Estimating the lateral margin of stability during walking and turning using inertial sensors

Peter C. Fino, Fay B. Horak, and Carolin Curtze

***Abstract*—There is growing interest in using inertial sensors to continuously monitor gait during free-living mobility. Inertial sensors can provide many gait measures, but they struggle to capture the spatial stability of the center-of-mass due to limitations estimating sensor-to-sensor distance. While the margin of stability (MoS) is an established outcome describing the instantaneous mechanical stability of gait relating to fall-risk, methods to estimate the MoS from inertial sensors have been lacking. Here, we developed and tested a construct, based on centripetal acceleration, to estimate the lateral MoS using inertial sensors during walking and turning. Using three sensors located bilaterally on the feet and lumbar spine, the lateral MoS can be consistently and reliably estimated based on the average centripetal acceleration over the subsequent step. Relying only on a single sensor on the lumbar spine yielded similar results at the expense of identifying left versus right stance foot. Additionally, the centripetal acceleration estimate of lateral MoS demonstrates clear differences between walking and turning, inside and outside turning limbs, and speed. While limitations and assumptions need to be considered when implemented in practice, this method presents a novel, reliable way to estimate the lateral MoS during free-living community ambulation using inertial sensors.**

***Index Terms*—Accelerometers, Balance, Gait, Inertial Sensors, Margin of Stability, Turning**

I. INTRODUCTION

Recent advances in wearable sensors have enabled biomechanical analyses of gait outside of the laboratory. Continuous monitoring of gait during free-living, daily activity provides a new window into community ambulation and presents a promising avenue for future gait research investigating older adults at risk of falls [1], neuropathological progression [2], intervention efficacy [3], and / or more ecologically valid gait assessments [4].

Many spatiotemporal gait parameters can be estimated using inertial sensors [5], but spatial stability has been difficult to assess using inertial sensors alone. Most continuous monitoring studies report dynamic, temporal stability that is derived from short-term maximum finite-time Lyapunov exponents or other dynamical systems constructs that describe the temporal stability of a system within a given state space [6]. While valid and predictive, these measures do not describe the instantaneous biomechanical stability during locomotion.

To describe the mechanical stability of gait, Hof and colleagues proposed extending the simple inverted pendulum model of human balance using the velocity of the center of mass (CoM) to extrapolate the velocity-adjusted position of the CoM (XcoM)[7, 8]. The relationship between the XcoM and the base of support (BoS) reveals the instantaneous mechanical stability of the system; if the XcoM falls outside the BoS, balance cannot be recovered with joint torque alone – a stepping response or external force / torque is required. Since the spatial distance between the XcoM and the BoS was defined as the margin of stability (MoS) [7, 8], the MoS has been widely used to assess gait stability [6, 9-15], and gait controllers have been proposed with objectives of maintaining constant MoS, or constant offset, through foot placement [16, 17].

Traditionally, MoS has been assessed using optical motion capture, gait carpets, and / or force platforms that can give accurate spatial information [14, 18-20]. Inertial sensors, comparatively, can provide accurate acceleration, angular velocity, and orientation estimates, but struggle to provide accurate positional distances from one sensor to another. To rectify this issue, static calibration poses and subject-specific anthropometric dimensions have been used to establish initial positions of each sensor [21, 22]. However, requiring the subject to hold a neutral pose for calibration before every data capture may not be a viable solution for continuous monitoring in free-living conditions. Recently, a custom combination of inertial sensors and pressure-sensitive insoles have been used to estimate the position of the CoM [23] and the MoS during walking [24]. While this system provides great promise for assessments of MoS during walking outside the laboratory, it relies on custom shoes and may not be feasible for large-scale or long-term monitoring.

Recently, the lateral MoS was estimated in a community-dwelling setting using camera-based systems [13]. While other spatiotemporal gait outcomes were assessed, the estimated lateral MoS was the only gait measure associated with prospective falls [13]. Data from Mehdizadeh and colleagues [13] support quantifying the lateral MoS in community settings to assess fall-risk. Yet, the novel, low-cost camera system used in that study relies on line of sight and cannot assess MoS in every environment. Inertial sensors are noninvasive, wearable,

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P.C. Fino is with the Department of Health, Kinesiology, and Recreation at the University of Utah, Salt Lake City, UT 84112 USA (e-mail: peter.fino@utah.edu).

F.B. Horak is with the Department of Neurology at Oregon Health & Science University, Portland, OR 97239 USA (e-mail: horakf@ohsu.edu).

C. Curtze is with the Department of Biomechanics at the University of Nebraska-Omaha, Omaha, NE 68182 USA (e-mail: ccurtze@unomaha.edu)

F.B. Horak has a significant financial interest in APDM, a company that may have a commercial interest in the results of this research and technology. This potential conflict has been reviewed and managed by OHSU. All other authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

capable of continuously quantifying ambulation in diverse environment, and becoming a predominant method of quantifying mobility in community settings, but there are few methods capable of quantifying MoS without a camera-based approach, and no established method to estimate MoS using only a single inertial sensor.

Our goal was to develop a method to estimate the lateral MoS during walking and turning using inertial sensors, with the goal of using a single inertial sensor. As a number of studies and publicly available datasets have utilized a single inertial sensor on the lumbar spine [4, 25, 26], and this location is in close proximity to the whole-body center-of-mass, we focused on using this lumbar-spine location for our estimation. We compared our estimates of MoS using the inertial sensor to the true MoS based on optical motion capture. To extend the estimation to include a variety of daily ambulatory tasks, we included steps during straight gait and a variety of different turning angles.

II. METHODS

A. *Model Framework*

Based on Hof et al. [7], dynamic balance can be achieved by placing the foot, and the CoP by extension, some offset outside of the XcoM (Fig 1) to generate a corrective torque.

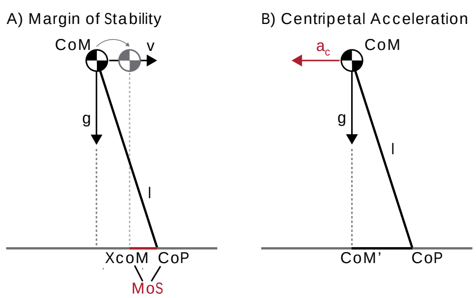

Fig 1. A) Model framework for the margin of stability (MoS). The MoS is based on the difference between the XcoM and the center of pressure (CoP), where the XcoM is dependent on the instantaneous velocity v of the CoM, gravity g, and pendulum length l. B) Diagram of centripetal acceleration a_c with vertical projection of the CoM CoM'.

The MoS is then the minimum difference between CoP and the XcoM for each step *n* based on

$$MoS(n) = \min(x_{CoP} - XcoM) \tag{1}$$

where the XcoM is defined by the position of the CoM, x_{CoM}, the velocity of the CoM, v, and the eigenfrequency of the inverted pendulum $\omega_0 = \sqrt{g/l}$ by

$$XcoM = x_{CoM} + \frac{v}{\omega_0}. \tag{2}$$

Based on this model and assuming the minimum occurs at or near initial contact, *IC*, [7] several simple controllers can be derived for control of forward and lateral foot placement [7, 17]. For lateral control, a change in CoM velocity, *v*, can be achieved through a change in foot position equal to $\Delta v/\omega_0$ [7], and the subsequent MoS at step *n* will be

$$MoS(n) = x_{CoP}(IC_n) + \frac{\Delta v}{\omega_0} - XcoM(IC_n). \tag{3}$$

In other words, the change in MoS is proportional to the change in CoM velocity.

Similarly, we can define the centripetal acceleration of the CoM, a_c, as the lateral acceleration orthogonal to gravity and the direction of travel. In the lateral direction, the change in the lateral velocity of the CoM over step *n* is given by the integral

$$\Delta v\ (n) = \int_{IC_n}^{IC_{n+1}} a_c(t)\ dt\ . \tag{4}$$

The lateral MoS at heel contact can therefore be estimated using the integral of the centripetal acceleration over the following step

$$MoS\ (n) \approx \frac{\int_{IC_n}^{IC_{n+1}} a_c(t)\ dt}{\omega_0}. \tag{6}$$

If all individuals are of relatively average stature and walking on earth, we can ignore the small contribution of ω_0, and (6) can be reduced to

$$MoS\ (n)\ \approx \int_{IC_n}^{IC_{n+1}} a_c(t)\ dt\ . \tag{7}$$

Finally, if the step time and sampling frequency is constant, (7) can be reduced to the average of the acceleration over each step

$$MoS\ (n) \approx \overline{a_c(t)} \text{ for} = [IC_n, IC_{n+1}]\ . \tag{8}$$

B. *Participants*

Ten neurologically healthy older adults (5 Female / 5 Male) were recruited for this study. All participants provided informed written consent to participate, and all protocols were conducted in accordance with the Declaration of Helsinki and approved by the Oregon Health & Science University Institutional Review Board. The study participants were an average (SD) of 72 (5.8) years of age, 169.1 (10.5) cm, and 71.5 (17.8) kg. One participant was excluded from the analysis due to a malfunctioning magnetometer throughout data collection.

C. *Experimental Protocol*

All walking trials took place within a 2.5 m radius circle, marked in 45° increments around the outside (Fig 2). Within each trial, participants were instructed to walk towards the center of the circle (marked in red), and then walk towards a specific colored line on the outside of the circle. For example, participants may have been given the following cue: "At your normal speed, make a right turn to the purple line." Thus, changing the destination color changed the turn angle. Walking trials were recorded in blocks of 10, with three blocks performed at a self-selected normal walking speed and three blocks performed at a self-selected fast walking speed. A total of 60 walking trials were obtained for each participant, with 10 straight walking trials per participant.

Seven inertial measurement units (Opal v1, APDM Inc., Portland, OR) were placed on the following body segments: forehead, sternum, lumbar spine around L3-L4, bilateral shank,

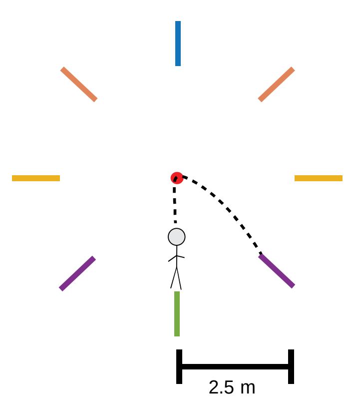

Fig 2. Schematic of the marked lines at 45 degree increments and center dot.

and bilateral dorsum of each foot. Inertial sensor data were collected at 128 Hz and continuously collected over each block. Each block started with at least three seconds of static stance to ensure a quiet period for the sensors, but no neutral pose or specific calibration pose was collected. Additionally, all subjects were outfitted with 30 retroreflective markers placed in a modified Helen Hayes marker configuration. Markers were placed on the head (front, back, and lateral), thorax and arms (acromion, sternum, offset, lateral epicondyle of humerus, and distal radius), pelvis (sacrum, anterior superior iliac spine (ASIS)), legs (thigh, lateral epicondyle of the femur, shank, lateral and medial malleolus), and feet (1st and 5th metatarsal head, and posterior calcaneus). Optical motion capture data were collected at 120Hz (Raptor-H (8) and Osprey (4), Motion Analysis Inc., Santa Rosa, CA).

D. Calculation of Margin of Stability

The optical motion capture data was used to calculate MoS values to validate the inertial sensor-based measures. All markers were tracked and gaps were filled using spline interpolation. All marker data were low-pass filtered using a 4th order phaseless 6 Hz Butterworth filter. The instantaneous position of the whole-body CoM was estimated as the weighted average of 15 segment using kinematic data and anthropometric tables [27]. To account for the constant change in coordination frame, all data were transformed to a CoM path-of-progression reference frame [28]. The position of the XcoM was determined using (2), and the MoS at each point in time was determined from (1), where the lateral position of the CoP was estimated using the average of the first metatarsal and posterior calcaneus of the foot. Initial contact was defined as the maximal distance between the heel and sacrum marker in fore direction [29], and the MoS at initial contact was extracted for each step as the primary outcome. Only the MoS at initial contact was considered as previous reports have indicated the significance of this event in locomotor control [17] and fall-risk assessments [13]. All XcoM, BoS, and MoS values were oriented relative to the position and of the CoM; Positive MoS occured when the BoS was to the left of the XcoM, and negative MoS when the BoS was to the right of the XcoM, regardless of stance limb.

E. Inertial Sensor Analysis

Raw inertial sensor data, including accelerometer, gyroscope, and magnetometer data were imported into MATLAB (r2018b, The Mathworks Inc., Natick, MA). Additionally, orientation estimates automatically calculated from the APDM Mobility Lab software were imported. These orientation estimates are based on Kalman filters that fuse acceleration, angular velocity, and magnetic field data to resolve quaternion between the sensor-axis and the global reference frame (Fig 3). For each block, the three-dimensional acceleration vectors at the lumbar spine were rotated to align with the global axis frame using the quaternion orientation estimates. Subsequent analysis was completed using two different sensor alignments:

1) Vertically Aligned Frame (VAF): The sensor-based coordinate frame was rotated to align with the global vertical axis. The sensor axes were allowed to rotate about the vertical axis such that the x-axis always aligned with the direction of travel, and the y-axis aligned with the orthogonal direction. In this way, the x-y plane was always horizontal, and only yaw about the z-axis was allowed.

2) Body-Fixed Frame (BFF): The sensor-based coordinate frame was fixed to the body. While initially aligned with the global frame, there was no requirement for axes to be aligned with the global frame at every instant in time throughout the trial. Sensor-based x- and y- axes may include vertical components through pitch or roll, respectively.

Practically, these two alignments were obtained through either a time-varying rotation matrix (VAF) or a constant rotation matrix based on the initial alignment (BFF) between the body and global frames.

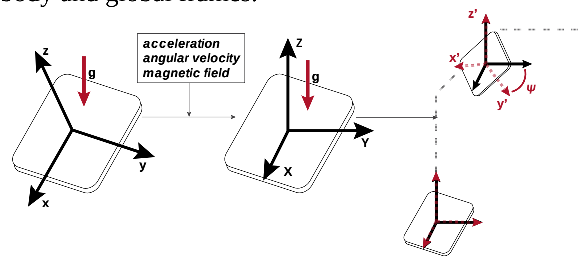

Fig 3. Depiction showing the use of sensor fusion to align the initial position of the IMU with global vertical. Initial IMU axes were aligned with the shell casing of the IMU. Measurement axes were aligned with the global vertical frame (VAF). In the VAF, the sensor-fixed z-axis was always aligned with the global vertical using a Kalman filter based on the acceleration, angular velocity, and magnetic field.

Walking trials were identified and segmented into separate trials from within each block. For each walking trial, heel contacts were identified using two methods: 1) identifying peaks in the normalized frequency content above 20 Hz of the left and right foot sensors [30], and 2) using a Gaussian continuous wavelet transform of the lumbar vertical acceleration [31]. These methods use 3 sensors and 1 sensor, respectively. All steps identified using both method were matched with steps detected from motion capture. Turns were identified within each trial using a threshold-based angular velocity algorithm (30°/s). Lumbar linear acceleration data were low-pass filtered using a 4th order phaseless 4 Hz Butterworth filter.

Centripetal acceleration at the lumbar sensor was extracted for each step (Fig 4). The acceleration was integrated between

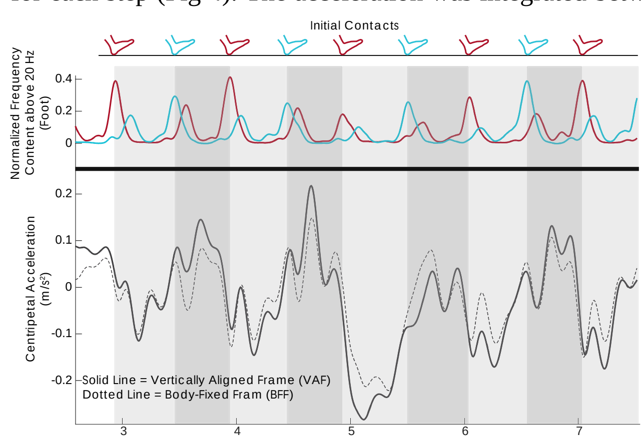

Fig 4. Top: Example of left and right gait event detection using inertial sensors on the feet. Bottom: Centripetal acceleration in both VAF (solid) and BFF (dotted).

successive heel contacts based on (7). Additionally, the average acceleration between successive heel contacts was calculated based on (8). Each of these outcomes (Normalized Integrated Acceleration, Integrated Acceleration, and Mean) were compared to the MoS at initial contact obtained from motion capture.

F. *Comparison Between MoS and Sensor-Based Centripetal Acceleration*

To compare the level of agreement between the centripetal acceleration, measured using inertial sensors, and the motion-capture-based MoS, linear regression, root-mean-square-error (RMSE), and intraclass correlation coefficients were assessed. Linear regression models were used to assess the amount of variance (R^2) and error (RMSE) in MoS explained by the centripetal acceleration. Intraclass correlation coefficients for consistency were assessed on a within-subject basis.

G. *Exploring Meaningful Differences*

To explore whether centripetal acceleration, calculated from inertial sensors, is sensitive to clinically meaningful differences, we descriptively compared the distribution of centripetal acceleration values between steps taken during straight gait and steps taken during turning. Additionally, we examined the distributions of centripetal acceleration between the inside and outside limbs during a turn, between the different turning angles, and between the different speeds.

III. RESULTS

Overall, 2609 steps were included in our analyses. On average, five steps were included for every trial. The remaining steps in each trial occurred outside the volume of the motion capture cameras and therefore could not be analyzed.

A. *Agreement between Sensor-Based Centripetal Acceleration and Margin of Stability*

Using the VAF resulted in good to excellent agreement between the IMU-derived centripetal acceleration and the motion-capture based MoS (Table 1). The average centripetal acceleration over each step agreed with the MoS better than the integrated centripetal acceleration. Importantly, a single lumbar-mounted sensor was equivalent to using three sensors (lumbar, left foot, right foot) when a VAF was used in conjunction with the mean centripetal acceleration over each step – both had excellent agreement with the MoS. The relationship between centripetal acceleration and MoS was consistent across subjects (Fig 5). ICCs ranged from 0.77-0.92 when using a VAF and the mean acceleration across the step.

TABLE I
AGREEMENT BETWEEN MOS AND IMU-BASED CENTRIPETAL ACCELERATION

	R^2	RMSE	ICC (Inter-Subject Range)
Three Sensors			
VAF - Integrated	0.75	0.04	0.69 – 0.83
VAF - Mean	0.77	0.04	0.77 – 0.92
BFF - Integrated	0.44	0.06	0.19 – 0.62
BFF - Mean	0.43	0.06	0.31 – 0.81
One Sensor			
VAF - Integrated	0.66	0.05	0.63 – 0.80
VAF - Mean	0.73	0.04	0.78 – 0.92
BFF - Integrated	0.35	0.07	0.19 – 0.56
BFF - Mean	0.37	0.07	0.34 – 0.83

VAF – Vertically-aligned frame; BFF – Body-fixed frame

B. *Straight Gait versus Turning*

Comparing straight walking and turning, straight walking had a much tighter distribution of centripetal acceleration, centered at 0, compared to turning (Fig 6), agreeing with the expectation that centripetal acceleration is minimal during straight travel.

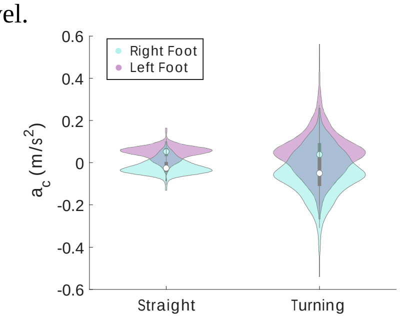

Fig 6. Violin plot depicting the distributions of centripetal acceleration values during straight and turning trials, stratified by stance limb. Note that the stratification is by trial, and therefore turning trials include all steps in the trial, including straight steps.

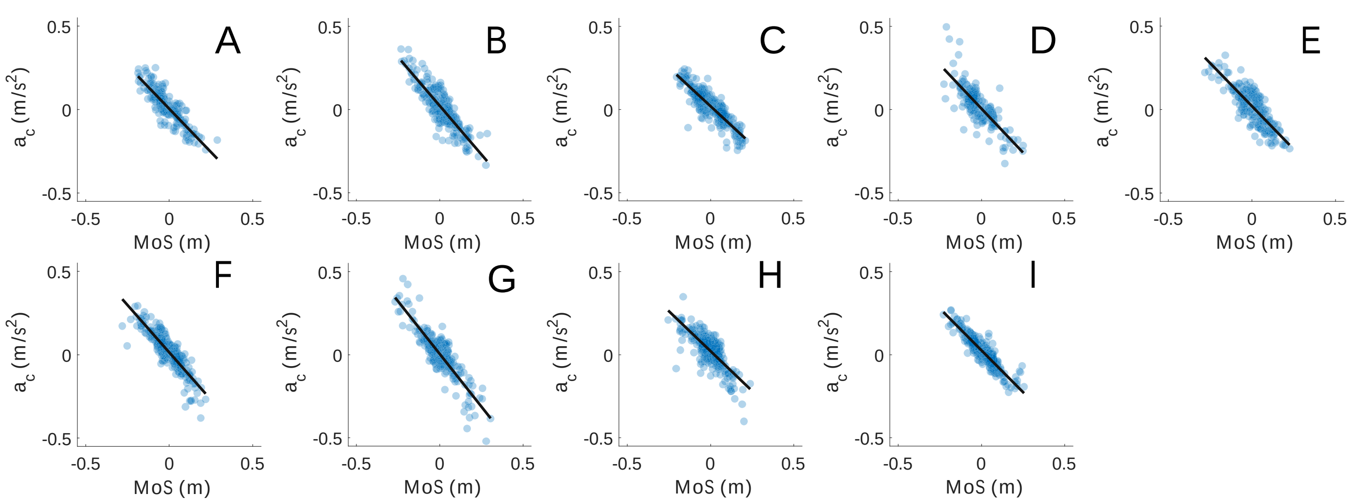

Fig 5. Individual subject scatter plots (A-I) between VAF-Mean centripetal acceleration using a single sensor and MoS with linear fits in black.

C. *Inside versus Outside Limb*

During both left and right turns, the distributions of the average centripetal acceleration when the inside foot was in stance (left foot during left turns, right foot during right turns) were close to zero, and overlapped more than during straight walking. Conversely, the distributions of the outside limb were both centered further away from zero and skewed towards extreme values (Fig 7).

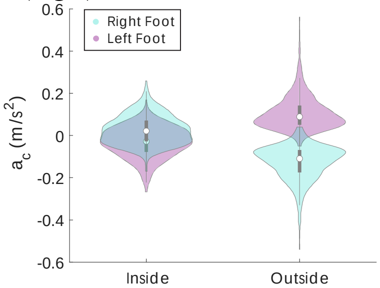

Fig 7. Violin plot depicting the distributions of centripetal acceleration between the inside and outside stance limb, stratified by foot.

D. *Difference between Turning Angles*

While sharper turning angles tended to widen distributions and increase the variance compared to shallower turning angles, this trend was only truly noted when comparing 45 degree turns to sharper turns (Fig 8). Note that, due to the protocol, all turns had a concentration of accelerations similar to straight gait due to the straight steps towards and away from the center dot.

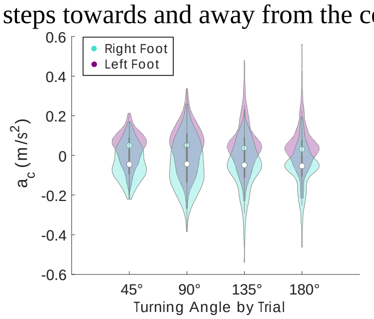

Fig 8. Violin plot depicting the distribution of centripetal acceleration at each turning angle. Qualitative differences can be noted as the turning angle increases, with more extreme values in centripetal accelerations. Note that all turning angles have a concentration resembling straight gait due to each trial including steps towards and away from the center dot.

E. *Difference between Speeds*

Speed primarily affected the centripetal acceleration on the inside limb of the turn. During fast trials, greater centripetal acceleration magnitudes were evident on the inside limb compared to normal walking trials (Fig 9).

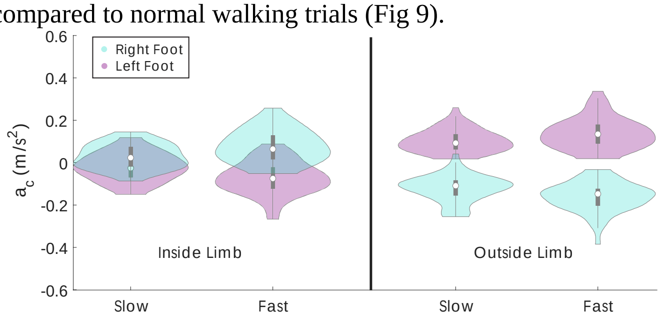

Fig 9. Violin plots for 90 degree turns only, stratified by left and right foot and inside and outside limb. Speed primarily changed the centripetal acceleration of the inside limb.

IV. DISCUSSION

Centripetal acceleration calculated from inertial sensors on the feet and the lumbar spine was able to reliably estimate lateral MoS during walking and turning. Notably, the correlation between average centripetal acceleration and MoS was consistent and strong across all subjects without the need to a subject-specific correction for anthropometry (Fig 5). However, the reliability of this estimation required using a VAF and the average of the centripetal acceleration over the following step. Restricting the analysis to a single sensor on the lumbar spine resulted in negligible decrements in performance, suggesting that MoS may be estimated using only a single inertial sensor located around the waist.

Interestingly, the best agreement between the centripetal acceleration and MoS was found by averaging, rather than integrating, the centripetal acceleration over each step. This result was curious because the construct of averaging relied on assumptions of constant step time. The improved performance of averaging, compared to integrating, can most likely be attributed to a lack of precision in our gait event detection. As seen in Fig 4, step transitions correspond to large shifts in the centripetal acceleration. Small errors in the timing of step detection, therefore, are more likely to compound when integrated, rather than averaged. The decrease in performance of the single-sensor, integrated acceleration algorithm provides further support along this line, as the precision of gait event detection decreases when using a single lumbar-mounted sensor compared to sensors on the lower extremities [32].

While the average centripetal acceleration over each step was consistent and reliable across subjects and sensitive to different conditions, underlying assumptions and limitations must be considered when using this method to estimate MoS. Specifically:

1) Correctly identifying left and right foot contacts may be problematic using only a single sensor. Previous methods have relied on using the lateral acceleration or angular velocities to determine the stance limb using a lumbar-mounted inertial sensor [31]. However, angular-velocity-based methods are not viable during non-straight gait, where roll and yaw angular velocities are strongly influenced by the turn. In these cases, left-right stance limbs are assumed based on alternating steps within a pair. While this is generally a robust assumption, it is not always true, particularly for sharp turns and in individuals with severe gait impairments. For this reason, if a primary outcome is dependent on identifying MoS on each foot, we recommend using the three-sensor approach until a validated method emerges addressing this problem.

2) Step-to-step based centripetal acceleration estimates of MoS may not be robust for comparisons with small effects. Inertial sensors matched motion-capture-based MoS with R^2 values exceeding 0.7 and, on average, were very reliable. However, ~ 25% of variance remained unexplained. As noted in Fig 5, many points fall along the correlation line of best fit, but some do not. Therefore, it is advisable to use aggregate summary statistics, rather than individual maximum or minimum values, to compare conditions. Further work should validate the accuracy and reliability of centripetal acceleration for individual perturbation recovery steps to assuage this concern.

3) Centripetal acceleration may not be reliable in scenarios with external forces (e.g., perturbations). Based on our model framework, the average centripetal acceleration over one step is dependent on the desired change in CoM velocity at initial contact. Therefore, there is a time lag in our framework that must be considered when external forces are applied. For instance, a lateral impulse J applied to the CoM during stance will change the centripetal acceleration of the CoM, but will not retroactively adjust the MoS at the initial contact preceding that stance. In this case, the average centripetal acceleration over stance will differ from the MoS by J/m, where m is the mass of the individual.

4) Mean centripetal acceleration may not be useful in some comparisons of continuous monitoring. As noted in Fig 6, the distribution of centripetal acceleration is distinct between walking and turning. However, comparing only mean values does not capture the full picture; the spread of the distribution is the most apparent difference between walking and turning. As daily walking is a continuous mixture of straight and turning steps, examining the variability of centripetal acceleration may be advisable and the underlying bi-modal distributions should be considered when resolving individual limbs is not possible (see Limitation 1 above).

5) Reliance on the VAF requires robust sensor fusion algorithms and stable magnetometer estimates. Average centripetal acceleration only matched MoS when the centripetal acceleration was confined within the global horizontal plane (VAF). To achieve this VAF, continuous estimates of the lumbar sensor orientation had to be resolved using a fusion of accelerometer, gyroscope, and magnetometer data. In unknown environments, changes in the local magnetic field may influence the magnetometer reading and alter the alignment of the VAF. Uses of centripetal acceleration as an estimate of MoS should consider using sensor fusion algorithms that are robust to potential environmental-induced changes in the magnetometer reading.

6) Reliability in pathological populations has not been established. Only healthy older adults were tested here. While the long-term utility of this approach may include continuous monitoring of pathological populations, it is unclear whether the centripetal acceleration will maintain its reliability. Populations with short, shuffling steps may pose particular problems associated with gait event detection.

7) Ignoring the eigenfrequency may have more significant effects in different populations. Our sample of adults was relatively homogenous in stature. It is possible that the effects of eigenfrequency, which were ignored in this analysis due to the small variance, may need to be accounted for in populations with widely varying stature and, by extension, pendulum length (e.g., children vs. adults).

V. CONCLUSIONS

Inertial sensors can provide reliable and consistent measures of the centripetal acceleration of the CoM that can estimate the MoS. While the best results were obtained using an inertial sensor on each foot and one on the lumbar region of the spine, output from a single sensor on the waist is also capable of providing reliable and robust estimates of the MoS. It is possible to obtain reliable MoS estimates during free-living walking in community settings using this approach, but caution should be applied when comparing the data. Several limitations and underlying assumptions prompt future work and validation.

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