Portable Gait Lab: Instantaneous centre of mass velocity using three inertial measurement units

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Abstract—Estimating instantaneous 3D Centre of Mass velocity (VCOM) using wearables can improve ambulatory gait monitoring. Inertial Measurement Units (IMU) are commonly used to estimate VCOM, although, studies have either measured only the magnitude, or use machine learning methods. Here, we propose a three IMU setup, where the VCOM is obtained by a complementary filter method. This method fuses high frequency information achieved using strapdown integration of accelerations measured at the pelvis with low frequency information of VCOM obtained from foot velocities. This method is applied in variable gait which includes turns. The root mean square of the error between the IMU estimated VCOM against a reference VICON measurement was found to be $0.1 \pm 0.02 \text{m/s}$ across all walking tasks. This method provides a drift free ambulatory estimation of CoM velocity using minimal IMUs.

I. INTRODUCTION

Estimation of the centre of mass (CoM) velocity (VCOM) has several practical applications, including measuring gait parameters, and balance measures such as extrapolated CoM (XCOM) [1]. Inertial Measurement units (IMUs) offer solutions for ambulatory estimation of VCOM [2], [3]. However, so far, studies have either measured the magnitude of VCOM [2], or used machine learning techniques [3] which require additional training.

Here, we propose a setup of three IMUs for estimating the VCOM; one IMU at the pelvis, and one on each foot. Information about VCOM is extracted from the movement of the pelvis and feet, and are fused using a complementary filter method [3], [4], resulting in drift free instantaneous estimation of 3D VCOM.

The following sections describe the methods used to obtain the instantaneous 3D VCOM in a special current step frame ($\psi_{cs}$) [5], and describes the performance of the method in variable overground gait.

II. METHODS

First, Section II-A provides a brief overview of reference frames used in this study [5]. Cyclical changes in VCOM was obtained by integrating pelvis accelerations and high pass filtering the output [2], [3]. Furthermore, average movement of the feet encode information about the VCOM. These two sources of VCOM can be fused using a complementary filter method. Section II-B shows the method used for strapdown integration of ACOM. Here we assume that gait is modelled as an inverted pendulum, with the pelvis IMU accelerations measuring the CoM accelerations (ACOM). Following this, Section II-C explains the estimations of an average VCOM from foot velocities, and the fusion of the two information sources.

A. Using a Current Step Frame $\psi_{cs}$

In this study, instead of a fixed global frame, a changing reference frame was employed [5]. The body centric current step frame, $\psi_{cs}$, was defined using the change in foot positions per step [5]. A graphical depiction is shown in Fig. 1. Fig. 2 summarizes the estimation of $R^{(k)}_{cs}(k)_{cs}(k-1)$ for the pelvis IMU. The steps are explained in detail in Mohamed Refai et al. [5]. To transform from sensor frame to current step frame makes, first a calibration to segment frame is performed.
were averaged. A low pass 2nd order zero phase Butterworth filter was applied to obtain the VCOM velocity estimates were obtained using an extended phase Butterworth filter was applied to obtain the VCOM pass filter of the system was used as the reference. Markers were placed on the foot on the midfoot region [5]. A MT Manager was used to read the data from the IMU wirelessly, which was sampled at 100 Hz. A VICON® (Oxford Metrics PLC.) motion capture system was used as the reference. Markers were placed on the following locations on both the left and right limbs: anterior superior iliac spine, posterior iliac spine, the second and fifth metatarsal, and heel. The VICON® was sampled at 100 Hz.

The CoM position obtained from VICON® (PCOM_{ref}) was assumed to lie at the centroid of the pelvis markers. The PCOM_{ref} was differentiatied and low pass filtered with a 2nd order zero phase Butterworth filter with cut off 10 Hz to obtain the VCOM_{ref}. These were transformed to the \( \psi_{cs(k)} \), determined independently using the foot position data of the VICON®.

Walking data was collected from trials by three healthy males. The mean height, weight, and age was 1.74 ± 3 m, 79.3 ± 9 kg, and 25 ± 3.5 years respectively. Leg length was 94 ± 3 cm [9]. 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.

### B. CoM Velocity using strapdown integration

As seen in Fig. 2, gravity was removed from ACOM in \( \psi_{cs(k)}(\text{acc}cs(k)) \), and then strapdown integrated using the direct and reverse integration method (DRI) [7] to obtain velocity VCOM_{sdi}. The velocities at the beginning and end of trial were set to 0, as required by the DRI method. VCOM_{sdi} is a time varying velocity estimate with drift that accumulates over time. Therefore, a high pass 2nd order zero phase Butterworth filter was applied to obtain the VCOM_{hf}.

### C. CoM Velocity from foot velocities

A low frequency estimate of the VCOM can be approximated from averaging the foot velocities. Drift free foot velocity estimates were obtained using an extended Kalman Filter and zero velocity constraints [8]. As seen in Fig. 2, the velocities of both feet (vel_{lf} and vel_{rf}) were averaged. A low pass 2nd order zero phase Butterworth filter was applied to obtain the VCOM_{lf}.

In order to employ a complementary filter [4], the cut off frequencies used for the high pass filter of VCOM_{hf} and low pass filter of VCOM_{lf} were the same. After a preliminary analysis, the optimal values were found to be 0.5, 0.2, and 1.4 Hz for X, Y, and Z axes respectively. The VCOM_{hf} and VCOM_{lf} were then fused to obtain the instantaneous VCOM_{est}.

### D. Measurement System and Participants

Three IMUs were used: One Xsens™ IMU was mounted on the sacrum using a strap, and one was placed on each foot on the midfoot region [5]. A MT Manager was used to read the data from the IMU wirelessly, which was sampled at 100 Hz. A VICON® (Oxford Metrics PLC.) motion capture system was used as the reference. Markers were placed on the following locations on both the left and right limbs: anterior

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**Fig. 3.** Comparing the high frequency VCOM_{hf} and low frequency VCOM_{lf} for a WT2 task. Shaded regions denote turning moments.

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**Table 1.** Comparison of percent and absolute mean square error.

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**Fig. 4.** Shows an example of the estimated instantaneous VCOM_{est} (blue line) compared with the reference VCOM_{ref} (red line). Here, we also depict the strapdown integrated VCOM_{sdi} (thin black line), which is seen to clearly drift. In both Fig. 3 and 4, the subject makes two 180° turns which are denoted by shaded light red rectangles. Also, in both figures, each subplot corresponds to an axis of the \( \psi_{cs(k)} \). Table 1 compares the average root mean square of the error between the VCOM_{est} and VCOM_{ref} across all subjects for different walking tasks as both absolute, and percentage error normalized to the range of VCOM_{ref}.
RMS
RMS
RMS

ψ
regarding a drift free change in this trend. In Fig. 3 and 4, the
information present in the VCOM. Our approach dis-

Note that the use of foot IMUs is two-fold: for defining the
learning to estimate the average VCOM. Our approach dis-
method is similar to Sabatini et al. [3], they used machine
VCOM during variable gait. Although, the complementary
VCOM

180◦ remain positive in the X axis even as the subject makes two
turns, as compared to
axis due to transformation to the
VCOM
the other axes, but exists, as evident during the last few steps.
Further, the VCOMref shows more drastic jumps during the
turns, as compared to VCOMest, more clearly seen in the Y
axis due to transformation to the ψcs. As we account for the
Rcs(k),cs(k−1) per step k, we can represent the kinematics in
a fixed global frame, or the frame of any other required step.

Table I shows that the errors are on average 13.1 ± 2.2% of
the range of VCOM across all axes and walking tasks.

The errors seem to be largest for the SIW task, as the gait
was always changing direction. The error margins are quite
low overall, about less than 19% of the range in the worst
case. The algorithm has lower errors for variable walking
when compared to the results of Sabatini et al. [3]. The
applicability of the method however, would dependent on
the application, and proposed error margins. Note that the
cut offs used in the complementary filter was optimized
across all subjects. The errors found could be further low-
ered if this was optimized per subject. A drawback of this
method is that it employs a DRI method for integration,

IV. DISCUSSION

The current method shows the feasibility of estimating 3D
VCOM during variable gait. Although, the complementary
method is similar to Sabatini et al. [3], they used machine
learning to estimate the average VCOM. Our approach dis-
cards the need for a training step by including the foot IMUs.
Note that the use of foot IMUs is two-fold: for defining the
ψcs(k) as well as obtaining a low frequency VCOM information.

Fig. 3 shows the complementary information present in
the VCOMhf and VCOMlf. VCOMlf derived from the foot
velocities encodes the trend and VCOMhf has information
regarding a drift free change in this trend. In Fig. 3 and 4,
the kinematics are expressed in ψcs, and hence, the velocities
remain positive in the X axis even as the subject makes two
180◦ turns, during the shaded regions. Note that in Fig. 4, the
drift in the vertical VCOMsd, is quite limited compared to
the other axes, but exists, as evident during the last few steps.
Further, the VCOMref shows more drastic jumps during the
turns, as compared to VCOMest, more clearly seen in the Y
axis due to transformation to the ψcs. As we account for the
Rcs(k),cs(k−1) per step k, we can represent the kinematics in
a fixed global frame, or the frame of any other required step.

Table I shows that the errors are on average 13.1 ± 2.2%

\[ \text{RMS}_{X} \quad \text{RMS}_{Y} \quad \text{RMS}_{Z} \]

\[ \text{NW} \quad 0.1 \pm 0.03 \quad 12.2 \pm 3.1 \quad 0.1 \pm 0.02 \quad 13.9 \pm 4.2 \quad 0.1 \pm 0.01 \quad 11.6 \pm 5.3 \]

\[ \text{LW} \quad 0.1 \pm 0.01 \quad 9.0 \pm 1.4 \quad 0.2 \pm 0.05 \quad 15.0 \pm 2.6 \quad 0.1 \pm 0.01 \quad 12.0 \pm 2.8 \]

\[ \text{WT} \quad 0.1 \pm 0.04 \quad 10.1 \pm 2.6 \quad 0.2 \pm 0.02 \quad 14.4 \pm 2.3 \quad 0.1 \pm 0.01 \quad 12.3 \pm 3.0 \]

\[ \text{WT2} \quad 0.2 \pm 0.04 \quad 11.5 \pm 1.8 \quad 0.2 \pm 0.07 \quad 11.9 \pm 2.0 \quad 0.1 \pm 0.02 \quad 12.1 \pm 2.8 \]

\[ \text{SIW} \quad 0.1 \pm 0.02 \quad 12.8 \pm 3.5 \quad 0.2 \pm 0.01 \quad 18.6 \pm 1.3 \quad 0.1 \pm 0.01 \quad 18.9 \pm 6.1 \]

\[ \text{AW} \quad 0.1 \pm 0.02 \quad 12.2 \pm 6.7 \quad 0.1 \pm 0.02 \quad 13.4 \pm 3.3 \quad 0.1 \pm 0.02 \quad 15.7 \pm 2.2 \]

NW: Normal Walk, LW: L Walk, WT: Walk and Turn, WT2: Walk and Turn Twice, SIW: Slalom
Walk, AW: Asymmetrical Walk.

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REFERENCES


