healthy individuals have their own intrinsic muscle recruitment and coordination characteristics for locomotion at various speeds, additionally, their synergy patterns exhibit predictability under speed variations.
*Significance:* This study develop reference synergy patterns for the lower limbs across 28 different walking speeds. The developed synergy patterns and the above findings may guide the study of gait synergy in rehabilitation and assistance.

## 1. Introduction

Recently, there appears to be an increasing trend in the use of exoskeletons for therapy. Researches on the control of lower limb rehabilitation exoskeletons are mainly focusing on the strategies which use the information of healthy side and then mapping to the affected side. In previous studies, direct position control was widely used and the desired position was mainly generated by the healthy leg (Bae et al., n.d.; Beyl, Van Damme, Van Ham, Vanderborght, & Lefeber, 2009; Lee et al., 2018) or by plantar pressures (Cao, Chen, Hu, Fang, & Wu, 2020), and then played back on the affected side with a delay of a half gait cycle. However, this strategy is incapable of asymmetric locomotion and needs high mechanical impedance, so as to track the calculated angle trajectories (Windrich, Grimmer, Christ, Rinderknecht, & Beckerle, 2016).

Surface electromyography (sEMG), considered one of the most essential biomechanical signals, reflects not only neural control but

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is also influenced by external forces and the interaction of various reflex loops (Feldman, 2015). sEMG has a wide range of applications in wearable robotics (Yang et al., 2022), including intent recognition (Li et al., 2019; Zhou, Yang, Liao, Liang, & Ye, 2021) joint torque estimation (Zhang et al., 2020), joint angle estimation (Qi et al., 2021), power effect characterization (Zhang, Tran, & Huang, 2019), and muscle activity evaluation for human-in-the-loop (HIL) optimization (Xu et al., n.d.; Steele, Jackson, Shuman, & Collins, 2017). Therefore, sEMG has become an ideal tool for guiding the rehabilitation process. Muscle synergy (extracted from sEMG signals) represents the neural control strategy and the activation state of muscles (Coscia et al., 2015), reflecting the deep muscle group recruitment and coordination of certain movements. Previous studies have pointed out that sEMG provides valuable information about disturbances in neurological disease (Pérez-Nombela et al., 2017) and synergy pattern extracted from sEMG signals is a good choice to understand the postinjury mechanisms of motor control and recovery (Cheung et al., 2012). Several studies have explored the relationship between exercise and the neuromuscular system from a physiological perspective (Ivanenko, Cappellini, Dominici, Poppele, & Lacquaniti, 2005; Safavynia, Torres-Oviedo, & Ting, 2011). Others have put their emphasis on muscle synergy characterization in the field of wearable robotics (Li, Liu, Yin, & Chen, 2019; Steele et al., 2017). For instance, Tan *et al* conducted a study involving eight stroke patients, assessing them both before and after a course of robotic intervention. The results demonstrated a significant improvement in the similarity of lateral synergies among the patients following the robotic intervention (Tan et al., 2018). Our group recently conducted a research utilizing muscle synergy patterns to guide the assistance strategy of exoskeletons. In the validation experiments, the assistance parameters generated through human-in-the-loop (HIL) optimization significantly enhance muscle synergy similarity during walking with exoskeletal assistance (Ma et al., 2024). However, if exoskeletons are enrolled into the rehabilitation of people with stroke, due to the influence of hemiplegia on the unaffected side, the muscle synergy patterns on the healthy side may not necessarily be common. To enhance the guidance of rehabilitation through exoskeletons and optimize rehabilitation strategies, introducing the similarity index between subjects' synergy patterns and reference synergy patterns is a promising direction. By incorporating Human-in-the-Loop (HIL) optimization and using algorithms such as Bayesian optimization to maximize the similarity index, we can fine-tune the parameters of the exoskeleton's torque profile. Synergy patterns from healthy individuals during normal walking can be collected as reference synergies for themselves. However, this approach is not directly applicable to hemiplegic patients. For patients, their gait is no longer normal, so the ideal reference synergies would be obtained from their own gait data when they were healthy. However, few people collect gait data while they are still healthy, so most of the time, the synergy data from other healthy individuals is used as a reference. Since patients and healthy individuals typically walk at different speeds, using synergy data obtained from healthy individuals as a reference for patients during rehabilitation lacks convincing evidence. Therefore, a comprehensive exploration of synergy patterns in healthy individuals across various walking speeds is necessary to determine if reference patterns should account for these speed variations.

This study aims to investigate whether reference synergies used for evaluating stroke patients should be categorized based on walking speed by analyzing how the synergy patterns of healthy individuals change with different walking speeds. This paper offers two major contributions. 1) Synergy patterns exhibit predictability under speed variations, even when there are differences in synergy patterns among individuals. 2) Development of reference synergy patterns for the lower limbs across 28 different walking speeds. To the best of our knowledge, this is the first in-depth investigation exploring the overall variations in lower limb muscle synergy patterns of different individuals in response to changes in walking speed.

## 2. Methods

### *2.1. Database introduction*

Current gait databases are mostly vision-based (Takemura, Makihara, Muramatsu, Echigo, & Yagi, 2018; Wang, Tan, Ning, & Hu, 2003; Zhu et al., 2021). A few databases are based on ground reaction force (Horsak et al., 2020; Horst, Slijepcevic, Simak, & Schöllhorn, 2021), IMU (Chereshnev & Kertész-Farkas, 2018) and sEMG signals (Camargo, Ramanathan, Flanagan, & Young, 2021). In order to systematically investigate the muscle synergy of healthy individuals at various walking speeds, a comprehensive, open-source database (Camargo et al., 2021) was enrolled in this study. The above database comprises biomechanical signals from 22 able-bodied adults (age 21 $\pm$ 3.4 yr, height 1.70 $\pm$ 0.07 m, mass 68.3 $\pm$ 10.83 kg) for 4 locomotion modes (level-ground, treadmill walking, stair ascent/descent, and ramp ascent/descent) and multiple terrain conditions of each mode (walking speed, stair height, and ramp inclination). In our study, we only use the treadmill walking data. 28 speeds ranging from 0.5 to 1.85 m/s in 0.05 m/s increments was included and each speed was held for 30 s. During walking, Raw sEMG data was collected from 11 muscles: gluteus medius (GD), right external oblique (RO), semitendinosus (SM), gracilis (GA), biceps femoris (BF), rectus femoris (RF), vastus lateralis (VL), vastus medialis (VM), soleus (SO), tibialis anterior (TA), and gastrocnemius medialis(GM). Considering practical circumstances, only 7 commonly encountered muscles (RF, VL, TA, SO, ST, BF, GM) were selected to draw the synergy patterns in this research.

### *2.2. Data processing*

The raw sEMG signals were collected at a sampling frequency of 1000 Hz and digitally conditioned using a bandpass filter (with a cutoff frequency of 20 Hz–400 Hz and a Butterworth order of 20), following the methodology outlined in the original research. Then, the sEMG data from 22 individuals was divided into single gait cycle sets according to the ground reaction forces (GRF) and treadmill speed. Whereafter, sEMG data of each gait cycle was interpolated to the same length for convenience in later calculation. Data collected during acceleration and deceleration were removed to ensure that the synergy patterns would not be influenced by initial acceleration and final braking.

### 2.3. Muscle synergy extraction

Non-negative matrix factorization (NMF) algorithm was used here to extract muscle synergies from sEMG data matrix of lower limb muscles. By using the NMF algorithm, the residual between the initial matrix and its decomposition was minimized, so the activities of selected muscles can be modeled as linear combinations of a sufficient number of muscle activation. The synergy extraction can be calculated by:

$$M_{m\times n} = W_{m\times k}H_{k\times n} + E_{m\times n} \tag{1}$$

where $M$ is the original sEMG matrix, $W$ is the matrix of synergy vectors, $H$ is the matrix of synergy activation coefficients, $E$ is the residual error matrix, $m$ is the number of muscles, $n$ is the number of time points, $k$ is the number of extracted muscle synergies.

To evaluate the goodness of the reconstructed matrix, the variance accounted for (VAF) was adopted in the following equation:

$$\mathrm{VAF} = \left(1 - \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}{E_{i,j}}^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}{M_{i,j}}^2}\right)\times 100\% \tag{2}$$

Iterative analysis was performed by varying the number of synergies from 1 to the selected number of muscles (Clark, Ting, Zajac, Neptune, & Kautz, 2010). The following metrics were employed to determine the fundamental number of extracted muscle synergies (k):

1. $\mathrm{VAF}_k \geq 90\%$;
2. $\mathrm{VAF}_k - \mathrm{VAF}_{k-1} \geq 5\%$;

The research computed the number of synergies meeting both the above criteria across 28 speeds for 22 participants, as depicted in Fig. 1. We can find that if the fundamental number of synergies is 3, then more than half of the total samples meet the above criteria. So in the aforementioned database with selected 7 muscles, the number of synergies was set to be three in order to enable comparisons across subjects walking at different speeds.

### 2.4. Similarities of muscle synergies

To assess the overall similarity between different synergy patterns so as to compare the muscle synergy patterns intra- and inter-subject at different walking speeds, similarity index $\alpha$ was introduced in this study (Ma et al., 2024), which is defined as:

$$\alpha = \frac{\sum_{s=1}^{k} c_s r_s}{\sum_{s=1}^{k} c_s} \tag{3}$$

$$c_s = \left(1 - \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}{E_{i,j}}^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}{M_{i,j}}^2}\right)\times 100\% \tag{4}$$

$$r_s = \frac{\mathrm{Cov}(W, W_0)}{\sigma_{\mathrm{w}}\sigma_{\mathrm{w}_0}} \tag{5}$$

Where the calculation method for $c_s$ is identical to VAF, $r_s$ is the pearson correlation coefficient between the s-th synergy and the reference synergy matrix, $\mathrm{Cov}(W, W_0)$ represents the covariance between W and $W_0$, $W_0$ is the reference synergy matrix, $\sigma_{\mathrm{w}}$ and $\sigma_{\mathrm{w}_0}$ are the standard deviations of $W$ and $W_0$ respectively. Compared to other methods, the similarity index used in this study allows for a more distinct observation of the variation trends between synergy patterns.

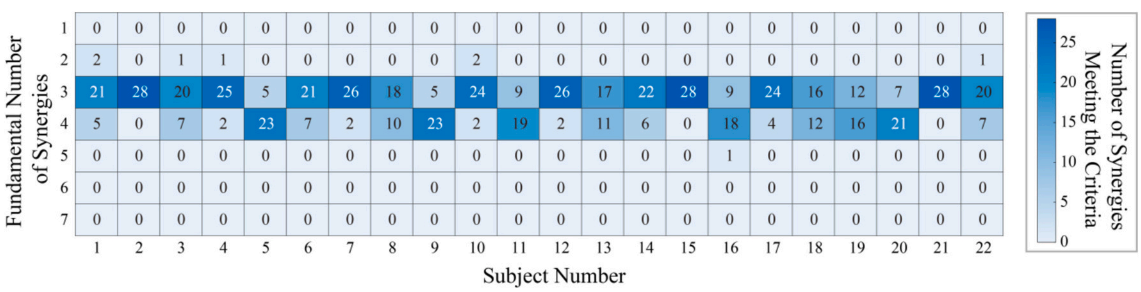


**Fig. 1.** 22 participants with the fundamental number of synergies meeting the criteria in 28 trials.

## 3. Results

### 3.1. *Muscle synergy discrepancy in same individuals across different walking speeds*

In order to better evaluate the effectiveness of exoskeleton assistance/rehabilitation through lower limb muscle synergy, it is necessary to know whether lower limb muscle synergy changes across speed and the degree of change. So this study calculated the similarity of muscle synergy patterns in 22 people walking at 28 speeds. Fig. 2 shows heatmaps of similarity indices across 22 subjects at 28 different walking speeds. The similarity indices for each gait cycle at a specific speed (abscissa) were calculated by referring to the mean synergy weights at a different speed (ordinate), and then the resulting mean value of these indices was obtained. Based on the characteristics of the heatmaps, two models were put forward based on whether there are significant and regular changes in similarity indices. Model 1 includes 10 subjects (3, 6, 8, 9, 13, 14, 15, 16, 17, 22), whose muscle synergy patterns do not change significantly

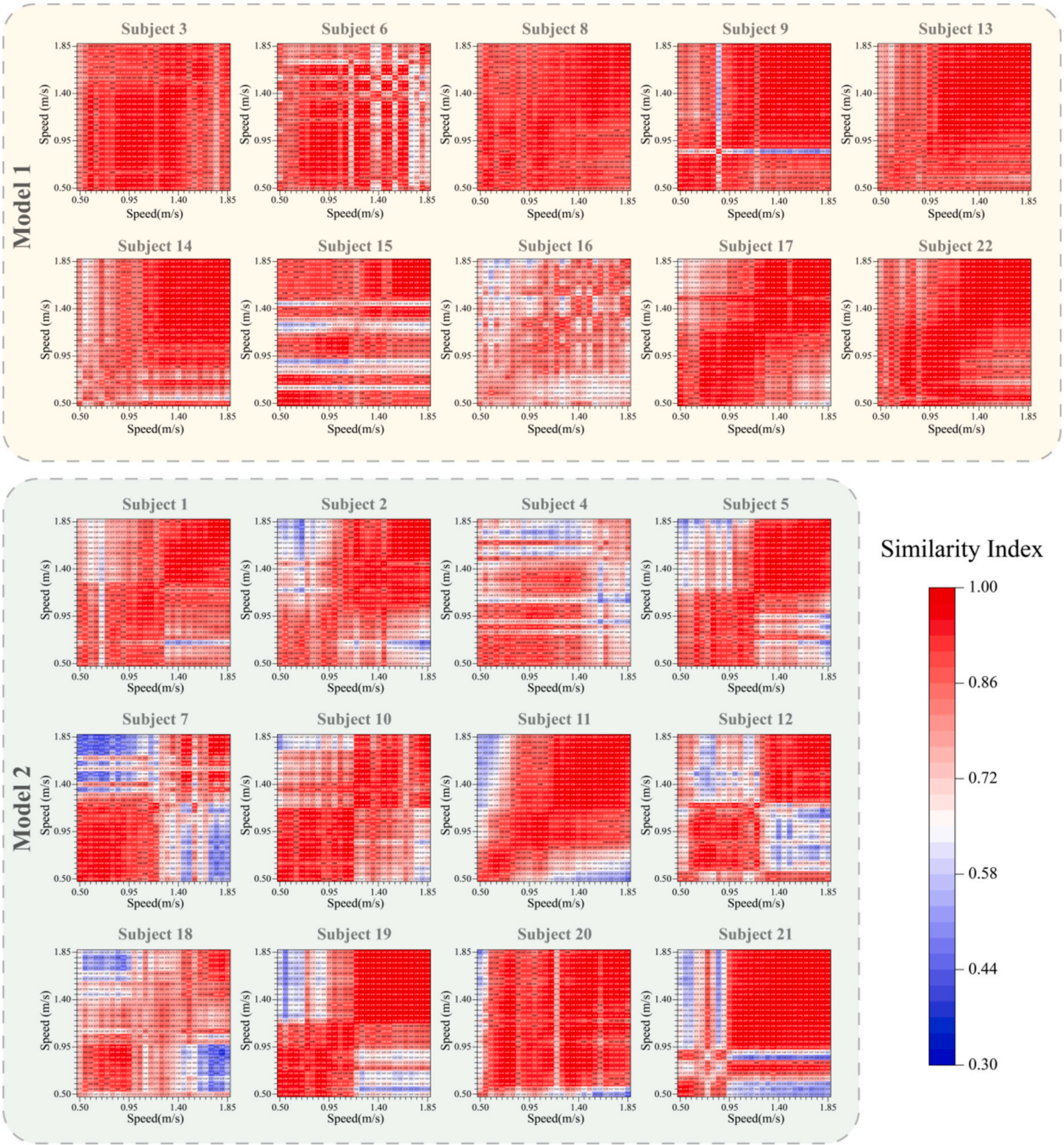


**Fig. 2.** Heat maps of similarity indices from 22 subjects walking at 28 speeds.

across different speeds. Model 2 includes the remaining 12 subjects, whose synergy patterns are relatively stable within a certain range of speeds, but when the speed increases or decreases to a certain value, the coordination pattern undergoes significant changes.

Take subject 8 and subject 19 for example. In heatmaps we can found that subject 8 demonstrates generally high similarity in muscle synergy patterns at different walking speeds (Similarity indices are all greater than 0.78). However, subject 19 gains low similarity between high walking speeds and low walking speeds (The similarity reached a minimum of 0.5).

Figure 3 shows the synergy weights of subject 8 and 19. The rows represent different muscle synergy components labeled from Synergy 1 to Synergy 3. The x-axis of each subplot represents different muscles: RF, VL, TA, SO, ST, BF, and GM. The y-axis displays the normalized muscle activation levels for each synergy component. Each subplot contains multiple lines representing the muscle activation synergy for each of the 28 speeds. These lines are color-coded based on subject number, as indicated by the color bar at the bottom of the figure. Unlike the patterns belong to subject 19 (Fig. 3 (b)), subject 8′ s synergy weights of seven muscles change slightly when the speed goes up. Subject 19′ s synergy weights of muscle TA change greatly in Synergy 1 (S1) and Synergy 2 (S2) when walking speed change from 0.9 to 0.95 m/s and from 1.1 to 1.3 m/s. We can also find in Fig. 3 that the general trends in the changes of synergy weights for most muscles appear to be similar. For example, synergy weights of muscle VL of subject 8 show a gradually growth in S1 and a gradually decline in S2, and the same degree of growth in S1 and the same degree of decline in S2 appear to be more pronounced in muscle VL of subject 19. For subjects in model 2, muscle synergy patterns can be so different across different speeds and we can find in Fig. 2 that different subjects have their own characteristics, and the speed ranges corresponding to the drastic changes in their synergy patterns are not consistent and lack discernible patterns.

### 3.2. Muscle synergy discrepancy among different individuals at same speeds

Many studies attempt to use the average electromyographic signals of healthy individuals as substitutes for the signals of individual healthy subjects and compare them with those of stroke patients. Previous research has found that the patterns of synergy between different healthy individuals vary. So, can the average synergy pattern of healthy individuals be used to replace the synergy patterns of all healthy individuals?

Figure 4 displays the weighting coefficient of muscle synergy for 22 subjects walking at 0.50, 1.00, and 1.50 m/s. The three columns correspond to the walking speeds: (a) 0.50 m/s, (b) 1.00 m/s, and (c) 1.50 m/s. The rows represent different muscle synergy components labeled from Synergy 1 to Synergy 3 for each walking speed. The x-axis of each subplot represents different muscles: RF, VL, TA, SO, ST, BF, and GM. The y-axis displays the normalized muscle activation levels for each synergy component. Each subplot contains multiple lines representing the muscle activation synergy for each of the 22 subjects. These lines are color-coded based on subject number, as indicated by the color bar at the bottom of the figure. Notably, the synergy weights exhibit significant fluctuations across the different subjects. The noteworthy point is that as the speed increases, the differences in synergy weights among different individuals decrease. To gain a deeper understanding of the physiological mechanisms that underlie muscle synergy and the differences between individuals and groups, the similarity index was introduced as a quantitative indicator of global muscle synergy.

Figure 5 (a) display the heatmaps of muscle synergy similarity across 22 subjects walking at 0.50, 1.00, and 1.50 m/s, respectively. The mean synergy of one subject was used as a reference to calculate the similarity indices for each gait, followed by obtaining the mean value of these indices. It can be seen that the similarity indices gradually increase as the walking speed increases. Significant variations in similarity indices are observed across different subjects, especially walking in low speed. The minimum similarity index among the 22 subjects is 0.38. To establish and evaluate a baseline synergy pattern, this study calculated the averaged synergy patterns

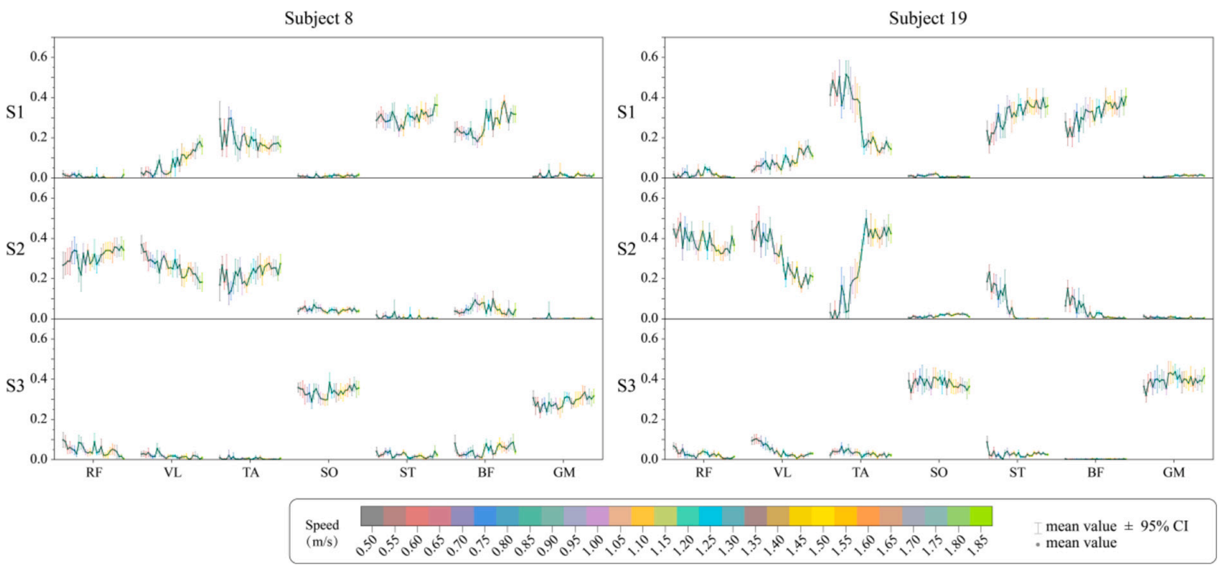


**Fig. 3.** Synergy weights of 2 subjects walking at 28 different speeds. S1, S2, and S3 stand for Synergy 1, Synergy 2, and Synergy 3, respectively.


**Fig. 4.** Synergy patterns of 22 subjects walking at 0.50, 1.00 and 1.50 m/s respectively.

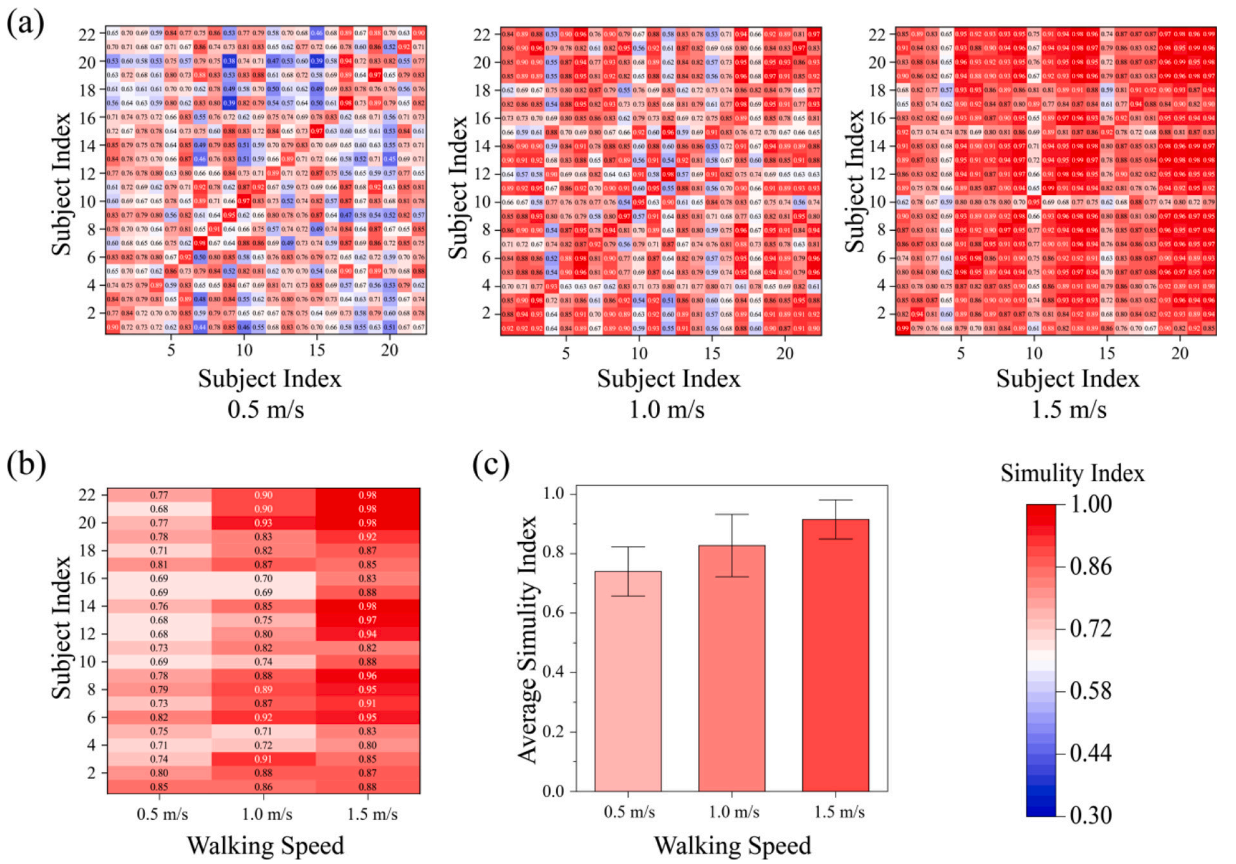


**Fig. 5.** Heatmaps of similarity indices. (a) Heat map of similarity indices about 22 subjects walking at 0.50 m/s, 1.00 m/s and 1.50 m/s, respectively. (b) Averaged similarity indices of gait units observed in 22 subjects walking at three different speeds. (c) Averaged similarity indices of 22 subjects walking at three different speeds.

for the same three speeds respectively from subject 1 to subject 20. Fig. 5 (b) shows the similarity indices between the synergy patterns of 22 subjects and the above averaged synergy patterns with walking speeds of 0.50, 1.00, and 1.50 m/s. Fig. 5 (c) displays the mean and variance of similarity indices of 22 subjects at the above three speeds. The high synergy similarity results (0.7469 ± 0.0484 for

0.50 m/s, 0.8293 ± 0.0744 for 1.00 m/s, 0.9017 ± 0.0616 for 1.50 m/s) between the reference synergy patterns and synergy patterns observed from 22 individuals suggest that the baseline synergy patterns can be utilized to qualify the similarities of other subjects, especially in high walking speed.

## 4. Discussion & conclusion

The primary aim of this study was to systematically investigate the similarities in muscle synergies of the lower limbs across various walking speeds, with the intention of providing insights for patients with gait disturbances. A key focus was placed on analyzing muscle synergies during treadmill walking.

Through the analysis of muscle synergy similarities, we observed that while half of the individuals showed no significant changes in synergy patterns with variations in walking speeds, the remaining individuals generally exhibited substantial changes in synergy across different walking speeds. This indicates that some subjects exhibit changes in the timing of lower limb muscle activation patterns when walking speed varies, and this variation is widespread.

Despite the significant differences in synergy similarity observed among individuals walking at same speed, the high similarity indices between reference synergy patterns and synergy patterns observed from 22 subjects(>0.75) validate the rationale behind the proposed reference synergy. Consequently, it seems reasonable to establish a reference synergy pattern based on synergy samples obtained from able-bodied individuals in databases. Hof *at el.* found that average EMG profiles varied in a predictable way with speed (Hof, Elzinga, Grimmius, & Halbertsma, 2002), and similarly, this study also found that muscle synergies varied more or less predictably with speed. As walking speed increases, the synergy patterns between individuals tend to become closer (similarity index improved from 0.75 to 0.90).

These findings hold promise for researchers studying human locomotion biomechanics and offer valuable insights into guiding force assistance and control strategies for exoskeletons. When performing HIL optimization based on synergy patterns, it is suggested to adjust our reference synergy patterns according to the subject's different walking speeds. In addition, the use of our evaluation index appears to be a promising approach for assessing muscle synergy patterns, as evidenced by its implementation in HIL optimization for exoskeleton torque generation (Ma et al., 2024).

Moreover, beyond these immediate implications, our study suggests a paradigm shift in rehabilitation approaches. Specifically, we advocate for individuals to collect their own gait data while they are healthy. Utilizing personal gait data during recovery could potentially yield superior rehabilitation outcomes compared to relying solely on reference data from other healthy individuals. This recommendation underscores the importance of personalized approaches in rehabilitation and warrants further exploration in future studies.

In conclusion, this study systematically evaluated human muscle recruitment and coordination through muscle synergy analysis of 22 healthy individuals. We proposed general reference synergy patterns and introduced a muscle synergy similarity index, which can aid in locomotion rehabilitation for stroke patients using exoskeletons. These findings contribute to the study of human locomotion biomechanics and provide guidance for exoskeleton force assistance and control strategies. However, it is important to note that while we utilized a database with a relatively large number of participants and 28 different speed conditions, the age range of participants was somewhat concentrated. Therefore, the results may primarily reflect the characteristics of individuals within this specific age group. Additionally, due to the limited number of participants, we were unable to further explore the deeper underlying principles behind the phenomenon. In our future research, we will extend this study to different scenarios, including overground walking and treadmill running.

## CRediT authorship contribution statement

**Luying Feng:** Writing – original draft, Formal analysis. **Linfan Yu:** Methodology, Data curation. **Hui Lyu:** Writing – review & editing, Resources. **Canjun Yang:** Supervision, Project administration. **Xiaoguang Liu:** Resources, Project administration. **Congcong Zhou:** Methodology, Conceptualization. **Wei Yang:** Writing – review & editing, Visualization, Supervision, Conceptualization.

## Data availability

Data will be made available on request.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.humov.2024.103300.

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