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ESTIMATION OF THE CENTER OF BODY MASS DURING FORWARD STEPPING USING BODY ACCELERATION

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Abstract – **The center of body mass (COM) calculation is a key factor in analyzing human postural control. In recent years there have been attempts to estimate the COM by body acceleration during standing. In this study, a parabolic model is used to estimate the COM trajectory during forward stepping, using the body segments' accelerations, which were measured by inexpensive and portable accelerometers placed on the trunk and swing leg. Paced and voluntary forward stepping was performed on different support surfaces and with different speeds of stepping. Forward steps were extracted by analyzing the ankle marker position in vertical direction. The model was calibrated by genetic algorithm and tested on forward stepping data using the leave one out method. The results are encouraging for the use of the proposed model as a mean to estimate the COM trajectory during forward stepping.**

Keywords – **center of body mass, forward stepping, genetic algorithm, accelerometer**

I. INTRODUCTION

Good balance during stepping and walking is important to avoid falls causing injuries. The need for good balance becomes more pronounced when walking outdoors, where unexpected conditions and disturbances, and stumbles, are inevitable. Balance impairment and mobility limitations occur as a result of: a) a singular disorder or condition, such as, stroke, traumatic brain injury or Parkinson disease, b) the contribution of several modest neuromuscular deficits, any one of which alone might not have caused falling. Many factors can contribute to the degradation of our balance system including a decrease in sensory information or the processing of spatial information. Stumbles and falls will occur if the center of body mass (COM) moves outside the base of support, or it has insufficient momentum to re-enter the base of support. This is especially important during stepping where there is a single limb support phase. COM trajectory is often used as a key index of both mobility and balance during stepping and walking.

Although fixed, predictable, level and firm support surfaces are the most common surfaces used for balance and walking assessment, different surface conditions such as compliant or uneven surfaces typical of outdoor terrains should also be taken into account to provide a complete assessment [1-2]. Studies have shown that standing and balancing on a sponge surface is an inexpensive and practical way to emulate the "sway-stabilizing" conditions of the Sensory Organization Test (NeuroCom International Inc.). This clinical test systematically eliminates and distorts visual and somatosensory information in order to increase task demands [3]. A sponge surface is compliant and alters or modifies the ground reaction forces in an unpredictable manner; thus introduces uncertainty to the system. This distortion will cause increased body sway that if not detected and compensated a fall will result.

3D Motion analysis systems required to accurately measure the COM trajectory are expensive and not portable for a routine clinical assessment. On the other hand, accelerometers are inexpensive and portable although they do not provide the COM trajectory. However, a recent study [4] shows that acceleration data can be used for COM estimation. A genetic algorithm sum-of-sines model was introduced to estimate the resultant COM trajectory during standing with the hip strategy, using trunk acceleration [4].

In addition to surface condition, stride velocity is also important in terms of accuracy of foot placement. Before evaluating steady state gait, we sought to examine the model during a single stepping task accelerating to break inertia and then decelerating to overcome any momentum. The momentum involved during a single stepping is lesser when compared to that during steady state gait; however the work load on the stance leg during single support phase and body segments is higher to provide the body with the initial momentum [5].

In the present study we extend the previous results obtained for standing tasks where the base of support is stationary to the stepping task; this involves forward body acceleration and single support phase. A new model was sought in this study for COM estimation using both the trunk and swing leg acceleration data. Stepping was performed on a firm fixed support surface and on a compliant surface (foam pad) at a self-paced and slow stepping speed.

II. METHODOLOGY

Nineteen healthy subjects (aged 26.6 ± 2.85, 9 females) with no history of neurological disorder or postural problems volunteered to participate in this study. Prior to recruiting subjects, ethics approval was granted by Ethics Committee, Faculty of Medicine, the University of Manitoba. All subjects gave informed consent.

A. *Experimental Setup*

A 10 cm thick foam pad No. 1 (dimensions 50.8 × 50.8 cm with a 25% indentation force deflection of 62.64 kg) and foam pad No. 2 (dimensions 50.8 × 50.8 cm with a 25% indentation force deflection of 31.82 kg) were used to emulate the uncertainty of outdoor terrain. A 2 cm thick wooden board (dimensions 25.4 × 40.6 cm) was placed on top of the foam pad to increase the surface area of the subjects' weight so as to minimize compression of the foam pad during stepping especially under the stance leg in swing phase.

A six camera VICON 3D motion analysis system (model 460, Vicon Peak, Centennial, CO, USA) and gait plug-in model software were used to obtain kinematic data. A total of 64 reflective markers were placed on the end points of each body segment. Marker coordinate data was sampled at 120 Hz and filtered using a 4^{th} order Butterworth low-pass filter with a cut-off frequency of 5 Hz.

Two tri-axial miniature (dimensions 2.95 × 1.16 × 1.53 cm) and light (15 g) accelerometers (model S2-10G-MF, Biometrics Ltd., Cwmfelinfach, Gwent, UK) were placed on the T2 Vertebra and lateral malleolus of swing leg to record upper trunk accelerations and swing leg accelerations, respectively. Data were digitized at a 1080 Hz sampling rate, using the VICON 16-bit DAQ. The acceleration signals were filtered by a 4th order Butterworth low-pass filter with cut-off frequency of 100 Hz.

B. *Protocol*

Subjects were instructed to stand with their feet parallel, approximately 10 cm apart on the fixed level firm surface, and take a forward step with their right leg at a self-paced speed and come to a complete stop for five seconds. They then brought their swing leg back to the starting position. During backward stepping, they were allowed to look down to make sure their right foot returned to the correct starting position. Once the subject was set at the correct starting position, s/he was instructed to take another forward step. This process was repeated until 10 forward steps were taken in each trial. A rest period was given before proceeding to the next trial. After 20 normal speed forward steps on the fixed floor surface, the subject was instructed to take 10 slow speed forward steps. These stepping tasks were repeated on each of the two foam pads; however, on the foam pad 1 only normal speed forward stepping trial was performed.

C. *Pre-processing*

The total number of stepping data collected in this study was 133; seven per subject. The trunk and swing accelerometers' data were decimated to a sampling rate of 120 Hz, which was that of the kinematic data. The data were normalized to account for physical differences between the subjects. In few trials, the COM trajectory was incomplete; hence, those trials were excluded from the COM estimation. The ankle marker position in vertical direction was used to detect and extract the forward stepping phase from swing foot lift to heel strike.

D. *Estimation Model*

Forward steps data were extracted from the original COM and acceleration signals. Preliminary investigation of the relationship between the acceleration signals and the corresponded COM suggested a parabolic model as the best fit. For a parabola opening to the right with vertex at (X_0, COM_0), the equation in Cartesian coordinate is

$$\left(COM - COM_0\right)^2 = a\left(X - X_0\right), \tag{1}$$

where X is the independent variable and a is the latus rectum which is the chord through a focus parallel to the conic section directrix [6]. Applying the equation (1) for the COM estimation from acceleration data, the following equation was used to estimate A-P and M-L components of the COM from the trunk and swing accelerations:

$$\hat{COM}_j(X_{ij}) = \pm a_{ij}\sqrt{X_{ij} - X_{ij_0}} + b_{ij}, \tag{2}$$

where X_{ij} is the body acceleration, a_{ij} and b_{ij} are the parameters to be estimated, the subscript i represents trunk acceleration when i = 1and swing leg acceleration when i = 2, the subscript j represents the A-P direction when j = 1 and the M-L direction when j = 2. Due to the geometry of a typical parabola opening to the right, X_{ij0} can be estimated as the minimum value of the independent variable. Then equation (2) becomes

$$\hat{COM}_j(X_{ij}) = \pm a_{ij}\sqrt{X_{ij} - \min(X_{ij})} + b_{ij}. \tag{3}$$

A linear combination of the two parabolic equations, i.e. trunk and swing leg accelerations, was then chosen to form the final equation for COM estimation by trial and error:

$$\hat{COM}_j\left(X_{1j}, X_{2j}\right) = a'_{1j}\hat{COM}_j\left(X_{1j}\right) + a'_{2j}\hat{COM}_j\left(X_{2j}\right) + b'_j, \tag{4}$$

where a'_{1j} and a'_{2j} are the updated coefficients of a_{1j} and a_{2j}, respectively, and b'_j is equal to $b_{1j} + b_{2j}$.

The model parameters were estimated by a genetic algorithm. Genetic algorithms are stochastic global search methods that imitate the natural evolution process. It applies the survival of the fittest strategy to improve a set of parameters for optimization and create a better approximation to a solution [7]. The genetic algorithm toolbox [7] with custom script in MATLAB 7.0 Release 14 (MathWorks, Natick, MA, USA) was used. The encoding type was Gray code, and upper and lower bounds were defined as [-1, 1], with a precision of 4. Thus 15 bits were required to encode the parameters according to the criterion [8]

$$L \cdot 10^p < E^b, \tag{5}$$

where L is the difference between upper and lower bounds, p is the precision, E is the base of the encoding, and b is the number of bits required. The maximum generation number was chosen as 100 by trial and error, and was used as the stopping criterion of training. The generation gap of 0.9 was used and the probability of successful reproduction was selected as 0.85. The objective function used in this study was the mean square error between the target and the estimated COM trajectory

Data from all subjects except one was used to calibrate the model and the left-out data was used to test performance of the model. This leave-one-out procedure was repeated until every subject's data were used for testing. The estimation error between the target and the estimated COM trajectory was computed by

$$e = \frac{\hat{COM} - COM}{COM} \cdot 100\%, \tag{6}$$

where $\hat{COM}$ and COM are the estimated and the actual COM trajectory, respectively. The mean and standard deviation of estimation error was then calculated among the subjects.

E. *Measure of Variability*

Trunk acceleration variability was measured by the amount of the correlation coefficient at the first dominant peak of the autocorrelation sequence of the trunk acceleration. The period from zero to the first dominant peak of the trunk acceleration autocorrelation sequence represents the phase shift equal to one step [9]. The trunk acceleration variability from stride to stride may be reflective of the specific motor control used to maintain the balance [9]. Hence, in this study trunk acceleration variability was calculated for both M-L and A-P directions for all experiments and the results were investigated for any correlation with the COM estimation error. The mean and standard deviation of trunk acceleration variability was then calculated among the subjects.

III. Results and Discussion

The body accelerations (trunk and swing leg) of a typical subject and the corresponded COM trajectory of a forward stepping in each of the A-P and M-L directions are depicted in Fig. 1. The actual and estimated COM trajectories of the same subject stepping on the fixed surface with normal speed and on the foam pad 2 with slow speed are shown in Figures 2 and 3, respectively. The mean, standard deviation, minimum and maximum values of trunk acceleration variability for each task condition in both A-P and M-L direction are listed in Table I. The mean and standard deviation of the COM estimation error for each task condition and in A-P, M-L directions and the combination of the two directions are shown in Table II.

As can be seen in Fig. 2, the estimated COM trajectory in A-P direction followed the actual COM well. The mean error range was from 5.7% to 12.9% on different surface conditions and stepping speed. The estimation error in A-P direction increased as the difficulty of the task increased, i.e. it was more on the foam pad 2. The estimation errors in M-L direction (12.3% to 17.6%) were more than those in A-P direction, and they were not affected by the task difficulty.

The higher estimation errors in M-L direction than those in A-P direction might be due to the increase in M-L motion range. This suggests a modification in the swing foot trajectory to set down the swing foot at a proper location that would establish a new base of support to oppose the balance disturbance and maintain stability for gait sequence. This speculation is supported by significantly positive correlations between the increased COM motion in M-L direction and the increased swing foot trajectory in M-L direction [10]. The finding of the increased COM motion in M-L direction is also addressed in [11], where the elderly who have experienced a symptom of dizziness or unsteadiness showed a significantly greater and faster motion of the COM in M-L direction compared to that of healthy elderly subjects.

According to the findings in [9], stride-to-stride trunk acceleration variability in M-L direction may represent a different aspect of motor control, and it may be an effective factor in balance control. As trunk contributes more than any other body segments to total body weight, changing position of the COM relative to the base of support is remarkably influenced by the changes in trunk position [12]. Our result, listed in Table I, indicate that trunk acceleration variability in M-L direction is significantly higher than that in A-P direction (p<0.05) only in case of fixed surface and normal stepping speed. When the subjects performed stepping on normal condition (fixed surface and normal speed), their trunk motion in M-L direction was increased – represented by the higher trunk acceleration variability in M-L direction – and this made it difficult to predict the COM trajectory in M-L direction, which resulted in higher estimation error for normal condition in M-L direction (Table II). However, the balance strategies played an important role on more difficult task conditions for stability in M-L direction, and thus produced lower estimation error in M-L direction than that of normal condition.

IV. Conclusion

This study sought to develop a model of the COM trajectory estimation during forward stepping as a function of trunk and swing leg accelerations. It was shown that the genetic algorithm parabolic model was able to estimate the COM trajectory by a mean error of 12.9% in A-P direction and 17.6% in M-L direction. The results are encouraging and pave the way for integrating the COM estimation models with a balance assessment system that is less expensive than traditional methods and available for routine clinical assessment.

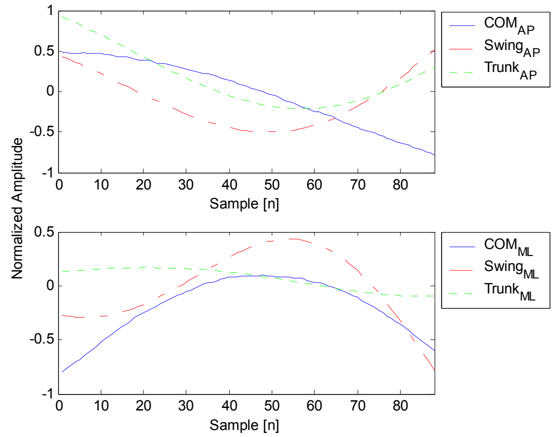

Fig. 1 Trunk and swing accelerations and the corresponded actual COM in A-P and M-L directions of a typical subject

Table I
Trunk Acceleration Variability

Task Condition (Surface/ Speed)	A-P direction			M-L direction		
	Mean±SD	Min	Max	Mean±SD	Min	Max
Fixed Normal*	0.31±0.20	<0.01	0.67	0.66±0.18	0.15	0.94
Fixed Slow	0.27±0.20	<0.01	0.68	0.26±0.20	<0.01	0.71
Foam 1 Normal	0.38±0.13	0.13	0.59	0.37±0.17	0.04	0.64
Foam 2 Normal	0.36±0.16	<0.01	0.68	0.29±0.18	0.03	0.69
Foam 2 Slow	0.15±0.12	<0.01	0.42	0.15±0.13	<0.01	0.47

Note: Task condition where trunk acceleration variability in M-L is significantly higher (p<0.05) than that in A-P marked with an asterisk.

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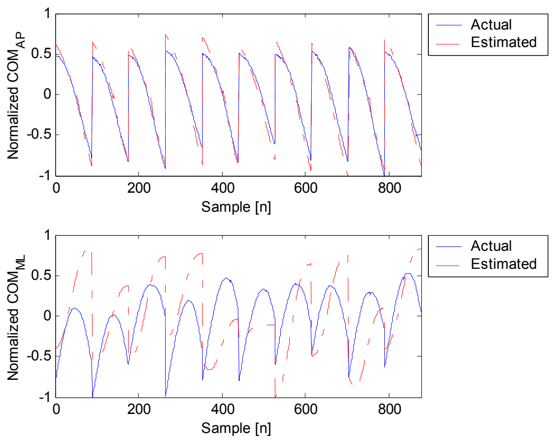

Fig. 2 Normalized actual and estimated COM trajectories of a typical subject for stepping task on fixed surface and normal speed. For display purpose, the end point of the previous forward step is connected to the start point of next forward step.

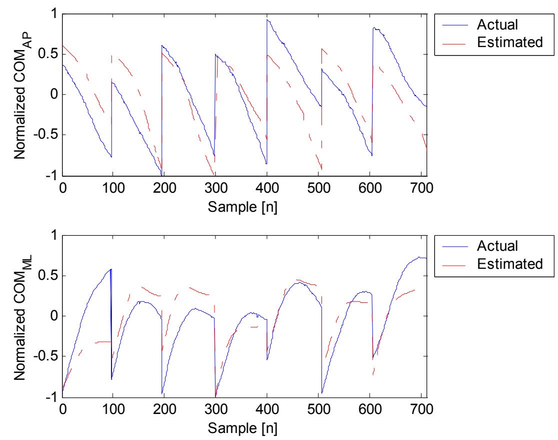

Fig. 3 Normalized actual and estimated COM trajectories of a typical subject for stepping task on foam pad 2 and slow speed.

Table II
COM Estimation Error

Task Condition (Surface, Speed)	A-P direction			M-L direction			Resultant		
	Mean±SD Error (%)	Min Error (%)	Max Error (%)	Mean±SD Error (%)	Min Error (%)	Max Error (%)	Mean±SD Error (%)	Min Error (%)	Max Error (%)
Fixed, Normal	5.7±2.5	3.1	14.2	17.4±5.0	9.8	29.4	17.3±4.5	9.7	28.5
Fixed, Slow	8.0±2.9	4.1	13.6	12.3±3.2	5.7	17.0	14.0±3.0	10.6	19.5
Foam Pad 1, Normal	8.9±3.3	5.4	17.0	15.5±4.8	9.9	25.7	19.2±.54	10.	23.1
Foam Pad 2, Normal	9.5±2.0	4.8	13.5	15.4±3.4	8.7	21.3	15.1±3.4	13.7	21.5
Foam Pad 2, Slow	12.9±2.8	8.3	16.5	17.6±5.2	11.3	25.7	17.2±7.2	13.4	28.8