Portable Gait Lab: Estimating 3D GRF Using a Pelvis IMU in a Foot IMU Defined Frame

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Abstract—Ground Reaction Forces (GRF) during gait are measured using expensive laboratory setups such as in-floor or treadmill force plates. Ambulatory measurement of GRF using wearables enables remote monitoring of gait and balance. Here, we propose using an Inertial Measurement Unit (IMU) mounted on the pelvis to estimate the GRF during gait in daily life. Calibration procedures and an Error State Extended Kalman filter (EEKF) were used to transform the accelerations at the center of mass (CoM) to the 3D GRF. The instantaneous 3D GRF was estimated for different overground walking patterns and compared with the 3D GRF measured using the reference ForceShoe™ system. Furthermore, we introduce a changing reference frame called the current step frame that followed the direction of each step made. This allowed direct comparison and validation of the feet, and the estimated GRF were expressed in this new frame. The mean and standard deviation of the error margin, normalized against the range of the reference, was 12.1 ± 3.3% across all walking tasks, in the horizontal plane. The error margins show that a single pelvis IMU could be a minimal and ambulatory sensing alternative for estimating the instantaneous 3D components of GRF during overground gait.

Index Terms—Ambulation, ground reaction forces, inertial measurement unit, minimal sensing, gait.

I. INTRODUCTION

Whole body ground reaction forces (GRF) are used to evaluate gait kinetics and balance measures [1], [2]. Traditionally, GRF are measured using force plates installed under either the floor, or special treadmills. These, indeed, cannot be used in an ambulatory manner.

If a simple inverted pendulum model of gait is assumed [3], the GRF is equal and opposite the sum of accelerations at the center of mass (CoM); and accelerations can be directly measured by Inertial Measurement Units (IMUs).

Ancillao et al. [4] reviewed several approaches where IMUs were used to estimate the GRF using either biomechanical models or machine learning methods. For instance, Karatsidis et al. [5] used several IMUs placed in a full body suit and applied inverse dynamics to obtain GRF. Others attempted to estimate GRF using a single sensor [6], [7]. However, these studies only assessed the vertical GRF (vGRF). Other studies estimated the 3D GRF using machine learning methods [8], [9]. These showed good estimates using models for straight line walking, but can be limited for variable gait. Gurchiek et al. [10] estimated the 3D GRF with only one pelvis IMU, but only during specific steps where the GRF vector changes its direction. To summarize, most of the studies reviewed by Ancillao et al. [4] measured only the vGRF using a single pelvis IMU, or the 3D GRF using machine learning methods or additional ancillary IMUs. A later study by Shahabpoor and Pavic [11] used dynamic time warping to estimate an average progression of only the vGRF. Estimating the lateral components of GRF is a critical aspect when using a one IMU approach [4]. It is therefore, of interest to estimate the instantaneous 3D GRF using a single IMU during variable gait.

A commonly used biomechanical assumption is that the CoM is encompassed by the rigid pelvis [1], [12], and thereby, an IMU at the pelvis could measure the CoM accelerations. Using Newton’s law, the product of body mass and CoM accelerations provides the whole body GRF. This is a simplification of the inverted pendulum model of gait and errors are expected [4], [11]. However, this allows us to minimize the measurement setup for ambulatory estimation of GRF. The challenge here is to estimate the CoM accelerations measured at the pelvis IMU in the three axes that correspond to the anterio-posterior, medio-lateral, and vertical axes of the GRF.

Gait kinematics and kinetics are usually expressed in a fixed global frame, defined using the non-portable measurement setup or certain pre-defined initializations. However, this can be restrictive in understanding GRF in an ambulatory manner. Expressing these forces along the changing walking direction can provide a more functional representation, which is body centric, especially during shuffling or turns. It is therefore, also of interest to define a changing reference frame, expressed along the direction of each step being made. This changing reference frame is referred to hereon as the current step frame.

Thus, the main goal in this study is to evaluate the feasibility of estimating 3D GRF from a pelvis IMU, for different walking patterns seen in daily life for the complete gait.

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A calibration procedure, and an Error State Extended Kalman Filter (EekF) were used to estimate body orientation, in order to determine the 3D components of the pelvis acceleration in a certain reference frame. Two additional IMUs were placed, one on each foot, and were used to define the current step frame. This frame was based on the direction of each step being made, and the GRF was then expressed in this frame. The estimates of the GRF were derived from the pelvis IMU, and the foot IMUs were only used to define the changing current step frame. Introducing this new frame is the second goal of this paper. The instantaneous 3D GRF was then compared with the reference system, the ForceShoe™, and also with results from literature.

II. METHODS

In this section, the methodology used to estimate 3D GRF from a pelvis IMU in the current step frame is explained. First, in Section II-A, the definition of reference frames used in this study are described. Section II-B sumarizes the assumptions considered for the models that will be described. Section II-C describes the IMU models used for the following sections. In Section II-D, the algorithms used for foot contact detection is explained. Using the IMU models described, and foot contact instances, Section II-E describes the estimation of the different reference frames as mentioned in II-A, and also the 3D GRF. Section II-F describes the measurement system used, and Sections II-G and II-H describe the participants, and the experimental protocol used to validate this study respectively. Finally, Section II-I describes the analysis of the results.

A. Reference Frames Used

The use of a fixed global frame of reference for gait analysis could be attributed to the fixed nature of force plates or optical motion capture systems. As shown in Fig. 1, the global frame $\varphi_g$ has a predefined and fixed frame throughout the measurement. However, wearable setups allow us to define frames that are associated with the direction of gait. For instance, pressure profiles, and center of pressure patterns are expressed in foot frames. Similarly, here we can define reference frames that are attached to the moving body.

There are two possible options; one is to have a reference frame defined by the heading of the body. This would be based on the measurements of the pelvis IMU and tracking CoM positions. Alternatively, we could define reference frames based on the direction of each step. Estimating changes in foot positions is feasible using strapdown inertial navigation, and zero velocity updates [13]. Further, the reference system used in this study, the ForceShoe™, can track changes in foot positions [14]. Therefore, the second method is preferred. This is made feasible by one additional IMU placed on each foot.

The current step frame is denoted as $\varphi_{cs(k)}$ and defined graphically in Fig. 1. It depends on the direction of the step $k$, and thus, changes for each step. Although this is similar to the local foot frame defined by other studies [15], [16], $\varphi_{cs(k)}$ is defined for each step. We define the X axis of this frame as positive in the forward direction, defined by the line between the beginning and end of a step. The Z axis is positive upwards along the vertical. This is the $\varphi_{cs(k)}$ for the current step $k$, and is redefined for the next step.

The sensors of the IMUs measure in their respective sensor frames denoted by $\varphi_s$. This has to be transformed to the $\varphi_{cs}$ per step. The transformation between frames are shown in Fig. 2. First, each sensor was transformed to their respective segment (seg) frames $\varphi_{seg}$ using a simple calibration method. The segments of interest in this study are the pelvis ($p$), left foot ($fl$), and right foot ($fr$). Then, during step $k$, the orientation of these segments were expressed in the current step frame of the previous step $\varphi_{cs(k-1)}$, as this $\varphi_{cs(k-1)}$ was already defined. EeKFs were used to estimate the change in orientation of the segments during this phase. At the end of step $k$, the change in position of the moving foot was used to estimate the orientation from $\varphi_{cs(k-1)}$ to $\varphi_{cs(k)}$ as $R_{\varphi cs(k), cs(k-1)}$ allowing transforming to $\varphi_{cs(k)}$.

This was redefined for each step, resulting in a $\varphi_{cs(step)}$ per step. In short, four frames of reference were used in this study: sensor frame ($\varphi_s$), segment frames (pelvis $\varphi_{p}$, right foot $\varphi_{fl}$ and left foot $\varphi_{fr}$), current step frame of the previous step ($\varphi_{cs(k-1)}$), and that of the current step $k$ ($\varphi_{cs(k)}$). The notations used in this study are listed in Table I.
Therefore, it becomes less important to identify the different not model the rolling of the foot during the stance phase. We are using IMUs to track the foot as one rigid body, we do can be estimated. A step is defined as the instance between IMUs are synchronized in time, the double stance instances estimate the foot contact instances for the two feet. As the midpoint of the next double stance.

D. Foot Contact and Step Detection

Step detection is important in estimating the current step frame. Here, the method of Skog et al. [17] was used to estimate the foot contact instances for the two feet. As the IMUs are synchronized in time, the double stance instances can be estimated. A step is defined as the instance between the heel strike of one foot to that of the other. However, as we are using IMUs to track the foot as one rigid body, we do not model the rolling of the foot during the stance phase. Therefore, it becomes less important to identify the different gait events during stance. Therefore, we define a step as the instance between the midpoint of a double stance event to the midpoint of the next double stance.

E. Orientation in the Different Reference Frames

The transformation between different frames is explained in the following sections. Static calibrations used to transform the sensor data to the respective segment frame is first described. Following this, the structure of the fusion filter, used to estimate changes in orientation of the segment during a step, expressed in the previous step frame is described. Finally the estimation and transformation to the current step frame is explained.

1) Sensor to Segment Calibration: The $R_{seg,s}$ was estimated using the mounting frame calibration techniques described by Bonnet et al. [18]. For all segments, the inclination estimate was estimated from (3a) during an initial standing still phase, during which the 3D accelerometer is expected to measure only gravity. The Y axis of the pelvis was estimated by asking the subject to bend forward. Principal component analysis was applied to the gyroscope output to find the axis measuring largest angular rotation. The X axis of the pelvis was estimated using right hand thumb rule, as seen in (3c). The Y axis was then updated using (3d). The orientation is given in (3e).

$$\begin{align*}
a_x &= y_A^s - g^s + e_A \quad (1) \\
y_G^s &= \omega^s + b^s + e_G \quad (2)
\end{align*}$$

Here, $a$ is the linear acceleration of the sensor, $g$ is gravity, and $e_A$ is Gaussian white noise. Also, $\omega$ is the angular velocity, $b$ is a slowly varying offset, and $e_G$ is the Gaussian noise. Both (1) and (2) are discrete time equations and are expressed for a given time instance $i$.

2) Error State Extended Kalman Filter: Now, the change in orientation of the segments during each step has to be estimated. The current step frame $\psi_{cs(k)}$ can only be defined at the end of the step $k$ as it requires the change in foot positions during that step. However, the previous current step frame $\psi_{cs(k-1)}$ has already been defined. Therefore, the change in orientation of the segment during step $k$ was first expressed in $\psi_{cs(k-1)}$ using an EEFK. The EEFK tracked the $R_{seg}^{cseg,seg}$, i.e., the orientation of the segment $\psi_{seg}$ with respect to $\psi_{cs(k-1)}$ for given instance $i$. Here, $i$ denotes the samples of the current step $k$. The EEFK filter used for the pelvis orientation is shown in Fig. 3 and was based on Kortier et al. [19], and Luining and Veltink [20]. The states included in the state vector ($x$) of the EEFK were orientation

C. Inertial Measurement Unit Model

The 3D accelerometer and 3D rate gyroscope present in the IMU provides the acceleration and angular velocities in the sensor frame $\psi_s$ respectively, and can be modelled as:

$$\begin{align*}
y_A^s &= a^s - g^s + e_A \\
y_G^s &= \omega^s + b^s + e_G
\end{align*}$$

The updated states are used to estimate $\psi_{seg}$ for the step $k$.

| Notation | Definition |
|----------|------------|
| $a_k$    | at k-th instant |
| $a_s$    | a expressed in frame $\psi_s$ |
| $\dot{a}$ | derivative of $a$ |
| $\hat{a}$ | estimate of $a$ |
| $\tilde{a}$ | a priori estimate of $a$ |
| $e_A$    | Gaussian white noise associated with $a$ |

### TABLE I

NOTATIONS USED, SHOWN FOR AN ARBITRARY VECTOR $a$

- $a_k$: a at k-th instant
- $a_s$: a expressed in frame $\psi_s$
- $\dot{a}$: derivative of $a$
- $\hat{a}$: estimate of $a$
- $\tilde{a}$: a priori estimate of $a$
- $e_A$: Gaussian white noise associated with $a$
error $\theta_e$ and gyroscope bias error $b_e$. The state vector was thus $x = (\theta_e \ b_e)^T$, and its covariance matrix was denoted as $P$. The advantage of using an EKFM for estimating orientation errors is that the inertial processes can be considered linear, if the errors are assumed to be small. Similar EKFs were built for the other segments.

3) Prediction: Prediction models were defined for each state. First, the gyroscope bias was modelled as a first-order Markov process:

$$b_i = b_{i-1} + e_{b,i}$$  \hspace{1cm} (4)

Here, $e_{b,i}$ is white Gaussian noise associated with the process. Thus, the gyroscope bias was predicted as

$$\hat{b}_i = \hat{b}_{i-1}$$  \hspace{1cm} (5)

The gyroscope bias error $b_e$ can modelled as

$$b_{e,i} = \hat{b}_i - b_i$$  \hspace{1cm} (6)

Equations 4, 5, and 6 gives us

$$b_{e,i} = b_{e,i-1} - e_{b,i}$$  \hspace{1cm} (7)

Next, orientation can be estimated from orientation error:

$$\hat{R}_i^{cx(k-1),seg} \approx R_i^{cx(k-1),seg}((I + \hat{\theta}_e,i))$$  \hspace{1cm} (8)

For any vector $V$, $\hat{V} = \begin{pmatrix} 0 & -v_z & v_y \\ v_z & 0 & -v_x \\ -v_y & v_x & 0 \end{pmatrix}$. (8) is valid when orientation errors are assumed to be small. Furthermore, we can derive orientation from angular velocity using [21]:

$$\hat{R}_i^{cx(k-1),seg} = \hat{R}_i^{cx(k-1),seg} (\tilde{\omega})$$  \hspace{1cm} (9)

Based on [21], we have the derivative of orientation error and its discretised form [22] as follows.

$$\dot{\theta}_e = \tilde{\omega} \theta_e - b_e$$  \hspace{1cm} (10)

$$\theta_{e,i} = (I + \frac{T^2}{2} \tilde{\omega}^2) \theta_{e,i-1} + (-TI - \frac{T^2}{2} \tilde{\omega}) b_{e,i-1}$$  \hspace{1cm} (11)

The Kalman filter prediction equation is given as [23]:

$$\hat{x}_i = F \hat{x}_{i-1}$$  \hspace{1cm} (12)

where, $F = \begin{pmatrix} I + \frac{T^2}{2} \tilde{\omega}^2 & -TI - \frac{T^2}{2} \tilde{\omega} \\ 0 & I \end{pmatrix}$

The covariance matrix is predicted using

$$\hat{P}_i = FP_{i-1}F^T + Q$$  \hspace{1cm} (14)

where, $Q$ is the process noise covariance matrix.

4) Measurement Update: It was assumed that on average, the accelerations at the pelvis measure inclination due to gravity. This can be true during forward walking or when making changes in walking direction. The orientation error was corrected based on the current prediction and expected inclination for the vertical axis. An estimate of the accelerometer output in the frame $\psi^{cx(k-1)}$ was derived using the estimate of the orientation matrix as

$$\hat{y}_{A,i}^{cx(k-1)} = \hat{R}_i^{cx(k-1),p} \cdot (\hat{y}_{A,i}^p)$$  \hspace{1cm} (15)

Then, (3a) was used to estimate inclination at instant $i$. The difference between measured $y_A^{cx(k-1)}$ and estimated $\hat{y}_A^{cx(k-1)}$ inclination, also referred to as $\hat{\psi}_{A,i}^{cx(k-1)}$ was then used to update the orientation error as shown below [19]:

$$\hat{\psi}_{A,i}^{cx(k-1)} = y_A^{cx(k-1)} - \hat{y}_A^{cx(k-1)}$$  \hspace{1cm} (16a)

$$= \hat{R}_i^{cx(k-1),p} (I + \tilde{\theta}_e) y_A^p - \hat{R}_i^{cx(k-1),p} \cdot y_A^p + e_A$$  \hspace{1cm} (16b)

Therefore,

$$z_{dV} = H_{dV} \cdot x + e_{dV} = \hat{\psi}_{A,i}^{cx(k-1)}$$  \hspace{1cm} (16c)

$$H_{dV} = [-\hat{R}_i^{cx(k-1),p} \cdot \hat{y}_A^p 0 3x3]$$  \hspace{1cm} (16d)

The measurement update at any instance $i$ is applied to the EKFM using the standard equations given in (16c). $e_{dV}$ is the noise associated with this measurement. When $H$ was known from (16d), the Kalman gain was estimated using (17a). Then, the state matrix and the error covariance matrix were updated with (17b) and (17c) respectively.

$$K_i = P_i^{-1} H^T (HP_i H^T + R)^{-1}$$  \hspace{1cm} (17a)

$$\dot{x}_i = \dot{x}_i^- + K_i (z_i - Hx_i^-)$$  \hspace{1cm} (17b)

$$P_i = (I - K_i H)P_i^-$$  \hspace{1cm} (17c)

5) Update States: The orientation estimate and gyroscope bias were then updated based on the state vector. Singular value decomposition was used to maintain orthonormality of $\hat{R}_i^{cx(k-1),seg}$. The error state vector was reset for the next iteration.

$$\hat{R}_i^{cx(k-1),seg} = \hat{R}_i^{cx(k-1),seg} (I - \theta_e)$$  \hspace{1cm} (18)

$$\hat{b}_i = \hat{b}_i^- + b_e,i$$  \hspace{1cm} (19)

6) Initialization: The initial orientation error $\hat{\theta}_{e,init}$ was assumed to be zero, and the initial gyroscope bias error $\hat{b}_{e,init}$ was estimated from gyroscope output while standing still. At the start of each step $k$, the $\hat{R}_i^{cx(k-1),seg}$ is known from the previous step. This is described in Section II-E8. However, an estimate of $\hat{R}_i^{cx(k-1),seg}$ is needed for the first step ever made. For this, the EKFM is run once for a few steps with an arbitrary initial heading estimate. The change in position between the start and end of these steps was the X axis, and the Z axis was taken to be along the vertical. After estimating the Y axis using cross product, and updating the X axis using (3c), the initial $\hat{R}_i^{cx(k-1),seg}$ was estimated using (3e).
7) Estimating Ground Reaction Forces: The accelerations measured at the pelvis IMU were transformed to the $\psi_{cs}(k-1)$ using the estimated $\hat{R}_{cs}^{k-1}(k-1)$ for each step $k$. As these are assumed to be the same as the accelerations at the CoM, the GRF was estimated as the product of acceleration and body mass.

$$\text{GRF}_{i}^{cs(k-1)} = \text{mass} \cdot \hat{R}_{cs}^{cs(k-1),p} \cdot (\mathbf{y}_i)_{p}$$  \hspace{1cm} (20)

8) Current Step Frame: The GRF has been expressed in the $\psi_{cs}(k-1)$, and has to be transformed to $\psi_{cs}(k)$ for the current step $k$. For this, the change in orientation of the feet as well as their positions need to be known. An extended Kalman filter (EKF) [14] was used to track the foot positions. The states of this EKF were the velocity and position of each foot. Strapdown inertial navigation was used to track these states, and ZV and ZH updates were used to improve these estimations. As we are only interested in the change in position for a given step, the state vector was reset to zero before the next step.

For example, in Fig. 1, the right foot (shaded green) changes direction while making the step $k$. The change in position in the horizontal XY plane between the start and end of this step, shown by the dotted line, was the X axis of the new $\psi_{cs}$ and was estimated from (21c). The vertical Z axis was defined as (21d). The Y axis of the pelvis was estimated using right hand thumb rule, as seen in (3d). The Z axis was then updated using (21e). The $R_{cs}^{k,cs(k-1)}$ is given in (21f), which gives us the transformation to the new $\psi_{cs}$ for the step $k$. This was redefined for every new step being made, and then we transformed the GRF$(k-1)$ to the new $\psi_{cs}(k)$ using (21g).

$$\mathbf{M} = [1 \hspace{0.5cm} 1 \hspace{0.5cm} 0] \cdot \mathbf{I}_{3 \times 3}$$  \hspace{1cm} (21a)

$$\delta\mathbf{pos} = \mathbf{M} \cdot (\mathbf{pos}_{\text{end}} - \mathbf{pos}_{\text{start}})$$  \hspace{1cm} (21b)

$$axX = \frac{\delta\mathbf{pos}}{||\delta\mathbf{pos}||}$$  \hspace{1cm} (21c)

$$axY = [0 \hspace{0.5cm} 0 \hspace{0.5cm} 1]^T$$  \hspace{1cm} (21d)

$$\begin{bmatrix} axX & axY & axZ \end{bmatrix}$$  \hspace{1cm} (21e)

$$R_{cs}^{k,cs(k-1)} = \begin{bmatrix} axX \hspace{0.5cm} axY \hspace{0.5cm} axZ \end{bmatrix}$$  \hspace{1cm} (21f)

$$\text{GRF}_{cs}^{k} = \text{GRF}_{cs}^{cs(k-1)} \cdot (\text{GRF}_{i}^{cs(k-1)})_k$$  \hspace{1cm} (21g)

9) Estimating Noise Values: The process and measurement noise were estimated from sensor specifications and static measurements. The measurement noise $\epsilon_{dV}$ was fine-tuned manually by minimizing the root mean square of error between the GRF$(k)$ from (21g) and the reference GRF. The $\epsilon_{dV}$ turned out to vary slightly for different trials across subjects, and an average value is reported here. The resulting noise values are tabulated in Table II.

10) Filtering Estimated Ground Reaction Forces: The estimated 3D GRF was found to have certain sharp peaks around foot contact instances, possibly due to foot impact. Different methods to selectively remove these peaks were tested. This resulted in an adaptive peak removal algorithm. In this method, first, the peaks were identified by finding the local minima or maxima around the foot contact. Then, a savitsky golay smoothing filter [24] of order 3 was used to smooth the signal around this peak and suppress it. Following this, a power spectral density analysis showed that each axis had different noise levels at different frequency bands. Therefore, a zero phase bandpass Butterworth filter of order 4 and bandwidth of 0.1-5 Hz and 0.1-3 Hz was used for the X and Y axis respectively, in order to account for high frequency noise as well as any offset errors. However, the Z axis was filtered using a zero phase Butterworth low pass filter of order 4.

F. Measurement System

Three Xsens™ MTw IMUs seen as orange boxes in Fig. 4 were used [25]. Using a strap, one IMU was mounted on the sacrum at the midway point between the line connecting the left and right posterior superior iliac spine. One IMU was placed on each foot on the midfoot region. The MT Manager (version 4.8) software was used to read the data from the IMU wirelessly, sampled at 100 Hz.

The reference system seen in Fig. 4 was the ForceShoe™ which consists of 6DoF Force and Torque sensor, and an IMU under each toe and heel of both feet [26]. It has been validated against force plates (AMTI®) for measurement of contact forces [1]. Although portable, it is bulky and not comfortable for everyday use [27]. However, it is a good wearable reference system for this study. The data were sent wirelessly to a PC, sampled at 100 Hz. It was then low pass filtered twice at 10Hz using a second order Butterworth filter to ensure zero-phase lag. The measured GRF on each foot was summed to obtain the total GRF, which reflected the accelerations at the CoM [1]. The GRF was then transformed to the $\psi_{cs}$ as defined in Section II-E8.

G. Participants

Eight healthy subjects were recruited for the study. The average and standard deviation of the height, weight, and age was $1.78 \pm 0.1$ m, $76.4 \pm 12.5$ kg, and $26.7 \pm 3.8$ years respectively. Six subjects were male. Leg length was
measured from the greater trochanter to the ground [28] and was 0.94 ± 0.06 m. 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.

H. Experimental Protocol

The subjects began by standing still for a few seconds, following which they were asked to bend the trunk forward thrice. This was used to calibrate the sensor to segment orientation for the pelvis sensor as seen in (3b). The subjects were then asked to perform variable gait starting with their feet placed parallel. Once the researcher gave the start sign, the subject walked along a given path. The time taken between start and stop of the walking was measured using a stopwatch. The following walking tasks were performed one after the other, with each task repeated four times:

1) **Normal Walk (NW):** The subject was asked to walk at his preferred walking speed for 10 m.
2) **L Walk (LW):** The subject was asked to walk for 15 m and then turn 90 degrees to the right and walk for another 10 m.
3) **Slow Walk (SW):** The subject was asked to walk at a slower pace. They were guided by the use of a metronome beating at 50 beats per minute. Each beat corresponded to a heel strike. This frequency was used so that the subjects walked slower than 0.6 m/s.
4) **Walk and Turn (WT):** The subject was asked to walk for 10 m and then turn and walk back to start position.
5) **Slalom Walk (SlW):** The subject was asked to walk in a slalom pattern. In order to guide them, two pylons were placed on the floor. These were placed slightly away and on either sides of an imaginary line from start to end.
6) **Asymmetric Walk (AW):** In this task, the subject was asked to walk in an asymmetric manner. The instruction given was to induce a stiff left knee and abduct the hip as much as possible on the right side.

I. Analysis of Results

First, an example of the estimations of GRF in 3D using the EEEKF (GRF<sub>KF</sub>) and that of the ForceShoe<sup>TM</sup> (GRF<sub>FS</sub>) is shown in the current step frame ψ<sub>cs</sub>. There were some noisy peaks in the GRF<sub>KF</sub>, which were removed, and an example of the post processed results are displayed. Then, the root mean square of the differences between the post-processed instantaneous GRF<sub>KF</sub> and GRF<sub>FS</sub> were studied across different walking tasks. Following this, Pearson’s correlations and its significance were analyzed. The difference in the angle of estimated GRF vectors from the reference in the horizontal plane was also measured. All analyses were done in MATLAB® 2018b (Mathworks, USA).

III. RESULTS

Some trials had to be excluded from the analysis due to issues with the reference system. However, it was made sure that each subject had at least three walking trials per task. The average walking speed measured for the included trials of NW task was 1.01 ± 0.12 m/s, LW was 1.14 ± 0.14 m/s, SW was 0.47 ± 0.07 m/s, WT was 0.98 ± 0.19 m/s, during SIW was 0.89 ± 0.11 m/s, and during AW was 0.52 ± 0.17 m/s.

An example of the estimated GRF<sub>KF</sub> in the current step frame ψ<sub>cs</sub> is seen in Fig. 5, along with the reference GRF<sub>FS</sub>. GRF<sub>KF</sub> is shown as the blue line, and GRF<sub>FS</sub> is the dotted red line. The forces were normalised to the body weight of the subject. Each row in the figure corresponds to an axis in ψ<sub>cs</sub>. The horizontal yellow and gray lines denote the left and right legs.
Foot contacts instances respectively. The figure is a five second snapshot of the walking trajectory. It shows peaks in GRF\textsubscript{KF} specifically around foot contact. They were removed using the method described in Section II-E10 and this results in Fig. 6. Note that Fig. 6 corresponds to the complete LW task, including the starting and stopping of the task, and also turning to the right at 35 seconds highlighted by a shaded light red rectangle. The figure includes the error between the GRF\textsubscript{KF} and GRF\textsubscript{FS} in black, with the Y axis described on the right.

In Table III, we compare the post-processed instantaneous GRF\textsubscript{KF} and reference GRF\textsubscript{FS}, for all walking tasks. The table shows the root mean square of differences (RMS) as a percentage of body weight, correlations (CORR), and also differences in 2D GRF vector angle in the XY plane ($\theta_{d}$) between the GRF\textsubscript{KF} and GRF\textsubscript{FS}. The average RMS and CORR across all subjects are displayed along with their standard deviations. The range of the GRF for the respective axes is also provided in the table. The CORR was found to be significant for all walking tasks.

IV. DISCUSSION

This study is the first to estimate 3D GRF over a complete gait using a pelvis IMU for different gait patterns. It has to be noted that the foot IMUs were not used to estimate the 3D GRF during gait, rather they were used to estimate the current step frames per step. Using a changing frame has two advantages. First, it provides a user centric expression of the kinetics convenient for real time gait assessment. Secondly, they could be also be compared with similar estimations made by the reference ForceShoe\textsuperscript{TM}. Nevertheless, it is possible to estimate the changing reference frame using only the pelvis IMU. For this, first, gait events should be detected using the measurements of the pelvis IMU [29]. Then, during each gait cycle, the change in CoM positions can be estimated using strapdown integration with arbitrary initial and final values [12], [30]. The change in CoM positions would be the X axis, and the vertical would define the Z axis of this new changing reference frame mentioned in Section II-A.

Estimations of the shear GRF are the most challenging using the single IMU approach [4], [11]. This is due to the large contribution of gravity, and the assumption that CoM lies at the center of the pelvis. The EEKF was tuned to be able to resolve the accelerations measured at the pelvis into 3D components of the GRF within the current step frame $\psi_{cs}$. Assuming that the CoM accelerations along the vertical measured inclination due to gravity seemed to be a sufficient measurement update. However, the resulting GRF was found to have high frequency noise in the three axes. Additionally, there were peaks seen during foot impact, as shown in Fig. 5. These peaks during foot contact could be due to impact impulse, or soft tissue artifacts, or that the CoM accelerations deviate further from the measured pelvis accelerations. These peaks were more conspicuous in the Y or the medio-lateral axis. Therefore, to improve the estimations, adaptive peak removal and filtering methods were applied.

Fig. 6 shows the post processed output of the GRF\textsubscript{KF} and the reference GRF\textsubscript{FS} for the LW task. Here, the subject was asked to make a right turn, and the moment this occurs is denoted by a shaded rectangle. We see that after the turn, the X and Y axis measure the anterio-posterior and medio-lateral GRF respectively, similar to that before the turn. As the frame used here is defined by the direction of steps being made, the profiles of $F_{X}$ and $F_{Y}$ remain unchanged after the turn. However, if a fixed global frame denoted as $\psi_{g}$ in Fig. 1 was used, the axes would have been interchanged. Thus, the $\psi_{cs}(k)$ represents the biomechanics of the body irrespective of the change in walking direction. The figure also shows that the error is relatively larger for the $F_{Y}$, and more so during the right turn.

Table III shows that the RMS between the GRF\textsubscript{KF} and GRF\textsubscript{FS} is quite low, less than 7.4 ± 2.3% of body weight.
TABLE III
COMPARING THE ESTIMATED AND REFERENCE GRF VALUES: ROOT MEAN SQUARE OF THE DIFFERENCES (RMS), CORRELATIONS (CORR), AND DIFFERENCE IN 2D GRF VECTOR ANGLE IN THE XY PLANE ($\theta_d$)

|     | $RMS_X$ (min,max) % BW | $RMS_Y$ (min,max) % BW | $RMS_Z$ (min,max) % BW | CORR_X | CORR_Y | CORR_Z | $\theta_d$ (deg) |
|-----|------------------------|------------------------|------------------------|--------|--------|--------|------------------|
| NW  | 4.8 ± 0.7 (323, 285)   | 4.8 ± 0.5 (127, 152)  | 6.5 ± 1.2 (721, 133,4) | 0.89±0.1  | 0.55±0.1  | 0.80±0.1  | 40.8 ± 6.1      |
| LW  | 7.3 ± 1.5 (389, 335)   | 6.6 ± 0.8 (241, 197)  | 7.2 ± 1.7 (661, 136,6) | 0.84±0.1  | 0.45±0.1  | 0.89±0.1  | 39.6 ± 9        |
| SW  | 5.1 ± 1.1 (258, 233)   | 4.2 ± 0.8 (132, 15,4) | 4.6 ± 1.7 (847, 124,2) | 0.72±0.2  | 0.51±0.2  | 0.55±0.2  | 48.8±13.6       |
| WT  | 5.6 ± 1.4 (362, 304)   | 5.5 ± 0.8 (158, 18.3) | 5.3 ± 1.2 (713, 135,5) | 0.81±0.1  | 0.37±0.2  | 0.85±0.1  | 51.2 ± 10       |
| SIW | 7.4 ± 2.3 (342, 321)   | 7.4 ± 1.4 (284, 28.4) | 6.8 ± 1.7 (724, 135,3) | 0.70±0.1  | 0.48±0.1  | 0.82±0.1  | 56.4±10.6       |
| AW  | 6.5 ± 1.7 (312, 232)   | 5.9 ± 1.0 (193, 18.4) | 5.7 ± 1.2 (768, 143,4) | 0.56±0.3  | 0.30±0.3  | 0.75±0.2  | 63.8±20.8       |

*p < 0.01. NW: Normal Walk, LW: L Walk, SW: Slow Walk, WT: Walk and Turn, SIW: Slalom Walk, AW: Asymmetrical Walk. (min,max) corresponds to the minimum and maximum values measured by the reference system.

in the worst case. On average, the normalized root mean square error expressed as percent of range of the reference measurement (NRMSE) was 12.1 ± 3.3% for the horizontal plane, which is better than previous studies [10]. It is similar to findings of Leporace et al. [8] who found an average NRMSE of 9.3 ± 6.4% in the horizontal plane. They employed a shank IMU and single multilayer perception to obtain the 3D GRF. However, comparing only the vertical, we found that the average NRMSE across different walking tasks was 10.2 ± 1.2% as compared to 4.2 ± 1.1% found by Shahabpoor et al. [11]. The reference study was able to obtain a better estimation of the vertical GRF for each gait cycle using a dynamic time warping method. On the other hand, in spite of a larger error margin, the current study estimated the instantaneous GRF during the complete gait, including starting and stopping of walking.

Table III also allows comparison with the actual range of the GRF measured using the reference system. This shows that the errors in Y axis are relatively larger compared to that of the other axes. We find that the correlations were highest for the X and Z axis, except for Z axis of SW task. The AW task shows least correlations as compared to the other walking tasks. This task was meant to simulate impaired gait and is not a standardized test. Though, the subjects were given instructions to walk asymmetrically, each of them chose a unique pattern. However, the results show that the algorithm can be used to measure 3D GRF in a simulated asymmetric gait. Additionally, $\theta_d$ shows quite some differences in the XY plane, which could be attributed to the low correlations in the Y axis.

The errors seen in Table III could be caused by differences in transforming the $GRF_{KF}$ and the reference $GRF_{FS}$ to their respective $\psi_{cs(k)}$ frames. One source of difference is that the IMUs used in this study were placed on top of the mid-foot, whereas the ForceShoe™ had IMUs under the toe region. Also, the reference system used the forces measured by the ForceShoe™ to determine foot contact. In the IMU only setup, some approximations were required for the true instances of foot contact.

Each step was first expressed in the previous step frame before transforming it to the $\psi_{cs}$. Alternatively, they could have been estimated in the global frame $\psi_g$, and then transformed to the $\psi_{cs}$. However, as the rotation between the $\psi_{cs}$ of each subsequent step is known, the GRF can be expressed in the current step frame of any specific step $m$ of choice. This may be used to visualize changes in shear forces between subsequent steps.

A. Limitations and Future Work

The GRF estimated in this study is the sum of the GRF acting under both feet [1]. If required, a smooth transition assumption could be used to resolve the 3D GRF into forces acting under each foot [5]. In this study, the IMU was placed at the pelvis, which is less susceptible to orientation or placement errors [31], when compared to the trunk. Furthermore, the errors associated with the assumption that the CoM lies within the centroid of the pelvis might be larger when we consider people with an unconventional or asymmetrical body posture. Modelling deviations between the true CoM and the placement of the IMU would help improve the results [12]. The subject was asked to bend forward to calibrate a sensor to segment orientation for the pelvis sensor. However, this could be avoided by exploring simpler calibration methods based on the user’s daily life functional movements, such as squatting or sit to stand. The algorithm needs to be run with an arbitrary initialization before it can converge to the optimal solution. In actual practice, this means that the subject has to make a few physical steps before output is produced.

As Xsens™ IMUs were used, well defined error specifications were available to initialise the EEKF. Further, the three IMUs were synchronized well. Any mismatch would have caused errors in the estimation of the current step frames,
which would be reflected in the estimated GRF. Therefore, good communication protocols are required. Furthermore, identifying foot contact using IMU signals [17] might be susceptible to errors. As we are interested at instances where the foot is completely still, we opted to use the midpoint of the foot contact. However, gait event detection can be further improved using other techniques [29].

The setup has to be further validated in other variable walking instances such as walking on an incline or stair climbing. The AW task performed in this study may not be similar to gait patterns exhibited by gait impaired populations. The same argument holds for rapid walking or running scenarios. Therefore, a similar experiment shown in this study for gait impaired populations and other gait variations must be performed as a follow up. Finally, the measurements were done when no external loads were acting on the body. Modelling an external load is not trivial, and its contribution to the GRF has to be measured with additional sensors.

As a next step, the 3D components of GRF can be used to estimate the inter-foot distances during gait [25, Eq. 6 and 7] following a Centroidal Moment Pivot assumption. This can reduce drift when using a three IMU setup to track the feet and CoM over time, and also during variable gait. Thus, the findings of this article can be useful to estimate relative foot positions. This will be described in a subsequent paper.

V. CONCLUSIONS

We show how to monitor 3D GRF in an ambulatory manner using a pelvis IMU. Foot IMUs were used to express the measured GRF with respect to the moving and turning body. The steps made for this study are useful for developing a minimized and portable gait lab.

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