Foot orientation and trajectory variability in locomotion: effects of real-world terrain

1 **Short title:** Foot biomechanics in real-world terrain

2 **Emma Gibson[1], Greg Douglas[1], Katelyn Jeffries[1], Julianne Delaurier[1], Taylor Chestnut[1],**

3 **Jesse M. Charlton[2,3]***

4 [1] University of British Columbia, Department of Physical Therapy, Vancouver, BC, Canada

5 [2] University of British Columbia, School of Kinesiology, Vancouver, BC, Canada

6 [3] University of British Columbia, School of Biomedical Engineering, Vancouver, BC, Canada

7

8 **<u>* Correspondence:</u>**

9 Dr Jesse Charlton, PhD

10 Postdoctoral Fellow, University of British Columbia

11 E-mail: jchar32@alum.ubc.ca

12

Abstract

Capturing human locomotion in nearly any environment or context is becoming increasingly feasible with wearable sensors, giving access to commonly encountered walking conditions. While important in expanding our understanding of locomotor biomechanics, these more variable environments present challenges to identify changes in data due to person-level factors among the varying environment-level factors. Our study examined foot-specific biomechanics while walking on terrain commonly encountered with the goal of understanding the extent to which these variables change due to terrain. We recruited healthy adults to walk at self-selected speeds on stairs, flat ground, and both shallow and steep sloped terrain. A pair of inertial measurement units were embedded in both shoes to capture foot biomechanics while walking. Foot orientation was calculated using a strapdown procedure and foot trajectory was determined by double integrating the linear acceleration. Stance time, swing time, cadence, sagittal and frontal orientations, stride length and width were extracted from discrete variables. These data were compared using a one-way repeated measures analysis of variance across terrain conditions. The physical constraints of the stairs resulted in shorter stride lengths, less time spent in swing, toe-first foot contact, and lower variability in several outcomes ($p<0.05$). Stride lengths increased when ascending compared to descending, and the sagittal foot angle at initial contact was greatest in the steep descent condition ($p<0.05$). No differences were found between conditions for horizontal foot angle in mid-stance ($p=0.32$). Our results show that walking on different terrain can alter foot biomechanics in healthy individuals. This may be an important factor to consider when making comparisons of real-world walking bouts, as greater proportions of one terrain feature in a data set could create bias in the outcomes. Classifying terrain in

unsupervised walking datasets would be helpful to avoid comparing metrics from different walking terrain scenarios.

Introduction

Locomotion is a fundamental human motor pattern that is critical in our daily lives. Control of the lower limbs and feet during locomotion are tightly managed by both the stance and swing limb kinematics and muscle action (1). This process involves both high- and low-level structures of the nervous system, where descending activity integrates with spinal sensorimotor loops that manage the cyclic patterns of the limbs (2, 3). This control allows for adjusting trajectories or orientations of the feet to manipulate the foot-ground clearance, foot placement, foot-ground interaction, and ultimately balance (4-7). This well-controlled but flexible motor program is critical to navigating the ever-changing world around us. When this control fails, a slip, trip, or loss of balance could occur with the potential for ending in a fall (5).

Much of the underlying research investigating foot motion in locomotor contexts was gathered in laboratory conditions with various experimental setups using both treadmill and over-ground walking (8). While important in understanding the neuromechanical control of foot motion while walking, these conditions don’t capture the dynamic and variable environments we normally navigate in our daily life. With the evolving technology of wearable motion capture systems, measuring body kinematics is not only becoming more accessible, but it can be done in real-world contexts (9). By leveraging this technology there is potential to collect large datasets during free-living and unsupervised walking, which could have implications for understanding how clinical conditions or functional changes impact locomotion over larger time scales (10, 11).

Untethering these data collections from the laboratory environment gives ready access to more diverse walking scenarios that can differ in terrain and context.

The last decade has seen a growing body of literature evaluating foot biomechanics while walking in real-world, or at least out-of-lab conditions. Frequently, this is achieved by using an inertial measurement unit (IMU) affixed to the foot (12). The acceleration, angular rate, and in some cases, magnetic field signals from the IMU are combined using various strategies to calculate the orientation and trajectory of the foot (13-15). Validating these algorithms and experimental setups is an important step in development, which has largely occurred in laboratory settings given that the ground-truth comparison is typically an optoelectrical motion capture system. Under controlled conditions of a lab, foot orientation can be estimated with an IMU to within 2.5° depending on the axis of interest (13, 16), while foot trajectories are accurate to approximately 20mm (17). Under more varied or complex conditions that are typical of real-world walking we see slightly inflated error; for example horizontal plane foot angles can exhibit errors up to 3.1° (18) and horizontal trajectory estimates within 1% (19). These small errors in estimation are largely outweighed by the advantage of being able to collect data in vast quantities and in nearly any environment.

A challenge facing real-world, unsupervised gait research is that the features of our built world can influence walking biomechanics to varying degrees (20). Therefore, we need information on how different terrain conditions affect gait, otherwise it becomes difficult to separate changes due to person-specific factors (e.g., disease, injury, functional decline) from simple changes in context or terrain. Initial developments in this area used foot mounted IMUs to classify what terrain the person was walking on as they navigated inclines, stairs, and flat ground (21, 22). Both studies used foot trajectory and gait event timing to generate the classification

with accuracies above 95%. It then becomes important to understand the extent in which terrain conditions affect foot biomechanics. Kowalsky, Rebula (23) investigated this during level ground walking while varying the surface features (concrete, gravel, dirt, grass, and woodchips). These authors noted that overall foot trajectory including foot clearance, stride lengths, and variability of these measures tended to increase under more challenging terrain (e.g., gravel vs concrete). While these studies are building the necessary fundamental methods and data to advance real-world gait research, we still lack a direct comparison of foot motion among geometrically different terrain, including flat ground, slopes, and stairs.

The objective of this study was to examine how foot trajectory and orientation change while walking on commonly encountered terrain in daily living activities. This was an exploratory study seeking to inform more directed, hypothesis-driven research in the future. However, we expect the physical constraints of the stair conditions will limit stride length and width compared to the slope and flat ground walking conditions.

Materials and methods

This study was a cross-sectional, experimental study of the walking mechanics exhibited by healthy adults while navigating typical environments we encounter in our daily lives. We recruited participants on a convenience basis from the surrounding university between November 2021 and august 2022. Prior to any data collection, participants provided written informed consent prior to beginning the methods that follow. The study was approved by the institutional ethics review board (H21-03053).

To be eligible, participants had to be at least 18 years of age, capable of walking intermittently for 60 minutes, and able to fit into the provided shoes which housed the IMUs

(sizes from women's 5 to men's 13). We excluded any person who reported recent lower body injuries or surgical procedures (previous 12 months), had an acute or chronic condition that inhibited normal physical activity levels or affected gait, or who required a gait aid.

Instrumentation and equipment

To record foot biomechanics during walking, we instrumented shoes with a wireless IMU embedded in the sole of each shoe, described in previous work (24, 25). The sensor (MPU-9150, InvenSense, CA, USA) measured acceleration (signal range: ±4g), angular rate (signal range: ±500°/s), and magnetic field strength (signal range: ±1200μT) and a microprocessor (STMicroelectronics, STM3F401, Switzerland; clock rate=84MHz) sampled these signals at 100 Hz before writing them to the onboard microSD chip (MicroSDHC Class 4, Transcend, China). The printed circuit board and components were housed in a custom 3D printed shell with an external power switch, reset button, and charging port. This system was embedded within the sole of both the right and left shoes, where a relief was cut to accommodate the sensor (Fig 1). The relief was positioned to minimize axial impacts under the heel and bending forces from the shoe throughout the gait cycle. The sensor y axis (green arrow) pointed along the long axis of the foot, the x axis (red arrow) pointed to the right on the plane of the shoe's sole, and the z axis (blue arrow) pointed vertically.

Figure 1. The IMU was placed in a relief cut within each shoe's sole that was designed to fit the module without play. The sole was deep enough to accommodate the IMU module without protruding above the interior sole surface. An insole was placed over top, as normal, to ensure foot comfort.

Data collection

While wearing both instrumented shoes, participants performed a series of linear walking bouts on four different terrain conditions (Fig 2). Each condition was completed first at a self-selected walking speed, and then at a self-selected slower and faster pace relative to their initial speed in order to gather data from the breadth of normal walking speeds one might use. Both an ascending and descending trial were collected.

Figure 2. Terrain conditions used in the experiment. A total of seven conditions were collected including ascending and descending for the slope and stairs, and the flat ground condition.

Data analysis

Drawing on previously published and validated methods, we developed a multi-stage analysis to calculate foot trajectory and orientation estimates of each foot from the raw IMU data. Analyses were performed in MATLAB (v 2021b, Mathworks, Natick, MA, USA). We extracted a series of IMU derived outcomes including stride length (m), stride width (m), stance time (s), swing time (s), cadence (steps/min), transverse plane foot angle relative to the walking direction during midstance (°), and sagittal plane foot angle at heel strike (°). Each outcome was calculated on a per-stride basis and summarized as the mean or standard deviation to quantify the magnitude and variability for each condition. The following methods were used to process signals, identify gait events, calculate foot orientation, and foot trajectory.

Pre-processing

145 Each walking bout (21 per limb, 42 per participant) was recorded to a single data file with
146 quiet standing for 1-2 seconds at the start and end of each file. Signals from the IMU were
147 filtered with a bidirectional Butterworth lowpass filter (cut off = 10 Hz, order 4) and these
148 filtered signals were stored for use in identifying gait events.

149 The filtered angular rate about the mediolateral axis of the sensor was then used to identify
150 the positive peaks during the swing phase of locomotion (mid-swing peak). First, the negative
151 peaks of this signal, characteristic of initial contact and toe-off, were roughly identified and the
152 average time between each negative peak was calculated. The mid-swing peak indices of this
153 signal were then identified based on the maximum positive value that were separated by at least
154 75% of the average time between negative peaks. This assisted with eliminating erroneous mid-
155 swing indices.

156 Gait event detection

157 Gait events (initial contact, mid-stance, and toe-off) were determined using two previously
158 published strategies, one for stairs (21) and the other for the slope and flat ground conditions
159 (26). For stair conditions, the toe-off event was identified first based on the second negative peak
160 in the mediolateral angular rate signal that occurred between two mid-swing events. Thereafter,
161 mid-stance was estimated as the minimum of the angular rate signal energy using a 200ms
162 sliding window. The terminal swing peak deceleration index was found based on the first
163 minimum of the anteroposterior acceleration signal from mid-swing to mid-stance. Initial contact
164 was calculated as the peak of the squared anteroposterior deceleration signal between the
165 terminal swing deceleration event and 60% of this event to the mid-stance event.

Slope and flat ground walking produced a more consistent and characteristic waveform which allows for a more simplistic event detection algorithm. Initial contact was first approximated by the first negative peak of the mediolateral angular rate signal. A 20-sample window around this point was then searched to locate the minimum value of the acceleration Euclidean norm. Mid-stance was found using a threshold approach for the angular rate (1.7 rad/s) and acceleration Euclidean norms (1.1 m/s^2) (19). Finally, toe-off was found in the same manner as initial contact, but the window was centered around the second negative peak of the mediolateral angular rate signal. A single stride was the time from a mid-stance instance to the subsequent mid-stance.

Orientation estimation

The orientation of each foot was estimated by sensor fusion using a complementary filter. This approach combined the favorable features of the accelerometer, gyroscope, and magnetometer to provide roll, pitch, and yaw angles at each time sample. Orientation estimates were performed on each stride independently, from $midstance_i$ to $midstance_{i+1}$ where i is the ith stride in the walking bout. To initialize the filter for each stride, orientation was estimated based on the acceleration at $midstance_i$ using the following equations:

$$ori_{a,y} = pitch\ (°) = \tan^{-1}\left(\frac{-a_y}{\sqrt{a_x^2 + a_z^2}}\right)$$

$$ori_{a,x} = roll\ (°) = \tan^{-1}\left(\frac{a_x}{a_z}\right)$$

where a comprises the 3 axes of normalized acceleration data.

The estimated pitch and roll were used to perform a correction to the yaw estimate based on the sensor tilt at the current frame. The rotation matrix representing the current orientation was multiplied with the magnetometer signals yielding the corrected magnetometer data.

$$mc = Rm;\ where\ R = R_p(pitch)^T R_r(roll)^T$$

$$ori_{a,z} = yaw\ (°) = -\tan^{-1}\left(\frac{-mc_x}{mc_y}\right)$$ where R is the rotation matrix representing the sensor attitude, m is the 3 axes of normalized magnetometer signals, and mc are the attitude corrected magnetometer signals.

Between each midstance instance, sensor orientation was calculated by integrating the angular rate signals over each time step and adding it to the previous orientation estimate. The weighted sum of the integrate angular rate and the accelerometer-based orientation estimate was calculated (weight = 0.985).

$$ori_{g,xyz} = ori_{j-1} g_j dt$$
$$ori_j = ori_g(weight) + ori_{am}(1 - weight)$$

where g is the 3 axes of angular rate data, dt is the time step between samples, ori_{am} is the roll, pitch, and yaw estimates from the accelerometer and magnetometer, ori_g is the roll, pitch, and yaw from the angular rate integration, and ori_i is the final estimate of the complementary filter for sample j.

Each orientation estimate was then converted into quaternion (q_j) form using the scalar first notation (q_w, q_x, q_y, q_z).

$$[q_w, q_x, q_y, q_z]_j = \begin{bmatrix} \cos(\phi)\cos(\theta)\cos(\psi) + \sin(\phi)\sin(\theta)\sin(\psi) \\ \sin(\phi)\cos(\theta)\cos(\psi) - \cos(\phi)\sin(\theta)\sin(\psi) \\ \cos(\phi)\sin(\theta)\cos(\psi) + \sin(\phi)\cos(\theta)\sin(\psi) \\ \cos(\phi)\cos(\theta)\sin(\psi) - \sin(\phi)\cos(\theta)\cos(\psi) \end{bmatrix},$$

where (ϕ,θ,ψ) are half the roll, pitch, and yaw, angles, respectively.

The orientation estimation was augmented by a modified strapdown method (27). For each stride (mid-stance to mid-stance), the orientation was estimated in both the forward and backward directions using the above complementary filter and anchored at the start and end sample by the static orientation estimate provided by the acceleration data alone. A linear combination of the forward (q_f) and backward (q_b) was used to correct the orientation based on the nearest zero-velocity update point (mid-stance).

$$q_{diff,j} = q_{b,j} \otimes q^*_{f,j}$$

where * indicates the conjugate and $\otimes$ is the quaternion product.

$$(a, \theta) = \left(\frac{[q_x, q_y, q_z]}{\sqrt{(q_x^2 + q_y^2 + q_z^2)}}, \qquad 2\tan^{-1}\sqrt{(q_x^2 + q_y^2 + q_z^2)} \right)$$

$$c_j = \frac{j - midstance_i}{mistance_{i+1} - midstance_i}$$

where c is the correction factor to be applied.

$$\theta_{c,j} = \theta_j c_j$$

$$q^c_{diff,j} = \left[\cos\frac{\theta_{c,j}}{2},\ a_x \sin\frac{\theta_{c,j}}{2},\ a_y \sin\frac{\theta_{c,j}}{2}, a_z \sin\frac{\theta_{c,j}}{2} \right]$$

$$q_{corr,j} = q^c_{diff,j} \otimes q_{f,j}$$

This elicited a corrected quaternion for each sample ($q_{corr,j}$) which was converted back to Euler angles (order = *xyz*). This process was performed on each *i*th stride across all walking conditions and for both right foot and left foot IMUs. The resulting sensor orientations were used to calculate outcomes including foot orientation at initial contact and mid-stance for each stride and to correct the acceleration data so the gravity vector could be removed.

Gravity correction and trajectory estimation

To determine linear accelerations of the IMU, the raw acceleration data was transformed into the global reference frame based on the sensor orientation and the gravity vector was removed to yield linear accelerations (*la*).

$$la = (q_{corr,j} \otimes [0, a_{x,j}, a_{y,j}, a_{z,j}] \otimes q_{corr,j}) - [0, 0, 9.81],$$

For each stride (mid-stance$_i$ to mid-stance$_{i+1}$) we integrated the linear acceleration to yield linear velocity. These velocities are prone to drift, due to accelerometer bias, which can lead to a non-zero IMU velocity at the next mid-stance event. Based on a zero-velocity assumption at each mid-stance we applied a previously reported correction (28). These corrected velocities were again integrated to yield position.

Finally, a correction to the trajectories was performed from the start of the first stride to the last stride of a walking bout. This was to set the linear real-world heading to zero such that the IMU trajectories were centered about the heading (no deviation from the heading equated to zero in the mediolateral trajectory). We achieved this by taking a linear fit of the mediolateral and anteroposterior trajectory data at each mid-stance event over the duration of the walking bout and then removed the interpolated linear fit from each trajectory datapoint. The resulting foot trajectories (Fig 3) were used to calculate discrete variables on a stride-by-stride basis.

Figure 3. Left and right foot trajectory data from a representative participant during each terrain condition. Light grey illustrates individual stride trajectories while the thick black line represents the ensemble average of the trajectories.

Statistical analysis

Trajectories were examined visually and presented as waveforms across each condition. Discrete variables were extracted as the mean and standard deviation of all the strides taken within each condition. We have presented the summary data, including mean and standard deviation of each outcome from each condition as the primary results. The statistical tests comparing conditions are considered a secondary analysis given the hypothesis generating goals of this study.

To examine statistical differences in the discrete variables we performed one-way repeated measures analyses of variance, with the repeated effect being the walking condition. Non-sphericity was addressed with a Greenhouse-Geiser correction. The effect size was evaluated using the generalized eta square (η_g^2). A significant main effect for condition ($\alpha = 0.05$) resulted in pairwise paired t-tests corrected for multiplicity using a Hommel correction (29). The limb side (right or left) was not significant in any model except sagittal plane foot angle at heel strike; therefore, models were run without the limb factor and with data combined from both limb sides.

Results

Ten healthy adults enrolled in the study with mean (standard deviation) age of 25.9 years (2.0), height of 1.73m (6.3) and body mass of 72.3kg (12.9). Five participants were female and five were male and all indicated their right limb as dominant.

Foot trajectories largely followed a similar shape for slope and flat walking conditions with the stair conditions being much shorter (Fig 4). Modest differences were observed between the right and left limb with regard to the shape of foot trajectory, mainly in the mediolateral components. Discrete variables are reported in Table 1, while full statistical results are included in S1 Tables.

Figure 4. Mean foot trajectories across all participants and conditions in the mediolateral and anteroposterior directions. Solid lines are flat or ascending conditions, while dashed lines are descending conditions.

Gait event timing significantly differed across the terrain conditions. Stance time differences (F=5.16, df=1.29/11.65, p=0.036, η_g^2=0.19) were dominated by the significantly shorter time required for descending steep slopes compared to the other conditions (comparisons all $p \leq 0.001$). Meanwhile, swing time (F=65.91, df=2.553/22.95, $p<0.001$, η_g^2=0.70) was shortest while descending stairs and steep slopes ($p<0.001$). The standard deviation of stance time (F=4.87, df=2.79/25.12, p=0.01, η_g^2=0.28) differed across conditions which was solely due to greater variability during stair descent, although the only significant pairwise comparisons was between stair descent and steep slope descent (p=0.035). We did not detect differences in swing time variability (F=1.14, df=6/54, p=0.353, η_g^2=0.08). Cadence was significantly different across conditions (F=11.823, df=1.3/11.68, p=0.003, η_g^2=0.34) with ascending shallow slopes having the lowest steps/minute (comparisons all $p<0.022$). The stair conditions and descending steep slopes required the highest cadence though not all comparisons were statistically significant.

Table 1. Biomechanical outcomes as mean (95% Confidence Interval) for each condition.

Outcome	All Conditions	Descend Shallow	Descend Steep	Descend Stairs	Flat ground	Ascend Shallow	Ascend Steep	Ascent Stairs
Stance time (s)	0.66 (0.65, 0.68)	0.64 (0.62, 0.66)	0.61 (0.58, 0.64)	0.71 (0.64, 0.78)	0.65 (0.63, 0.68)	0.66 (0.63, 0.69)	0.66 (0.63, 0.70)	0.71 (0.64, 0.77)
Stance time SD (s)	0.05 (0.05, 0.06)	0.05 (0.03, 0.06)	0.04 (0.03, 0.05)	0.07 (0.06, 0.09)	0.04 (0.03, 0.05)	0.05 (0.04, 0.05)	0.06 (0.04, 0.07)	0.05 (0.04, 0.06)
Swing time (s)	0.38 (0.37, 0.40)	0.40 (0.38, 0.41)	0.38 (0.37, 0.39)	0.28 (0.26, 0.30)	0.41 (0.39, 0.43)	0.42 (0.40, 0.43)	0.42 (0.40, 0.44)	0.40 (0.37, 0.42)
Swing time SD (s)	0.03 (0.03, 0.04)	0.04 (0.03, 0.04)	0.03 (0.02, 0.03)	0.03 (0.02, 0.04)	0.03 (0.02, 0.04)	0.03 (0.03, 0.04)	0.04 (0.03, 0.05)	0.04 (0.02, 0.05)
Cadence (strides/min)	62.04 (60.34, 63.73)	59.54 (57.64, 61.45)	65.17 (62.43, 67.92)	70.45 (63.48, 77.43)	59.00 (56.37, 61.63)	57.73 (55.74, 59.71)	59.27 (56.95, 61.60)	63.08 (58.03, 68.14)
Stride length (m)	1.10 (1.02, 1.18)	1.23 (1.17, 1.28)	1.21 (1.15, 1.28)	0.60 (0.58, 0.62)	1.28 (1.22, 1.34)	1.39 (1.33, 1.44)	1.40 (1.33, 1.47)	0.58 (0.55, 0.60)
Stride length SD (m)	0.14 (0.13, 0.16)	0.16 (0.14, 0.19)	0.15 (0.10, 0.19)	0.07 (0.06, 0.08)	0.15 (0.12, 0.18)	0.16 (0.14, 0.18)	0.16 (0.13, 0.19)	0.16 (0.11, 0.21)
Stride width (m)	0.07 (0.07, 0.08)	0.09 (0.07, 0.10)	0.08 (0.06, 0.10)	0.06 (0.05, 0.07)	0.07 (0.07, 0.08)	0.07 (0.06, 0.09)	0.07 (0.06, 0.08)	0.05 (0.04, 0.06)
Stride width SD (m)	0.06 (0.05, 0.06)	0.07 (0.06, 0.08)	0.06 (0.05, 0.08)	0.05 (0.04, 0.05)	0.06 (0.06, 0.07)	0.06 (0.05, 0.07)	0.06 (0.06, 0.07)	0.04 (0.03, 0.05)
Sagittal plane foot angle at IC (°)	13.45 (9.85, 17.04)	25.26 (23.61, 26.90)	26.08 (24.28, 27.89)	-15.75 (-17.12, -14.39)	23.42 (21.82, 25.02)	21.77 (20.25, 23.29)	16.05 (14.87, 17.23)	-2.71 (-3.96, -1.45)
Sagittal plane foot angle SD at IC (°)	5.72 (5.36, 6.07)	5.30 (4.97, 5.63)	7.33 (6.61, 8.05)	7.04 (6.54, 7.55)	5.44 (4.97, 5.91)	5.41 (4.92, 5.90)	6.21 (5.44, 6.98)	3.28 (2.90, 3.66)
Horizontal plane foot angle at mid-stance (°)	-11.32 (-12.69, -9.96)	-12.34 (-16.39, -8.29)	-11.33 (-14.64, -8.02)	-12.41 (-17.39, -7.42)	-12.01 (-15.57, -8.44)	-10.38 (-13.19, -7.57)	-10.01 (-13.37, -6.65)	-10.80 (-14.51, -7.08)
Horizontal plane foot angle SD at mid-stance (°)	5.81 (5.03, 6.59)	5.74 (3.86, 7.62)	7.08 (5.57, 8.58)	9.40 (6.48, 12.33)	4.84 (3.53, 6.16)	4.03 (2.57, 5.50)	4.89 (3.51, 6.26)	4.68 (2.77, 6.60)

Abbreviations: SD, standard deviation; IC; initial contact. Positive sagittal plane foot angles indicate the toe was above the heel while positive horizontal plane foot angles indicate the toe is more medial than the heel (toe-in).

Both stride length (F=329.72, df=2.48/22.32, p<0.001, η_g^2=0.94) and width (F=7.06, df=6/54, p<0.001, η_g^2=0.30) were significantly different across conditions. Expectedly, stride length was shortest during both stair conditions given the physical dimensions (comparisons all p<0.001). Every other comparison was significant with the exception of ascending or descending steep versus shallow slopes (both p=0.685). Despite a significant omnibus test, the only significant difference in stride width was between shallow descent and ascending stairs; however, the narrowest widths were observed during stair navigation. The standard deviation of stride length (F=6.10, df=6/54, p<0.001, η_g^2=0.29) and width (F=7.92, df=6/54, p<0.001, η_g^2 =0.34) were different across conditions with stair descent showing the lowest stride length (comparisons all p<0.011) and stride width (comparisons all p<0.049) standard deviation.

Different sagittal plane foot angles were used in nearly all conditions (F=791.2, df=2.38/21.38, p<0.001, η_g^2=0.98). When navigating stairs, participants contacted the ground with their forefoot first (negative angle), which resulted in a significantly different angle compared to the other conditions that used a 'heel first' strategy depicted by positive foot angles (comparisons all p<0.001). The steeper the slope, the smaller the angle when ascending with the opposite effect for descending slopes (comparisons all p<0.002). The standard deviation of sagittal plane foot angles was different among conditions (F=35.15, df=2.29/20.58, p<0.001, η_g^2 =0.69) with the descending steep slopes and stairs exhibiting the largest variability (comparisons all p<0.027). Ascending stairs showed approximately half the variability of the other conditions (comparisons all p≤0.002). Lastly, horizontal plane foot angle during mid-stance was not significantly different between the conditions we studied (F=1.22, df=2.14/19.28, p=0.320, η_g^2 =0.024). Although the standard deviation differed across conditions (F=4.57, df=2.42/21.77,

p=0.017, η_g^2=0.271) the only significant comparison was between shallow ascent and steep descent (p<0.001).

Discussion

The increasing use of wearable IMU systems to capture gait in the real-world necessitates a better understanding of how locomotion is controlled and expressed in the varied terrain that we often encounter. Our study evaluated how healthy adults adjust their foot biomechanics while walking on stairs, flat ground, and sloped terrain. In order to collect data while walking on these real-world terrain conditions, we used a custom designed IMU embedded in the sole of the shoes, though our results would apply to any shoe-mounted IMU system with appropriate calibration procedures. The primary contribution of this study is the direct comparison of foot trajectory, orientation, and spatiotemporal metrics across seven different terrain conditions. Many of the outcomes we investigated were different between these conditions, with the most notable differences arising from stair navigation. These results and the extant literature demonstrate that different terrain generate unique foot biomechanics during locomotion, which should be accounted for when analyzing real-world data, particularly when there is limited knowledge of what terrain someone was walking on.

Adjusting stride length while navigating different terrain is not unusual. Our results support this given that nearly every condition exhibited different stride lengths, highlighting the sensitivity of this measurement to terrain geometry. In an observational study of pedestrians offloading a ferry, people descending a ramp showed a clear reduction in stride length compared to those ascending the same ramp (30). The authors hypothesized that this arose from different frictional demands of the foot-ground interface, where a slip is more likely during descent.

346 Adapting stride length to avoid a slip during downhill walking makes sense, but a lengthened
347 stride in other situations could come at a cost. Previous research using both modelling and
348 human experimental results during level ground walking showed that mechanical work and
349 metabolic costs increased by the fourth power relative to a unit increase in step length (31), while
350 other work reported a 3-fold increase in knee joint power during uphill walking at longer stride
351 lengths (32). That is, adopting a longer stride length could require greater energy (33). Despite
352 this, our participants opted to increase stride length by approximately 8% while ascending slopes
353 compared to level ground. This stride length increase appears to be concomitant with an increase
354 in forward trunk and pelvis inclination and is thought to be a strategy that can aid in whole body
355 forward momentum (34). From our results, stride lengths are readily adapted to different terrain
356 conditions, though some may result in higher metabolic costs. It would be important to
357 categorize terrain conditions when comparing large real-world datasets as there are likely
358 differential changes in stride length simply due to terrain.

359 As lateral balance needs to be actively controlled while walking (7, 35), adjusting step
360 width to accommodate different terrain could be expected. However, we did not have the ability
361 to measure step width; an estimation of balance control with relevance to functional status or
362 aging (36, 37). Instead, we measured stride width, which quantifies the mean change in
363 mediolateral position of a single foot from stride to stride. Generally, we did not detect
364 significant differences in the mean stride width across conditions after our p-value correction,
365 though stair navigation had the narrowest widths by nearly 40% and the lowest variability. The
366 smaller width changes from stride to stride while navigating stairs may reflect a strategy of more
367 constrained motor control due to a more cognitively demanding task (38) or instability,
368 compared to the other walking conditions.

Quantifying the orientation of the foot during gait has several clinically relevant implications. The sagittal foot angle just before contact will dictate how the foot will impact the ground, which could provide information on the potential for a slip incident (39). In the controlled settings of a laboratory, measurements of sagittal plane foot angle at initial contact suggest people use separate strategies when placing their foot on flat ground and slopes compared to stairs. Flat and sloped walking are usually associated with a heel-first contact with mean angles ranging from 10-32° (39-41). Our data largely corroborates these past findings while also showing that the angle increased as the ascending slope angle increased, and the opposite occurred during descending.

Navigating stairs usually requires a different strategy compared to level ground, where the toe contacts the ground first (toe-below heel) both when ascending (-4.7°) and descending (-16.6°) (42). While our specific foot angle values differed compared to Riener, Rabuffetti (42), we did observe the same trend relative to flat and sloped ground. Contacting toe-first during descending stairs is likely a strategy to dissipate the vertical forces during stance but may also arise due to the horizontal length of the individual stair relative to the foot length. The physical constraints of stairs also demand high knee and hip flexion while ascending, placing too great a demand on dorsiflexion range of motion to achieve a heel-first contact (42). Apart from different mean angles, we also observed lower sagittal foot angle standard deviation during stair ascent. This could represent the maintenance of more control over foot trajectory and foot-ground contact to minimize the risk of catching the toe on a stair during the swing phase and inducing a trip. Lastly, a possible source of between-subject variability in sagittal foot angle measures during our ascent conditions more broadly could be dorsiflexion range of motion. Lower inherent range of motion could limit sagittal plane foot angles relative to the ground (43). It is unlikely

392 this played a prominent role in our slope conditions given we used a slope of 6° (Kwon and Shin
393 (43) = 20°), though the stairs were 36° which may have interacted with individual dorsiflexion
394 range of motion. Future studies using steeper inclinations than we used may need to consider this
395 when stratifying a sample population or excluding participants in order to avoid unwanted
396 variance in their results.

397 The horizontal plane foot angle during mid-stance was similar throughout the study. The
398 magnitude of horizontal plane foot angles can vary quite widely among individuals, partly due to
399 boney anatomy (44). We observed a range from -10° to -12.4 indicating an externally rotated
400 foot relative to the direction of walking, which was well within usual measurements (45-47).
401 Tracking this metric using wearable IMUs has utility in gait modification interventions where
402 people learn to increase or decrease the angle relative to the direction of walking (usually called
403 foot progression angle) (48, 49). In recent years, our group has implemented wearable
404 technology to monitor this metric in real-world settings (50), where the present studies results
405 will be valuable in contextualizing the data collected while participants walked on different
406 terrain in their community over weeks and months.

407 The timing of gait is closely related to the speed and cadence in which one walks (51, 52)
408 which is liable to change while navigating different terrain in the real world. We collected data
409 over a range of self-selected gait speeds for each terrain condition (except stairs for safety). As a
410 result, we observed few differences amongst the slope and flat terrain conditions in stance and
411 swing timing, the magnitudes of which were largely similar to past literature in both laboratory
412 (52) and real-world conditions (53). The most notable difference was a significantly shorter time
413 spent in stance when descending steep slopes, likely having arisen from the terrain lending to
414 faster overall speeds and shorter stride length. Additionally, we observed a larger ratio of stance

415 to swing times (longer stance relative to swing) while participants navigated stairs similar to past
416 research (42, 54). This was opposite of the findings from Nadeau, McFadyen (55); however, our
417 stair condition had more stairs and were slightly steeper (33° vs 36°), which may have prompted
418 participants to adopt a different strategy.

419 Several limitations need to be considered when interpreting our results. We examined a
420 sample of healthy adults, all of which had no sensorimotor deficits or neuromuscular conditions
421 that could affect their ability to walk. This allowed for a controlled evaluation of the effects that
422 terrain induces on gait. However, we could not capture the potential terrain-dependent effects
423 that could arise in other populations, such as older adults. For example, older adults tend to
424 reduce stride lengths with increasing slopes or multi-surface terrain compared to healthy adults
425 (56, 57). We only collected data on slopes of shallow (3°) and steep (6°) inclination. There are
426 situations in our built and natural world that may require navigating slopes of much steeper
427 conditions, or perhaps slopes in between the conditions we examined. Ultimately, we used
428 representative and publicly accessible terrain conditions but a more refined comparison with
429 smaller increments of slope inclination could warrant comparisons with more resolution. We did
430 not explicitly control walking speed during our data collections. Instead, we opted to collect data
431 across a range of speeds governed by the participants' own preferences in each condition. This
432 increased the between-subject variability in our data but captured the natural differences in how
433 people navigate different terrain at different speeds. It is likely that a more strict control of
434 speeds could result in more detectable differences between these terrain conditions, as can be
435 found in laboratory experiments (55). Finally, while we conducted our study out of the
436 laboratory, it was still reasonably controlled as participants walked on linear paths and in
437 contexts with limited distraction. Continued investigations in this area should also consider the

context of a walking bout (e.g., commute, walking the dog, shopping etc.), surrounding environment (e.g., busy side walk, park path) and evaluate more realistic scenarios as the context of a walking bout may influence gait dynamics (58).

Taken together, our results indicate that it may be important to consider terrain when collecting gait data in ecologically valid environments or in unsupervised conditions. As wearable IMUs become the dominant data collection modality in gait data, the opportunities for real-world collection continue to expand. Given the inherent and uncontrollable variability in real-world, unsupervised conditions, it is important to understand the extent to which different data collection conditions could impact results. Our study highlights these often small, but potentially meaningful differences based the data we collected on a set of common real-world terrain.

Funding

JMC was supported by the Banting Research Fellowship (FRN187436) and the Michael Smith Health Research BC Research Trainee award (RT-2022-2528). There was no direct funding for the project.

References

1. Winter DA. Foot trajectory in human gait: A precise and multifactorial motor control task. Physical Therapy. 1992;72(1):45-53.

2. McCrimmon CM, Wang PT, Heydari P, Nguyen A, Shaw SJ, Gong H, et al. Electrocorticographic encoding of human gait in the leg primary motor cortex. Cerebral Cortex. 2018;28(8):2752-62.

3. Takakusaki K. Neurophysiology of gait: from the spinal cord to the frontal lobe. Movement disorders : official journal of the Movement Disorder Society. 2013;28(11):1483-91.

4. Winter DA. Human balance and posture control during standing and walking. Gait Posture. 1995;3(4):193-214.

5. Potocanac Z, Duysens J. Online adjustments of leg movements in healthy young and old. Experimental Brain Research. 2017;235(8):2329-48.

6. Hoogkamer W, Potocanac Z, Duysens J. Quick foot placement adjustments during gait: direction matters. Experimental Brain Research. 2015;233(12):3349-57.

7. Kuo AD. Stabilization of lateral motion in passive dynamic walking. The International Journal of Robotics Research. 1999;18(9):917-30.

8. Siragy T, Russo Y, Young W, Lamb SE. Comparison of over-ground and treadmill perturbations for simulation of real-world slips and trips: A systematic review. Gait & Posture. 2023;100:201-9.

9. Benson LC, Clermont CA, Bosnjak E, Ferber R. The use of wearable devices for walking and running gait analysis outside of the lab: A systematic review. Gait & Posture. 2018;63:124-38.

10. Shull PB, Jirattigalachote W, Hunt MA, Cutkosky MR, Delp SL. Quantified self and human movement: a review on the clinical impact of wearable sensing and feedback for gait analysis and intervention. Gait & Posture. 2014;40(1):11-9.

11. Tamburini P, Storm F, Buckley C, Bisi MC, Stagni R, Mazzà C. Moving from laboratory to real life conditions: Influence on the assessment of variability and stability of gait. Gait & Posture. 2018;59:248-52.

12. Küderle A, Roth N, Zlatanovic J, Zrenner M, Eskofier B, Kluge F. The placement of foot-mounted IMU sensors does affect the accuracy of spatial parameters during regular walking. PLOS ONE. 2022;17(6):e0269567.

13. Hannink J, Ollenschläger M, Kluge F, Roth N, Klucken J, Eskofier BM. Benchmarking foot trajectory estimation methods for mobile gait analysis. Sensors. 2017;17(9):1940.

14. Sabatini AM, Martelloni C, Scapellato S, Cavallo F. Assessment of walking features from foot inertial sensing. IEEE transactions on bio-medical engineering. 2005;52(3):486-94.

15. Okkalidis N, Camilleri KP, Gatt A, Bugeja MK, Falzon O. A review of foot pose and trajectory estimation methods using inertial and auxiliary sensors for kinematic gait analysis. Biomed Tech (Berl). 2020.

16. Wouda FJ, Jaspar SLJO, Harlaar J, van Beijnum B-JF, Veltink PH. Foot progression angle estimation using a single foot-worn inertial sensor. Journal of NeuroEngineering and Rehabilitation. 2021;18(37):1-10.

17. Kitagawa N, Ogihara N. Estimation of foot trajectory during human walking by a wearable inertial measurement unit mounted to the foot. Gait & Posture. 2016;45:110-4.

18. Tan T, Strout ZA, Xia H, Orban M, Shull PB. Magnetometer-free, IMU-based foot progression angle estimation for real-life walking conditions. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2021;29:282-9.

19. Rebula JR, Ojeda LV, Adamczyk PG, Kuo AD. Measurement of foot placement and its variability with inertial sensors. Gait & Posture. 2013;38(4):974-80.

20. Twardzik E, Duchowny K, Gallagher A, Alexander N, Strasburg D, Colabianchi N, et al. What features of the built environment matter most for mobility? Using wearable sensors to capture real-time outdoor environment demand on gait performance. Gait & Posture. 2019;68:437-42.

21. Roth N, Küderle A, Prossel D, Gassner H, Eskofier BM, Kluge F. An inertial sensor-based gait analysis pipeline for the assessment of real-world stair ambulation parameters. Sensors. 2021;21(19):6559.

22. Song M, Kim J. An ambulatory gait monitoring system with activity classification and gait parameter calculation based on a single foot inertial sensor. IEEE transactions on bio-medical engineering. 2018;65(4):885-93.

23. Kowalsky DB, Rebula JR, Ojeda LV, Adamczyk PG, Kuo AD. Human walking in the real world: Interactions between terrain type, gait parameters, and energy expenditure. PLOS ONE. 2021;16(1):e0228682.

24. Xia H, Xu J, Wang J, Hunt MA, Shull PB. Validation of a smart shoe for estimating foot progression angle during walking gait. Journal of Biomechanics. 2017;61(8):193-8.

25. Charlton JM, Kuo C, Hunt MA. The Number of Steps for Representative Real-World, Unsupervised Walking Data Using a Shoe-Worn Inertial Sensor. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2023;31:1566-73.

26. Mariani B, Rouhani H, Crevoisier X, Aminian K. Quantitative estimation of foot-flat and stance phase of gait using foot-worn inertial sensors. Gait & Posture. 2013;37(2):229-34.

27. Falbriard M, Meyer F, Mariani B, Millet GP, Aminian K. Drift-Free Foot Orientation Estimation in Running Using Wearable IMU. Frontiers in Bioengineering and Biotechnology. 2020;8.

28. Laidig D, Jocham AJ, Guggenberger B, Adamer K, Fischer M, Seel T. Calibration-free gait assessment by foot-worn inertial sensors. Frontiers in Digital Health. 2021;3.

29. Hommel G. A stagewise rejective multiple test procedure based on a modified bonferroni test. Biometrika. 1988;75(2):383-6.

30. Sun JIE, Walters M, Svensson N, Lloyd D. The influence of surface slope on human gait characteristics: a study of urban pedestrians walking on an inclined surface. Ergonomics. 1996;39(4):677-92.

31. Donelan JM, Kram R, Kuo AD. Mechanical work for step-to-step transitions is a major determinant of the metabolic cost of human walking. J Exp Bio. 2002;205(23):3717-27.

32. Schwameder H, Lindenhofer E, Müller E. Effect of walking speed on lower extremity joint loading in graded ramp walking. Sport Biomech. 2005;4(2):227-43.

33. Zarrugh MY, Todd FN, Ralston HJ. Optimization of energy expenditure during level walking. European Journal of Applied Physiology and Occupational Physiology. 1974;33(4):293-306.

34. Leroux A, Fung J, Barbeau H. Postural adaptation to walking on inclined surfaces: I. Normal strategies. Gait & Posture. 2002;15(1):64-74.

35. Bauby CE, Kuo AD. Active control of lateral balance in human walking. Journal of Biomechanics. 2000;33(11):1433-40.

36. Owings TM, Grabiner MD. Step width variability, but not step length variability or step time variability, discriminates gait of healthy young and older adults during treadmill locomotion. Journal of Biomechanics. 2004;37(6):935-8.

37. Brach JS, Berlin JE, VanSwearingen JM, Newman AB, Studenski SA. Too much or too little step width variability is associated with a fall history in older persons who walk at or near normal gait speed. Journal of NeuroEngineering and Rehabilitation. 2005;2(1):21.

38. Luu TP, Brantley JA, Nakagome S, Zhu F, Contreras-Vidal JL. Electrocortical correlates of human level-ground, slope, and stair walking. PLOS ONE. 2017;12(11):e0188500.

39. Redfern MS, Cham R, Gielo-Perczak K, Grönqvist R, Hirvonen M, Lanshammar H, et al. Biomechanics of slips. Ergonomics. 2001;44(13):1138-66.

40. Holbein-Jenny MA, Redfern MS, Gottesman D, Chaffin DB. Kinematics of heelstrike during walking and carrying: implications for slip resistance testing. Ergonomics. 2007;50(3):352-63.

41. Halder A, Nordin A, Miller M, Gao C. Gait biomechanics while walking down an incline after exhaustion. Fire Technology. 2023;59(4):1833-63.

42. Riener R, Rabuffetti M, Frigo C. Stair ascent and descent at different inclinations. Gait & Posture. 2002;15(1):32-44.

43. Kwon Y, Shin G. Foot kinematics and leg muscle activation patterns are altered in those with limited ankle dorsiflexion range of motion during incline walking. Gait & Posture. 2022;92:315-20.

44. Hudson D. The rotational profile: A study of lower limb axial torsion, hip rotation, and the foot progression angle in healthy adults. Gait & Posture. 2016;49:426-30.

45. Guo M, Axe MJ, Manal K. The influence of foot progression angle on the knee adduction moment during walking and stair climbing in pain free individuals with knee osteoarthritis. Gait & Posture. 2007;26(3):436-41.

46. Lynn SK, Costigan PA. Effect of foot rotation on knee kinetics and hamstring activation in older adults with and without signs of knee osteoarthritis. Clinical Biomechanics. 2008;23(6):779-86.

47. Cochrane CK, Takacs J, Hunt MA. Biomechanical mechanisms of toe-out gait performance in people with and without knee osteoarthritis. Clinical Biomechanics. 2014;29(1):83-6.

48. Reeves ND, Bowling FL. Conservative biomechanical strategies for knee osteoarthritis. Nat Rev Rheumatol. 2011;7(2):113-22.

49. Simic M, Hinman RS, Wrigley TV, Bennell KL, Hunt MA. Gait modification strategies for altering medial knee joint load: A systematic review. Arthritis Care & Research. 2011;63(2):405-26.

50. Charlton JM, Xia H, Shull PB, Eng JJ, Li LC, Hunt MA. Multi-day monitoring of foot progression angles during unsupervised, real-world walking in people with and without knee osteoarthritis. Clinical Biomechanics. 2023;105:105957.

51. Nilsson J, Thorstensson A, Halbertsma J. Changes in leg movements and muscle activity with speed of locomotion and mode of progression in humans. Acta Physiologica Scandinavica. 1985;123(4):457-75.

52. McGrath D, Greene BR, O'Donovan KJ, Caulfield B. Gyroscope-based assessment of temporal gait parameters during treadmill walking and running. Sports Eng. 2012;15(4):207-13.

53. Renggli D, Graf C, Tachatos N, Singh N, Meboldt M, Taylor WR, et al. Wearable inertial measurement units for assessing gait in real-world environments. Frontiers in Physiology. 2020;11(90):1-13.

54. Demura T, Demura S-i, Shin S. Comparison of gait properties during level walking and stair ascent and descent with varying loads. Health. 2010;2(12):1372.

55. Nadeau S, McFadyen BJ, Malouin F. Frontal and sagittal plane analyses of the stair climbing task in healthy adults aged over 40 years: what are the challenges compared to level walking? Clinical Biomechanics. 2003;18(10):950-9.

56. Scaglioni-Solano P, Aragón-Vargas LF. Age-related differences when walking downhill on different sloped terrains. Gait & Posture. 2015;41(1):153-8.

57. Marigold DS, Patla AE. Age-related changes in gait for multi-surface terrain. Gait & Posture. 2008;27(4):689-96.

58. Baroudi L, Barton K, Cain SM, Shorter KA. Understanding the Influence of Context on Real-World Walking Energetics. bioRxiv. 2023:2023.06.12.544651.

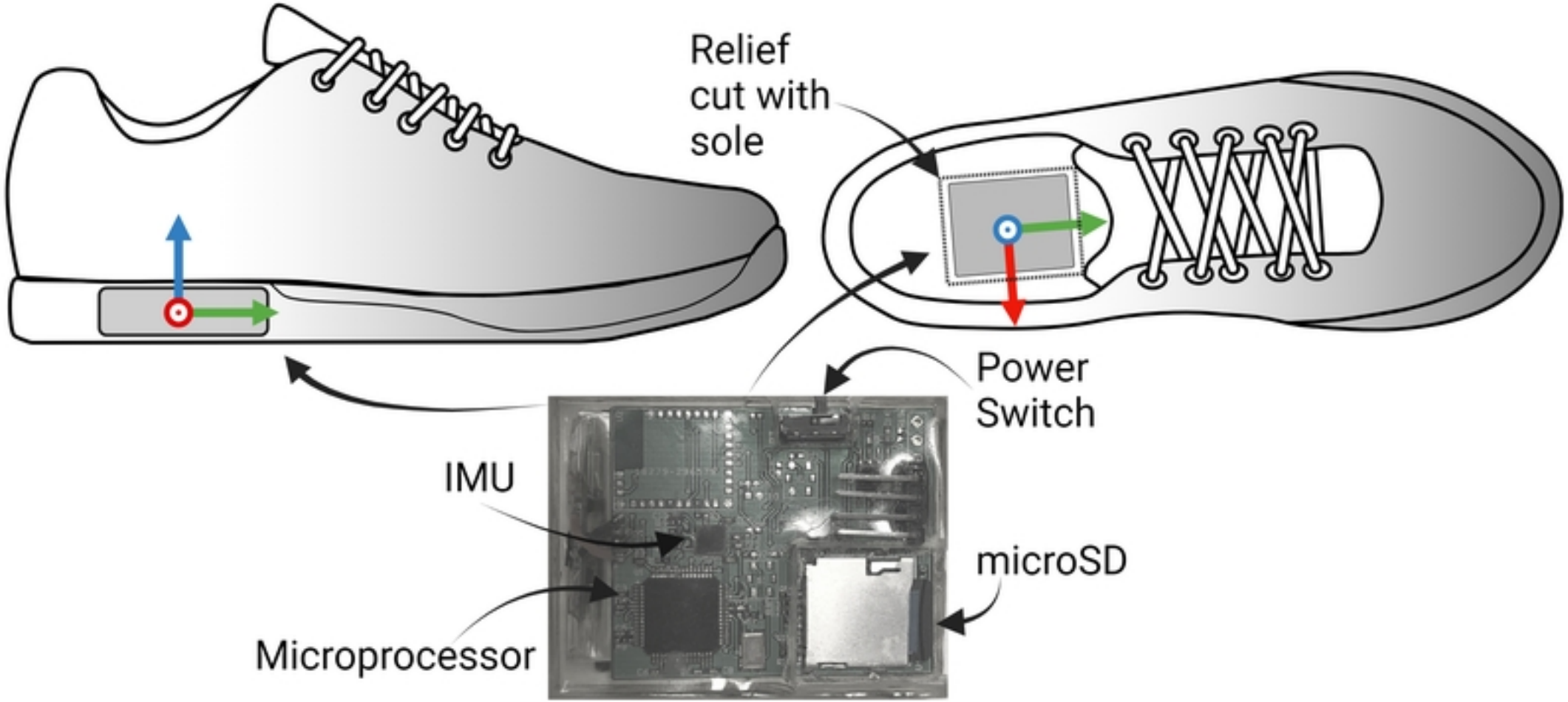
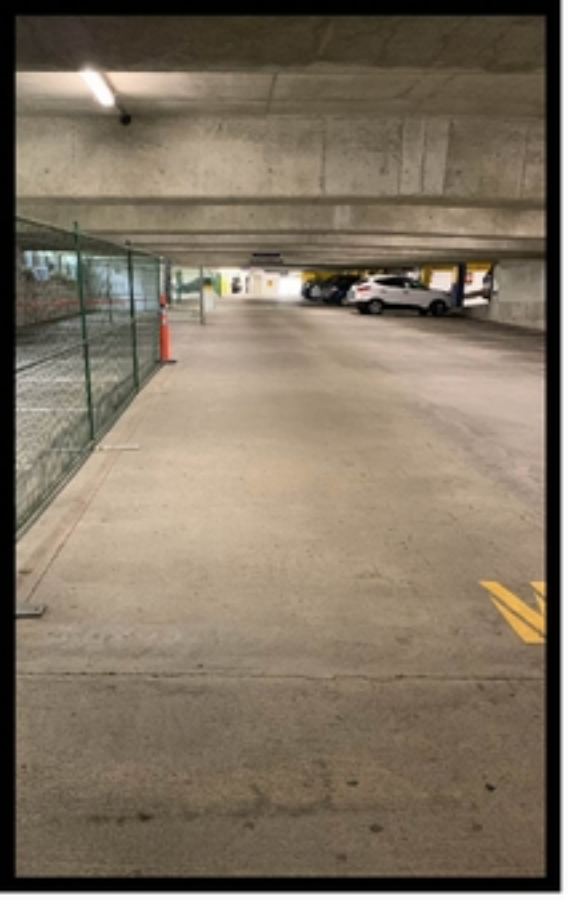
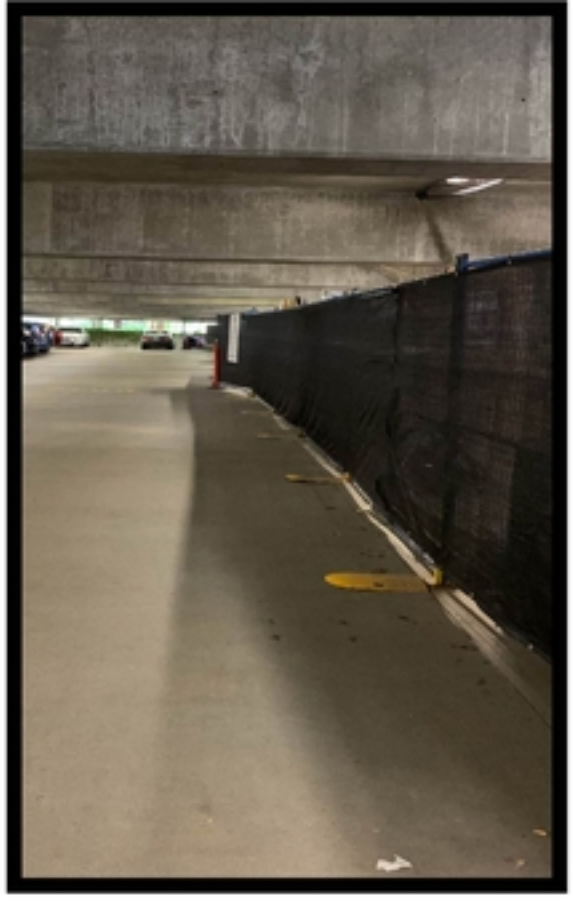

Relief
cut with
sole
Power
Switch
IMU
microSD
Microprocessor

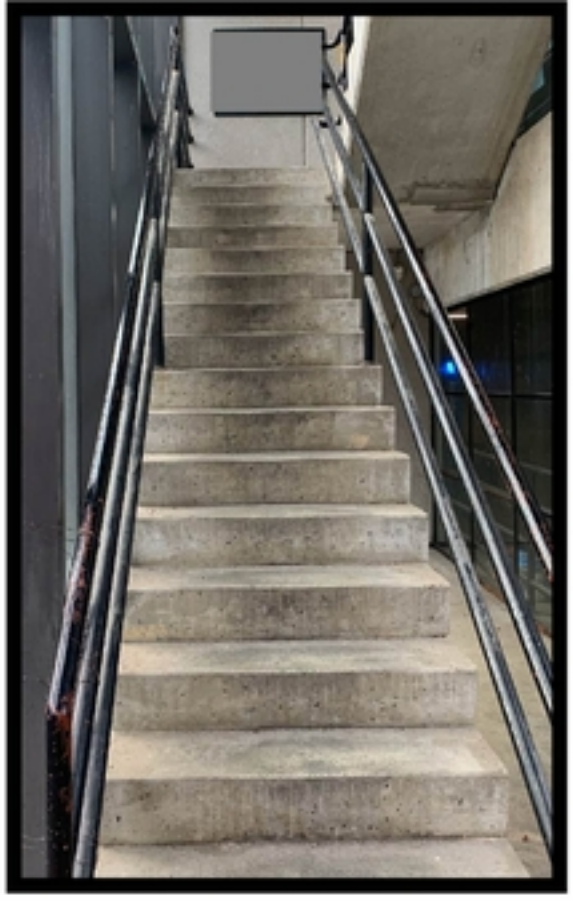
Figure 1



Shallow Slope (3°)



Flat Level Ground (0°)



Stairs (18cm x 27.5cm 36°)

Steep Slope (6°)

Figure 2

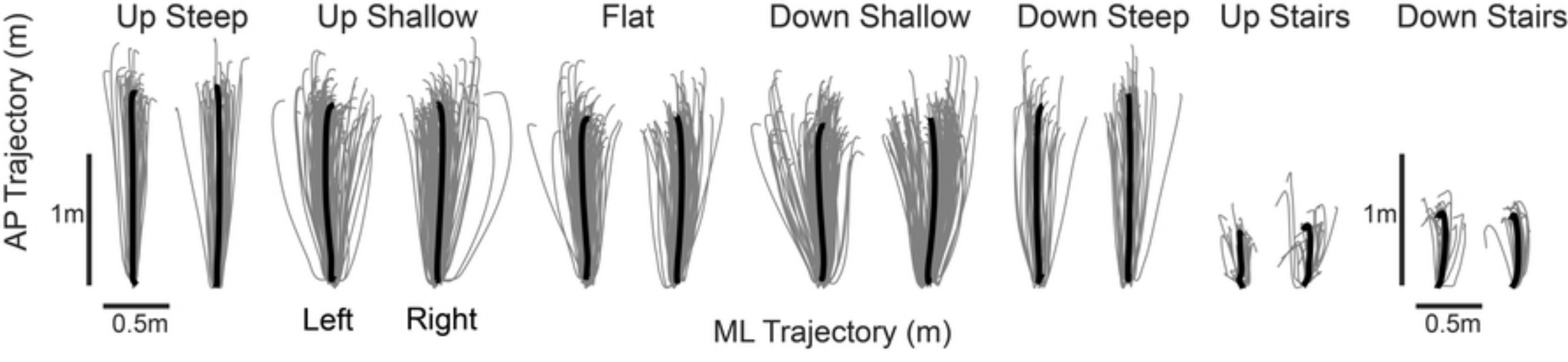

Up Steep
Up Shallow
Flat
Down Shallow
Down Steep
Up Stairs
Down Stairs
AP Trajectory (m)
1m
0.5m
Left
Right
ML Trajectory (m)
1m
0.5m

Figure 3

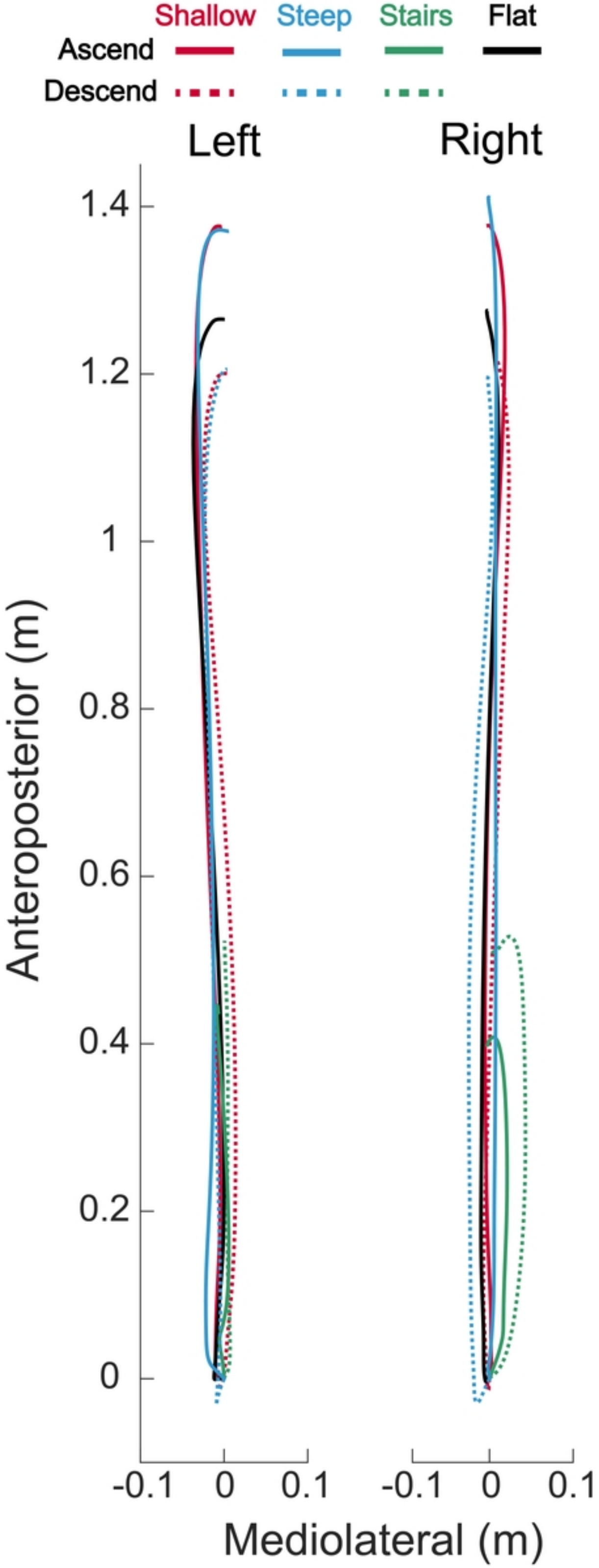

Shallow
Steep
Stairs
Flat
Ascend
Descend
Left
Right
1.4
1.2
1
0.8
0.6
0.4
0.2
0
Anteroposterior (m)
-0.1
0
0.1
-0.1
0
0.1
Mediolateral (m)

Figure 4