

Gait and Dynamic Balance Sensing Using Wearable Foot Sensors

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Abstract—Remote monitoring of gait performance offers possibilities for objective evaluation and tackling impairment in motor ability, gait, and balance in populations, such as elderly, stroke, multiple sclerosis, and Parkinson's. This requires a wearable and unobtrusive system capable of estimating ambulatory gait and balance measures, such as the extrapolated center of mass (XCoM) and dynamic margin of stability. These estimations require the knowledge of 3-D forces and moments (F&M) and accurate foot positions. Though an existing ambulatory gait and balance system (AGBS) consisting of 3-D F&M sensors and inertial measurement units can be used for the purpose, it is bulky and conspicuous. Resistive pressure sensors were investigated as an alternative to the onboard 3-D F&M sensors. Subject-specific regression models were built to estimate 3-D F&M from 1-D plantar pressures. The model was applicable for different walking speeds. Different pressure sensor configurations were studied to optimize the system complexity and accuracy. Using resistive sensors only under the toe and heel, we were able to estimate the XCoM with a mean absolute rms error of 2.2 ± 0.3 cm in the walking direction while walking at a preferred speed, when compared to the AGBS. For the same case, the XCoM was classified as ahead or behind the base of support correctly at $97.7 \pm 1.7\%$. In conclusion, this paper shows that pressure sensors, minimally under the heel and toe, offer a lightweight and inconspicuous alternative for F&M sensing, toward estimating ambulatory gait and dynamic balance.

Index Terms—Ambulatory sensing, extrapolated center of mass, dynamic balance, margin of stability, gait, wearable sensors.

I. INTRODUCTION

ASSESSMENT of motor impairment periodically during rehabilitation is crucial in understanding recovery. This is feasible via clinical outcome measures, and instrumented

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laboratory facilities, particularly in subjects with motor impairment, such as stroke, Parkinson's, multiple sclerosis, etc., and also others prone to instability such as frail elderly. Clinical outcomes indicate a subjective change in capacity or function of given tasks whereas instrumented systems offer objective quantification of kinematic and kinetic changes on impairment level of said tasks. Once the patient is discharged from the clinic, she/he is expected to continue functional training to maintain recovery and increase independence in activities of daily life (ADL) [1]. Continuing objective monitoring after discharge helps quantify recovery, and identify compensatory patterns if present [2], [3]. As instrumented laboratory facilities are expensive and restrictive in measurement space, wearable systems can be explored as alternatives.

ForceShoeTM (Xsens Technologies B.V., Enschede, The Netherlands) is a shoe with onboard sensors and was developed as an ambulatory gait lab [4], [5]. It consists of two Inertial Measurement Units (IMUs) and two 3D force and moment (F&M) sensors on each foot. It has been validated against commonly used systems, such as force plates (AMTI[®]) and motion capture (VICON[®]), for measurement of contact forces and foot position estimations respectively [5]–[7]. Unlike these systems, ForceShoeTM has the advantage of being portable, and not restricted by area of measurement setup or marker placement. It is used to reconstruct the kinematics and kinetics of the feet during walking [8]–[10].

Gait measures such as step length and width, and foot positions can be estimated using IMUs on the ForceShoeTM. Weenk *et al.* [5] reduced the drift in position estimation using an Extended Kalman Filter (EKF), and validated it with motion capture. The EKF fused foot positions from the IMUs, and relative foot distance from an ultrasound sensor. The ForceShoeTM, along with ultrasound sensor, EKF, and additional processing will be referred to as Ambulatory Gait and Balance System (AGBS).

Using the AGBS, Schepers *et al.* [6] derived Center of Mass (CoM) of the body during gait. Subsequently, van Meulen *et al.* [9] estimated the Extrapolated Center of Mass (XCoM), which is the CoM extrapolated in the direction of the walking velocity. The trajectory of the XCoM projected on the ground with respect to the Base of Support (BoS), which is the region between two feet when they are in contact with the ground, is an indication of dynamic stability [11]. van Meulen *et al.* [9] used the shortest distance from the

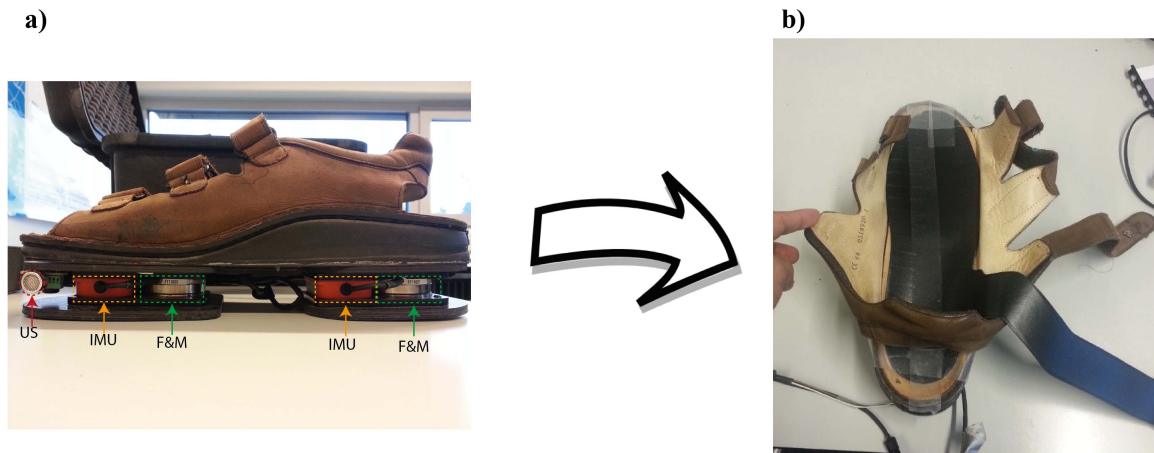


Fig. 1. (a) Side view of right ForceShoe. The ultrasound transmitter (US), the 3D F&M sensors (F&M), and inertial measuring units (IMU) are seen on the side. (b) Top down view of the ForceShoe fitted with pressure insole.

XCoM and the frontline of the BoS as a condition of stability during continuous gait, called as the dynamic Margin of Stability (MoS) [11]. Bruijn *et al.* [12] suggested that XCoM (and eventually MoS) can objectively indicate balance quality, and van Meulen *et al.* [9] showed that MoS varies with differences in subject's balance impairments. Balance quality is otherwise estimated using clinical outcomes such as Berg Balance Scale, Dynamic Gait Index, Tinetti Falls Scale, *etc.* However, the construct of these outcomes show that they are subjective to the assessor. Using a system like AGBS, one can objectively evaluate gait and dynamic balance in an ambulatory or home setting for different populations including stroke, multiple sclerosis, Becker's Muscle Dystrophy, Parkinson's, elderly, *etc.*

However, the system has its limitations. Liedtke *et al.* [7] showed that gait pattern is slightly modified when wearing the AGBS. Moreover, it is not practical to use them every day due to the bulky 3D F&M sensors. These make each shoe weigh close to 1kg and increases the sole height by 2.5cm [9], increasing discomfort and chances of tripping, especially for people with gait impairments. Alternative systems for ambulatory estimation of 3D F&M can be achieved by using an IMU-only setup. Karatsidis *et al.* [14] solved this using 17 IMUs placed in a full body suit [13]. However, the system requires a full body setup and the effect of a reduced IMU setup for this purpose has not yet been studied.

Insoles with pressure sensors can be used as an alternative to the bulky 3D F&M sensors. They can be slipped into everyday use shoes, are lightweight, and inconspicuous. They provide 1D plantar pressures under the feet during walking and can be used for estimating a range of gait parameters [15]–[17].

Pressure insoles can only provide the vertical plantar pressure. However, 3D F&M of the feet (along with its positions) are required to estimate the CoM, XCoM and MoS [6]. Studies have shown estimations of 3D F&M from 1D plantar pressures by using analytic and machine learning methods. Forner Cordero *et al.* [18] showed analytic derivation of 3D forces from 1D plantar pressure data, but his method relies on force plate data. Sim *et al.* [19] showed the use of a wavelet

neural network to estimate time-normalized 3D F&M from 1D plantar pressure. Other studies use other machine learning methods to achieve the same [20]–[23]. In spite of a few disadvantages, such as the need for training data, or possible failure in untrained scenarios, machine learning methods have some potential use in this study.

The goal of this study is to evaluate 1D plantar pressure sensing as a lightweight alternative to the 3D F&M sensors in AGBS for estimating dynamic balance measures. To do so, linear regression models were built to predict 3D F&M from 1D plantar pressures. The models are subject specific and independent of walking speeds. The predicted 3D F&M along with foot positions are used to estimate CoM, XCoM, and MoS. The estimations are compared with those of the AGBS for different pressure sensor configurations. The study throws light on pressure sensors as a replacement to the 3D F&M sensors, the influence of the number of sensors on the estimation of XCoM and MoS, and insights on the algorithms used during the process.

II. METHODS

A. Measurement System

Fig. 1(a) shows the ForceShoe™ containing two 3D F&M sensors, two IMUs, and an ultrasound. Only the IMU located at the forefoot was used for analysis. The data from the 3D F&M sensors and IMUs were sent to an Xbus that transmits data wirelessly to a PC. The transmitter and receiver of the ultrasound system was placed on the right and left foot respectively. They were synchronized and the data were transmitted via Bluetooth to a PC. Fig. 1(b) shows the pressure insole system (medilogic® insoles, T&T medilogic Medizintechnik GmbH, Germany) placed in the ForceShoe™. It has 151 resistive pressure sensors and was held in place using tape to eliminate slippage. The wireless transmitters of the pressure insoles and ForceShoe™ were worn as a belt around the waist. The 3D F&M sensors, IMUs, and the pressure insoles were sampled at 50 Hz. The data was then low pass filtered twice at 10Hz using second order butterworth filter to ensure

zero-phase lag. The data was then transformed to the global coordinate frame, where X axis is along the walking direction and Z axis is the vertical axis pointing upwards.

B. Participants

Six healthy subjects were recruited for the study. All participants signed an informed consent before the experiment. The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Ethical Committee of the faculty. The inclusion criteria included subjects with no history of impaired gait or leg injury. Five subjects were males and the size of the shoe used was 44 (European Size Chart). The average and standard deviation of the height, weight, and age was 1.81 ± 0.06 m, 81 ± 9 kg, and 25 ± 1 years respectively. Leg length was measured from the greater trochanter to the ground [24] and was 1.04 ± 0.05 m.

C. Experimental Protocol

The ultrasound system and 3D F&M sensors were calibrated before each measurement. The subjects were then asked to perform different walking tasks. In each of the walking tasks, the subject was asked to walk for 10 meters along a straight unobstructed path. The subject was instructed to begin with their feet placed parallel. Once the researcher gave the start sign, the subject walked along a straight line. The time taken between start and stop of the walking was measured using a stopwatch. This activity was repeated six times. The walking tasks were performed in four different scenarios which are as follows:

- 1) *Normal Walking*: During this task, the subject was asked to walk at his *preferred* walking speed.
- 2) *Slow Walking*: During this task, the subject was asked to walk at a slower pace. The speed was guided by the use of a metronome that beat at a frequency of 37 beats per minute. Each beat corresponds to heel strike of the same foot on the ground. The frequency was found using trial and error such that the subjects reduced their walking speed to 0.8 m/s.
- 3) *Very Slow Walking*: During this task, the subject was asked to walk at a much slower pace. The frequency of the metronome was set at 27 beats per minute. This frequency was found so as to reduce the walking speed to 0.4 m/s.
- 4) *Bag Walking*: During this task, the subject was asked to walk at his *preferred* walking speed while wearing a backpack weighing 5 kg. This is to represent an extra, yet minimal load people may carry during daily life tasks, such as a shopping bag.

D. Objective Evaluation of Gait and Dynamic Balance

1) *Gait*: Ultrasound and IMUs were used for estimating foot positions, from which gait parameters such as step length, and step width were obtained. The EKF predicted states of position, instantaneous velocity, orientation error and gyroscope bias error [5, Fig. 3]. Error between predicted and measured data was used to correct the states for every measurement

sample. Measurement updates included foot position and instantaneous velocity measured from the IMU, zero velocity instances, height of IMU during zero velocity and relative feet distance from the ultrasound system [5]. The ultrasound updates were used in the EKF at an update frequency of 13Hz [9, Fig. 2].

2) *Dynamic Balance*: Estimation of CoM is the first step towards evaluating dynamic balance. Low and high frequency components of CoM were estimated using two separate algorithms and fused using a complementary filter, to improve estimation accuracy [6]. The first stage estimates CoM from both foot kinetic and kinematic information by low pass filtering the Center of Pressure (CoP) to estimate the position of CoM, referred to as Stage Low Frequency (Stage LF). Here, the CoP for each foot is estimated as follows.

$$\mathbf{x}_{CoP,foot} = \left(\frac{-M_Y}{F_Z}, \frac{M_X}{F_Z}, 0 \right) \quad (1)$$

In Equation 1, F_Z is the vertical ground reaction force (GRF), and M_Y and M_X denote the moments in the respective axes. The CoP trajectory over the walking trial was weighted with the relative magnitude of the vertical GRF under each foot and is given as follows.

$$\mathbf{x}_{CoP} = \frac{F_l}{F_l + F_r} \mathbf{x}_{CoP,l} + \frac{F_r}{F_l + F_r} \mathbf{x}_{CoP,r} \quad (2)$$

Here, the F_l and F_r represent the vertical GRF in the left and right foot respectively. The \mathbf{x}_{CoP} was then low pass filtered at 0.4 Hz to obtain the $\mathbf{x}_{CoM,LF}$. The cut off was found to be optimal for continuous walking [6]. The Stage LF CoM is estimated from both foot kinetic and kinematic information.

The second algorithm estimates CoM from kinetic information alone by double integration of the net forces based on Newton's second law, referred hereafter as Stage High Frequency (Stage HF). The body mass m_{body} can be embodied at the CoM and it's acceleration is given as follows.

$$\mathbf{a}_{CoM} = \frac{\mathbf{F}_t}{m_{body}} + \mathbf{g} \quad (3)$$

Here, \mathbf{F}_t is the net force acting on the body, and \mathbf{g} is the gravitational acceleration. The CoM position was derived from integrating the \mathbf{a}_{CoM} twice. This results in $\mathbf{x}_{CoM,int}$ which was high pass filtered with a cut off at 0.4 Hz to obtain $\mathbf{x}_{CoM,HF}$. This is the same cut off as that of Stage LF low pass filter. The $\mathbf{x}_{CoM,LF}$ and $\mathbf{x}_{CoM,HF}$ were fused using a complementary filter to obtain the trajectory of CoM. Fig. 2 shows the extrapolated center of mass (XCoM) that can be obtained by the following equation.

$$XCoM = CoM + \frac{\mathbf{v}_{CoM}}{\omega_0} \quad (4)$$

Here \mathbf{v}_{CoM} is the velocity of CoM and an indicator of the direction of movement, ω_0 is given as $\sqrt{g/l_0}$, where $g = 9.8$ m/s² (gravity), and l_0 is the vertical CoM position [10], [11]. Fig. 2 shows the dynamic Margin of Stability (MoS) as the shortest distance between the vertical projection of XCoM on the ground (XCoM') from the frontline of BoS [9].

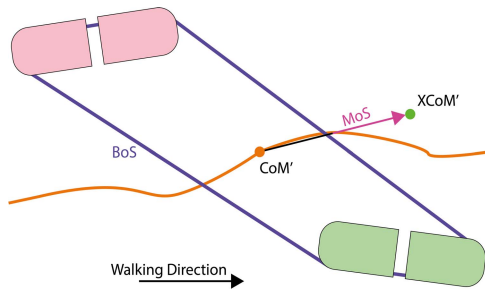


Fig. 2. Visual representation of the projected Center of Mass (CoM), projected Extrapolated Center of Mass (XCoM), and dynamic Margin of Stability (MoS). The orange line is the trajectory of CoM. The blue lines denote the borders of the Base of Support (BoS). The pink arrow denotes the length of the MoS, measured from the frontline of the BoS to the XCoM.

E. Estimation of 3D F&M From Pressure Insoles

The AGBS provides positions, and 3D F&M of the feet. This is used to estimate CoM, XCoM, and MoS as shown earlier. However, pressure insoles are only able to provide the 1D plantar pressures. Therefore, subject specific models (SSRM) were created to estimate 3D F&M from 1D plantar pressure data.

First, the data from IMUs, 3D F&M, and pressure insoles were synchronized. Trials that had sensor issues or measurement errors were removed. It was made sure that each subject had at least three trials for each walking task. Fig. 3(a) shows the workflow of building an SSRM. First, all walking trials from the 'Normal', 'Slow', and 'Very Slow' tasks are appended. This forms one extended dataset containing 1D pressures for all walking trials with all speeds as inputs for the SSRM. Then, the SSRM is built as a linear regression model fitted between the inputs and targets (3D F&M) using least squares method. This results in six different models, one for each dimension of the F&M. The SSRM built using the walking profiles for three different speeds is then used to estimate the 3D F&M for each walking speed separately, and also for the *Bag* task which was not included in building the SSRM. Walking velocity was not used as an input to the SSRM. The same model can predict forces and moments during quiet standing, initiation of walking, cyclical walking and deceleration of walking and stopping for different walking speeds. The modeling process was repeated to create SSRMs for each subject. Fig. 3(b) shows the sensors used for the two stages, Stage LF and HF, and how the 3D F&M estimated using the SSRMs was used to calculate the CoM (along with foot positions), XCoM, and MoS. These measures were then compared with the measurements from the AGBS.

F. Influence of Sensor Choice

The influence of the sensor configuration on the estimation of CoM, XCoM, and MoS was studied next. By reducing the number of pressure sensors used, the contribution of foot kinematics and kinetics can be understood better. Additionally, this could serve as a reference to design sensor setups with required error margins of stability parameters. Therefore, the number of pressure inputs used in building the SSRMs is varied. Fig. 4

shows the placement of the 151 individual pressure sensors on the insole as 'pluses'. Initially, an SSRM was built using all the sensors. This was followed by building SSRMs with different sensor configurations. To do so, specific foot regions were selected using an IEE (IEE S.A, Luxembourg) pressure insole as reference. The IEE insole has 8 sensors placed strategically under four foot regions; two under the toe, three under the metatarsal, one covering the arch, and two under the heel. They can be seen in Fig. 4 as green regions. The different configurations used are described as follows.

- 1) *All*: All 151 sensors are used to build the SSRM.
- 2) *FF*: The pressure sensors in the medilogic[®] insole that corresponded to the 8 sensor locations were used for building the SSRMs. This covered the four foot regions.
- 3) *T + H*: This configuration covered only the toe and heel regions.
- 4) *T*: This configuration covered the toe region alone.
- 5) *H*: This configuration covered the heel region alone.
- 6) *None*: In this the accuracy of estimating CoM, XCoM, and MoS is studied under the absence of any force or moment information. Therefore, only foot positions are used in this configuration. In order to proceed, a few assumptions are made. First, the position of the CoP during standing is assumed to lie equidistant from the center of two feet. Secondly, during single stance, the CoP lies entirely at the center of the foot in contact with the ground. Thirdly, during double stance phase, a smooth transition assumption (using spline interpolation) is used to smoothly shift weight from the lagging to the leading foot [25]. These assumptions were used in Stage LF to obtain CoM. The Stage HF estimation of the CoM is not performed as there is no data about the force acting on the body in this configuration.

G. Classification of Stability

The MoS, an indication of dynamic balance, both in anterior-posterior as well as medio-lateral directions, gives information about walking stability [10], [11]. However, here only the gross placement of the projection of XCoM (XCoM') in 2D w.r.t the frontline of the BoS is studied. The BoS is estimated using the AGBS setup. The XCoM' could then be classified as either ahead or behind the BoS. Instances when the XCoM' is ahead of the BoS can be termed as unstable. This is compared between the SSRM and AGBS estimated XCoM's. This exercise is done to study how closely the SSRM based system can identify instances of instability as compared to the AGBS.

H. Analysis of Results

The root mean square (RMS) of the differences normalized to the range of measured values was calculated between estimations by SSRMs and results obtained from the AGBS. This is done for the 3D forces (*rmsdF*) and moments (*rmsdM*), and compared with results seen in literature. This is an estimation of the error margin present when the 3D F&M are predicted by the SSRMs. Following this, the absolute RMS of the differences (*rmsdX*) for the XCoM was found, which quantifies the uncertainty in measurement. Then, a study of

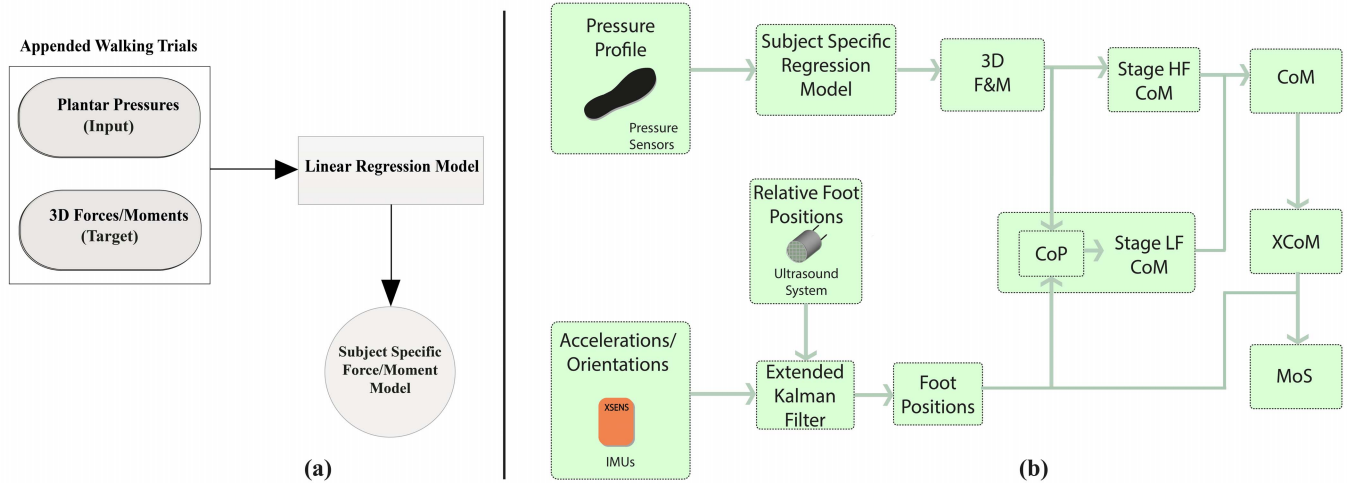


Fig. 3. (a) All ‘Normal’, ‘Slow’, and ‘Very Slow’ walking trials per subject are appended before training a subject specific regression model. (b) Workflow capturing the sensors and algorithms used to estimate the Center of Mass (CoM), Extrapolated Center of Mass (XCoM), and dynamic Margin of Stability (MoS) when using pressure sensors.

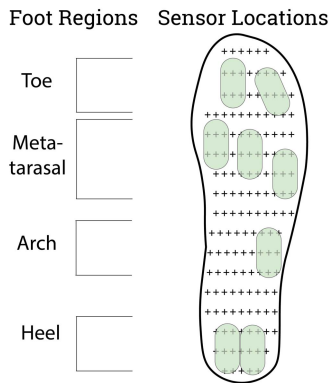


Fig. 4. The four foot regions are depicted here. The pluses denote the medilogic[®] pressure sensors. The shaded regions denote the sensors of IEE. The sensors in the medilogic[®] insole that correspond to the shaded regions are used for analysis.

the contribution by the two stages, Stage LF and HF, to the accuracy of the XCoM was done. In this case, the Mean Absolute Distance ($madt$), the 2D distance in the XY plane, is calculated. Finally, the percentage of correctly classified (PCC) samples of stability by the SSRMs was studied.

III. RESULTS

A. Forces and Moments

The mean (standard deviations) walking speeds of the subjects for the *Normal*, *Slow*, *V Slow*, and *Bag* walking tasks are 1.03 (0.15), 0.6 (0.1), 0.42 (0.05), and 0.98 (0.2) m/s respectively. The regression models were built using walking trials in the *Normal*, *Slow*, and *Very Slow* tasks. The total number of steps (averaged between left and right) for each of the six subjects used in building the SSRMs were 97, 100, 116, 133, 162, and 200. The number of steps vary as each subject differed in number of valid trials used, and also step sizes. Fig. 5(a) shows the comparison between the 3D forces

estimated by the SSRM and measured by the 3D F&M sensors (of the AGBS). The mean values of each subject is displayed as a boxplot. The distributions are shown for the different walking tasks for each sensor configuration (‘All’, ‘T+H’, ‘H’, ‘T’) used in the SSRM. The values are averaged over the left and right leg. In the figures, the white filled circle denotes the inter-subject mean of the distribution. The filled box contains the distribution that lies between 25% to 75% of the data. The outliers of the distribution beyond 1.5 times the interquartile range is denoted by stars.

In Fig. 5(a), the forces estimated by the SSRM built with ‘All’ sensors shows relatively small error margins with the AGBS measured forces. This is seen to be the case for *Normal*, *Slow*, and *Very Slow* tasks. This shows that the model can be applied to different walking speeds, making it robust to changes in walking speeds. The SSRMs were used to estimate the forces in the *Bag* walking task to test its validity in an untrained scenario. The *Bag* task involves walking at the *preferred* walking speed while carrying a bag weighing 5kg. Fig. 5(a) shows that when using ‘All’ sensors, the forces can be estimated accurately for the untrained *Bag* task. The $rrmsdF$ in all three axes is 6% or less. This shows that the model is not only capable of reproducing the forces during an untrained walking profile, but can also be used when the subject is carrying a small additional load. This could be due to the subject specificity of the SSRMs, enabling it to map the walking profile of each subject under different conditions.

The estimations remain relatively accurate when we consider the ‘FF’ sensor configuration. The $rrmsdF$ is below 12% in all the three axes, for all walking tasks. Other sensor configurations show decreasing correlation coefficients and increasing RMS errors when reducing number of sensors for all walking tasks. When considering the ‘T’ or ‘H’ sensor configuration, we see that the error margin in $rrmsdF$ increases to 20%. This is expected as these configurations do not contain pressure profile during either the toe off or heel strike. Additionally, as the number of sensors are reduced,

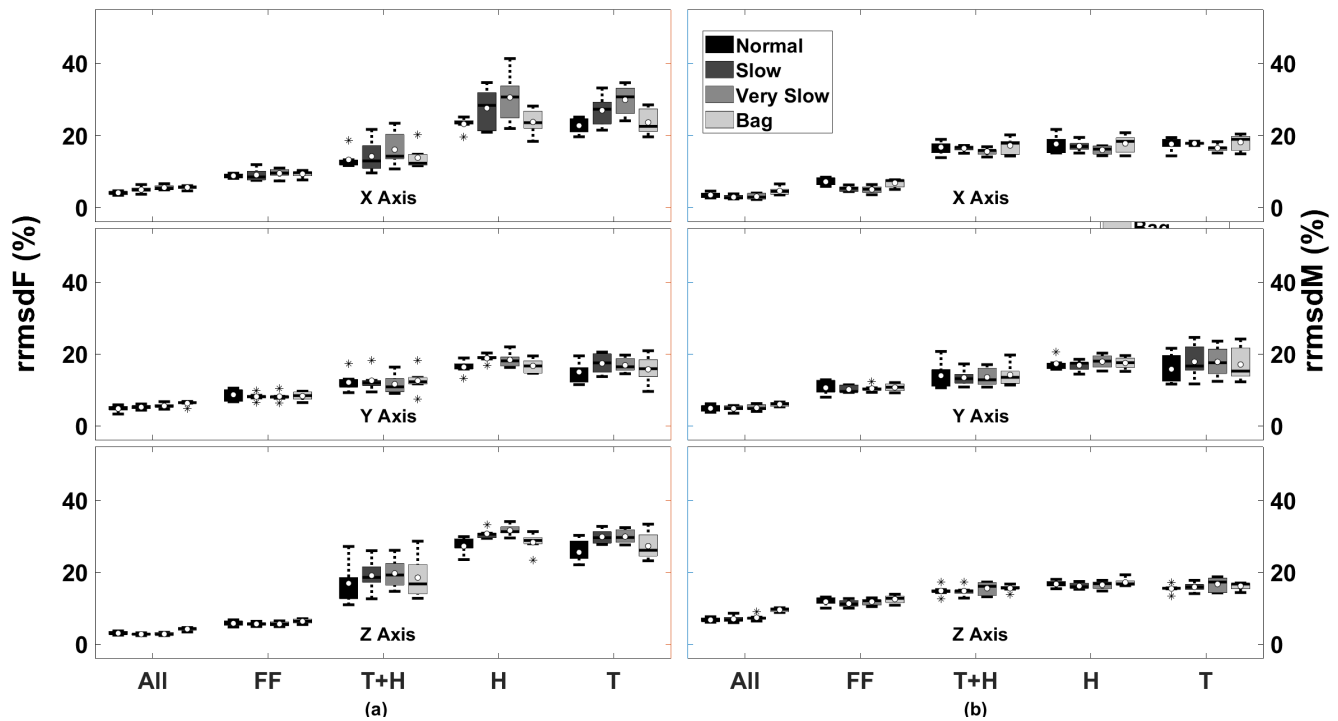


Fig. 5. (a) shows the range normalized RMS ($rrmsdF$) between the forces, and (b) the range normalized RMS ($rrmsdM$) between the moments, estimated using SSRMs and measured from AGBS. Box plots of the mean values are shown for the different walking tasks for each sensor configuration used: All (All), Four foot regions (FF), Toe+Heel (T+H), Toe (T), and Heel (H).

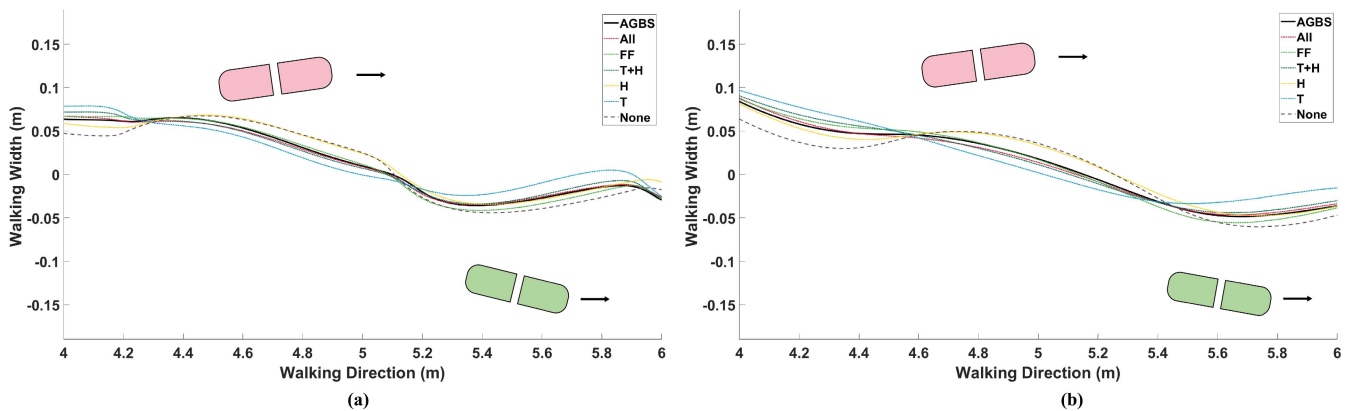


Fig. 6. Representative trajectory of (a) CoM and (b) XCoM from a *Normal* walking task. The black line shows the reference trajectory estimated using the AGBS. The other dotted lines show the trajectory with respect to different sensor configurations. The feet of the subject is shown in pink and green.

the regression model uses lesser sensors to estimate the forces. Fig. 5(b) shows the comparison between the 3D moments estimated by the SSRM and measured by the AGBS. Similar results as seen in forces can be observed in the estimation of moments. Good accuracy in estimating the moments is seen while using the ‘All’ sensor configuration for *Normal*, *Slow*, and *Very Slow* tasks, and also for the untrained *Bag* task. Moments, however, show larger errors than forces as they are a cross product of distance and forces in the two orthogonal axes. Subsequently, the estimation worsens as the number of sensors are reduced. In both Fig. 5(a) and (b), the results

for ‘None’ sensor configuration is not shown as there is no force or moment information in these cases.

B. Dynamic Balance

The 3D F&M from AGBS and SSRM are then used to estimate the CoM using Stage LF and Stage HF. Fig. 6 shows representative trajectories of the CoM and XCoM for a *Normal* task. The CoM fluctuates between the two feet as the stance changes. Simultaneously, in 6(b) the XCoM can be seen to oscillate with changes in the instantaneous

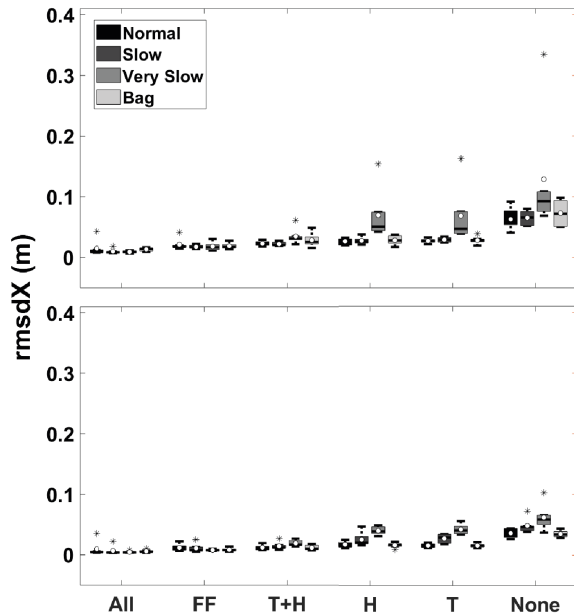


Fig. 7. RMS of the differences between the XCoM estimated using regression model and measured from AGBS ($rmsdX$). Box plots of the mean values are shown for the different walking tasks for each sensor configuration used.

velocity of the CoM. The SSRM trajectories deviate from the reference trajectory estimated by the AGBS, as they have different accuracies in estimating the forces and moments. Fig. 7 shows the comparison of XCoM in only the X and Y axes as we are interested only in the projection of XCoM, i.e., XCoM' on the ground as $rmsdX$. When using 'All' sensors, the accuracy of estimating XCoM' for all walking tasks is high. The $rmsdX$ is less than 2cm for the X and Y axes respectively. This is the case for all walking tasks. For other sensor configurations ('T+H', 'T', and 'H'), the $rmsdX$ does not change drastically as seen with 3D F&M in fig. 5(a) or (b). Although there is no force or moment information of the feet in the 'None' configuration, the XCoM' has low errors in both X and Y axes. The $rmsdX$ for the X and Y axis is less than 12 and 8 cm respectively. Assuming step width during quiet stance as 15 cm, maximum step width and length as 40 cm and 70 cm respectively, the BoS can range between 700cm^2 to a maximum of 2400cm^2 . Comparing error margins of XCoM with respect to the BoS gives an idea about the relative magnitude of the error.

The previous paragraph threw light on the influence of 3D F&M estimation accuracy on the estimation of XCoM. Next, the contribution of Stage HF on the estimation of XCoM is studied. Here, we hypothesize that for lower walking speeds, there is lesser useful information in the higher frequencies. This is acceptable as our primary applications are towards people with gait impairment. Also, the Stage HF relies on the need for good kinetic information. Lesser reliance on this translates to the possibility of eliminating kinetic sensors. Therefore, the XCoM' with and without the Stage HF is considered. Then, the $madt$ is calculated between the estimations by the SSRMs and AGBS. Fig. 8 shows the distribution of $madt$ in two

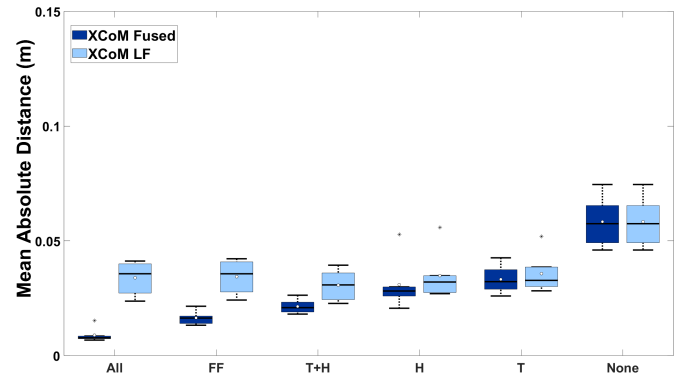


Fig. 8. Error between XCoM with both low and high frequency (XCoM fused) and XCoM with only low frequency content (XCoM LF) for the *Slow* task.

cases during the *Slow* task. One case (XCoM Fused) contains the $madt$ between the fused XCoM' from the SSRM from the AGBS. The second case (XCoM LF) contains the $madt$ between the XCoM' with only low frequency information and the fused XCoM' of the AGBS. In Fig. 8, the XCoM Fused shows lower $madt$ than XCoM LF when compared with the estimations from the AGBS. The average $madt$ for XCoM LF in all sensor configurations (except 'None') is about 3cm. The distribution of the $madt$ for XCoM LF shows larger variance, but remains robust with reduction in sensor configuration. This suggests that for walking at low speeds, the low frequency information of CoM is sufficient to estimate XCoM given an error margin of 3 cm. This could translate to advantages in terms of lower sampling rates of sensors, which may influence power consumption, or the possibility to eliminate kinetic sensors. Note that in case of 'None', the XCoM LF and XCoM Fused distributions are similar as this sensor configuration does not have any Stage HF information.

C. Classification of Stability

Once the XCoM' estimated by the SSRMs is classified as ahead or behind the frontline of the BoS, it is compared with the classifications done by the AGBS, which is assumed to be the ground truth. Fig. 9 shows the percentage of sample points rightly classified as ahead (PCC Ahead) or behind (PCC Behind) the frontline of the BoS.

In order to classify, the frontline of the BoS is needed, which is measured only during quiet standing or instances of double support. During quiet standing, the XCoM' lies well within the BoS, as there is no movement. During these instances, XCoM' is most correctly classified. It can be seen from Fig. 9(a) that the percentages are very high for any sensor configuration in all walking tasks. The inset table shows the percentage of actual time behind or ahead the BoS. Simultaneously, during double support phase the XCoM' is usually 'ahead' of the BoS in healthy people. However, as double support phases are very short in a gait cycle, the number of samples where the XCoM' is ahead of the BoS is limited. Subsequently, there is a higher chance of error or mismatch in the placement of XCoM' ahead of the BoS. Fig. 9(b) shows that the distributions are wider and the mean PCC is lower as compared to Fig. 9(a).

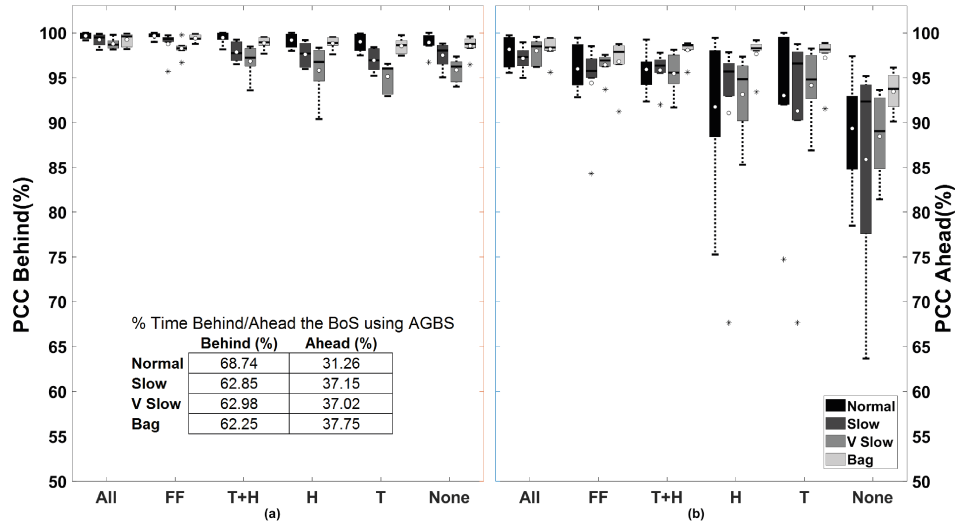


Fig. 9. Classification of XCoM' as (a) Behind or (b) Ahead of the BoS: The percentage of total time when the XCoM' is correctly classified is displayed as a box plot distribution. The classifications by the AGBS are considered to be true and used as the reference. The percentage of time ahead or behind the BoS as measured by AGBS is shown in the inset table.

TABLE I
COMPARISON OF THE CORRELATIONS FOUND
IN THIS STUDY AND SIM *et al.* [19]

—	This Study (%)	Sim <i>et al.</i> (%)
F_X	95.5	97.6
F_Y	95.3	85.3
F_Z	99.6	98.8
M_X	97.9	87
M_Y	96.3	88.1
M_Z	87.1	84.7

For 'All' sensors, the figure shows that the SSRMs has high PCC in estimating the dynamic stability. The mean PCC is above 95% (for both ahead and behind) for all four walking tasks. In Fig. 9, the PCC reduces as the number of sensors are reduced.

IV. DISCUSSION

In this study, subject specific models were built instead of a generic model for all subjects. This choice was made as preliminary studies showed poor performance of a generic regression model built using trials from different subjects. Additionally, this method could be expected to perform better for people with gait impairment. Correlations between the estimated and measured 3D F&M as average percentages among both foot were estimated, and compared with [19] and tabulated in Table I. Their study used fast, normal, and slow walking speeds for training a wavelet neural network that estimated the 3D F&M from plantar pressures. It is seen that in both, this study and Sim *et al.*, forces in the Z axis show the highest correlation, followed by the X axis. This is expected as plantar pressures are defined by the vertical ground reaction force. In case of moments, Z axis showed the least correlation. Comparatively, except for forces in X axis, this study shows slightly higher correlations with the

reference, than that in [19]. Note that the current study doesn't use a normalized gait cycle for building the SSRMs, as Sim *et al.* [19] do. Therefore, the SSRMs contain information of the gait cycle during initiation and decelerations, allowing better prediction even when making short steps or shuffling at home.

The most interesting observation is found when we study the influence of F&M estimation on the estimation of XCoM'. We know from fig. 5, that the estimation of F&M deteriorates as we reduce the number of sensors. However, fig. 7 shows that this has little effect on the estimation of XCoM'. It has to be noted that the foot position used is the same for all sensor configurations. This could give rise to the argument that accuracy of foot position is more important than force or moment sensing, highlighting the relative influence of foot kinetics and kinematics towards accuracy of XCoM. This argument is strengthened when considering the 'None' configuration. We see low $rmsdX$ values in fig. 7 for this configuration. However, it must be noted that some of the assumptions, especially the smooth transition assumption, in 'None' may fail during instances of daily life such as shuffling of feet, or while turning. Nonetheless, the comparisons show that in order to identify the XCoM', we must have good accuracy in estimating the foot position. Currently, EKF and ultrasound range updates are used to improve the foot position estimation provided by the IMUs. Fig. 9 can serve as a reference for choosing the right sensor configuration based on the required task. If we are to consider an 'optimal' case that has less number of sensors while providing good accuracy, the 'FF' sensor configuration seems to be the right choice. However, the 'T+H' sensor configuration can be used if a more minimal setup is preferred. This configuration has only sensors under the heel and toe, but the model shows good accuracy in estimating the XCoM'. This shows that for minimal sensing of ADL, a simple sensor set with at least two pressure sensors (one under the heel and other under the toe), IMUs on the

forefoot, and updates of the distance between the two feet is required for a confident estimation of the XCoM and dynamic stability.

A. Limitations and Future Work

Though the recruitment was not selective to sole size or gender, the participating group is not very diverse. There is only one shoe size tested and only one female subject in the study. However, this would not have any effect on validity of the method as the models are subject specific. Also, as the study was performed on healthy subjects, the results might vary in populations with gait impairment.

Walking trajectories were required to create the SSRMs, which in practice, would translate to a calibration phase where the subject should walk a few times using the measurement setups. As seen earlier, an average of 134 steps is needed to achieve the results shown. Though this is an extra effort, it eliminates the use of bulky 3D F&M sensors in daily life which can modify gait pattern and cause discomfort during extended wear [7], [9]. Alternatives to create subject specific models could be building models generic to any subject and calibrating them before use.

In this study, the SSRMs are linear regression models. Studies have shown other possibilities for improving accuracy in predicting 3D forces/moments [20]–[22]. Further, this study finds that Stage LF is sufficient for CoM estimation. Therefore the CoP, essential for estimating CoM in Stage LF, can be found using only the pressure sensors [26]. This eliminates the conversion from 1D pressure to 3D F&M, thereby reducing the complexity in generating SSRMs.

The subjects were asked to walk in straight lines in this study. Shuffling or turning can introduce shear forces directed towards the direction of turning. The accuracy of the SSRMs in these conditions should be studied further. Additionally, the study is missing assessments of MoS in the medio-lateral direction as it is highly relevant in understanding gait stability [12]. This study shows the feasibility of pressure sensors over 3D F&M sensors. The IMUs can be embedded inside the insoles, as designed by Moticon® [27], allowing design for a thinner, and wearable AGBS. However, the ultrasound range estimator requires further improvement. The range estimator requires synchronized receiver and transmitter placed in a direct line of sight. Alternatives, such as using infrared, may contribute towards the design of an inconspicuous AGBS [28].

V. CONCLUSIONS

The AGBS in this study can thus be replaced with a setup containing pressure sensors and IMUs on each foot, and an ultrasound range estimator. During straight line walking, pressure sensors under the toe and heel can be sufficient (along with foot positions), to study the XCoM and dynamic stability of a healthy subject. Also, low frequency information of the CoM is sufficient for estimating the XCoM trajectory. Using a few assumptions, XCoM could also be estimated using only the estimations of foot position, ignoring any kinetic information. In addition, the current study highlights the contribution of foot kinematics and kinetics while estimating XCoM. These

results could be used in the design of a lighter and wearable AGBS system. Such a system can contribute towards objective quantification of gait and balance quality in an ambulatory setup. This, unlike current clinical outcomes, can help monitor functional recovery.

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