Estimation of 2-D Center of Mass Movement During Trunk Flexion–Extension Movements Using Body Accelerations

Aimee L. Betker, Tony Szturm, and Zahra M. K. Moussavi, *Senior Member, IEEE*

***Abstract*—Motions of the center of body mass (COM) and body segment acceleration signals are commonly used to indicate movement performance and stability during standing activities. The COM trajectory is usually calculated by video motion analysis, which has a time consuming setup and also is not readily available in all clinical settings. In this paper, we present a novel method to estimate the COM trajectory from the upper and lower limb accelerations, based on experimental data. We have modeled the relationships that exist between the 2-D hip and trunk acceleration data with the 2-D COM trajectory in the sagittal plane, during four trunk flexion–extension movement tasks and estimated the COM trajectory based on that model. The model accounted for between 93 ± 9% to 97 ± 3% of the resultant COM trajectory's variability, depending on the task. This corresponded to a range of absolute error between the true and estimated COM trajectories of 0.65 ± 0.62 to 1.07 ± 1.13 cm. The advantage of this model compared to our previous work on COM trajectory estimation is that it does not require any calibration and provides a reasonably accurate estimation of the COM trajectory, which can be used to study human balance performance in any clinical setting.**

***Index Terms*—Body acceleration, center of body mass (COM), modeling, standing balance, trunk flexion–extension movement.**

I. Introduction

BALANCE is a functional term, which involves the dynamic stability of multiple body segments. It is commonly defined as the ability to maintain and control the position and motion of the total center of body mass (COM) relative to the base of support [1]. Hence, the analysis of the COM trajectory is often used to index balance performance during many functionally-relevant standing and walking tasks. Clinically, this can be applied to neuromuscular disorders or injuries affecting balance and mobility injuries, for example, acquired brain injuries, spinal cord injuries, cerebral palsy, peripheral vestibular disorders, and older people with mobility limitations. As the COM trajectory is dependent on the segment lengths and orientations in space (i.e., endpoint coordinates of each segment), it accounts for whole body movement performance. Thus, it is commonly used for analyzing balance and stability. Standing balance can be described by inverted pendulum dynamics. In this paper, we are interested in trunk flexion–extension movements at the hips and concurrent backward–forward rotation of the shank segment over the foot (base of support) at the ankle. Forward trunk bending is a common voluntary movement observed in many daily activities. A polite bow or hip strategy balance reaction (two-segment trunk-shank rotation) occurs in response to many sudden body disturbances [2], [3].

The COM trajectory is generally calculated using a video-based motion analysis system, via motion trajectories of markers placed on each body segment and anthropometric models. These motion systems are not easily portable, can be time consuming, and can be costly, rendering them impractical for use by the average clinician in daily practice. To overcome these limitations, various other methods have been employed to obtain an approximation of the COM. Custom software was developed in [4], in order to use commercially available video systems to estimate the COM without the use of markers. Instead, easily identifiable locations on the body are tracked over a sequence of video frames. The center of foot pressure (COP) has been used to estimate the COM or center of gravity (COG) trajectory as an alternative to video-based motion systems [1], [5], [6]. Three common methods to obtain the COM from the COP are: a kinematic model used to derive the COM trajectory, low-pass filtering the COP, or double integrating the COP trajectory [5]. Currently, there are even at-home products, such as Nintentdo's Wii Fit, that provide visual feedback of the user's COG. However, this signal would not be appropriate for clinical analysis. Another widely used method of evaluating balance is the analysis of body segment accelerations and inertias [7], [8]. For example, in [9], balance was evaluated during standing tasks using a tri-axial accelerometer. The accelerometer was placed on the back at a position which approximated the location of the COM and the displacement and velocities of the signals were analyzed. In this study, we also used acceleration data to develop a method to estimate the COM trajectory.

In our initial investigation, we fit the COM trajectory to acceleration data during standing and three mathematical models were presented: a neural network, an adaptive fuzzy system, and a genetic sum-of-sines equation [10]. However, the coefficients of these models were tuned through a calibration process, which relied on experimental data. In other words, the models were derived through training with a specific set of experimental acceleration data and hence, could be dependent on the data sets used.

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A. L. Betker and Z. M. K. Moussavi are with the Department of Electrical and Computer Engineering, University of Manitoba, Winnipeg, MB R3T 5V6 Canada (e-mail: abetker@ieee.org; mousavi@ee.umanitoba.ca).

T. Szturm is with the School of Medical Rehabilitation, University of Manitoba, Winnipeg, MB R3T 5V6 CANADA (e-mail: ptsturm@cc.umanitoba.ca).

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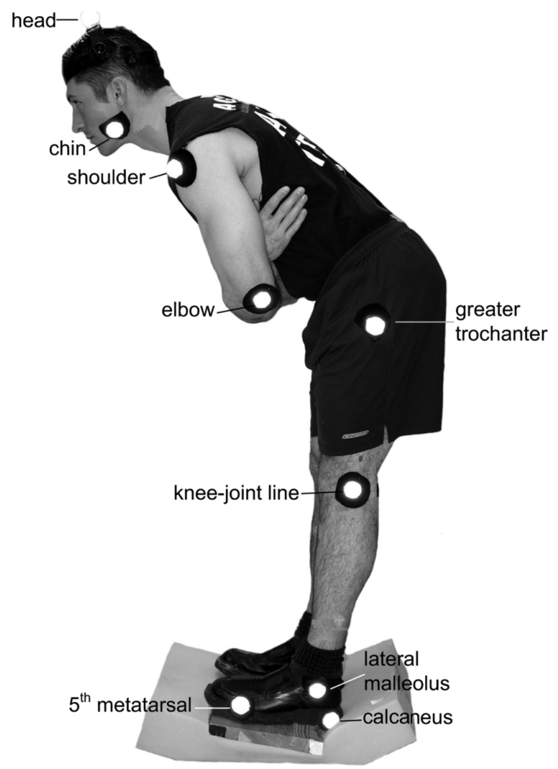

Fig. 1. Experimental setup, indicating the video motion system's marker placements, the foam and board surface the subject stands on, and the placement of the subject's arms during the movement.

Thus, that model could not replace COM trajectory estimation derived from video-based motion systems, as motion system data were required during the calibration stage. Recently, we developed a calibration free model to estimate the COM trajectory during walking [11]. This motivated us to revisit our initial calibration-dependent model. Hence, in this study, a new calibration-free model was developed for trunk flexion–extension movements. The following sections elaborate on the developed model and its use in studying human balance performance.

II. Methodology

A. Subjects

Twelve healthy subjects (four females) aged 30 $\pm$ 7.1, of height 171.3 $\pm$ 9.6 cm and weighing 68.8 $\pm$ 14.8 kg, with no history of postural or balance problems, volunteered to participate. Ethics approval was granted prior to recruiting subjects by The University of Manitoba, Faculty of Medicine, Ethics Research Board. All subjects gave their informed consent and were briefed about the tasks and instrumentations before the experiments.

B. Experimental Setup and Protocol

A diagram of the system setup and video motion analysis marker placement is given in Fig. 1. The data from our initial investigation was revisited; a full description of the experimental setup and protocol can be found in [10]. Note that in the current study, the accelerometers data were not used; instead, motion markers were double differentiated to obtain accelerations in the vertical and anterior–posterior (AP) directions. The reason for using only motion data was that we wanted acceleration data in a direction that the old dual-axis accelerometers were not oriented for. In the future, studies could be done using accelerometers. The subjects stood with their feet apart at their preferred normal position and kept their arms crossed in front of their chest (Fig. 1). Four test conditions were performed, where the subjects were asked to produce movement in a cyclical fashion, involving flexion and extension of the upper body, head, arms, and trunk, with the knee held in extension, in time with the beat of a metronome: 1) subjects stood on a firm fixed surface with eyes open; 2) subjects stood on a firm fixed surface with eyes closed; 3) subjects stood on a sponge surface with eyes open; and 4) subjects stood on a sponge surface with eyes closed. The two-segment movement was performed in the AP direction at a frequency of approximately 0.67 (2/3) Hz. The duration of the trials was 25 s, with a 2 min rest period between the trials.

The AP, vertical (VT), and resultant (sagital plane) COM trajectories were obtained using the Peak 2-D Motion Analysis System (Vicon Peak, Centennial, CO) [10], [12]. The signals were sampled at 60 frames per second (the maximum sampling rate of the system) and then filtered using a fourth-order low-pass Butterworth filter, with a cutoff frequency of 5 Hz, prior to digitization. The first 10 s of data was then digitized using the Peak 2-D Video Motion Analysis System. This data was used to validate the results of the COM trajectory estimation techniques. Acceleration signals in the AP and VT directions were obtained for the hip and trunk segments through double differentiation of the position data for the greater trochanter and shoulder markers, respectively. As the movements were paced at 0.67 Hz, the acquired acceleration signals were filtered at 1.5 Hz in order to sufficiently smooth the signal and differentiation errors, while satisfying the Nyquist–Shannon theorem. Note that while this cutoff frequency may cause loss of some acceleration data, we are not interested in analyzing the acceleration signals themselves, but rather we are manipulating them to estimate the COM trajectory.

C. Data Conditioning

In total, 12 data sets were collected per test condition. However, the digitized COM trajectory for one trial on the firm surface with eyes open and one trial on the firm surface with eyes closed were incomplete. The COM is dependent on the endpoint coordinates of each segment (i.e. segment lengths and orientations in space) and the mass center of each segment. These segment lengths and masses are unique for each person and are incorporated into the COM trajectory computation. Hence, the data was divided by the subject's body mass index (BMI), $\mathrm{BMI} = \mathrm{weight}/\mathrm{height}^2\ [\mathrm{kg}/\mathrm{m}^2]$, in order to normalize the data across subjects. The COM trajectories were normalized to zero mean, to normalize for the position of the reference marker between subjects. Signal conditioning was done via a custom written script in Matlab (The MathWorks, Natick, MA).

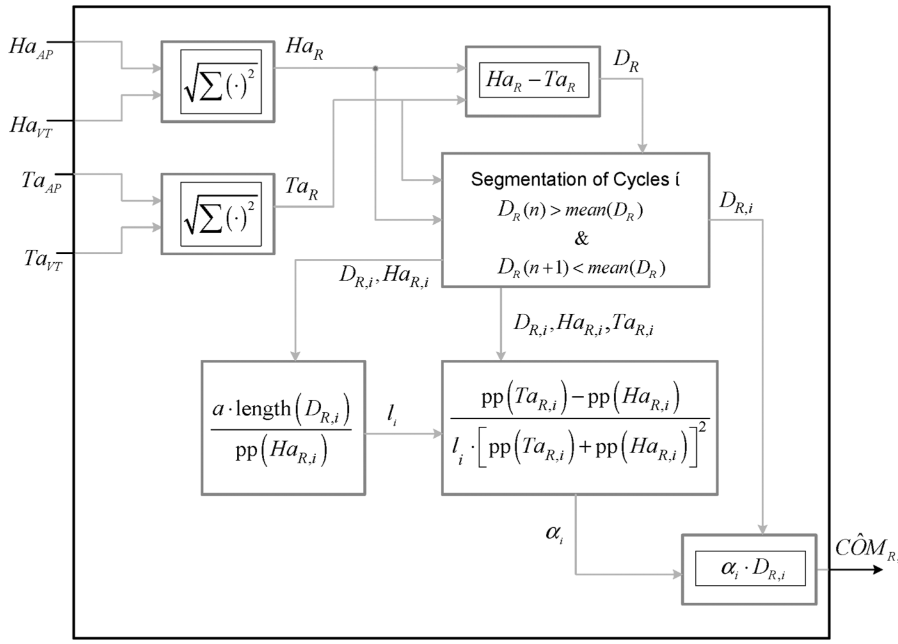

Fig. 2. Block diagram of resultant COM trajectory model. Inputs to the block are the hip AP acceleration $(\mathrm{Ha}_{\mathrm{AP}})$, the hip vertical (VT) acceleration $(\mathrm{Ha}_{\mathrm{VT}})$, the trunk AP acceleration $(\mathrm{Ta}_{\mathrm{AP}})$, and the trunk VT acceleration $(\mathrm{Ta}_{\mathrm{VT}})$. The 2-D estimated resultant COM trajectory for each cycle of movement $(\hat{\mathrm{COM}}_{\mathrm{R,i}})$ is then determined.

III. COM Trajectory Approximation

A. 2-D Resultant COM Trajectory Model

As mentioned, our initial investigation fit the COM trajectory to acceleration data using three different methods: a neural network, an adaptive fuzzy system, and a genetic sum-of-sines equation [10]. Each of these methods presents a generic system with unknown coefficients that are calibrated to a specific data set through training [10]. Hence, the validity of these models can be dependent on the data set used to train and validate the model. Revisiting the data from [10], it is desired to create a new model in which the coefficients are not learned through a training process; instead, the model coefficients will be based on the properties of the data itself. Hence, no calibration process is required.

The resultant 2-D COM trajectory, $\mathbf{COM}_R$, accounts for the overall COM motion in the sagittal plane and the coupling that occurs between the AP and VT movements. The $\mathbf{COM}_R$ obtained from the Peak system is calculated according to

$$\mathbf{COM}_R = \sqrt{\mathbf{COM}_{\mathrm{AP}}^2 + \mathbf{COM}_{\mathrm{VT}}^2}. \tag{1}$$

In order to estimate $\mathbf{COM}_R$, the relationships between the acceleration signals and $\mathbf{COM}_R$ were investigated. During the trunk flexion–extension movements, the body can be approximated as a dual-segment inverted pendulum, with the trunk as one segment and the lower limbs as the second. The upper body muscles are contracted causing movement at the hip in order to maintain balance. In this study, the hip and trunk accelerations were obtained through double differentiation of the greater trochanter and shoulder marker trajectories, respectively. The movement of the lower limb segment is in phase with the resultant COM trajectory and can be represented by the resultant sagittal hip acceleration $\mathbf{Ha}_R = \sqrt{\mathbf{Ha}_{\mathrm{AP}}^2 + \mathbf{Ha}_{\mathrm{VT}}^2}$, where $\mathbf{Ha}_{\mathrm{AP}}$ and $\mathbf{Ha}_{\mathrm{VT}}$ are the hip accelerations in the AP and VT directions, respectively. Conversely, the movement of the trunk segment is out of phase and can be represented by the resultant sagittal trunk acceleration $\mathbf{Ta}_R = \sqrt{\mathbf{Ta}_{\mathrm{AP}}^2 + \mathbf{Ta}_{\mathrm{VT}}^2}$, where $\mathbf{Ta}_{\mathrm{AP}}$ and $\mathbf{Ta}_{\mathrm{VT}}$ are the shoulder accelerations in the AP and VT directions, respectively. Thus, to characterize the overall movement, we investigated the signal represented by the difference between the two segments' overall movements

$$\mathbf{D}_R = \mathbf{Ha}_R - \mathbf{Ta}_R. \tag{2}$$

The signal $\mathbf{D}_R$ provided the basic signal from which the resultant COM trajectory could be estimated. Properties of the acceleration signals, such as the standard deviation and amplitude range, were used to appropriately scale $\mathbf{D}_R$, i.e., to scale the input amplitude to the output amplitude. Thus, no calibration is required for the model, i.e., no parameters of the model were fit to specific data, rather, the model was fit to properties of the signals consistent across all subjects. The equation developed for the resultant COM trajectory is described as follows and in Fig. 2.

For each trial, the cycles of the produced cyclical movement were sequestered using the negative mean crossing of $\mathbf{D}_R$; each segment i is represented by $\mathbf{D}_{R,i}$. Subjects had between 5–6 cycles in the 10 s time period. A scale factor α was calculated for and applied to each $\mathbf{D}_{R,i}$; it was calculated as

$$\alpha_i = \frac{\mathrm{pp}(\mathbf{Ta}_{R,i}) - \mathrm{pp}(\mathbf{Ha}_{R,i})}{l_i \cdot [\mathrm{pp}(\mathbf{Ta}_{R,i}) + \mathrm{pp}(\mathbf{Ha}_{R,i})]^2} \tag{3}$$

where $\mathrm{pp}(\cdot)$ indicates the peak–peak amplitude of a given signal, the subscript i indicates the given cycle of the movement, and l is a factor a of the cycle duration (in seconds) compared to the overall hip movement amplitude

$$l_i = \frac{a \cdot \mathrm{length}(\mathbf{D}_{R,i})}{\mathrm{pp}(\mathbf{Ha}_{R,i})}. \tag{4}$$

The scale factor was determined empirically by investigating how the parameter values changed with a change in the overall amplitude of the target signal. Thus, the estimated resultant COM trajectory, $\hat{\mathbf{COM}}_R$, is given by

$$\hat{\mathbf{COM}}_{R,i} = \alpha_i \cdot \mathbf{D}_{R,i}. \tag{5}$$

B. Outcome Measures

Model Performance: For each test surface, the following outcome measures were calculated: 1) the correlation coefficient (CC) R between the actual ($\mathbf{COM}_R$) and estimated ($\hat{\mathbf{COM}}_R$) resultant COM trajectories; 2) the coefficient of determination (CD) between the $\mathbf{COM}_R$ and $\hat{\mathbf{COM}}_R$, calculated as R^2, representing the amount of variability the model accounts for; 3) the mean squared error (mse) between $\mathbf{COM}_R$ and $\hat{\mathbf{COM}}_R$, $[\mathrm{cm}^2/\mathrm{BMI}^2]$, according to

$$\mathrm{mse} = E\left[(\hat{\mathbf{COM}}_R - \mathbf{COM}_R)^2\right] \tag{6}$$

and 4) the mean absolute error between $\mathbf{COM}_R$ and $\hat{\mathbf{COM}}_R$ in centimeters, $E[(\hat{\mathbf{COM}}_R - \mathbf{COM}_R)]$.

Balance Cost Indicators: The following measurements were calculated for the actual $\mathbf{COM}_R$ (derived by the motion analysis system) and the estimated $\hat{\mathbf{COM}}_R$, and served to quantify the subject's performance: 1) *signal peak-to-peak amplitudes*, calculated across all subjects [cm/BMI] [13]; 2) *signal phase lag*, calculated across all subjects using the procedure described in [14], [15], in milliseconds. The phase lag equivalent to movement periodicity was calculated from the unbiased autocorrelation sequence, as the time index representing the first dominant peak [15]; and 3) *signal variability*: a signal representing the mean cycle trajectory for each signal was calculated across all subjects. The correlation coefficient was then calculated between each cycle and the mean trajectory.

C. Validation

The proposed model was validated from two aspects (refer to Section III-B): 1) the actual and estimated resultant COM trajectories were compared in terms of the mean squared error between the two curves; and 2) the outcome measures derived from the actual and estimated COM trajectories were compared. In all statistical tests, the means were compared using a one-way analysis of variance (ANOVA), with the significance value set as $p = 0.05$. The independent variables were the trajectory type: actual or estimated. The dependent variables were each of the balance cost indicators. The analysis was performed in Matlab (The MathWorks).

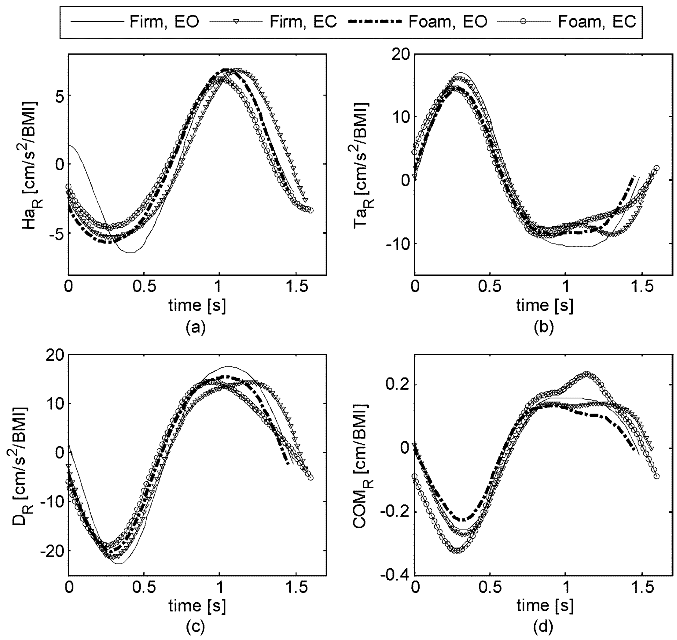

Fig. 3. Model inputs and actual resultant COM, for the firm surface, eyes open (EO) (−), firm surface, eyes closed (EC) (▽), foam surface, EO (−.−) and foam surface, EC (−o−). (a) Resultant hip acceleration ($\mathrm{Ha_R}$). (b) Resultant trunk acceleration ($\mathrm{Ta_R}$). (c) Hip acceleration minus trunk acceleration ($\mathrm{D_R}$). (d) Resultant center of mass ($\mathrm{COM_R}$). Note that all signals are normalized by the subject's BMI $[\mathrm{kg/m^2}]$.

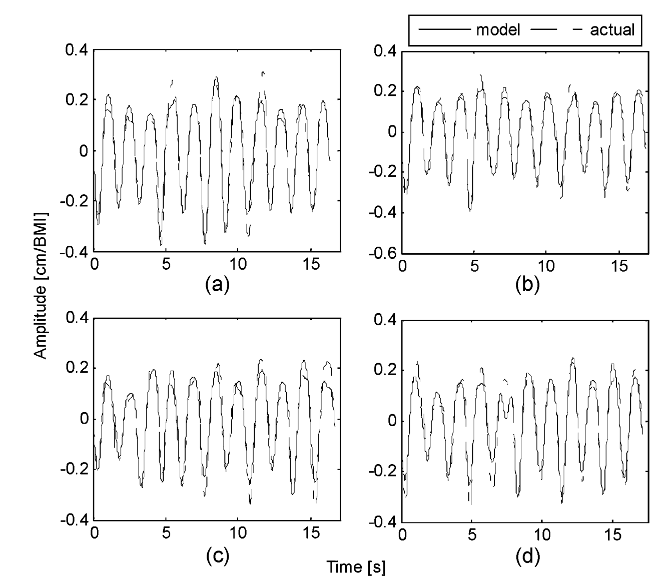

Fig. 4. Model results: modeled (−) and true (−−) normalized resultant COM trajectory for: (a) the firm surface with eyes open; (b) the firm surface with eyes closed; (c) the foam surface with eyes open; and (d) the foam surface with eyes closed. One cycle is shown for each of the subjects. Each cycle is shown as a function of time, however note that the time is not continuous across cycles. All signals are normalized by the subject's BMI $[\mathrm{kg/m^2}]$.

IV. RESULTS

The system inputs and the estimated resultant COM trajectory (system output) of a typical subject for the normal and foam surfaces are shown in Fig. 3. The results for one movement cycle of each subject, for each trial, are shown in Fig. 4. Results for a cycle of movement for each subject are given in order to demonstrate the similarity of the model output across different subjects.

TABLE I
COMPARISON OF MODEL DERIVED $\hat{\mathbf{COM}}_R$ AND RECORDED $\mathbf{COM}_R$: CORRELATION COEFFICIENT, COEFFICIENT OF DETERMINATION, AND THE ERROR. $\mathbf{COM}_R$ RANGE IS GIVEN FOR COMPARISON

Trial	Correlation Coefficient (mean ± SD)	Coefficient of Determination (mean ± SD)	MSE [cm^2/BMI^2] (mean ± SD)	Absolute Error [cm] (mean ± SD)	COM_R Range [cm] (mean ± SD)
Firm Surface, Eyes Open	0.98±0.04	0.96±0.07	0.0035±0.0086	0.78±0.82	7.62 ± 3.43
Firm Surface, Eyes Closed	0.99±0.01	0.97±0.03	0.0015±0.0024	0.65±0.62	7.84 ± 2.75
Foam Surface, Eyes Open	0.98±0.02	0.96±0.04	0.0018±0.0020	0.76±0.65	6.99 ± 1.91
Foam Surface, Eyes Closed	0.96±0.05	0.93±0.09	0.0043±0.0080	1.07±1.13	12.28 ± 5.38

TABLE II
OUTCOME MEASURES (ACROSS ALL SUBJECTS) FOR $\hat{\mathbf{COM}}_R$ AND $\mathbf{COM}_R$: PEAK-TO-PEAK AMPLITUDE, PHASE LAG, AND CORRELATION COEFFICIENT

Surface Condition	Signal	Peak-to-peak Amplitude [cm/BMI] (mean ± SD)	Phase Lag [ms] (mean ± SD)	Correlation Coefficient (mean ± SD)
Firm Surface, Eyes Open	$\hat{\mathbf{COM}}_R$	0.46±0.10	92.7±3.2	0.97±0.02
	$\mathbf{COM}_R$	0.47±0.12	93.3±2.7	0.97±0.05
	Pr > F (F)	0.1078 (2.62)	0.6712 (0.19)	0.3677 (0.82)
Firm Surface, Eyes Closed	$\hat{\mathbf{COM}}_R$	0.44±0.06	93.5±2.5	0.98±0.02
	$\mathbf{COM}_R$	0.47±0.10	93.6±2.4	0.97±0.03
	Pr > F (F)	0.12 (2.45)	0.9324 (0.01)	0.2462 (1.36)
Foam Surface, Eyes Open	$\hat{\mathbf{COM}}_R$	0.41±0.10	92.3±3.4	0.91±0.24
	$\mathbf{COM}_R$	0.42±0.11	92.6±3.4	0.90±0.19
	Pr > F (F)	0.9412 (0.01)	0.9595 (0.03)	0.8137 (0.06)
Foam Surface, Eyes Closed	$\hat{\mathbf{COM}}_R$	0.40±0.13	91.8±4.5	0.95±0.10
	$\mathbf{COM}_R$	0.42±0.13	100.4±24.4	0.96±0.07
	Pr > F (F)	0.353 (0.87)	0.2431 (1.44)	0.7428 (0.12)

A. *Model Performance*

In all parts of the COM trajectory estimation, the correlation coefficients with respect to the actual COM trajectory were quite high ($\geq$0.96). Table I presents the summary, as well as the error defined in (5) and standard deviation (SD). The results show a very high correlation between the actual and estimated COM trajectories. In terms of absolute difference in centimeters, the errors were 0.78 ± 0.82 cm, 0.65 ± 0.62 cm, 0.76 ± 0.65 cm, and 1.07 ± 1.13 cm for the firm surface with eyes open, firm surface with eyes close, foam surface with eyes open, and foam surface with eyes closed trials, respectively.

B. *Balance Cost Indicators*

The mean and SD for each outcome measure (peak-to-peak amplitudes, phase lags, and correlation coefficient) for $\mathbf{COM}_R$, and $\hat{\mathbf{COM}}_R$, for each subject and trial, are given in Table II. Congruent with the results presented in Table I, the estimated COM trajectory resulted in balance cost indicators similar to those calculated from the actual COM trajectory and no significant differences were observed.

V. DISCUSSION AND CONCLUSION

Drawing on the novelty of our calibration-free model developed for COM trajectory estimation during walking, we revisited the data we acquired when subjects performed voluntary cyclical trunk flexion–extension movements at the hip [10]. The relationship between acceleration and the 2-D resultant COM trajectory in the sagittal plane was modeled. This resultant COM trajectory accounts for the overall COM motion and the coupling that occurs between each movement direction in the sagittal plane. The trunk flexion–extension movement was performed on two different surfaces (firm and foam), with eyes open and closed. The flexion–extension movements were generally rhythmic and cyclical. When the participant's eyes were closed and/or they were standing on the foam surface, the information provided by one or more sensory inputs is eliminated or distorted. Hence, these conditions became more challenging. This in turn produces deviations in the segment accelerations and resulting COM movements (Fig. 3) [2], [3].

The model accurately accounted for the variability in the $\mathbf{COM}_R$ signal, with coefficients of determination values ranging between 93 $\pm$ 9% to 97 $\pm$ 3% for the four tasks. This corresponded to a range of absolute error between the actual and estimated resultant COM trajectories of 0.65 $\pm$ 0.62 to 1.07 $\pm$ 1.13 cm, which is relatively small in comparison with the overall $\mathbf{COM}_R$ movement range (Table I) and therefore does not indicate large deviations from the true trajectory. Hence, the model with inputs from two miniature accelerometers could estimate the COM trajectory without the need for calibration for every subject or the need for coordination of data from all body segments. In other words, the model does not depend on any specific set of training data, nor does it need to be adjusted for a specific subject. Accelerometers also have the benefit of decreased cost when compared to video motion analysis systems and pressure mats or force plates, making them easily available to a wide range of clinics. In [9], the acceleration signals alone were used to analyze stability, rather than having to calculate the COM. One drawback of the method in [9] is some of the stability parameters require the projection of the signal to the floor. In the case where a compliant or irregular surface is used, errors would be introduced. Conversely, our model can accurately determine the balance cost indicators even when a compliant surface is used.

For each of the four tasks, the estimated COM trajectory closely followed the actual COM trajectory. As the tasks became more difficult, there were deviations in the signal due to the uncertainty added to the signal via the removal or distortion of visual and/or somatosensory information. In these cases, we anticipated an increase in the absolute error. However, similar to the findings in [8], the absolute error for the fixed surface, eyes closed and foam surface, eyes open tasks were lower than the absolute error for the fixed surface, eyes open task. This is most likely due to the fact that the subjects became more cautious as the task difficulty increased as two sensory systems were still available, the subjects were able to compensate through slowing down. Conversely, for the foam surface, eyes closed task, the distortion or elimination of two sensory modalities outweighed the benefits of slowing down.

Model validation was also done through the calculation of balance cost indicators (Table II). For all tasks, no significant differences $(p < 0.05)$ were observed in the peak-to-peak amplitude, the phase lag between, or the variability between $\hat{\mathbf{COM}}_R$ and $\mathbf{COM}_R$. Thus, the derived relationship could accurately represent the amplitude excursions and phase information for $\mathbf{COM}_R$.

In addition to modeling error, other sources of error exist for the given setup: 1) the target signal $(\mathbf{COM}_R)$ was acquired using the Vicon camera system, which requires placement of reflective markers on segment endpoints. Hence, an inconsistent placement of these eight markers (refer to Fig. 1) would contribute to the overall error, as our target signal used for model validation could be incorrect; 2) when filtering the signals, the cutoff frequencies were low, but sufficient to capture the movements we recorded. However, if movements outside the frequency range occurred, the system could potentially lose pertinent information, resulting in inaccurate modeling of the signal; and 3) the inverted pendulum model assumes the trunk and lower limb segments are rigid. However, a human induced variation of the movement, e.g., a bending of the knees or back, could produce larger signal variations that our model could not estimate.

In summary, we developed a model to estimate the 2-D resultant COM trajectory relative to space in the sagittal plane, and used a foam surface to uncouple the center of foot pressure from the COM movement. Furthermore, the model gives an estimation of the COM motions which are independent of calibration for every subject. The models accounted for between 93 $\pm$ 9% to 97 $\pm$ 3% of the $\mathbf{COM}_R$ variability for the four tasks, corresponding to a range of absolute error between the true and actual $\mathbf{COM}_R$ of 0.65 $\pm$ 0.62 to 1.07 $\pm$ 1.13 cm. In addition, the balance cost indicators of Section III-B were accurate for all four tasks. The motivation for this research was the development of a minimal system and test protocol to provide stability information in a simple manner, using a variety of test surfaces. The tests are geared towards people with balance impairments affecting tasks related to basic and instrumental activities of daily living. The model shows promising results for being incorporated into such a test protocol. Future work includes testing of the developed model using accelerometers placed at the hip and shoulder, and development of a model for estimating the COM trajectory in three dimensions.

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Aimee L. Betker received the B.Sc., M.Sc., and Ph.D. degrees in computer and electrical engineering, from the University of Manitoba, Winnipeg, MB, Canada, in 2002, 2004, and 2008, respectively.

Her current research interests include the development a simple tool and test protocol that will permit reliable evaluation of balance and movement interaction on different support surfaces, for a hierarchy of increasing dynamics and functional tasks.

Dr. Betker received a Manitoba Health Research Council (MHRC) Award, in 2004, and a Natural Sciences and Engineering Research Council (NSERC) Award for work on her Ph.D. dissertation project, in 2006.

Tony Szturm was born in Thunder Bay, ON, Canada, in 1995. He received the B.Sc. degree in biology and the B.Sc. degree in physical therapy from University of Western Ontario, London, ON, Canada, in 1980, and the Ph.D. degree in neurophysiology from the University of Manitoba, Winnipeg, MB, Canada, in 1988.

His research focus is in the field of human postural control in health and disease. He worked as a Physiotherapist from 1980 to 1984, at Health Sciences Centre, Winnipeg, MB, Canada. Presently, he is an Associate Professor, School of Medical Rehabilitation, University of Manitoba, and Adjunct Professor, Department of Electrical and Computer Engineering and Department of Physiology.

Dr. Szturm is a member of the College of Physiotherapy of Manitoba, Canadian Physiotherapy Association, and International Society of Posture and Gait.

Zahra M. K. Moussavi (M’98) received the B.Sc. degree from Sharif University of Technology, Tehran, Iran, in 1987, the M.Sc. degree from the University of Calgary, Calgary, AB, Canada, in 1993, and the Ph.D. degree from University of Manitoba, Winnipeg, MB, Canada, in 1997, all in electrical engineering.

Having done her postdoctoral fellow at Johns Hopkins University, Baltimore, MD, in 1999, she joined the University of Manitoba, Department of Electrical and Computer Engineering as a faculty member, where she is currently an Associate Professor and Canada Research Chair on Biomedical Engineering. She is also an Adjunct Professor at the TRLabs of Winnipeg. Her current research includes respiratory and swallowing sound analysis, postural control and balance, rehabilitation, and study of human temporal and spatial perceptions.