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Consistency of muscle activation signatures across different walking speeds

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ABSTRACT

Background: Using a machine learning algorithm, individuals can be accurately identified from their muscle activation patterns during gait, leading to the concept of individual muscle activation signatures.

Research question: Are muscle activation signatures robust across different walking speeds?

Methods: We used an open dataset containing electromyographic (EMG) signals from 8 lower limb muscles in 50 asymptomatic adults walking at 5 speeds (extremely slow, very slow, slow, spontaneous, and fast). A machine learning approach classified the EMG profiles based on similar (intra-speed classification) or different (inter-speed classification) walking speeds as training and testing conditions.

Results: Intra-speed median classification rates of muscle activation profiles increased with walking speed, from 92 % for extremely slow, to 100 % for self-selected fast walking conditions. Inter-speed median classification rates increased when the speed of the training condition was closer to that of the testing condition. Higher median classification rates were found across slow, spontaneous, and fast walking speed conditions, from 56 % to 96 %, compared with classification rates involving extremely and very slow walking speed conditions, from 6 % to 62 %.

Significance: Our findings reveal that i) muscle activation signatures are detectable for a large range of walking speeds, even those involving different gait strategies (intra-speed median classification rates from 92 % to 100 %), and ii) muscle activation signatures observed during very low walking speeds are not consistent with those observed at higher speeds, suggesting a difference in motor control strategy. Caution should therefore be exercised when assessing gait deviations of a slow walking patient against a normative database obtained at higher speed. Identifying the robustness of individual muscle activation signatures across different movements could help in detecting changes in motor control, otherwise difficult to detect on classical time-varying EMG patterns.

1. Introduction

Signatures are distinctive patterns by which an individual can be identified. During walking at self-selected speed, individuals were successfully identified by a machine learning algorithm using their kinematics and kinetics patterns [1,2], supporting the existence of individual movement signatures. Furthermore, individuals were identified using their muscle activation patterns during walking at a fixed speed [3], supporting the existence of unique muscle activation strategies, and thus muscle activation signatures. These movement and muscle activation signatures have been shown to persist over time [2,3].

This suggests that the control of locomotion is unique to an individual. However, it is still unclear whether individuals' muscle activation signatures differ across tasks with different mechanical constraints such as walking at different speeds. Addressing this question will help to: i) understand motor control strategies during gait, in both healthy and pathological populations; ii) interpret the changes in individuals' signatures over time or following an intervention.

Specifically, muscle activation signatures have been identified during walking at a single speed, whereas activities of daily living require a wide range of walking speeds. Individuals use different walking speeds during daily activities to adapt their pace to the context; an increase in

Abbreviations: EMG, Electromyography; SVM, Support Vector Machine.

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walking speed can be required at pedestrian crossings [4]. It is well-documented that walking speed variations are associated with changes in lower limb kinematics and muscle activations [5–8]. These changes are predictable for some range of walking speeds [9–11]. However, transitions in gait strategies have been found for very low and very high walking speeds. While the last one represents the walk-run transition speed [9,12–14], walking at very low speed is thought as a transition between the locomotion task and a more postural control task [10,11].

It is unknown whether the muscle activation signatures during gait are robust across walking speeds. The two sub-objectives of this study were: a) to evaluate the detectability of muscle activation signatures for different walking speeds; and b) to evaluate the consistency of muscle activation signatures across different walking speed conditions.

By using a dataset of adults walking from very low to high speeds [15], this study examined primarily the robustness of individual muscle activation signatures across different walking speeds. A machine learning approach was used to classify participants based on their muscle activation patterns [3], using similar (intra-speed classification) or different (inter-speed classification) walking speeds as training and testing conditions. High classification rates of the algorithm would indicate a successful classification, and therefore the presence of individual muscle activation signatures [3].

We hypothesize that muscle activation signatures are consistent across different walking speeds, meaning that individuals walking at a certain speed could be identified using their muscle activation patterns measured during walking at a different speed.

2. Methods

2.1. Dataset

This study used a publicly available dataset recorded in accordance with the Declaration of Helsinki and its later amendments [15].

This dataset includes records from 50 asymptomatic adults (24 women and 26 men; mean age 37 ± 13.6 years; Table 1) walking overground at five different walking speeds: between 0 and 0.4 m/s (condition C1) – extremely slow speed; between 0.4 and 0.8 m/s (C2) – very slow speed; between 0.8 and 1.2 m/s (C3) – slow speed; self-selected spontaneous walking speed (C4); and self-selected fast walking speed (C5).

Gait data included 3D trajectories of 52 reflective markers from a full-body marker set, 3D ground reaction forces and moments, gait events (i.e., timings of foot strikes and foot offs), and surface EMG signals for the following eight right lower limb muscles: gluteus maximus; gluteus medius; rectus femoris; vastus medialis; semitendinosus; gastrocnemius medialis; soleus; tibialis anterior. EMG signals were sampled at 1500 Hz (Desktop DTS, Noraxon, USA), and band-pass filtered between 30 and 300 Hz (4th order Butterworth filter). The experimental protocol is fully detailed in [15].

Between three and five gait trials were collected for each walking speed and each participant. For each trial, one gait cycle was extracted between two consecutive right foot strikes to match with the side of the collected EMG.

Table 1
Participants' characteristics ($n = 50$).

	Mean (SD)	Range
Age (year)	37.0 (13.6)	19–67
Height (m)	1.74 (0.09)	1.55–1.92
Body mass (kg)	71.2 (12.3)	50–98
BMI (kg m^{-2})	23.5 (2.8)	17.2–29.6

2.2. Data processing

Electromyography signals were processed using MATLAB (R2018b, The Mathworks, USA). To obtain EMG envelopes, EMG signals were rectified and low-pass filtered using a 2nd order Butterworth filter, with a variable cut-off frequency. Filtering parameters have been shown to greatly influence EMG patterns [16,17]. Furthermore, cut-off frequency of EMG low-pass filtering should be adapted when different movement velocities are compared [18], to maintain a similar level of smoothing. We investigated the best cut-off frequency for EMG comparisons at different walking speeds.

Eight cut-off frequencies were tested: fixed cut-off frequencies of 3 Hz, 6 Hz, 9 Hz, 12 Hz, 15 Hz, 18 Hz, and 21 Hz (reflecting the low-pass filters commonly used in gait; [19]), and a walking speed-customized cut-off frequency. Specifically, the actual walking speed for each gait cycle of each participant was calculated using the difference in horizontal position of the posterior iliac spine marker between two consecutive foot strikes and the associated time. Additionally, the Froude number [20], representative of the dimensionless walking speed, was calculated by dividing walking speed by the square root of the product of the leg length and the gravitational constant. Then, the customized cut-off frequency was calculated using a linear relation between the cut-off frequency and the walking speed, using the reference of 9 Hz for 1.1 m/s [3]. These two processes (fixed and customized cut-off frequencies) led to eight different datasets.

Finally, each EMG envelope of each gait cycle was interpolated to 200 time points and amplitude-normalized to its maximal value. Each gait cycle was normalized to its maximal value to ensure that data from all muscles and all gait cycles had an equivalent weight in the classification [3].

2.3. Intra-speed classification

All support vector machines analyses were realized using MATLAB (R2018b, The Mathworks, USA).

An intra-speed classification was performed for each of the five walking speed conditions, and for each of the eight cut-off frequency datasets. Each dataset was composed of five $c \times m$ matrices [$c = 50$ participants \times number of gait cycles (between 3 and 5); $m = 200$ time points \times 8 muscles]. As in [3], a leave-one-out cross-validation approach was used, i.e., for each walking speed condition, the corresponding $c \times m$ matrix was separated into a training set, including all-except-one randomly chosen gait cycles for all participants, and a testing set including the remaining gait cycle. After being trained with the training set, the classifier was applied to the testing set.

The number of total possibilities for establishing the training and testing sets was the number of cycles to the power of the number of participants (i.e., between 3^{50} and 5^{50} according to the number of cycles). However, all possibilities could not be tested since the calculation time would have been too high. A compromise needed to be made between an acceptable calculation time, requiring a low number of iterations, and stable classification results, requiring a sufficiently high number of iterations. The value of 200 iterations was determined given the most stable classification results (Supplementary material 1). Therefore, for each condition, we performed 200 testing iterations, with 200 random testing sets trained with their corresponding training set.

2.4. Inter-speed classification

Based on the results for the intra-speed classification (reported below in the Results section), the inter-speed classification was only performed for the customized cut-off frequency dataset. Each walking speed condition was tested against each of the four remaining walking speed conditions, resulting in 20 inter-speed combinations (called "pairs"). For each pair, the training dataset was a $c \times m$ matrix (where $c = 50$ participants \times 3–5 gait cycles from the training walking speed condition; m

= 200 time points \times 8 muscles). The testing dataset was a $c \times m$ matrix (where $c = 50$ participants \times 1 randomly selected gait cycle from the testing walking speed condition; $m = 200$ time points \times 8 muscles). Likewise, 200 iterations of the testing were performed using 200 random testing sets.

2.5. Machine learning

Similarly to Aeles et al. [21] and Hug et al. [3], the classification of time-varying EMG profiles was performed using support vector machines, consisting in a supervised machine learning algorithm for pattern recognition. The Liblinear Toolbox 2.11 [22] was used with the solver L2-regularized L2-loss support vector classification (primal) and a linear kernel function. The option "find C" was selected such that the model ran a cross-validation to find the best cost C value, with the highest cross validation accuracy. The cost C value rules the trade-off between regularization and correct classification.

2.6. Classification performance

The classification performance was reported by its sensitivity, providing the percentage of correctly classified cycles (called "classification rate" hereafter). A median intra-speed classification rate was reported for each walking speed condition. A median inter-speed classification rate was reported for each pair of walking speeds. The classification was interpreted as invalid if the rate was $< 50\%$, poor between 50% and 70% , acceptable between 70% and 80% , excellent between 80% and 90% , and outstanding when $> 90\%$ [23].

2.7. Statistics

The studied data were the 200 classification rates, for each walking speed condition and each cut-off frequency. For each analysis, the distribution normality was examined through histograms. Due to the 100% upper limit of the classification rate data, the data distributions were either skewed or half-normal. Nevertheless, ANOVAs were still performed, due to the robustness for these types of data distributions with equal and high group sample sizes [24].

To determine the best low-pass filtering parameter, the effect of the cut-off frequency was analyzed on the intra-speed classification rates using a one-way ANOVA (factor: cut-off frequency), for each walking speed condition.

Then the analyses were performed according to two secondary objectives: a) The effect of the walking speed condition on the intra-speed classification rates for the best cut-off frequency dataset was analyzed using a one-way ANOVA (factor: walking speed condition); b) The effect of the pair of walking speed conditions on the inter-speed classification rates of EMG profiles was analyzed using a one-way ANOVA (factor: pair of conditions, e.g., C1-C2). Tukey post-hoc tests were used when appropriate. For all analyses, the significance threshold was set at 0.05. All statistical analysis were realized using MATLAB (R2018b, The Mathworks, USA).

3. Results

3.1. Walking speeds and cut-off frequencies

Table 2 shows the means and standard deviations of walking speeds, the associated Froude number, and their associated customized cut-off frequencies for the five conditions.

Fig. 1 illustrates the inter-individual variability of EMG patterns of the eight muscles during three selected walking conditions.

Fig. 2 shows the intra-speed classification rates for each walking speed condition for each of the eight datasets. The classification rates correspond to the percentage of cycles allocated to the correct participant based on their muscle activation profiles.

Table 2

Walking speeds and related customized cut-off frequencies for the five walking speed conditions, given as means with standard deviations (SD).

Condition	Mean walking speed (SD) (m/s)	Mean Froude number (SD)	Mean custom cut-off frequency (SD) (Hz)
C1	0.29 (0.05)	0.10 (0.02)	2.3 (0.4)
C2	0.61 (0.08)	0.21 (0.03)	5.0 (0.7)
C3	0.98 (0.10)	0.35 (0.04)	8.0 (0.9)
C4	1.15 (0.16)	0.41 (0.06)	9.4 (1.3)
C5	1.61 (0.23)	0.57 (0.09)	13.1 (1.9)

The cut-off frequency had a significant effect on the intra-speed classification rate for all walking speed conditions: C1: $F(6,1393) = 12.67, P < 0.001$; C2: $F(6,1393) = 10.24, P < 0.001$; C3: $F(6,1393) = 15.64, P < 0.001$; C4: $F(6,1393) = 10.71, P < 0.001$; C5: $F(6,1393) = 134.13, P < 0.001$. For all walking speeds combined, the SVM analysis accurately identified individuals based on their activation profiles with the following median (interquartile range) classification rates: $100(4)\%$ for the customized frequency, $98(6)\%$ for a cut-off frequency at 3 Hz , $98(4)\%$ at 6 Hz , $98(4)\%$ at 9 Hz , $98(4)\%$ at 12 Hz , $98(4)\%$ at 15 Hz , $98(4)\%$ at 18 Hz , $98(6)\%$ at 21 Hz . Considering these results, only the customized frequency dataset was used in the following analyses.

3.2. Intra-speed classification rates

Fig. 3 shows the intra-speed classification rates when considering only the customized cut-off frequency dataset. The classification revealed outstanding performances for all walking speeds. The higher the walking speed, the higher the classification rate (main effect of walking speed: $F(4,995) = 511.08; P < 0.001$): $92(4)\%$ for C1, $96(4)\%$ for C2, $100(2)\%$ for C3, $100(0)\%$ for C4, and $100(0)\%$ for C5. Significant differences were found between all the conditions, except between C4 (self-selected spontaneous speed) and C5 (self-selected fast speed).

3.3. Inter-speed classification rates

Inter-speed classification rate results are summarized in Table 3. The classification model was trained with a specific walking speed condition and tested on another walking speed condition. The median rate ranged from 6% to 96% , depending on the pair. Overall, the higher the difference in walking speed between the training and testing conditions, the lower the classification rate.

Interestingly, for comparable differences of walking speed (e.g., $\Delta_{\text{speed,C1-C2}} = 0.33$ vs. $\Delta_{\text{speed,C2-C3}} = 0.39$ m/s) different classification performances were found. Higher classification rates were found across the C3-C5 conditions, compared with those found when using C1 or C2 walking speeds as the training or testing condition.

4. Discussion

This study examined the robustness of muscle activation signatures across five different speeds (extremely slow, very slow, slow, spontaneous, and fast) in adults during overground walking, by using a machine learning algorithm to classify EMG profiles in eight lower limb muscles. The main results were that a/ muscle activation signatures were detectable for a large range of walking speeds (intra-speed classification rates from 92% to 100%), and b/ muscle activation signatures at very low speeds are not consistent with those at higher speeds, confirming changes in motor control strategy.

Methodologically, using the same cut-off frequency of the low-pass filter across walking speeds induced a different smoothing level on the time-varying EMG profiles. The use of a custom cut-off frequency adapted to the walking speed maximized successfully the classification rate for each walking speed condition.

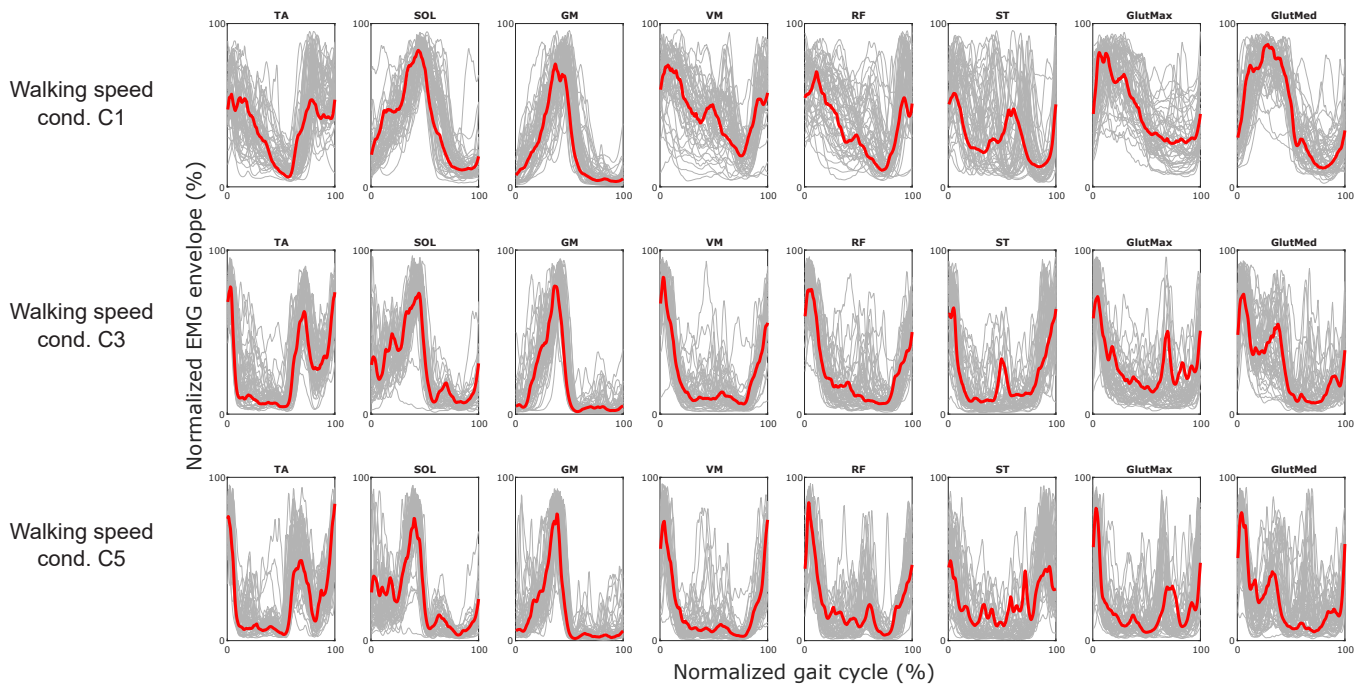


Fig. 1. Inter-individual variability of electromyography (EMG) patterns during walking for the walking speed conditions C1 – extremely slow (top), C3 – slow (middle), and C5 – fast (bottom). The mean EMG profiles of each participant are shown in gray. The mean profile over all participants is shown in red. *Note.* TA: tibialis anterior; SOL: soleus; GM: gastrocnemius medialis; VM: vastus medialis; RF: rectus femoris; ST: semitendinosus; GlutMax: gluteus maximus; GlutMed: gluteus medius.

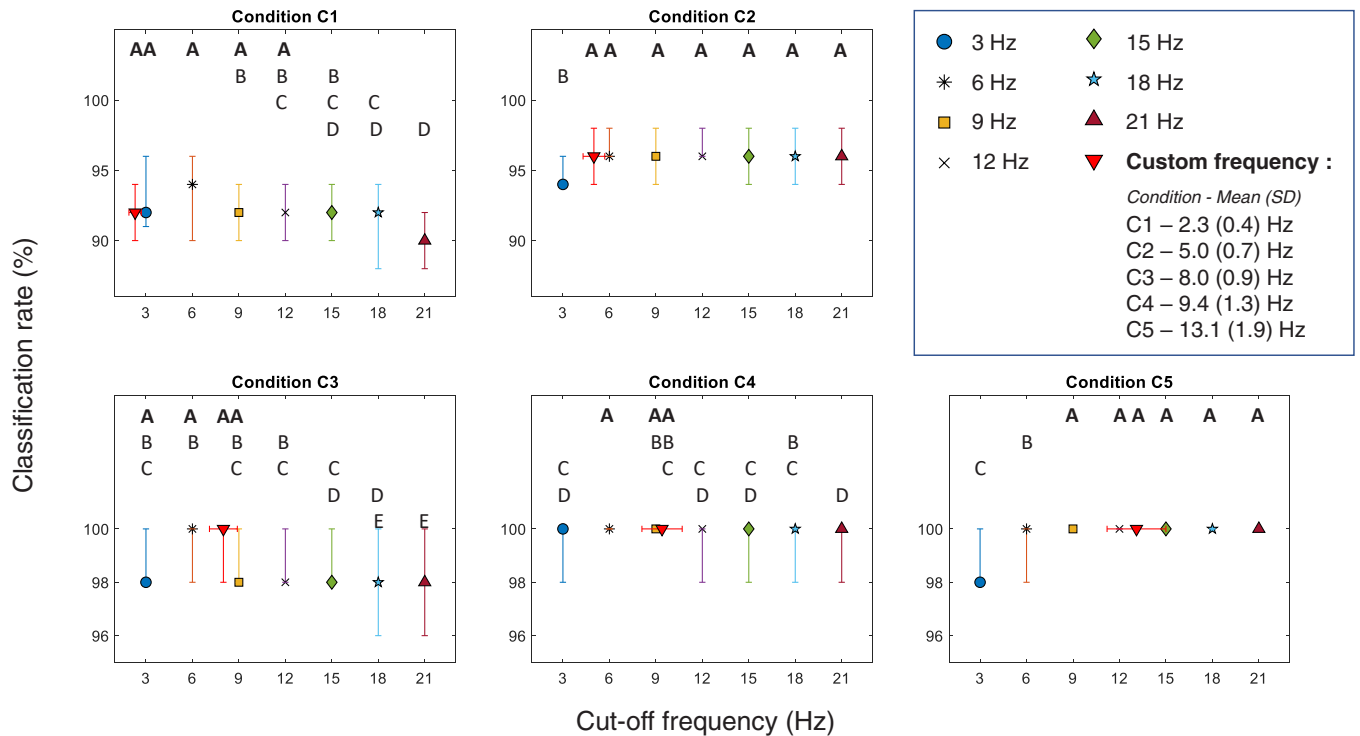


Fig. 2. Intra-speed classification rate median and interquartile range (%) as a function of the cut-off frequency (Hz). Results are presented for each of the five walking speed conditions. The custom cut-off frequency varies within each condition so the standard deviation is also displayed. Statistical results are indicated for the Tukey post-hoc tests: frequency subgroup means that do not share a letter are significantly different ($P < 0.05$), A being the highest subgroup mean, and E being the lowest subgroup mean.

The walking speeds varied from 0.29 to 1.61 m/s, representing a Froude number from 0.1 to 0.6. The C4 – spontaneous and C5 – fast conditions, with mean walking speeds of 1.15 m/s and 1.61 m/s, can be

interpreted respectively as a stroll walking speed and a brisk walking speed of a healthy adult. The C3 – slow condition, with a mean walking speed of 0.98 m/s, can be interpreted as the walking speed of a healthy

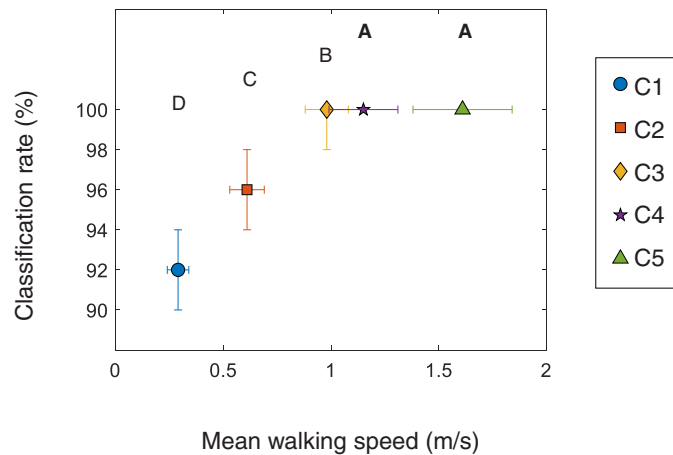


Fig. 3. Intra-speed classification rate - using the custom cut-off frequency - median and interquartile range (%) as a function of the mean and standard deviation of walking speed (m/s), for the five conditions (C1 – extremely slow: between 0 and 0.4 m/s; C2 – very slow: between 0.4 and 0.8 m/s; C3 – slow: between 0.8 and 1.2 m/s; C4 – spontaneous: self-selected spontaneous walking speed; C5 – fast: self-selected fast walking speed). The Tukey post-hoc test results are indicated by letters: walking speed conditions that do not share a letter are significantly different ($P < 0.05$).

Table 3

Inter-speed classification rates. For all walking speed conditions, the definition of the condition (in *italics*), and the mean and standard deviation of the condition walking speed (m/s) (in **bold**) are indicated. Median (interquartile range) inter-speed classification rate (%) is indicated for all pairs of walking speed conditions: the model was trained with the training condition, and tested with one randomly selected cycle of the testing condition. The mean difference in speed (m/s) between the two conditions (Δ Speed) is indicated below the classification rate. Cells colored in red, orange and green indicate invalid ($< 50\%$), poor ($50\text{--}70\%$), and excellent to outstanding ($> 80\%$) classification performances, respectively.

Testing cond. \ Training cond.	C1 <i>0 – 0.4 m/s</i> 0.29 (0.05) m/s	C2 <i>0.4 – 0.8 m/s</i> 0.61 (0.08) m/s	C3 <i>0.8 – 1.2 m/s</i> 0.98 (0.10) m/s	C4 <i>Spontaneous</i> 1.15 (0.16) m/s	C5 <i>Fast</i> 1.61 (0.23) m/s
C1		38 (4) % Δ Speed = 0.33 m/s	14 (2) % Δ Speed = 0.70 m/s	12 (4) % Δ Speed = 0.86 m/s	6 (2) % Δ Speed = 1.32 m/s
C2	38 (6) % Δ Speed = 0.33 m/s		60 (6) % Δ Speed = 0.37 m/s	42 (4) % Δ Speed = 0.54 m/s	20 (6) % Δ Speed = 1.00 m/s
C3	12 (4) % Δ Speed = 0.70 m/s	62 (6) % Δ Speed = 0.37 m/s		94 (4) % Δ Speed = 0.17 m/s	66 (6) % Δ Speed = 0.63 m/s
C4	8 (2) % Δ Speed = 0.86 m/s	32 (6) % Δ Speed = 0.54 m/s	96 (2) % Δ Speed = 0.17 m/s		88 (2) % Δ Speed = 0.46 m/s
C5	10 (2) % Δ Speed = 1.32 m/s	16 (4) % Δ Speed = 1.00 m/s	56 (6) % Δ Speed = 0.63 m/s	86 (4) % Δ Speed = 0.46 m/s	

older adult without walking aid. The C2 – very slow condition, with a mean walking speed of 0.61 m/s, can be interpreted as the walking speed of an older adult with strong risk factors for poor health outcomes. Finally, the C1 – extremely slow condition, with a mean walking speed of 0.29 m/s, can be interpreted as the walking speed of a dependent older adult in hospital or geriatric rehabilitation settings [25].

Muscle activation signatures were well defined for all walking speeds, with outstanding intra-speed classification rates (92–100%). Such high rates were rather unexpected since the SVM model was

trained with only 2–4 gait cycles for each condition. Our results were in total accordance with those of Hug et al. [3]: mean classification rate of 98.86 % vs. 99.04 % in the current C4 – spontaneous condition, closest to their imposed walking speed of 1.11 m/s, showing that muscle activation signatures can be observed during both treadmill and overground walking.

A transition in gait strategy has been found for very low walking speeds, around a Froude number of 0.2 (C2 – very slow condition), a likely transition between locomotion and a more postural task [10,11].

For the first time, individual movement signatures were shown below the Froude number 0.2. Surprisingly, they were highly detectable with outstanding classification rates, even if lower than for higher speeds. Slightly lower classification rates could be explained by a higher intra-individual variability and lower inter-individual variability, related to the increase of the postural-demanding task and specific stride length/economy relationship [10,26], which might result in adaptation of muscle activation patterns. The second walk-run transition takes place around a Froude number 0.7, so higher than the walking speeds currently tested.

Muscle activation signatures were found poor to outstanding across C3 – slow, C4 – spontaneous, and C5 – fast walking speeds, for Froude number > 0.35, with inter-speed classification rates superior to 56 % (for C5 – fast/C3 – slow) and up to 96 % (for C4 – spontaneous/C3 – slow). Muscle activation signatures involving slowest speeds (Froude number < 0.2) were less or not at all consistent (6–62 %). This confirms a change in motor control strategy at the Froude number 0.2, with an inconsistency of the muscle activation signatures across this threshold. This is coherent with the strong modifications of muscle activation amplitude and timing at very low speeds. Specifically, higher lower limb proximal muscles co-activation has been found for very slow walking speeds [27,28]. Additionally, muscle activation signatures between C1 – extremely slow and C2 – very slow were inconsistent, meaning that the motor control strategy for a Froude number < 0.2 is specific to the movement speed and cannot be easily identified across very low speeds.

In clinical practice, a movement or gait disorder is usually assessed by quantifying the deviations of a patient's data from normative data. Based on this study results, extreme caution must be exercised when assessing the gait of a patient with a slow walking speed, since normative data are usually collected at self-selected walking speed [15]. Deviations observed could be linked to the gait transition highlighted in this study and not to the patient's gait disorder, and clinical decisions could be directly impacted. The use of a normative database with an adjusted mean walking speed, such as the one presented in [15], is therefore highly recommended.

For C3 – slow to C5 – fast, the higher the difference in walking speed within a pair, the lower the classification rate (e.g., 66 % for the C3 – slow/C5 – fast pair vs. 88 % for the C4 – spontaneous/C5 – fast pair). This is coherent with the predictability of the evolution of individual gait signatures with walking speed, as described for lower limb kinematics by Moissenet et al. [10], and for muscle activation patterns by Den Otter et al. [28]: within a range of normal walking speeds (0.2 < Froude < 0.7), EMG patterns are described as the superposition of speed-dependent gain functions and a basis speed-independent pattern [28,29]. The larger the speed difference between the training and testing speeds, the larger the gain of speed-dependent functions, and therefore the larger classification difficulty for the machine learning algorithm.

Current results provide solid evidence about individual muscle activation signatures across different walking speeds, especially for speeds of daily living movements involving automatic locomotion governed by spinal central pattern generators [30,31]. Interestingly, across a wide range of walking speeds (C3 – slow to C5 – fast), specific motor signatures are highly consistent with each other.

Some limitations must be acknowledged. First, the SVM algorithm was performed on the basis of eight muscles, whereas further muscles are involved in human gait. Also, due to the EMG normalization, inter-muscle amplitude comparisons were not considered by the SVM analysis, which could have limited its performance [3]. Second, we could not exclude that the observed signatures were partly due to extrinsic variability [32], i.e., variability in sensor placement or skin preparation. However, the same experienced operator managed all the measurements following identical guidelines between trials [15]. We used the same machine learning implementation as in [3] where between-session classifications were assessed with good results. We could, therefore, confidently present only these one-session results.

5. Concluding remarks

The use of a machine learning algorithm on muscle activation patterns revealed movement signatures, and automatically highlighted changes in gait strategy for very low speeds compared to low to high walking speeds. Similar methodology could be applied to different populations and movements, to detect changes in motor control, otherwise difficult to detect by manually observing EMG patterns. Note that for clinical applications, a higher number of gait cycles would be recommended to ensure representativeness of the muscle activation patterns. This could help adjusting rehabilitation, by making sure that the imposed exercises do invoke the targeted motor control strategy (e.g. treadmill training with an incline for cerebral palsy patients).

Declaration of Competing Interest

In the name of the authors of the manuscript entitled “*Consistency of muscle activation signatures across different walking speeds*” I declare that we do not have any financial or personal relationship with other people or organizations that could have inappropriately influenced this study.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gaitpost.2023.09.001.

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