Monocular 3D Sway Tracking for Assessing Postural Instability in Cerebral Hypoperfusion During Quiet Standing

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Abstract—Postural instability is prevalent in aging and neurodegenerative disease, decreasing quality of life and independence. Quantitatively monitoring balance control is important for assessing treatment efficacy and rehabilitation progress. However, existing technologies for assessing postural sway are complex and expensive, limiting their widespread utility. Here, we propose a monocular imaging system capable of assessing sub-millimeter 3D sway dynamics during quiet standing. Two anatomical targets with known feature geometries were placed on the lumbar and shoulder. Upper and lower trunk 3D kinematic motion was automatically assessed from a set of 2D frames through geometric feature tracking and an inverse motion model. Sway was tracked in 3D and compared between control and hypoperfusion conditions in 14 healthy young adults. The proposed system demonstrated high agreement with a commercial motion capture system. Between-condition differences in sway dynamics were observed in anterior-posterior sway during early and mid stance, and medial-lateral sway during mid stance commensurate with decreased cerebral perfusion, followed by recovered sway dynamics during late stance with cerebral perfusion recovery. This inexpensive single-camera system enables quantitative 3D sway monitoring for assessing neuromuscular balance control in weakly constrained environments.

I. INTRODUCTION

Postural control is crucial for maintaining independence and quality of life. The two components of posture, orientation and balance, require continual adjustment and coordination between afferent sensory inputs and neuromuscular control [1], [2], [3]. Aging and neurodegenerative diseases (e.g., Parkinson’s disease, multiple sclerosis) can cause deterioration in postural control, which is associated with increased risk of falls, and thus decreased quality of life [4], [5], [6]. Dual-task, attention, and cortical recording paradigms have demonstrated the involvement of higher cortical centers during balance control [7], supporting the notion that underlying mechanisms to age-related balance decline may include decreased cortical function.

Instability and falls in older adults is a complex multifactorial problem, with risk factors such as muscle control, visual impairment and effects from prescription medication [8], [9]. One underlying mechanism for instability and falls in older adults is low cerebral blood flow (CBF), and thus cerebral hypoperfusion, from impaired cardio- or cerebrovascular regulation [10], [11], [12]. Two factors commonly affected by underlying disease pathophysiology are cerebral perfusion pressure and arterial partial pressure of carbon dioxide (Paco2) [13]. Cerebral autoregulation maintains relatively constant CBF across a range of perfusion pressures, but rapid changes in arterial blood pressure, such as during a supine to stand transition, can result in an acute reduction of cerebral perfusion pressure, and subsequent reduction in blood flow to the brain. This reduction in perfusion causes a decrease in energy metabolism and activity in the brain and central nervous system [14], which may affect cardio-postural balance control [15]. There is a clinical need to objectively monitor posture and balance control for assessing treatment efficacy and rehabilitation [16].

Balance control during quiet standing has been largely investigated by measuring variation in center of pressure (CoP) using baropodometric platforms and center of mass (CoM) using 3D camera analysis. Laboratory grade camera-based measurement technologies have traditionally been restricted to assessment in controlled environments and to validate novel technologies, but are often too expensive or cumbersome to incorporate within clinical settings. Camera-based systems have traditionally been used to assess CoM sway. Specifically, marker-based motion capture systems have been widely used for estimating and tracking CoM during quiet standing, in which participants are fitted with retroreflective or actively illuminated markers and 3D kinematic data of body segments are tracked by a multi-camera laboratory setup. Although these systems are able to assess whole body motion, system expense, setup burden, and technical expertise have limited their clinical utility [17], [18]. Less expensive multimodal alternatives using an iPad and 3D camera with retroreflective markers have been proposed for static posture assessment during lying posture [19], but currently lack the ability to track dynamic sway in standing. Markerless technologies, such as multi-camera voxel reconstruction [20] and Microsoft Kinect-
based technologies [21], [22], have the benefit of ambient imaging without markers, but existing methods have not demonstrated sub-millimeter accuracy at anatomically relevant locations during quiet standing and require specialized imaging setups. Nevertheless, computer vision solutions for human pose estimation have shown tremendous promise in other motion-based applications, such as activity and gesture recognition. Although applications have largely been restricted to estimation in 2D space, integrating a priori kinematic models with camera parameters has shown strong performance in 3D anatomical tracking of the hand joints [23] and arm [24]. The ability to accurately capture and track postural change dynamics associated with falls-related factors (such as CBF in aging) using low cost technical advances would be clinically useful for identifying an individual’s potential falls risk beyond subjective assessment.

In this paper, we propose a monocular 3D motion tracking imaging system for assessing sub-millimeter 3D sway dynamics during quiet standing. This system was designed to enable postural assessment in clinical or naturalistic environments. Traditional motion tracking systems require unnecessarily complex whole-room configuration for sway tracking. This burden was alleviated through a one-time camera calibration and affixing physical targets with known unique a priori geometries (“geometric target models”) on anatomically relevant locations. Using targets with known geometric models enabled high spatial accuracy estimation across the set of 2D frames by fitting a kinematic target motion model to the data. Thus, the camera can be affixed in any position and orientation as long as the targets are within the field of view. By calibrating to the scene orientation, upper and lower trunk sway coordinates were tracked in relevant biomechanical axes (anterior-posterior, medial-lateral, superior-inferior) during quiet standing. This two-factor model (lower and upper trunk) was used to assess sway characteristics in anatomical planes using a repeated measures design with young healthy adults. For each participant, sway was monitored at baseline and under compromised cerebral perfusion (hypoperfusion), induced by pre-stand guided hyperventilation, to investigate sway dynamics related to cerebral perfusion levels.

II. METHODS

A. Data Collection and Experimental Design

Fourteen young healthy adults (9/5 male/female, age 24.7 ± 4.3, mass 74.3 ± 11.7 kg) free from a history of cardiovascular, neurological and musculoskeletal disorders completed testing. Participants were instructed to refrain from caffeine and food consumption 2 hours prior to testing, and alcohol and strenuous exercise 24 hours before the laboratory visit. Study protocols and procedures were approved by a University of Waterloo Research Ethics Committee and conformed to the Declaration of Helsinki (ORE 19831). All participants provided written informed consent before testing procedures.

Data was collected in the RIA Research Apartment, which is a purpose-built apartment to simulate realistic retirement and long-term care living conditions. At the start of each testing session, anthropomorphic data were collected. Participants were then instrumented with an electrocardiogram to measure heart rate (Pilot 9200; Colin Medical Instruments, San Antonio, TX, USA), continuous arterial blood pressure finger plethysmograph to estimate cardiac stroke volume via Modellflow (Finapres Pro; FMS, Amsterdam, The Netherlands), transcranial Doppler ultrasound (WAKle; Atys Medical, Soucieu en Jarrest, France), which insonated the right middle cerebral artery to estimate CBF, and a nasal cannula connected to a capnograph to measure $P_{ET}$CO$_2$ (CD-3A CO$_2$ Analyzer, AMETEK Inc., Pittsburgh, PA, USA). Additionally, a spatially resolved near infrared spectroscopy probe (Portalite; Artinis Medical Systems, Elst, The Netherlands) was placed on the forehead above the right eye brow to measure cerebral tissue oxygenation index (TSI). Arterial blood pressure, stroke volume (SV), ECG, $P_{ET}$CO$_2$, and cerebral blood flow velocity (CBFv) were recorded at 1000 Hz (PowerLab, LabChart, version 7.3.7; ADInstruments, Colorado Springs, CO). After instrumentation, participants assumed a supine position for 10 min before finger blood pressure was calibrated.

Participants completed two stands in pseudorandomized order: (1) supine to stand transition followed by 60 s of quiet standing, and (2) 2 min voluntary guided hyperventilation (20 breaths/min), immediately followed by a supine to stand transition and 60 s of quiet standing with resumed normal breathing. The stands were repeated once, and data were averaged for each type of stand. In accordance with the French Posturology Association guidelines, participants were instructed to stand without shoes, with their heels 2 cm apart, and feet angled at 30° [25]. Participants were instructed to keep their eyes closed and arms crossed to eliminate afferent visual feedback and reduce anticipatory arm movement [26].

During hyperventilation, participants were coached on depth of breathing to attain a drop of at least 10 mmHg end-tidal PCO$_2$ ($P_{ET}$CO$_2$), which was used as a proxy for $P_a$CO$_2$. Participants completed a practice stand prior to data collection, and all four stands were completed in the same session to avoid between-day sway variations [27].

B. Monocular 3D Sway Tracking

The main goal was to develop a monocular imaging system for tracking 3D sway characteristics to assess balance control in weakly constrained (non-laboratory) environments. The problem was posed as a single-view (monocular) a priori geometric model and inverse kinematic estimation problem with embedded anatomical target models. Fig. I depicts an overview of the imaging system. A temporal sequence of 3D sway coordinates $z_i \in \mathbb{R}^3$ was sought from a single sequence of 2D frames, where sway is represented across the anterior-posterior (AP), medial-lateral (ML), and superior-inferior (SI) axes. Given a video from a single posterior-facing camera, model feature coordinates from a shoulder and lumbar target were automatically tracked in 2D calibrated camera space (Section II-B1). Then, using known a priori target model geometries, we fit a kinematic model to estimate the absolute sway position in 3D camera space (Section II-B2). Finally, we projected the lumbar kinematic orientation into the center of the body to track a virtual lower trunk sway coordinate. These coordinates were transformed into anatomical Euclidean space described by the AP, ML, SI axes (Section II-B3).
Fig. 1: Overview of the monocular 3D sway estimation imaging system. Frames were captured posterior to the participant. Target features were tracked in 2D, and using a priori 3D geometric model, 3D sway coordinates were estimated and transformed into anatomical space. Upper and lower trunk sway coordinates were estimated by tracking shoulder and lumbar targets, resulting in a global 3D sway profile (blue: early stance, red: late stance).

1) Model Feature Tracking: We adopted a two-segment hinged biomechanical model of motion, with hinging effects between lower and upper trunk. To separate sway from these two components, unique anatomical targets were affixed to the left shoulder and lumbar. The targets were secured using adjustable torso harnesses with rigid attachment points positioned at the acromion process and L3 vertebra, identified through bony landmarks. Since differences in balance control result in lower trunk sway differences on the order of millimeters [28], 3D tracking estimation was guided by a priori geometric models to increase 3D estimation accuracy. The mathematical formulation presented here is generalizable to asymmetric target models with known root-relative feature coordinates. This asymmetry guarantees an orientation-dependent unique mapping onto 2D image space.

A single monocular grayscale camera (GS3-U3-41C6NIR, FLIR) was positioned 1 m behind the participant. Due to the high accuracy requirements of the system, optical distortions were estimated once and removed frame-by-frame using a two-step global-local camera calibration procedure [29]. Images of a planar checkerboard pattern were recorded, and intrinsic and extrinsic camera parameters were modeled as a linear projection from 3D world coordinates to 2D image coordinates:

\[
\alpha \theta X = K \cdot c_w M \cdot w X
\]  

where \( \alpha \) is an arbitrary scale parameter, \( \theta X \) and \( w X \) are the checkerboard corner coordinates in the image plane and world coordinate system respectively, \( c_w M \) is the extrinsic transformation matrix from 3D world to 3D camera coordinates, and \( K \) is the intrinsic camera matrix:

\[
K = \begin{bmatrix}
    f_x & s & x_0 \\
    0 & f_y & y_0 \\
    0 & 0 & 1 \\
\end{bmatrix}
\]  

where \((f_x, f_y)\) is the focal length, \(s\) is skew, and \((x_0, y_0)\) is the principle point in the image plane. This matrix is fixed for the camera, and will be used later for estimating sway target positions. From this, we can define the world-to-image projection transformation function:

\[
\Pi(w X) = \frac{1}{\alpha} K \cdot c_w M \cdot w X
\]  

The optical field distortion was estimated by refining the closed-form solution using nonlinear least squares minimization of a two-coefficient radial distortion [29], [30]. This parameterization was used to undistort each frame prior to spatial processing to guarantee distance-independent homogeneous pixel spacing, and thus accurate sway tracking across the field of view.

In this study, we designed an asymmetric target model with equally spaced locally salient features. This is described by the a priori feature model geometry matrix \( G \in \mathbb{R}^{n \times 3} \), which consists of 3D coordinates in world space (i.e., the space defined by the target coordinate system) and will be used for kinematic model fitting in Section II-B2. Feature point coordinates \( p_i \in \mathbb{R}^2 \) were automatically detected using multi-orientation kernel convolution with non-maxima suppression.
and sub-pixel localization [31]. Specifically, an interest point likelihood map was computed by convolving four feature kernels with the frame, and per-pixel feature likelihood was calculated by the maximum response over all prototype combinations. Sub-pixel feature localization was accomplished by solving a gradient orthogonality minimization problem:

\[
p_i = \arg \min_{q_i} \sum_{n_j \in N(q_i)} (\nabla q_i (n_j - q_i'))^2
\]

where \(q_i\) is a feature coordinate candidate, \(N(q_i)\) and \(\nabla q_i\) are the pixel neighborhood and image gradient at point \(q_i\), respectively, and \(n_j\) is a neighboring pixel. Thus, \(P = \{p_i\}\) describes the set of feature coordinates after undergoing optical projection onto the image plane according to the camera intrinsics \(K\). The (unknown) 3D orientation of the geometric model was estimated by fitting a kinematic model to these data, which is discussed next.

2) Kinematic Model Fitting: Given the set of 2D feature coordinate predictions \(P\), we fit a kinematic motion model of the a priori geometric model \(G\) to these data, where \(G\) is a set of 3D feature coordinates in world space (see Fig. [1]). The kinematic model was designed to model the non-deformable nature of sway in free space with a fixed base of support. The model was parameterized by \(\Theta = (t, R)\), where \(t \in \mathbb{R}^3\) is 3D translation, and \(R \in \mathbb{R}^3\) are the Euler angles describing 3D orientation. The optimal kinematic transformation, parameterized by these six degrees of freedom, was found by transforming the a priori geometric model into the image plane using the calibrated camera model, and seeking a least squares fit to the feature prediction data:

\[
\hat{\Theta} = \arg \min_{\Theta} \sum_i ||\Pi(G_i(\Theta)) - p_i||^2_2
\]

where \(\Theta\) is the set of kinematic motion parameters, \(\Pi\) is the projection transformation from 3D world coordinates to the 2D image plane from Eq. [3], \(G_i(\Theta)\) are the transformed 3D coordinates of point \(i\) from the geometric model \(G\), and \(p_i\) is the feature prediction in image space.

This problem was solved using a two-step approach, consisting of an initializing and refinement step. To motivate this approach, we note that sway dynamics during quiet standing exhibit small and relatively smooth changes between each time point. In the first frame, we initialized the parameters \(\Theta\) using a closed form planar estimation solution of the camera extrinsics [32]. In subsequent frames, noting that frame-to-frame sway differences are generally small (sub-millimeter), we set the initial conditions for the current frame (at time \(t_c\)) to the previous frame kinematic parameters (\(\Theta_{t_c-\Delta t}\)), and computed the optimal fit using Levenberg-Marquardt non-linear least-squares minimization. This approach avoided potential erroneous fits in local minima in other parts of the energy field, and we empirically found it produced higher accuracy than randomly initialized iterative optimization.

This optimization was performed on both the shoulder and lumbar targets separately, using their respective geometry priors. The target origin \(z_u\) was used to track upper trunk motion. The torso kinematic parameters were used to project a virtual coordinate 10 cm deep into the body, which was used to track lower trunk motion:

\[
z_l = M_{\Theta} \Delta_l
\]

where \(\Delta_l\) is the torso vector in homogeneous world space coordinates, and \(M_{\Theta}\) is the motion matrix parameterized by \(\Theta \in \mathbb{R}^6\), described by Eq. (7).

3) Anatomical Space Transformation: To analyze posture sway patterns in anatomically relevant space, the kinematic parameters \(\Theta\) were transformed from camera coordinate system into an anatomical coordinate system described by 1D axes (AP, ML, and SI) and derivative 2D planes (sagittal, transverse and coronal). A forward-facing calibration board was positioned in the scene, and its extrinsic orientation matrix was estimated using the calibration procedure from Section II-B1. Denoting this matrix as \(E\), sway in anatomical space coordinates was computed as:

\[
z_u' = E^{-1} z_u
\]

\[
z_l' = E^{-1} z_l
\]

where \(z_u'\) and \(z_l'\) are the upper and lower trunk sway coordinates in the anatomical coordinate system defined by \(E^{-1}\), the inverse of the planar target orientation in camera coordinates. The signals were denoised using a second order Savitzky-Golay filter [33] with 0.5 s time window, which empirically modeled the smooth nature of sway well.

C. Data Analysis

The interval between ECG R-waves was used to calculate heart rate (HR). Cardiac output (CO) was calculated as the product of HR and SV. Systolic blood pressure (SBP), diastolic blood pressure (DBP), and mean arterial pressure (MAP) were the respective maximum, minimum and mean arterial pressures within each cardiac cycle. Identical analysis was performed to determine systolic, diastolic, and mean cerebral blood flow velocity (CBFv). \(P_{ET}\) was determined by identifying the peak \(CO_2\) concentration at the end of each exhalation, and the concentration was then converted to partial pressure. TSI was recorded at 50 Hz (Oxysoft, version 3.0.95, Artinis, Medical Systems, Elst, The Netherlands) and was averaged into 1 s bins. Beat-by-beat cardiovascular and breath-by-breath \(P_{ET}\) data were linearly interpolated to 1 s time points, and subsequently time aligned with the cerebral oxygenation data for analysis. For all variables, supine baseline values were calculated as 30 s averages (from 45 s to 15 s before the posture transition). Cardiovascular variables during early, mid, and late stance were calculated as averages during the first 10 s of stance time.

To compare sway variations in control and hypoperfusion conditions, sway dynamics were assessed at three time bins during quiet standing according to expected cardiovascular response relative to upright stance time (t=0 s): initial cerebrovascular decrease ("early stance", 0–20 s), overshoot and recovery onset ("mid stance", 20–40 s), and sustained recovery ("late stance", 40–60 s). The start of stand (0 s) was determined at the time when the participant’s full weight was transferred onto a pressure platform following the initial
downward force overshoot. For each time bin, the total path length (TPL) in each anatomical axis (AP, ML, SI) and anatomical plane (transverse, sagittal, coronal) was computed as a summary metric for balance control [33]:

\[
\mathcal{L}_A(T) = \sum_{t_i \in T} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}
\]

where \((x_i, y_i)\) are projected coordinates in the anatomical plane \(A\), and \(T\) is the stance time bin. \(\mathcal{L}\) within a 1D anatomical axis (i.e., AP, ML, SI) was computed by setting \(y_i = 0\). This formulation is analogous to the average velocity magnitude during the time frame [35].

Two-way repeated measures ANOVA, with within-subject factors of condition (control vs. hypoperfused) and time (baseline, early, mid, late stance), was performed on physiological measures. Normality was confirmed by the Shapiro-Wilk test, as well as visual inspection by using histograms and q-q plots of the residual distributions for each variable. Post hoc analysis was performed using paired sample t-tests to test differences across conditions within each time bin, and non-parametric ANOVA for non-normal sway TPL data [36], [37]. The \(p\)-values were adjusted via Bonferroni correction for assessing statistical significance. Between-participant variance was removed using Cousineau-Morey normalization for reporting descriptive statistics. We reported Cohen’s \(d\) effect size and statistically significant results when \(p < 0.05\). Data are presented as mean ± SEM.

System accuracy was evaluated against a commercial active motion capture system with an accuracy of 0.1 mm and resolution of 0.01 mm (Optotrak, Northern Digital Inc, Canada). The global coordinate system was calibrated to the standing position such that target positions were within the manufacturer’s characterized measurement volume. A subset of four participants (3/1 male/female) was used to assess system accuracy. Each participant stood quietly for 60 s across four trials to simulate different sway patterns: eyes open on foam, eyes closed on foam, eyes open on ground, eyes closed on ground, totalling 16 unique stands. During “eyes open” stance, the participants looked at a visual target approximately 3 m in front at eye level. Three infrared emitting diodes were affixed to the same rigid bodies as the video camera targets. All motion tracking data were recorded simultaneously. Optotrak based kinematic data was sampled at 120 Hz, resampled to 30 Hz by linear interpolation to match the frame rate of the monocular kinematic system, and the coordinate system origins were aligned. Bland-Altman analysis was used to compare the two measurement systems. Specifically, all data were concatenated across participants for each of the kinematic systems, and the point-by-point differences were quantified through correlation and equality.

### III. Results

Section [III-A] presents the accuracy of the monocular imaging system compared to a gold standard motion capture system. Section [III-B] presents repeated measures analysis of sway characteristics in control versus cerebral hypoperfusion across the relevant time bins. Video 1 (Supplementary Materials) shows the integration of cardiovascular response and postural sway estimation during a postural transition.

#### A. 3D Estimation Accuracy

Fig. 2 shows the agreement results between the proposed monocular system and the gold standard motion capture system. Bland-Altman analysis demonstrated no systematic error between the systems (error \(1.5 \times 10^{-4}\) mm, \([-0.52, 0.52]\), and no proportional error (\(y = 1.00x + 1.49 \times 10^{-4}\), \(r^2 = 0.9792\)). The equality line fell within the confidence interval of the mean difference. Thus, the monocular imaging system demonstrated comparable postural sway tracking results to a whole-room gold standard method during quiet standing tasks.

#### B. Postural Sway and Cardiovascular Response

Both cardiovascular and sway showed the largest difference between control and hypoperfusion conditions during early stance, with gradual recovery to baseline by late stance, demonstrated by a significant main effect of time on all sway measures. Normal respiratory rate (11.5 min\(^{-1}\), SD = 2.9) was successfully attained upon standing. Fig. 3 shows the primary time-synchronized cardiorespiratory and cerebrovascular responses to standing (at \(t = 0\)) in both the control (blue) and hyperventilation (red) conditions. There were no significant main effects on perfusion condition in blood pressure measures (mean, diastolic, systolic), indicating preserved central arterial pressure across conditions. Significant Condition \(\times\) Time interaction terms were observed in all physiological measures, and are expanded and discussed below. Table I provides summary time-binned cardiovascular measures alongside statistical significance.

1) Hyperventilation Caused Hypoperfusion: Cerebral hypoperfusion was attained for each participant through hyperventilation-induced respiratory alkalosis. \(P_{\text{ET}}\text{CO}_2\) was significantly lower in the hyperventilation compared to the control conditions during all time points (\(p < 0.001\); see Table I). In the hyperventilation condition, \(P_{\text{ET}}\text{CO}_2\) was a significant different across all stance times (\(p < 0.001\)) except from mid to late stance (\(p = 0.43\)). In the control condition, there were no significant differences in \(P_{\text{ET}}\text{CO}_2\) across time points.

In both perfusion conditions, all participants demonstrated vasopressor response to upright posture with a transient reduction in blood pressure from baseline to early stance.
Fig. 2: Accuracy of the proposed monocular system compared to a whole-room motion capture system. (a) Bland-Altman analysis of systematic error shows strong agreement and sub-millimeter accuracy (error $1.5 \times 10^{-4}$ mm, $[-0.52, 0.52]$). (b) Example monocular and Optotrak time series signals showing upper trunk anterior-posterior sway during 60 s quiet stand with eyes closed on foam.

Fig. 3: Cardiovascular response to standing during normal and reduced cerebral perfusion (mean, standard error). Data were time-normalized based on established upright posture at $t=0$ s. Binned summary statistics are reported in Table I. (CBFv: cerebral blood flow velocity; PCO$_2$: partial pressure of carbon dioxide) $(p < 0.001)$, and compensatory increase in HR. There were no differences between conditions in systolic, diastolic, or mean blood pressure, hence between-condition differences in CBF and oxygenation were attributed to differences in P$_{ET}$CO$_2$ from hyperventilation. CBFv variables (systolic, diastolic, mean) and TSI all had significant Condition $\times$ Time interaction effects due the compensatory mechanisms of CBFv after the termination of hyperventilation and acclimation to upright posture.

Fig. 4 shows sway traces of a representative participant with decreased CBF during hyperventilation, and demonstrates the primary effects of standing on postural control. During early stance (black), sway TPL increased in hypoperfused (248.3 mm) versus control (166.2 mm). At this time, arterial blood pressure, CBFv and TSI are transiently low due to active standing. During mid stance (teal), the TPL difference between hypoperfused (151.9 mm) and control (113.2 mm) starts to diminish as CBF and perfusion start to recover. By late stance (pink), balance control had been re-established (132.5 vs. 130.0 mm) owing to cerebral reperfusion and cardiovascular homeostasis. Whole-sample results binned by stance time are presented and discussed below. Table II presents whole sample TPL results, and Fig. 5 shows TPL distributions calculated across selected anatomical axes for each time bin.

2) Early Stance: Significant between-condition reductions in all CBFv and oxygenation variables were observed in both
Baseline supine ($p < 0.001$) and early stance ($p < 0.03$), indicating acute onset of hypoperfused state during hyperventilation. Within the hypoperfusion condition, no significant differences were observed from baseline to early stance in mean CBFv or TSI, indicating sustained impaired cerebrovascular perfusion and oxygenation during the initial stance phase. A concomitantly statistically significant ($p = 0.039$) increase in lower trunk AP sway from control to hypoperfusion conditions was observed (147.1 mm vs. 177.8 mm, $d = 0.92$), as well as large differences in upper trunk AP sway (191.2 mm vs. 232.0 mm, $d = 0.93$), and AP-derivative planes of motion in both lower trunk (transverse: 183.3 mm vs. 221.1 mm, $d = 0.89$; sagittal: 165.0 mm vs. 200.3 mm, $d = 0.91$) and upper trunk (transverse: 227.9 mm vs. 272.7 mm, $d = 0.84$; sagittal: 202.5 mm vs. 252.7 mm, $d = 0.86$).

3) Mid Stance: During mid stance, significant reductions in all CBFv variables were observed ($p < 0.02$), but TSI was no longer statistically different ($p = 0.11$). Within the hypoperfusion condition, mean CBFv and TSI increased from early to mid stance ($p < 0.001$), indicating initial cerebral perfusion recovery onset. AP sway decreased, showing decreased magnitude and effect size compared to early stance in both lower trunk ($d = 0.84$ vs. 0.92) and upper trunk ($d = 0.81$ vs. 0.93). However, there were large ML sway differences in both lower trunk (50.5 mm vs. 59.9 mm, $d = 0.81$) and upper trunk (53.9 mm vs. 63.3 mm, $d = 0.80$), and a statistically significant ($p = 0.040$) increase was observed in upper trunk coronal sway (66.5 mm vs. 76.4 mm, $d = 0.68$).

4) Late Stance: During late stance, cerebral perfusion levels were largely recovered through no between-condition significant differences in diastolic CBFv or TSI, but mean CBFv and systolic CBFv remained low ($p < 0.04$). Within the hypoperfusion condition, cerebral perfusion continued to recover, demonstrated by significant increases in mean CBFv and TSI compared to mid stance ($p < 0.01$). There was no significant between-condition difference in any sway measures in late stance, and effect sizes across all directions were small ($d < 0.3$), indicating regained balance control following initial hypoperfusion onset.

Fig. 4: Example sway data of a participant with decreased cerebral blood flow during hypoperfusion. AP-ML only is shown for visual clarity. Standing in a hypoperfused state caused larger early (black) and mid (teal) stance sway dynamics compared to control. By late stance (pink), sway stabilized in both conditions.

In this study we proposed a novel 3D monocular imaging system for monitoring postural sway in weakly constrained imaging environments. The system distinguished between upper and lower trunk movement using two unique wearable targets with a priori geometric models, yielding a two-segment kinematic model assuming hinging effects between upper and lower trunk segments. Lower spinal displacement has been shown to accurately estimate CoM changes during gait tasks [38]. Additional anatomical targets may provide enhanced dynamic CoM measurement at the expense of increased physical setup.

Balance control involves neuromuscular coordination to maintain the CoM within the base of support [39, 40] and stabilization following intrinsic or extrinsic disturbances [41]. It has been commonly assumed that the role of CoP is to correct CoM deviations through neuromuscular control of ankle and hip torque [42]. Recent studies have suggested that the link between CoP and CoM may be more complex [43], and play complementary roles in balance control. The prevalence of baropodometric CoP monitoring may be due to the ease of setup and technology acquisition. However, 3D body motion may be able to provide complementary indicators of neuromuscular insufficiency in addition to baropodometric monitoring. Motion capture systems are often used for assessing segmental and CoM displacement, but are expensive and require complex setups compared to baropodometric platforms. Thus, a less expensive portable imaging system may allow for new CoP-CoM co-analysis for balance assessment in naturalistic environments.

A hyperventilation protocol was used to modulate cerebral perfusion through hypocapnia-induced cerebral vasoconstriction resulting in relative cerebral hypoxia [44]. In healthy older adults, impaired cerebral vasoreactivity, but not impaired cerebral autoregulation, is associated with increased falls risk [45] primarily in the form of orthostatic intolerance (OI) [46]. Similarly, responses to head up tilt in OI groups following parabolic flight have been linked to cerebral vasoconstriction and not to systemic hypotension [47]. Similar responses have been observed in classic OI population, specifically increased heart rate, decreased CBFv, and increased cerebrovascular resistance [48]. These manipulations demonstrate similar effects to traditional OI, and thus appear to be effective proxies for studying imbalance in older adults.

Differences in sway were commensurate with physiological changes in cerebral perfusion. Baroreflex response modulates heart rate through orthostatic reduction of blood pressure during posture transition [49]. Baroreflex sensitivity decreases with age [50, 51], and has been linked to autonomic dysfunction, including orthostatic hypotension [52]. Antihypertensive treatment for older adults living needs to assess risk for orthostatic hypotension and consider the risk for cerebral hypoperfusion [53]. Significant between-condition differences in early and mid stance were observed in CBFv and not blood pressure measures, with concomitant differences in sway magnitude. Cerebrovascular autoregulation [45] promoted recovery of CBFv in late stance, which was reflected by recovered
sway dynamics. Thus, combining blood pressure data, or direct measures of CBFv or cerebral oxygenation, with functional measures of balance control may increase diagnostic aid and treatment efficacy in individuals with orthostatic hypotension.

Differences were observed for both lower and upper trunk sway kinematics during the hypoperfused state support a multi-joint model of motion. Traditional body segment analysis requires placement of many optical markers on the body, and reconstruction of body segments using a multi-camera setup. The proposed system alleviates the setup load by distinguishing between upper and lower trunk motion through two individual unique targets, which may reduce the barrier to adoption in clinical settings. Furthermore, since the imaging system tracks posterior anatomical markers, no facial information is recorded or required for 3D sway analysis, and participant or patient privacy can be maintained. Thus, if paired with baropodometric assessment, sway motion can be additionally assessed while maintaining patient privacy. This may be beneficial in home care and health care environments where privacy is an important factor in technology adoption.

The study was designed as a repeated measures study with pseudorandomized stand ordering to minimize confounding factors such as order and demographic effects. The manipulation of increased respiration to reduce CBFv was stopped prior to standing so should not have affected postural movement, and self-reported symptoms of dizziness and light-headedness suggested that the predominant factor in increased sway was cerebral hypoperfusion; this is commensurate with previous findings. Our model was able to achieve aging-like...
TABLE II: SWAY TOTAL PATH LENGTH (MM) Binned By Direction and Stance Time (mean ± SEM).

|               | Control          | Lower Trunk Hyperventilation | d   | Control          | Upper Trunk Hyperventilation | d   |
|---------------|------------------|------------------------------|-----|------------------|------------------------------|-----|
| AP T1         | 147.1 ± 5.9      | 177.8 ± 11.1                | 0.92| 191.2 ± 8.3      | 232.9 ± 14.7                | 0.93|
| T2            | 99.0 ± 4.8       | 114.3 ± 4.9                 | 0.84| 129.0 ± 7.5      | 147.7 ± 4.5                 | 0.81|
| T3            | 96.1 ± 4.3       | 97.4 ± 3.4                  | 0.09| 126.6 ± 6.4      | 131.3 ± 5.1                 | 0.22|
| ML T1         | 80.9 ± 3.6       | 94.2 ± 8.5                  | 0.55| 90.3 ± 3.1       | 98.6 ± 9.0                  | 0.33|
| T2            | 50.5 ± 3.4       | 59.9 ± 2.8                  | 0.81| 53.9 ± 3.5       | 63.3 ± 2.8                  | 0.81|
| T3            | 47.2 ± 4.4       | 48.3 ± 1.8                  | 0.09| 51.1 ± 5.0       | 52.3 ± 1.9                  | 0.08|
| SI T1         | 67.4 ± 3.3       | 82.1 ± 6.3                  | 0.78| 41.1 ± 3.0       | 57.7 ± 10.9                 | 0.55|
| T2            | 44.5 ± 2.3       | 50.4 ± 2.3                  | 0.67| 29.9 ± 2.7       | 31.2 ± 2.3                  | 0.14|
| T3            | 41.5 ± 2.2       | 43.6 ± 1.8                  | 0.28| 29.1 ± 1.8       | 26.7 ± 3.6                  | 0.22|
| APML T1       | 183.3 ± 7.1      | 221.1 ± 14.3                | 0.89| 227.9 ± 8.8      | 272.7 ± 18.1                | 0.84|
| T2            | 120.8 ± 5.8      | 141.0 ± 5.6                 | 0.94| 149.6 ± 8.2      | 172.8 ± 5.1                 | 0.91|
| T3            | 116.2 ± 6.7      | 118.5 ± 3.7                 | 0.12| 145.5 ± 8.8      | 150.9 ± 4.9                 | 0.21|
| APSI T1       | 165.0 ± 6.8      | 200.3 ± 13.1                | 0.91| 202.5 ± 9.2      | 252.7 ± 20.0                | 0.86|
| T2            | 110.8 ± 5.4      | 127.3 ± 5.5                 | 0.82| 137.2 ± 8.1      | 155.9 ± 5.0                 | 0.74|
| T3            | 106.9 ± 4.8      | 108.8 ± 3.9                 | 0.12| 134.6 ± 6.5      | 138.0 ± 6.3                 | 0.14|
| MLSI T1       | 116.6 ± 4.9      | 139.4 ± 10.7                | 0.73| 106.3 ± 4.3      | 128.2 ± 13.4                | 0.59|
| T2            | 74.7 ± 4.1       | 86.8 ± 3.7                  | 0.83| 66.5 ± 4.1       | 76.4 ± 3.6                  | 0.68|
| T3            | 69.7 ± 5.2       | 72.3 ± 2.5                  | 0.17| 63.8 ± 5.1       | 63.4 ± 3.9                  | 0.02|

AP: anterior-posterior; ML: medial-lateral; SI: superior-inferior; T1: early stance; T2: mid stance; T3: late stance d: Cohen’s d

hypoperfusion in healthy young adults. Further investigations are needed to evaluate the monocular imaging system with individuals with chronically impaired balance control. Furthermore, additional investigations are required to evaluate a formal linear relationship between target motion and multi-segmental CoM analysis.

V. CONCLUSION

In this paper, we proposed a novel monocular kinematic imaging system for assessing 3D postural sway during quiet standing following postural transition under varying cerebral perfusion levels. By physically embedding geometric priors, lower and upper trunk kinematic motion was automatically tracked through feature tracking and 3D orientation inverse estimation. Lower trunk sway was estimated by forward projecting a virtual coordinate from the lumbar midway through the body, and transforming the data into an anatomical coordinate system. System accuracy was assessed using a commercial motion capture system and demonstrated sub-millimeter accuracy across different types of sway. Hypocapnia-induced cerebral hypoperfusion showed increases in sway total path length in anterior-posterior motion during early and mid stance, as well as increases in medial-lateral and coronal sway during mid stance. No differences were found during late stance, suggesting recovered cerebral perfusion and neuromuscular control. This system provides cost effective, accurate quantitative postural sway tracking in weakly constrained (non-laboratory) environments, and may be used as a screening tool for cerebrovascular sufficiency and balance control in resource constrained settings.

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