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Center of Mass Approximation During Walking as a Function of Trunk and Swing Leg Acceleration

A. L. Betker[1], T. Szturm[2] and Z. Moussavi[1]

[1]Department of Electrical Engineering, University of Manitoba, Manitoba, Canada

[2]Department of Rehabilitation, University of Manitoba, Manitoba, Canada

Email: abetker@ieee.org, ptsturm@ms.umanitoba.ca, mousavi@ee.umanitoba.ca

Abstract—**The 3D center of body mass (COM) trajectory provides us with a measure of movement performance and level of stability while walking. As an alternative to directly calculating the COM from motion trajectories and anthropometric data, we propose developing models to estimate the COM trajectory during walking on irregular surfaces. The inputs to the models were acquired via two accelerometers, one representing the trunk segment placed on T2 and the second representing the swing leg placed on the lateral malleolus. The subjects walked on a fixed surface and encountered an uneven, irregular surface, causing instability in the balance system. The results were encouraging, providing an estimate of the COM trajectory with a low error of 4.17 ± 1.94 %. The reasonable accuracy, portability, ease of use and low cost (compared with video motion analysis systems) of the accelerometers increases the range of clinical applications of the proposed method.**

Keywords— **accelerometer, center of body mass, genetic algorithm, modeling**

I. Introduction

Poor balance, fear of falling, fall injuries and mobility limitations are serious problems facing many older adults and people with neurological and musculo-skeletal disorders [1]. In this research, we are concerned with developing objective clinical tools for predicting fall risk and evaluating performance of important tasks related to community ambulation and instrumental activities of daily living. The center of body mass (COM) trajectory provides us with a measure of movement performance and level of stability; during locomotion, while maintaining a constant forward COM progression, the medial-lateral (ML) motion must be restrained within the mobile single support base. This becomes increasingly difficult when irregular, unpredictable and unstable surfaces are encountered [2]. Walking outdoors on varied terrains is a high risk task for many older adults and people affected with balance impairments.

As an alternative to directly calculating the COM from motion trajectories and anthropometric models, without the attempt to model the biomechanics of the system, we propose the estimation of the COM trajectory using accelerometer data. This will allow for an inexpensive and portable alternative method for obtaining the COM trajectory that can be applied to daily clinical practice.

In a previous study, we successfully modeled the COM trajectory in the sagittal plane during standing tasks [3]. The subjects induced voluntary sinusoidal movement, emulating the hip strategy. Four trials were performed in attempt to eliminate and distort sensory information: 1) eyes open, fixed surface; 2) eyes closed, fixed surface; 3) eyes open, foam pad surface; and 4) eyes closed, foam pad surface. A comparison of three different modeling techniques was given: a feedforward backpropagation neural network, an adaptive fuzzy system and a hybrid genetic algorithm sum-of-sines model. The results were encouraging; the genetic sum-of-sines model developed provided an estimate of the resultant COM trajectory with an average relative error (RE), across all four trials, of only 9.4 ± 0.9 %.

In order for the test to incorporate a wider range of movements and dynamics, COM estimation during walking tasks should be included. In [4], the ML COM component was estimated using a 3-layer artificial neural network, during walking on firm surfaces and while stepping over obstacles. The model inputs were temporal-distance parameters and EMG recordings. The model estimated the ML COM displacement with correlation coefficient values between 0.73 to 0.89.

Continuing our previous study, we attempt to use a minimal number of inputs to estimate the anterior-posterior (AP), ML and vertical (VT) COM components, while walking on a fixed surface and encountering an irregular surface. We propose to use data from trunk and swing leg accelerations. The following sections elaborate on the developed models, their results and their use for COM estimation as an alternative to computing the COM from the recorded motion.

II. Methodology

Fifteen healthy subjects (8 females) aged 28.9 ± 4.5, of height 170.1 ± 11.6 cm, weighing 67.3 ± 16.7 kg, with no history of postural problems, volunteered to participate in this study and gave informed consent. Ethics approval was granted prior to recruiting subjects by The University of Manitoba, Faculty of Medicine, Ethics Committee.

A. *Experimental Setup*

A diagram of the 7 m long walkway, consisting of a fixed floor surface, an irregular doweling surface and a firm surface, is given in Fig. 1. The length of the fixed floor surface was selected such that two steps could be taken prior to a single right foot step on the doweling surface. The

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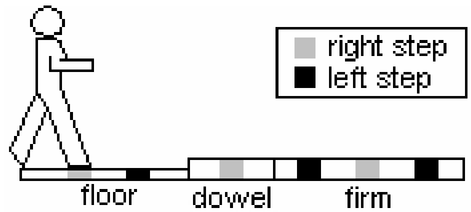

Fig. 1. Walkway diagram, indicating surface type and step location.

doweling surface measured 1.2 m x 0.8 m (W x L) and had pieces of doweling 2.4 cm in diameter of length 2.5 cm spaced in an grid 5.6 cm apart; this surface was used to emulate environmental uncertainty.

Two tri-axial accelerometers (Biometrics S2-10G-MF) were affixed to the subject using double-sided tape: 1) representing the trunk segment placed on vertebra T2; and 2) representing the swing leg, placed on the lateral malleolus. The 3D sway was recorded by each accelerometer using the Biometrics DataLOG II, at 1080 Hz. Kinematic data was obtained using the VICON 460 video motion analysis system, with six digital video cameras. The data was sampled at 120 Hz. The reflective markers were placed on the end points of each segment and the coordinates were captured via VICON's Plug-in Gait software, according to the Helen Hayes Model [5]. From the coordinate data, the 3D COM position was computed.

B. Protocol

The subjects stood on a fixed floor surface at the beginning of the walkway, with their arms bent 90 degrees at their sides to ensure VICON marker visibility (Fig. 1). The subjects began walking at a comfortable pace beginning with the right foot, with the second right footfall landing on the doweling surface. Foot contact with the irregular surface produces an unpredictable reaction force acting on the body, causing a disturbance to the planned segmental trajectories; this sudden balance disturbance requires a feedback compensatory reaction. Four trials were performed on this surface for each subject, with both normal and other compliant surface trials taking place in between. Each walk trial was separated by a one minute rest period.

C. Data Conditioning

The total number of data sets collected for the doweling surface was 60; four per subject. The accelerometers' data were downsampled to a rate of 120 Hz; i.e., to that of the kinematic data. The data were normalized to lie between (0,1). Next, the right step on the doweling surface was extracted from the data, by applying a threshold to the vertical trajectory of the ankle marker, in order to determine the on/off times of the swing leg. This was done via a custom written script in Matlab. Thus, the data for the duration of the single-stance phase for the right step on the surface was obtained.

D. Model Design and Parameters

The models used for estimating each component of the COM trajectory were selected by plotting the COM components against the swing leg and trunk accelerations and testing different models for a best fit.

The AP component of the normalized COM trajectory was estimated via a Gaussian relationship with the AP component of the trunk acceleration

$$\mathbf{A}_{TAP} = \exp\left[-\left(\mathbf{C\hat{O}M}_{AP} - b_{AP}\right)^2 \Big/ 2a_{AP}\right]. \qquad (1)$$

Solving for $C\hat{O}M_{AP}$

$$\mathbf{C\hat{O}M}_{AP}(\mathbf{A}_{TAP}) = \pm\sqrt{-2a_{AP}\log(\mathbf{A}_{TAP})} + b_{AP}, \qquad (2)$$

where $C\hat{O}M_{AP}$ is the estimated AP COM trajectory, A_{TAP} is the AP component of the trunk acceleration, a_{AP} is the half width of the Gaussian curve and b_{AP} is the center variable. The values for a_{AP} and b_{AP} will be estimated by the genetic algorithm that is explained later in this section.

The ML component of the normalized COM trajectory was estimated via a linear combination of two models: 1) a Gaussian relationship with the ML component of the swing leg acceleration, similar to (1). Thus, solving for $C\hat{O}M_{ML}$

$$\mathbf{C\hat{O}M}_{ML}(\mathbf{A}_{SML}) = \pm\sqrt{-2a_{ML}\log(\mathbf{A}_{SML})} + b_{SML}, \qquad (3)$$

where $C\hat{O}M_{ML}$ (A_{SML}) is the estimated ML COM trajectory as a function of the ML swing leg acceleration A_{SML}, a_{ML} is the half width of the Gaussian curve and b_{ML} is the center variable. The values for a_{ML} and b_{ML} will be estimated by the genetic algorithm; and 2) a polynomial relationship with the ML trunk acceleration component

$$\mathbf{C\hat{O}M}_{ML}(\mathbf{A}_{TML}) = p_1\mathbf{A}_{TML}^2 + p_2\mathbf{A}_{TML} + p_3, \qquad (4)$$

where $\mathbf{C\hat{O}M}_{ML}$ ($\mathbf{A}_{TML}$) is the estimated ML COM trajectory as a function of the ML trunk acceleration $\mathbf{A}_{TML}$ and p_i, i=1,2,3 are the polynomial coefficients to be estimated by the genetic algorithm. Thus the estimated ML COM component, as a function of $\mathbf{A}_{SML}$ and $\mathbf{A}_{TML}$, is given by

$$\begin{aligned}\mathbf{C\hat{O}M}_{ML}(\mathbf{A}_{SML}, \mathbf{A}_{TML}) &= p_4\mathbf{C\hat{O}M}_{ML}(\mathbf{A}_{SML}) \\ &+ p_5\mathbf{C\hat{O}M}_{ML}(\mathbf{A}_{TML}) + p_6\end{aligned}, \qquad (5)$$

where p_i, i=4,5,6 are the polynomial coefficients to be estimated by the genetic algorithm.

The VT component of the normalized COM trajectory was estimated via a linear relationship with the VT component of the trunk acceleration

$$\mathbf{C\hat{O}M}_{VT}(\mathbf{A}_{TVT}) = p_7\mathbf{A}_{TVT} + p_8, \qquad (6)$$

where $\mathbf{C\hat{O}M}_{VT}$ is the estimated VT COM trajectory, $\mathbf{A}_{TVT}$ is the VT component of the trunk acceleration and p_i, i=7,8 are the polynomial coefficients to be estimated by the genetic algorithm.

The estimated components from each of the models was then combined to form the resultant COM trajectory $\mathbf{C\hat{O}M}_R$ according to

$$\mathbf{C\hat{O}M}_R = \sqrt{\mathbf{C\hat{O}M}_{AP}^2 + \mathbf{C\hat{O}M}_{ML}^2 + \mathbf{C\hat{O}M}_{VT}^2}. \qquad (7)$$

This estimation was then compared to the true resultant COM trajectory.

The model parameters were estimated using a genetic algorithm; a stochastic algorithm employing the theory of evolution to optimize a set of parameters based on an objective function [6]. In this study, the genetic algorithm toolbox (GA Toolbox, [6]) was used along with custom written code in Matlab 6.0 R12 (The MathWorks). Gray code was used to encode the parameters, bounded by [-5,5] for the polynomials and [0,5] for the Gaussian curves, with a precision of 4, requiring 17 bits to encode the parameters. A population of 100 individuals was randomly initialized, with generation gap of 0.9. Training stopped when the number of generations reached the maximum of 100 (determined through trial and error). Increasing the number of generations beyond this value produced either no effect or had a detrimental effect on the system's performance. The mean squared error (MSE) between the actual and estimated COM trajectory was used as the objective function, with probability of successful reproduction of 0.9.

The leave-one-out method was employed for training the models, where data from all but one subject were used to train the model; the left out subject's data was used for testing the ability of the models to generalize new inputs. This procedure was repeated until every subject's data was used for testing. The RE between the true ($\mathbf{COM}$) and estimated ($\hat{\mathbf{COM}}$) resultant COM trajectory components was then calculated as

$$\mathrm{RE} = \left[\left(\hat{\mathbf{COM}} - \mathbf{COM} \right) \big/ \mathbf{COM} \right] \cdot 100\% , \tag{8}$$

Thus, the RE represents how much $\hat{\mathbf{COM}}$ deviated from $\mathbf{COM}$ on average.

III. Results

System inputs and outputs for a typical subject are given in Fig. 2. The results for one trial of each subject when used as test data are given in Figs. 3-6 for the AP, ML, VT and resultant trajectories, respectively. The mean, standard deviation, minimum and maximum RE for each of the COM components and resultant COM trajectory are summarized in Table I. The mean RE for the models were 2.92 ± 3.06 %, 6.79 ± 4.87 %, 2.49 ± 2.68 %, and 4.46 ± 3.66 %, for the AP, ML, VT and resultant trajectories, respectively. Overall, the average RE for the models was 4.17 ± 1.94 %.

In terms of the average peak-peak amplitude ranges of the absolute COM (Table I), the RE for each of the models translates into displacements of 1.61 ± 0.16 cm, 0.19 ± 0.08 cm, 0.14 ± 0.03 cm and 0.95 ± 0.28 cm, for the AP, ML, VT and resultant trajectories, respectively.

IV. Discussion

The COM trajectory during walking on a fixed firm surface is generally rhythmic. When challenging surface conditions are encountered, in which foot contact information and ground reaction forces are distorted and unpredictable, the gait rhythm becomes disrupted. In particular, the doweling surface causes disturbing and temporarily unopposed ground reaction forces, which in turn produces errors in the movement/balance system's predictions.

TABLE I

COM Peak-Peak Amplitude Range and Model Results for Test Data: RE (%) and RE in terms of Range.

COM	Mean RE (% ± SD)	Min. RE (%)	Max. RE (%)	Range (cm ± SD)	Mean RE (cm ± SD)
AP	2.92 ± 3.06	0.59	22.15	55.10 ± 5.16	1.61 ± 0.16
ML	6.79 ± 4.87	1.10	21.64	2.81 ± 1.72	0.19 ± 0.08
VT	2.49 ± 2.68	0.53	16.12	5.46 ± 1.21	0.14 ± 0.03
R	4.46 ± 3.66	1.34	24.25	21.30 ± 7.62	0.95 ± 0.28

The subjects were instructed to walk to the end of the 7 m walkway. The results show that forward progression was maintained; the COM in the AP direction was virtually a straight line. In this case, the Gaussian relationship closely described the AP COM component. In the vertical direction, the linear relationship with the vertical component of the trunk acceleration closely described the VT COM component.

Control of balance in the ML plane becomes more difficult when walking on irregular and compliant surfaces, or when avoiding obstacles. For example, in [7] it was found that during locomotion elderly subjects had a difficult time controlling ML momentum. This results in ML accelerations being more phasic; hence in single support stance, the COM must be accelerated and decelerated quickly. Thus, ML movements are the hardest to perceive and predict; however, it is important to retain the information contained in this signal. This is reflected in the estimation of the ML COM component. There was higher variability in the ML COM signal, leading to higher estimation errors. In order to decrease the error of the ML COM estimation, its relationship with two inputs were linearly combined.

Combining the AP, ML and VT COM components as in (7), the resultant COM trajectory is obtained. In this case,

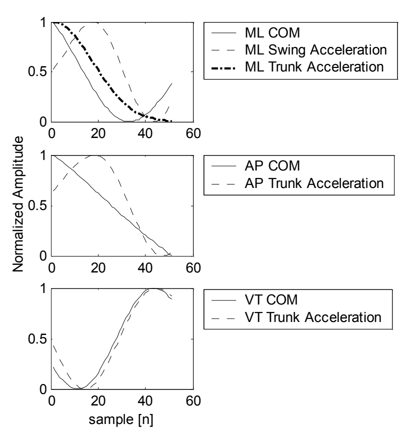

Fig. 2. System inputs and outputs for the ML, AP and VT models.

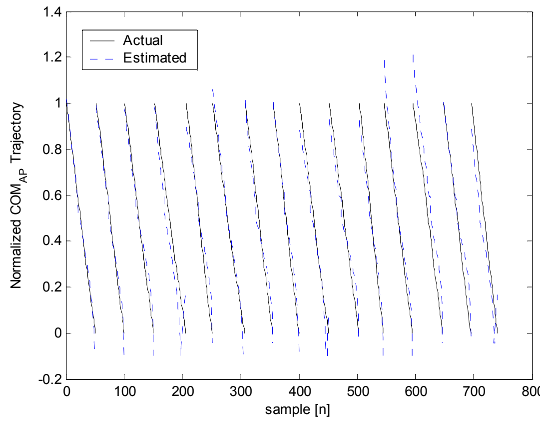

Fig. 3. Actual (-) and estimated (--) normalized AP COM trajectory; 15 steps of test data shown, one per subject.

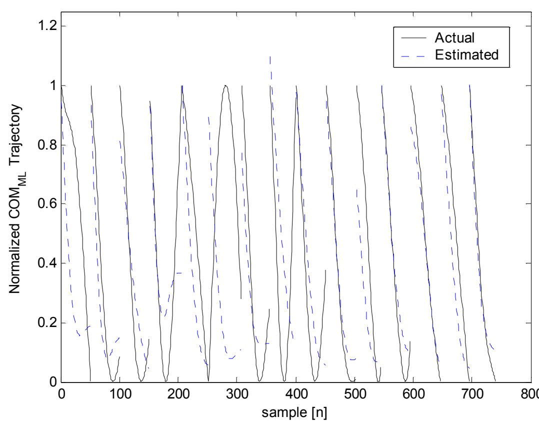

Fig. 4. Actual (-) and estimated (--) normalized ML COM trajectory; 15 steps of test data shown, one per subject.

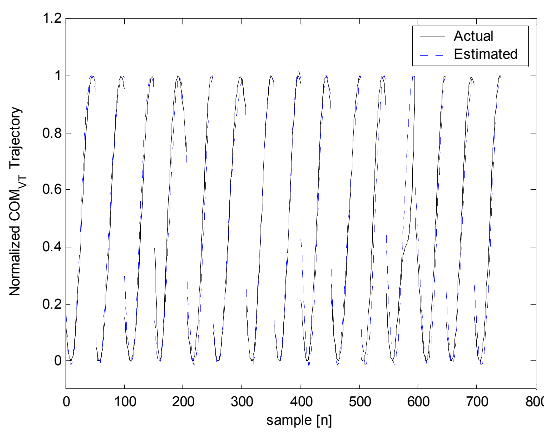

Fig. 5. Actual (-) and estimated (--) normalized VT COM trajectory; 15 steps of test data shown, one per subject.

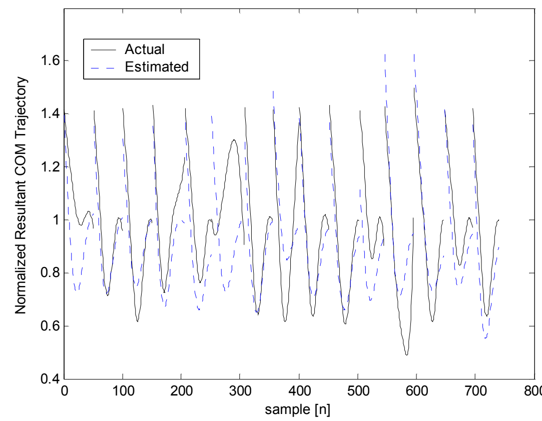

Fig. 6. Actual (-) and estimated (--) normalized resultant COM trajectory; 15 steps of test data shown, one per subject.

the RE was lower than that of the ML COM case, however the information contained in the ML component is still retained.

Therefore, based on the models developed in this study and our previous study [3], a simple tool and test protocol can be designed that will permit reliable evaluation of balance and movement interaction on different support surfaces for a hierarchy of increasing dynamics and functional tasks. The tool will be designed for application to patients with balance impairments, such as diabetics, stroke clients and the elderly, with tasks related to basic and instrumental activities of daily living. Thus far, the tasks include a stationary base of support with the body moving as a single and dual inverted pendulum and walking on firm, compliant and irregular surfaces.

V. CONCLUSION

This research continued the development a minimal assessment protocol that provides the same information as traditional systems and is available for clinical assessment. The 3D COM was estimated, when walking on a firm surface and encountering an irregular doweling surface. The models provided an estimate of the COM trajectory with a low average error of $4.17 \pm 1.94\,\%$. The proposed COM estimation method therefore shows encouraging results for incorporation into the assessment system.

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