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Analysis of biases in dynamic margins of stability introduced by the use of simplified center of mass estimates during walking and turning

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ABSTRACT

The ability to control the body's center of mass (CoM) is critical for preventing falls, which are a major health concern in aging populations. Control of the CoM has been assessed by characterizing dynamic margins of stability (MoS) which capture the dynamic relationship between the CoM and the base of support. Accurate estimation of CoM dynamics is best accomplished using a full-body marker set. However, a number of simplified estimates have been used throughout literature. Here, we determined the biases and sources of bias when computing MoS using four simplified CoM models, and we characterized how these biases varied in straight walking versus turning. CoM kinematics were characterized using a full-body marker set, the lower extremities and trunk, lower extremities only, an average of four pelvic markers, and one pelvic marker alone. Significant bias was demonstrated for most methods and was larger during turning tasks compared to straight walking. In the fore-aft direction, only overestimates in the MoS were observed, and these ranged from 15 to 110% larger than the true MoS value. In the mediolateral direction, both under- and over-estimates were observed and ranged from −175 to 225%. Across tasks, bias was smallest when using the lower extremity plus trunk (−23 to 62%) and pelvis average methods (−71 to 43%). Sources of bias were attributed to misestimates of CoM height, velocity, and position. Together, our findings suggest that the 1) lower extremity and trunk model and 2) pelvis average model should be considered in future studies to minimize bias when simplified models of CoM dynamics are desired.

1. Introduction

Upwards of 30% of older adults fall every year, some sustaining serious injuries [1–3]. Many falls involve destabilizing events during locomotion, such as turning, slipping or tripping on an object [1,4–6]. Decreased balance and mobility skills have been shown to predict the likelihood of falls [7] and, as a result, various balance assessments have been developed to evaluate control of posture as a proxy for fall risk. In particular, for one class of these metrics, researchers have used various methods to quantify dynamic control of the center of mass (CoM) relative to the base of support (BoS) during functional tasks.

The classically held condition for maintaining balance during stance was that the horizontal CoM position must remain within the boundaries of the BoS. However, Pai and Patton [8] highlighted that both the position and velocity of the CoM are key determinants for balance control. To account for this, Hof et al. [9] developed a measure termed the 'dynamic margin of stability,' defined as the distance between the velocity adjusted or extrapolated position of the CoM (XCoM) and the boundaries of the BoS. Two of the key advantages of using the dynamic margin of stability (MoS) are: 1) it provides a single outcome measure that takes into account both the position and the velocity of the CoM, and 2) it allows quantitative analysis of dynamic control of the CoM on a step-to-step basis.

The magnitude and interpretation of dynamic margins of stability are likely to depend on the method used to estimate CoM dynamics. Estimating CoM position from segmental kinematics during locomotion can be done several ways, but the gold standard involves calculation of a weighted average of the CoM of each body segment based on a full body kinematic marker set. Disadvantages such as a long set-up time, tedious data analysis, and accounting for undetected markers have led to estimations of CoM dynamics based on simplified marker sets. One approach is to use a single point or average of several points on the pelvis to quantify the CoM position [10–13]. Alternatively, lower extremity marker sets typically used for analysis of locomotion, with or without the trunk, have been used [14,15]. Researchers have shown various levels of agreement between CoM position estimates made using simplified marker sets and the gold standard [10,12,15,16]. However, whether these simpler methods can be applied to calculate

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dynamic postural outcome measures accurately has not been systematically explored. This is of particular importance because differentiating position to compute velocity could compound errors in the calculation of the CoM position and XCoM.

Errors in dynamic margins of stability when using simplified kinematic models may be larger when tasks beside straight walking are considered. For example, tasks that involve turning are important to investigate because of their association with falls [1]. They also challenge the postural control system by introducing a decoupling of the lower extremities and trunk [17]. Because of this, CoM models that only account for pelvis motion may not accurately reflect whole body motion during turns.

Thus, the purposes of this study were to 1) quantify the bias and sources of bias associated with estimates of MoS calculated using four simplified kinematic models and 2) determine how these errors varied across walking and turning tasks. We hypothesized that simplified models 1) of the lower extremities and trunk would have small bias [15] 2) of the lower extremities only would have large bias due to underestimates of CoM height, 3) using only a posterior pelvis marker would have large bias in the anteroposterior direction, and 4) would demonstrate larger bias during turns when compared to straight walking.

2. Methods

2.1. Participants

Twelve healthy young adults (6 males, mean age = 26 ± 3 yr, height = 169 ± 9 cm, mass = 67 ± 14 kg) were recruited to participate in this study. Exclusion criteria included any orthopedic conditions associated with the lower extremity or low back and any neurological disorders that would impair participants' ability to perform this study's tasks. Before participation, the procedures were explained to the participants, and they subsequently provided informed consent as approved by the Institutional Review Board at the University of Southern California, Health Sciences Campus protocol number HS-13-00795. All study procedures conformed to the principles put forth in the Declaration of Helsinki.

2.2. Procedures

Three-dimensional marker data were collected at 100 Hz using a 10-camera motion capture system (Qualysis AB, Gothenburg, Sweden). Using a full body marker set, 25 mm reflective markers were placed over specific anatomical landmarks to define participants' body segments, similar to our previous work [18]. Marker clusters were secured to participants' arms, forearms, thighs, shanks, and shoes using nylon/lycra bands. Once all markers were placed, marker positions were calibrated using a five-second standing trial. All joint markers were removed following the calibration, but marker clusters remained on participants.

Participants were instructed to perform three tasks over-ground: 1) straight walking across an 8 m walkway, 2) 90° turns to the left and 3) 90° turns to the right. During turns, participants walked 4 m, turned, and continued walking for 4 m. Participants were not constrained to turn type and performed both step (i.e., planting with one foot and turning to the opposite direction of the plant foot) and spin turns (i.e., planting with one foot and turning to the same direction of the plant foot) [17]. All trials were conducted at the participant's self-selected walking speed, and participants performed five trials of each task.

2.3. Data analysis

Markers were labeled in Qualysis Track Manager (Qualysis, Inc., Sweden) and low-pass filtered at 6 Hz using a fourth-order Butterworth filter. Each limb segment was modeled in Visual 3D v4.8 (C-Motion, Inc., Rockville, MD, USA), and individual segment properties were estimated based on anthropometric tables. The weighted average of each of 15 segment's CoM was used to compute the whole body CoM [19], and this was considered the gold standard for computing CoM kinematics.

Data were exported and analyzed further in Matlab version R2013a (The MathWorks, Natick, MA, USA). In addition to the full-body marker set, four methods were used to estimate the whole-body CoM. First, for the L5S1 model, the coordinates of the single marker placed between the 5th lumbar and 1st sacral vertebrae were used as an estimate of CoM position [10]. For the Pelvis Average Model (PAM), CoM position was estimated by averaging the coordinates of four markers placed on the left and right anterior and posterior superior iliac spines [11,13]. For the lower extremity model (LE), CoM position was estimated based on the weighted average of the lower extremities (feet, shanks, thighs, pelvis) [15]. Finally, for the lower extremity plus trunk model (LETr), the trunk segment was included with the lower extremities to estimate the body's CoM [15].

The CoM position and velocity were then used to compute the extrapolated center of mass (XCoM, Eq. (1)).

$$XCoM = z + \frac{\dot{z}}{\sqrt{\frac{g}{L}}} \tag{1}$$

Here, z and $\dot{z}$ are the CoM position and velocity in the transverse plane, respectively, g is the acceleration due to gravity, and L is the height of the CoM during the calibration trial [9]. CoM velocity was computed by differentiating CoM position with respect to time. The XCoM was used to compute dynamic margins of stability (MoS) in the fore-aft and mediolateral directions for all walking trials.

In the sagittal plane, the fore-aft margin of stability (FA-MoS) was computed as the anterior-posterior distance between the XCoM and the anterior boundary of the BoS at foot strike, determined by toe marker position [11]. Positive FA-MoS values indicate that XCoM is posterior to BoS. For the frontal plane, the minimum mediolateral margin of stability during the stance phase (ML-MoS) was calculated as the minimum distance between the XCoM and the lateral boundary of the BoS, determined by lateral heel marker position [11]. Positive ML-MoS values indicate that the XCoM is medial to edge of the BoS, while negative ML-MoS values indicate that XCoM is lateral to it. For turns, both the FA-MoS and ML-MoS were determined during the stance phase of the inside foot during the turn and averaged for right and left turns. ML-MoS was smallest during the stance phase of the inside foot, which was the pivot foot for spin turns and the contralateral, approach foot for step turns. For each trial, we computed the error between the MoS computed using each candidate method relative to the gold-standard. For FA-MoS, positive errors indicate that the simplified method overestimates the MoS. For ML-MoS, positive error may indicate over- or under-estimates depending on the direction of ML-MoS for the gold standard.

In order to assess the sources of observed errors in the dynamic margins of stability, we also computed errors in each variable from Eq. (1) for the corresponding methods. Errors in CoM height, CoM velocity, ML CoM position relative to the BoS, and FA CoM position relative to the BoS were averaged across tasks. All errors were averaged across participants.

2.4. Statistics

A Shapiro-Wilk test of normality determined that the MoS data were not normally distributed ($p < 0.05$). Thus, non-parametric tests were used for statistical analysis. The agreement between the MoS computed using the gold standard, and simplified models were quantified using the 95% limits of agreement method for repeated measures [20]. In this method, a graphic representation of bias for each task was generated through Bland-Altman plots. Here, the difference in MoS between the gold standard and one simplified method is plotted as a function of the