

Gait Event Detection and Travel Distance Using Waist-Worn Accelerometers Across a Range of Speeds: Automated Approach

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Abstract

Estimation of temporospatial clinical features of gait (CFs), such as step count and length, step duration, step frequency, gait speed, and distance traveled is an important component of community-based mobility evaluation using wearable accelerometers. However, accurate unsupervised computerized measurement of CFs of individuals with Duchenne muscular dystrophy (DMD) who have progressive loss of ambulatory mobility is difficult due to differences in patterns and magnitudes of acceleration across their range of attainable gait velocities. This paper proposes a novel calibration method to detect steps and to estimate stride lengths and travel distance using a combination of clinical observation, machine learning-based step detection, and regression-based stride length prediction that is highly accurate in children with DMD and typically developing controls (TDs) and regardless of the participant's level of ability. Fifteen children with DMD and 15 TDs underwent supervised clinical testing across a range of gait speeds using 10 or 25m run/walk (10MRW, 25MRW), 100m run/walk (100MRW), 6-minute walk (6MWT) and free-walk (FW) evaluations while wearing a mobile phone-based accelerometer at the waist near the body's center of mass. Following calibration by a trained clinical evaluator, CFs were extracted from the accelerometer data using a multi-step machine learning-based process and results were compared to ground-truth observation data. Model predictions vs. observed values for step counts, distance traveled, and step length showed a strong correlation (Pearson's $r = -0.9929$ to 0.9986 , $p < 0.0001$). The estimates demonstrated a mean (SD) percentage error of 1.49% (7.04%) for step counts, 1.18% (9.91%) for distance traveled, and 0.37% (7.52%) for step length compared to ground truth observations for the combined 6MWT, 100MRW, and FW tasks. Our study findings indicate that a single, waist-worn accelerometer calibrated to an individual's stride characteristics using our methods accurately measures CFs and estimates travel distances across a common range of gait speeds in both DMD and TD peers.

Methods

Gait and Events Detection and Data Analysis

We collected the raw accelerometer signal from 30 participants, which included the x, y, and z-axes (vertical, mediolateral, and anteroposterior), along with the corresponding timestamps. Based on the findings of Zijlstra [3], we observed that the IC events were more distinguishable in the anteroposterior axis (z-axis) compared to the other axes. Therefore, we used the anteroposterior signal from the raw accelerometer data to develop our method for counting the number of steps, estimating step length, and calculating the total distance individuals walked at different speeds.

Method of Step Detection

Figure 3A presents a raw accelerometer signal of the anteroposterior movement (z-axis) from a TD participant during fast-walk speed calibration (SC-L4) for 2.4 s. The steps in the anteroposterior signal are characterized by long wavelengths (low frequency), while other wavelengths (high frequency) represent noise signals. To extract the steps, a trained clinical evaluator reviewed testing videos and applied a low-pass filter [18] to individual participants' data at each speed from a slow walk to a jog/run (range 0.5 Hz to 60 Hz) to smooth the signal and remove short-term fluctuations while preserving the longer-term trend indicating each step (Figure 3A,B). We then identified the peak values of the filtered signal as the peaks occur only once per step in the filtered signal (Figure 3C). The number of peaks corresponds to the number of steps taken by the participant. Figure 4A shows the estimated number of steps using our method as blue dots, compared to the ground truth represented by a black line. The built-in pedometer steps estimation is shown in red.

Method of IC Detection

To detect the IC events, we find the midpoint between two peaks in the filtered signal (Figure 3D), which corresponds to the toe-off (TO) events during the gait cycle based on observation. We then identify all the peaks that occur within each step duration in the original acceleration signal (Figure 3E). Next, we determine the maximum peak value (anteroposterior G), which corresponds to the time point of each IC (Figure 3F).

Method of Step Length Estimation Using Regression

We create an individualized nonlinear regression model [19] for each participant to associate average peak acceleration values with step lengths. Figure 1A depicts the data flow of our model training and prediction process. Each model is trained using five different participant-selected calibration speeds (SC-L1 to SC-L5). For each speed, we calculate the average acceleration peak values by taking the mean of all the peaks as described in Section 2.3.2. To calculate the average step length for training, we divide the observed ground-truth distance by the number of steps obtained from Section 2.3.1. This process is repeated for each of the five calibration speeds (e.g., point SC-L4 in Figure 1A). The resulting individualized equation through all five points allows us to input the peak acceleration value of any step within the participant's range of ambulatory velocity to estimate that step's length (shown as the green line in Figure 1A).

Estimating the Distance

After establishing the individualized model, it can be used on unseen data. We calculate the step lengths of all identified steps from a previously unseen event and accumulate them to calculate the total distance traveled by the individual. In this project, we used 100 MRW, 6 MWT, and FW as input signals during the inference stage, as shown in Figure 4B, and compared the calculated distances with the ground-truth observed distances and the device's internal pedometer.

Calculating the Average Step Length

During the inference stage, to calculate the average step length of an individual, we divide the distance estimated from Section 2.3.4 by the number of steps obtained from Section 2.3.1. Figure 4C shows the estimated average step length using our ML model as blue dots, compared to the ground-truth average step length represented by a black line. The red dots represent the average step length estimated by the built-in pedometer.

Results

In this study, we assessed the accuracy of step counts during walking, jogging, and running using our Walk4Me system compared to the iPhone pedometer [20]. We validated our results by comparing both systems with ground-truth data. Our findings, indicate that the Walk4Me system had an average step count error rate of 3.46%, demonstrating reliable performance in accurately tracking steps at different speeds. For distance measurement, our Walk4Me system showed an average error rate of 5.83%, with the lowest error rate of 3.9% during the fast-walk SC-L4 pace and the highest error rate of 7.74% during the fast 100 m run. For step length measurement, our Walk4Me system showed an average error rate of 5.80%, with the lowest error rate of 3.68% at a comfortable walking pace (SC-L3) and the highest error rate of 8.64% during the short-term jog/run SC-L5 task.

Conclusion

This study introduces a novel signal processing and machine learning technique that accurately identifies steps and step length based on the individual's gait style. Our findings demonstrate that using a single accelerometer worn near the body's center of mass can be more accurate than a standard pedometer. Our method can be applied to both healthy individuals and those with muscle disorders without the need for ground reaction force (GRF) measurements. To our knowledge, this is the first study to propose a method that extracts CFs from raw accelerometer data across the attainable range of gait speeds in healthy participants and those with muscle disease. On average, our method of counting steps and estimating stride length and distance traveled performs well when applied to longer structured sub-maximal clinical testing efforts and free-roaming self-selected pace travel. In these settings, our methods surpass the pedometer functions native to the mobile devices we use. This will allow us to extend basic elements of gait analysis to community settings using commonly available consumer-level devices.

Tables and Figures

Figure 1. (A) The relationship between step length and acceleration of the body's center of mass at various speeds for TD individuals and those with DMD. (B) The diagram depicts the data flow of our model training and prediction process.

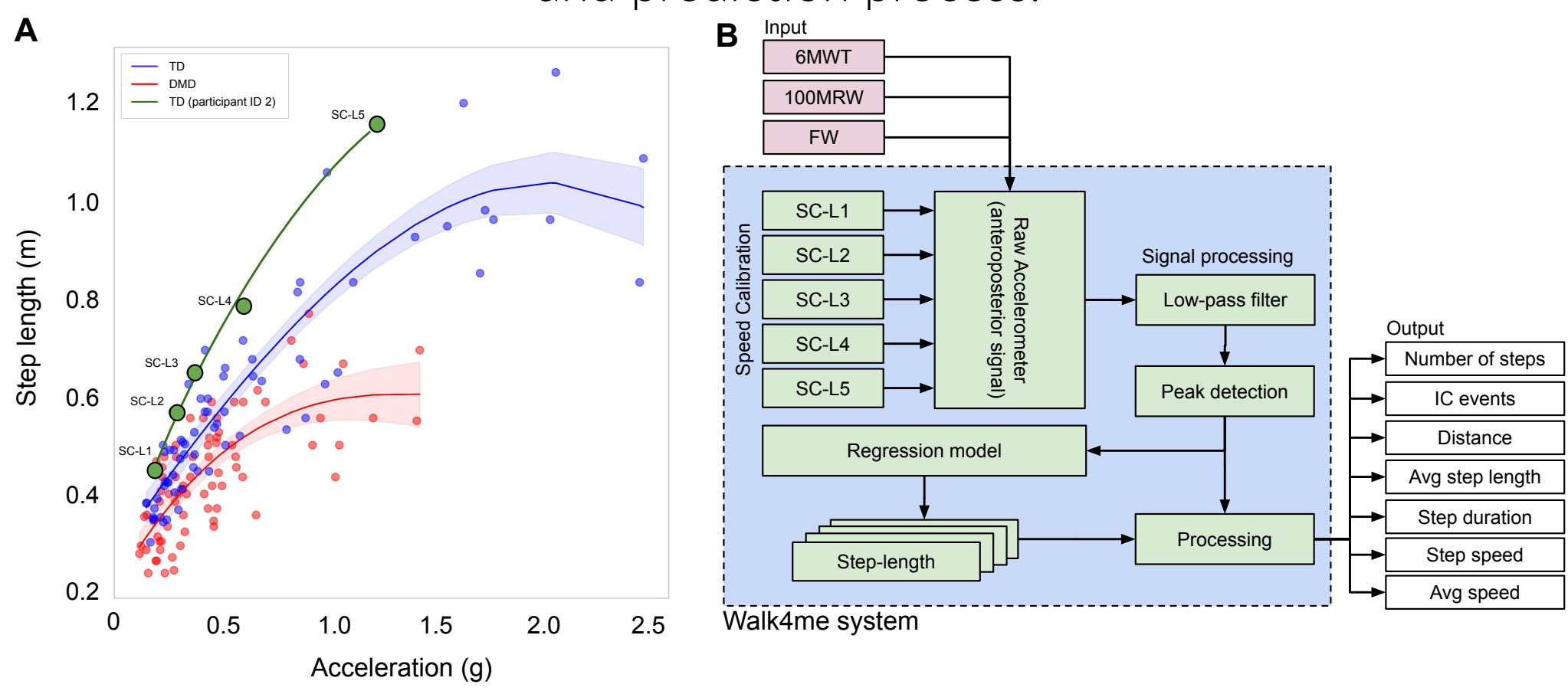


Table 1. Characteristic of the children in the study. Figure 2. (A and B) Showcasing depicting the corridor.

Case (Status)	Value	Age (Years)	Weight (kg)	Height (cm)	NSAA (/34)
DMD (N = 15)	Mean	9.5	37.7	127.1	20.5
	(SD)	(3.9)	(16.0)	(16.2)	(8.2)
	Min	3	17.2	101.6	8.0
	Max	16	67.7	153.3	34.0
	Mean	7.7	34.2	130.8	33.8
TD (N = 15)	(SD)	(3.0)	(21.6)	(15.8)	(0.8)
	Min	4	18.6	108.5	31.0
	Max	15	101.0	165.5	34.0
	p-value	0.1664	0.6229	0.5331	<0.0001

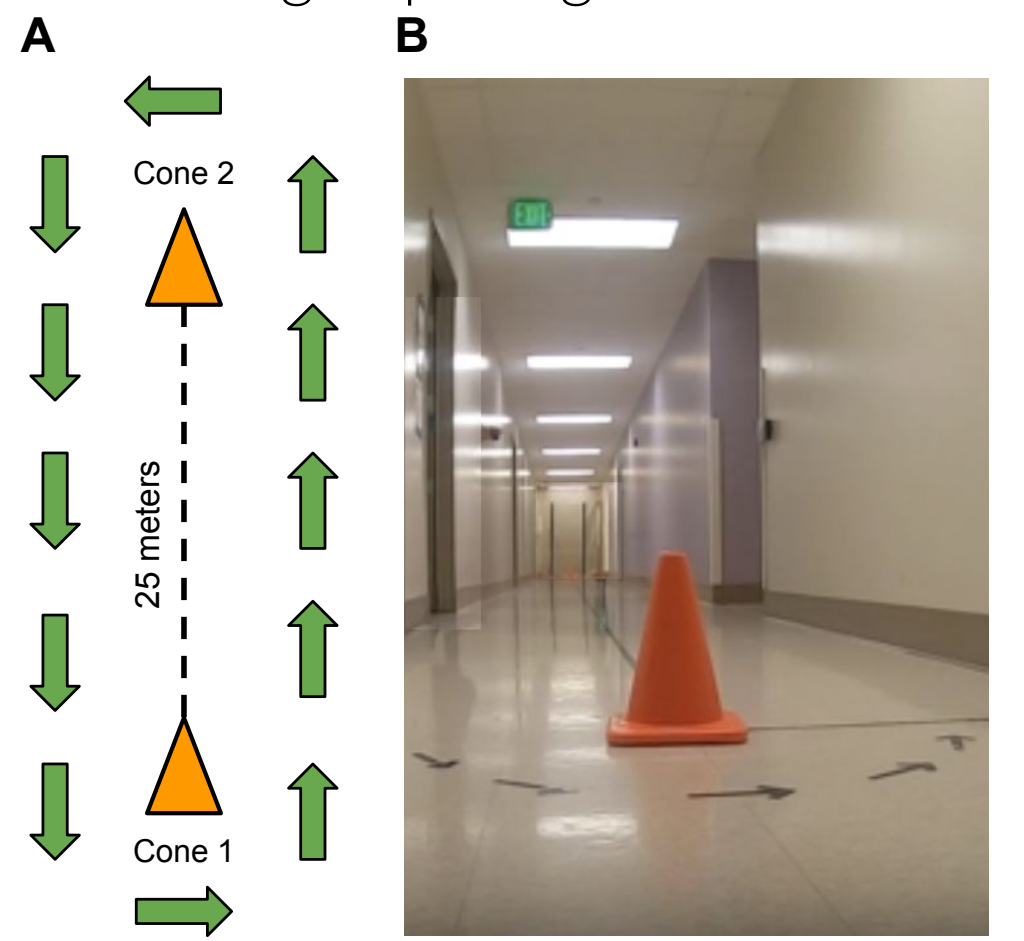


Figure 3. This figure presents the signal processing of the raw accelerometer signal of the anteroposterior movement (z-axis) of participant ID 2 on fast-walk speed calibration (SC-L4) for 2.4 s. (A) Original raw accelerometer signal. (B) Filtered signal. (C) Peak detection of the filtered signal. (D) Locate the beginning and the end of each step. (E) Peaks detection of the original signal. (F) Locate the highest peak in the original signal.

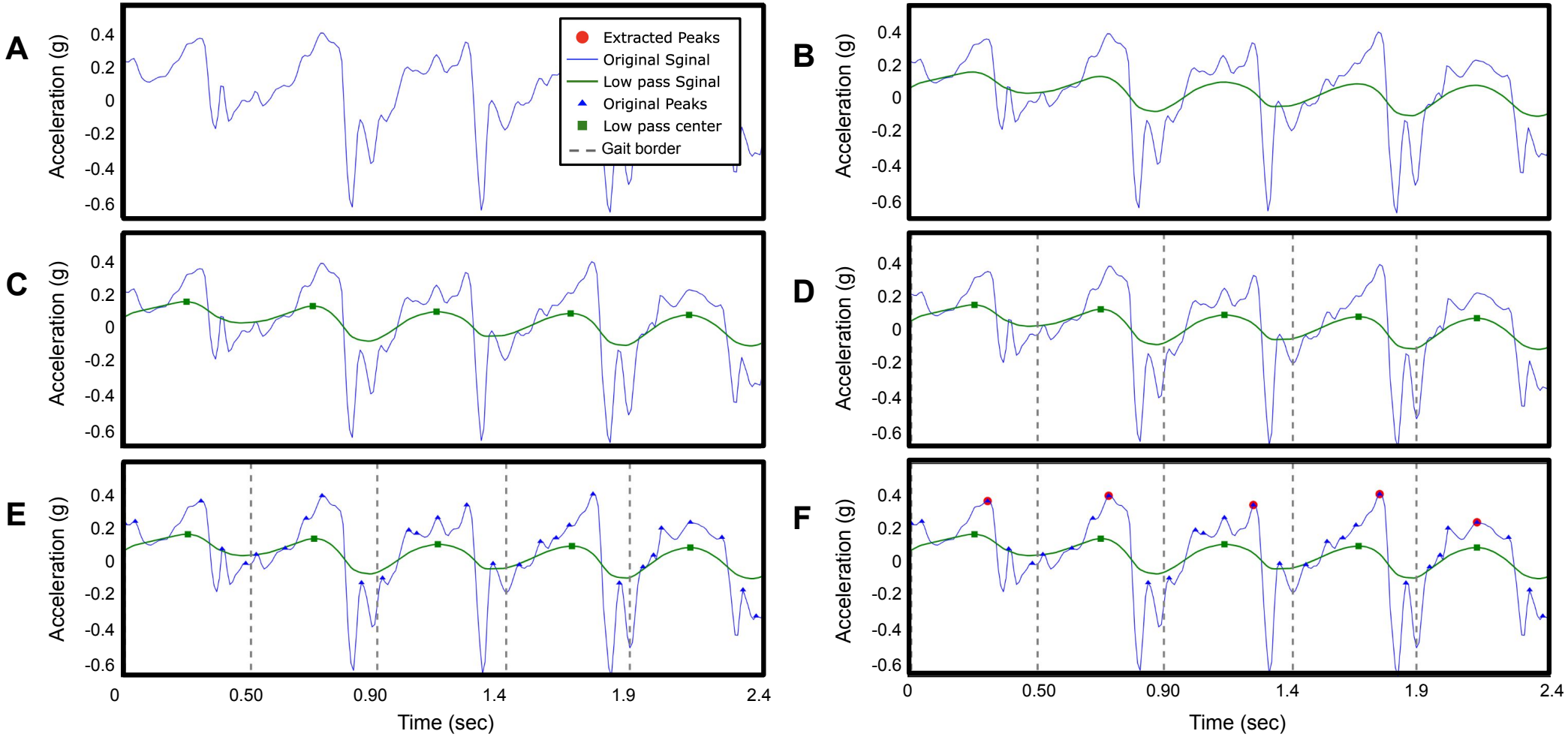


Figure 4. Comparison between the estimates and ground-truth values for both pedometers and our Walk4Me system to illustrate the accuracy across four key metrics.

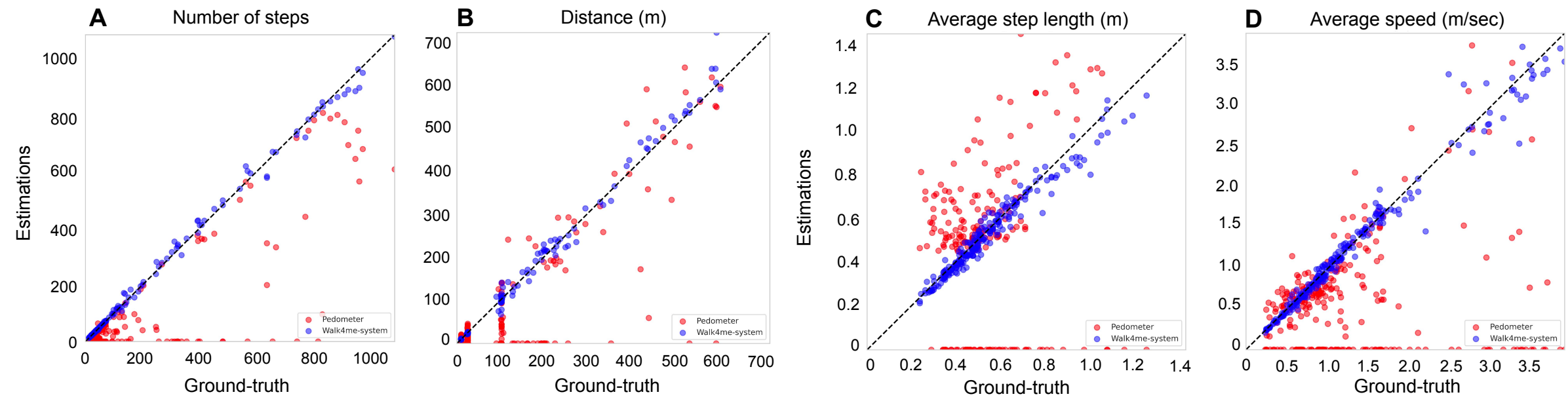
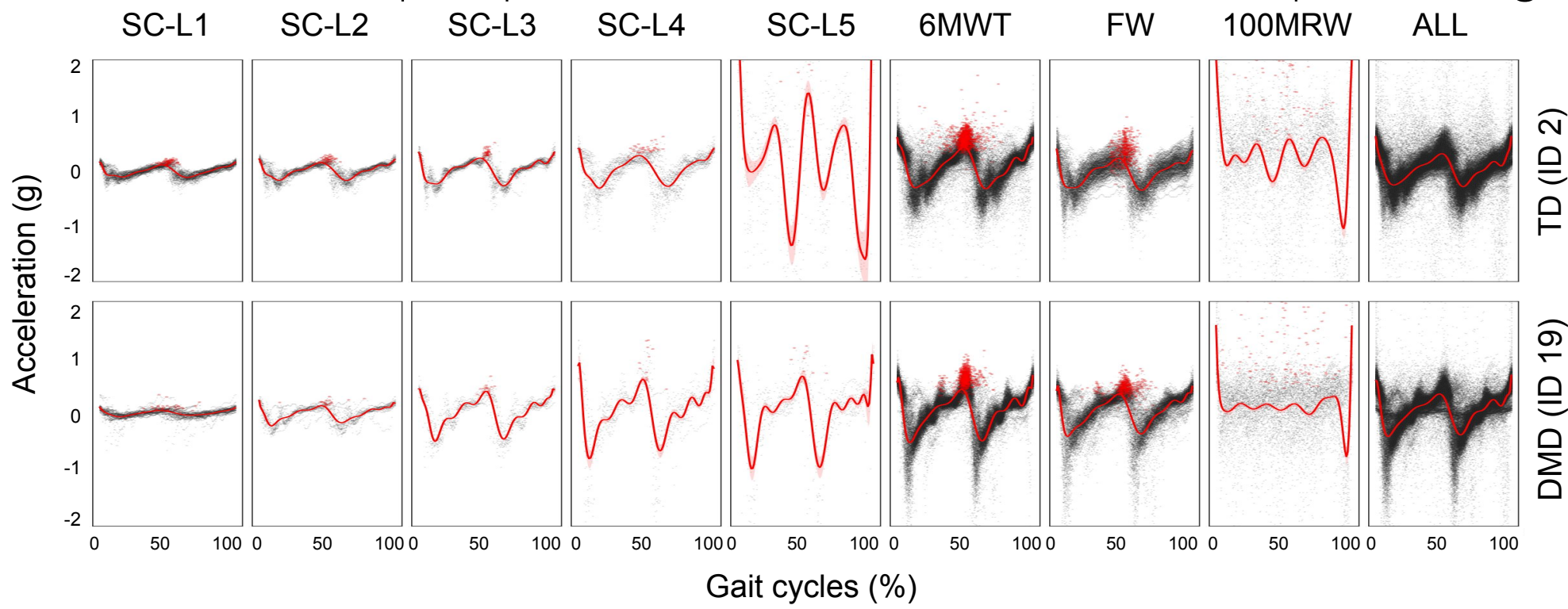


Figure 5. The gait pattern comparison of an individual with TD and an individual with DMD at varying speeds and a combination of multiple speeds and the effects of different speeds on gait pattern.



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Publications and More Information



* Gait Characterization in Duchenne Muscular Dystrophy (DMD) Using a Single-Sensor Accelerometer: Classical Machine Learning and Deep Learning Approaches. [Sensors 2024, 24(4), 1123; <https://doi.org/10.3390/s24041123>]
* Gait Event Detection and Travel Distance Using Waist-Worn Accelerometers across a Range of Speeds: Automated Approach. [Sensors 2024, 24(4), 1155; <https://doi.org/10.3390/s24041155>]