Dynamic *in situ* Calibration of an Instrumented Treadmill for Systems Identification and Parameter Estimation

Tina R. Amirtha, BS; Supervisors: Lizeth Sloot, MSc, Juriaan de Groot, PhD, Erwin de Vlugt, PhD; Committee Chairperson: Frans van der Helm, PhD

**Abstract**—Existing re-calibration methods for instrumented treadmills have mainly been performed when the instrumented treadmill has been in static operation *i.e.* the belts are not running. The effect re-calibrating during experimental operation, *i.e.* while the belts are running, on the ground reaction force (GRF) and the center of pressure (CoP) accuracy has not yet been studied due to difficulties of obtaining a range of test points across the treading area during experimental operation. Therefore, the effect of the dynamics of the treadmill’s moving parts on the re-calibration process is not known. In addition, the GRF and CoP accuracy requirements are not known for systems identification and parameter estimation (SIPE) experiments on instrumented treadmills. Here, a technique is described to comprehensively recalibrate a split-belt, instrumented treadmill, while it operates under experimental conditions, for SIPE of the lower extremity dynamics during gait. Re-calibration matrices are created with datasets that were generated under static and experimental treadmill operation and are assessed on validation datasets. No relationship was determined between the treadmill’s dynamics and the GRF and CoP errors. The dynamic re-calibration resulted in lower root-mean-square GRF and CoP errors than the static re-calibration did and was more rapid to calculate. The dynamic re-calibration matrix was additionally validated by performing SIPE of a load on the treadmill, which resulted in a relative error of 2%.

**Index Terms**—Force platform, Force plate, Calibration, Center of pressure, Ground reaction force, Gait, Treadmill, Accuracy, Motion analysis, Optimization, System identification, Parameter estimation

1 **INTRODUCTION**

Instrumented treadmills, which are treadmills that incorporate force transducers or force plates into their structures, have recently been used in gait analysis studies to measure the evolution of the ground reaction force (GRF) and center of pressure (CoP) over the course of numerous strides. Gait analysis laboratories e.g. [1] employ instrumented treadmills to measure the GRF and estimate the CoP as an alternative to force plates. Traditional gait analysis studies that use inverse dynamic models have shown that the root-mean-square errors (RMSE’s) of < 1N and Nm in the GRF and < 1cm in the CoP are desired for carrying out accurate inverse dynamic estimates [2]. Correctly calibrating an instrumented treadmill can help reduce the RMSE to these levels.

Performing a calibration to improve a previously-done calibration is called re-calibration. Re-calibrating the instrumented treadmill in the laboratory, or *in situ*, ensures the accuracy of the GRF and CoP is needed in order to account for measurement errors that arise from treadmill installation and general use. Errors in measured GRF and CoP errors in treadmills have been shown to be similar to those of force plates [3]. Bending under loading in force plates results in a nonlinear spread of CoP errors across the surface, with the CoP error being higher near the posts and edges. Such a phenomenon applies to any flat surface that is suspended on top of four posts, which is the case of an instrumented treadmill. Therefore, the CoP error is an indication of the spatial nonlinearity of the treadmill structure. In such cases, re-calibration has been advocated by [4] and [5], who have shown that the presence of cross-talk terms in the re-calibration correction matrix corrects the spatial nonlinearities. Therefore, re-calibration produces cross-talk, or off-diagonal, terms in the correction matrix that account for nonlinear relationships between the measured and expected forces. Re-calibration should be repeated when any changes are made to the mounting of the instrumented treadmill’s components or the data acquisition system.

Both static and dynamic loading induce moments in the treadmill structure. Static loading employs a non-varying force application over time, while dynamic loading makes use of time-varying applied forces. In both loading cases, it has been shown that the force readings will be distorted by bending occurring at the support posts [6]. Using static loading to create a correction matrix is called static calibration, and using dynamic loading to create a correction matrix
is called dynamic calibration and is convenient from a time perspective [7]. Correction matrices that result from the calibration process and consist of static, linear terms are called static correction matrices. Static correction matrices have been used to correct the spatial, or static, nonlinearities in the CoP error. Other static correction matrices have been proposed that employ nonlinear correction terms in order to further reduce the CoP error, but these methods either require \textit{a priori} knowledge [8] or implement unconvincing generalizations in building their nonlinear correction terms [9], neither of which are desirable in the current study. Correction matrices that consist of either linear or nonlinear terms that incorporate the dynamics \textit{i.e.} velocity and/or acceleration of the treadmill belt and/or load are called dynamic correction matrices, and no such matrix has yet been reported in the literature.

No re-calibration method has been thoroughly performed during experimental conditions \textit{i.e.} while the belts are running on an instrumented treadmill. Such a method could produce a better correction matrix by accounting for the interaction of the force transducers to the dynamical performance of the treadmill’s moving parts, possibly requiring a dynamic correction matrix. Previously, Collins [10] attempted to perform the PILS procedure while the belts were running on his instrumented treadmill, but he was not able to obtain a large spatial distribution of test points. Kram [11] let a load run and fall off of the moving belt of his instrumented treadmill but was not able to develop a re-calibration procedure with this loading type. Therefore, it is neither known whether re-calibration during experimental conditions is necessary nor whether static correction matrices would be suitable for a dynamic calibration during experimental conditions.

Currently, a new application of GRF and CoP measurements from a novel instrumented treadmill is being investigated. The accuracy of the treadmill’s GRF and CoP is optimized through re-calibration in order to perform systems identification and parameter estimation (SIPE), which is a new application for instrumented treadmills. The application of instrumented treadmills for SIPE experiments has not yet been reported in the literature due to the paucity of such treadmills in the literature and the difficulty of applying a suitable perturbation signal with the state of the art. The current split-belt, instrumented treadmill is capable of applying high-speed, ground perturbations in both the positive and negative AP directions, which enables SIPE of the human ankle when the ground perturbations are applied to the foot. Since no accounts of SIPE on instrumented treadmills exist in the literature, it is not known what level of accuracy is required of the GRF and CoP to perform SIPE on the lower extremities. In addition, a re-calibration method is presented that has been performed under experimental conditions, which covers the entire treadmill surface. The method takes advantage of the novel treadmill’s capability to move the belts in both the positive and negative anterior-posterior (AP) directions. Therefore, the aims of the current study are to: (1) investigate whether a dynamic calibration under experimental conditions is necessary, (2) determine whether static, linear correction can be applied to the dynamic calibration under experimental conditions, and (3) establish how suitable the calibration method is for SIPE by estimating the mass of a load on the treadmill.

2 Methods

The support posts of a dual-belt, instrumented treadmill (ForceLink BV, Culemborg, The Netherlands), were anchored to a common baseplate, which was, in turn, anchored to the building foundation. Each belt was controlled with a DC motor and was situated on top of a force plate, measuring 183cm x 50cm. Each plate contained seven uni-directional strain-gage force transducers: four (4) vertical force transducers, two (2) medio-lateral (ML) force transducers and one (1) anterior-posterior (AP) force transducer. In total, 14 transducers signals were sampled at 1000Hz and sent to a data acquisition system (Speedgoat GmbH, Liebefeld, Switzerland). The I/O box of the Speedgoat device was incorporated with a temporary electromagnetic shield, which consisted of general-purpose aluminum foil. The motor input and force output signals were then visualized and read with Simulink (Mathworks, Natick, MA) in volts. Then, all signals were filtered with a 41-point moving average filter.

The treadmill manufacturer supplied a \(12 \times 14\) correction matrix, \(C_{man}\), to convert the 14 measured signals, \(s\), to 12 force signals, \(S\): three (3) forces in Newtons and three (3) moments in Newton-meters per belt. The matrix contained no cross-talk values among the intra-belt or inter-belt signals and consisted of static, linear terms. A right-handed coordinate system was used to designate the force directions: \(+x\) was forward, \(+y\) was to the left and \(+z\) was upwards. The origin was located between the left and right belts. The left belt lies in the \(+y\) region, and the right belt lies in the \(-y\) region. The \(x\) and \(y\) directions are also referred to here as the AP and ML directions, respectively. The treadmill conventions are depicted in Figure 1.

Simulink was used to send velocity control signals to each belt’s motors, which were independent of one another. On both belts, there was a velocity bias in the \(+x\) direction, so a custom bias corrector was implemented into Simulink to minimize deviations between the control signal and the output velocity in the \(+x\) direction. Offsets were measured before data collection and subtracted from each measurement reading.
The position of objects on the belts over time was recorded at 100Hz with the Optotrak Certus motion-capture system (Northern Digital Inc., Waterloo, Ontario). The \(xyz\)-coordinates of the motion recordings were transformed to the local coordinate system of the treadmill, with the origin and axis conventions as depicted in Figure 1. The force measurements were downsampled to 100Hz in order to match the sampling frequency of the motion capture data. All force and motion capture data were treated with custom Matlab (Natick, MA) scripts.

### 2.1 Static Calibration

Steel, cylindrical loads, each weighing 1.1kg, were stacked in arrangements of 16.5kg and 22kg. For the static calibration dataset, 22kg loads were placed at six (6) equidistant points spanning Regions I and III and Regions II and IV, which are indicated in Figure 1, resulting in 12 test points per belt. For the static validation dataset, 16.5kg loads were placed at three (3) new equidistant points, spanning Regions II and IV on the left belt and Regions I and III on the right belt. The different load level was chosen for the validation dataset in order to demonstrate the robustness of the recalibration. Other static calibration and validation data was taken at more test points and load levels but had to be discarded because the signals were corrupted. Static force measurements were recorded for five (5) seconds per test point in order to minimize variability in the measurement.

The reference CoP was determined as follows. First, two markers were fixed onto the outer edge of the calibration load. Then, the vector in the \(xy\)-plane that connected the two markers was determined from their recorded positions, followed by the unit vector that was perpendicular to it in the \(xy\)-plane. The position of the center of mass (CoM) was determined by multiplying the known load radius to the perpendicular unit vector and visually verified by superimposing the marker signals and the calculated CoM trajectory in a time-series plot. For the static loads, the CoP was determined as the projection of the CoM on the \(xy\)-plane. The CoP position \((X,Y)\) was manually synchronized with the force recordings for each static test position. The vertical reference signal, \(F_z\), was calculated as the known load weight in the \(-z\) direction, while AP and ML reference forces were, respectively, \(F_x = 0\) and \(F_y = 0\). The reference moments \((M_x, M_y, M_z)\) were determined through the cross product \([X, Y, Z] \times [F_x, F_y, F_z]\), where \(Z = 0\). The opposite sign of \(M_y\) was taken as the reference \(M_x\) signal in order to stay in convention with the calculation of the AP CoP coordinate, \(X = \frac{M_y}{F_z}\).

The general relationship between the reference signals, \(R = [F_x, F_y, F_z, M_x, M_y, M_z]\), and the measured signals, \(S\), is assumed to be

\[
R = f(S), \tag{1}
\]

where \(S = C_{man} \cdot s\), and \(s\) represents the force transducer signals minus the offsets. The linearized relationship is taken as the first-order Taylor approximation,

\[
R = C \cdot S. \tag{2}
\]

The higher-order, nonlinear Taylor series terms in 2 were neglected because it was assumed that the off-diagonal, cross-talk terms in the matrix \(C\) would account for the nonlinearities that could exist between \(R\) and \(S\). The matrix \(R\) was a \(12 \times n\) matrix, the matrix \(S\) was a \(12 \times n\) matrix, and \(C\) was an unknown \(12 \times 12\) matrix. The approximate solution of \(C\) in 2 was calculated with the pseudo-inverse method, which minimizes the mean-square error between the reference signals and the newly calculated signals, as in 3.

\[
C = R \cdot S^T (SS^T)^{-1} \tag{3}
\]

The pseudo-inverse method was executed with the backslash operator in Matlab. Through this operation, the matrix \(C\) was found to be the linear matrix that best transforms \(S\) onto \(R\). Because the linearized relationship in 2 establishes the relationship between \(R\), in Newtons, and \(S\), in Newtons, around a working point, it was necessary to define \(S\) as the \(C_{man}\)-calculated force signals in Newtons and not the raw force transducer signals in volts, in order to define...
a small, linear transformation. Small, linear transformations are needed in order to stay in the region near the working point around which the linearized relationship in 2 localizes 1.

The correction matrix that was determined with the static dataset was named $C_{\text{stat}}$ and was validated on the validation data in order to verify that the calibration data was not over-fitted. Then, the root-mean square errors (RMSE’s) were computed between $R$ and the re-calibrated signals, $C_{\text{stat}} \cdot S$, for each 5s recording and averaged ($\alpha = 0.05$) for several regions of the belts. The RMSE’s of the Euclidean distance of the reference and calculated CoP’s were also calculated and averaged for several regions of the belts. In order to determine the robustness of the matrix $C_{\text{stat}}$ to correcting errors with dynamic data, $C_{\text{stat}}$ was also validated on the dynamic validation dataset, which is described in the next section. The RMSE’s of the reference and re-calibrated GRF and CoP were also calculated for $C_{\text{man}}$ and compared to those of $C_{\text{stat}}$.

### 2.2 Dynamic Calibration

A completely new re-calibration was done with dynamic data, where a new correction matrix, $C_{\text{dyn}}$, was created, which had no relationship to $C_{\text{stat}}$. For the dynamic calibration data, a 22kg load was moved with a sinusoidal motor input signal, with amplitude 0.21m/s and frequency 0.10Hz, through each of the regions I through IV, on each belt, for 20s. For the dynamic validation data, a 16.5kg load was moved with the same sinusoidal input signal through Regions II and IV on the left belt and Regions I and III on the right belt for 20s. Other dynamic calibration and validation datasets were taken in more belt regions, the right belt for 20s. Other dynamic calibration and validation datasets were taken in more belt regions, load levels and speeds, but they had to be discarded because the signals were corrupted.

The reference CoP was determined by following the steps in the static calibration procedure, with the added step of modeling the displacement of the CoP from the CoM as a function of the acceleration of the load, using the model in Figure 2.

In Figure 2, only the AP coordinate of the CoP, $X$, is considered, as movement in the $Y$ direction is neglected. First, $X$ is defined about $P_1$ as

$$X = \frac{M_y, P_1}{F_z}$$

(4)

where

$$M_y, P_1 = a \frac{F_a}{2} + b \frac{F_z}{2}$$

(5)

Substitution of 5 in 4 results in

$$X = \frac{a m \ddot{x} + b}{2 mg} + \frac{b}{2}$$

(6)

$$X = \frac{1}{2} \left( \frac{a}{g} \ddot{x} + b \right)$$

(7)

where $a, b$ are the height and width of the load, respectively, $m$ is the known mass of the load, $x$ is the load’s position in the AP direction, and $g = -9.81m/s^2$. As a check, when the load in Figure 2 starts to tip over, $X = b$, which happens when

$$\ddot{x} = \frac{bg}{a}.$$  

(8)

At this moment at $P_1$, $F_z, P_1 = 0$. This can be verified by substituting 8 into the moment balance around $P_2$,

$$M_y, P_2 = a \frac{F_a}{2} + b \frac{F_z}{2} - F_z, P_1$$

and was determined as in the static calibration case, using the pseudo-inverse procedure. The $C_{\text{dyn}}$ correction matrix

$$M_y, P_2 = 0,$$

(9)

(10)

where $F_a = m \dddot{x}$, and $F_z = mg$, which results in $F_z, P_1 = 0$.

Therefore,

$$X = f(\ddot{x})$$

(11)

$$Y = y_{\text{CoM}}$$

(12)

The CoP data was synchronized with the force measurement data by calculating the time delay between $X$ and the $C_{\text{man}}$-calculated $M_y$ through the method of cross-correlation. Then, the time delay was used to shift the CoP vector accordingly and visually checked by super-imposing the shifted $X$ over the $M_y$ signal. Then, the reference forces for calculating $C_{\text{dyn}}$ were:

$$F_x = -m \dddot{x}$$

(13)

$$F_y = 0$$

(14)

$$F_z = mg,$$

(15)

where $\dddot{x}$ was the double-differentiated CoM trajectory from Optotrak, and $M_x, M_y, M_z$ were determined as in the static calibration case.

The correction matrix that was determined with the dynamic dataset was named $C_{\text{dyn}}$ and was determined as in the static calibration case, using the pseudo-inverse procedure. The $C_{\text{dyn}}$ correction matrix
was validated on both the dynamic and static validation datasets in order to determine the robustness of the correction matrix to both static and dynamic data. The RMSE’s of the reference and re-calibrated GRF and CoP were also calculated for $C_{\text{man}}$ and $C_{\text{stat}}$ and compared to those of $C_{\text{dyn}}$. Then, the most accurate correction matrix was chosen to perform SIPE. The matrices $C_{\text{man}}, C_{\text{stat}}, C_{\text{dyn}}$ each can be used interchangeably in 2, in order to calculate the instrumented treadmill’s GRF.

### 2.3 Systems Identification

A 22kg load was perturbed in the AP direction by sending a crested multisine signal in volts to the left belt motor, with power between 0Hz and 10Hz, for 60s, in order to perform systems identification of the load’s mass, $m$, on the belt. The recorded signals were $F_x$, as calculated with $C_{\text{dyn}}$, and $u(t)$, the control signal that was sent to the motor. The velocity of the belt was not directly measurable in the experimental set-up. A best-fit parametric model was fitted to the spectral estimate of the frequency response function (FRF), $H(s)$:

$$H(s) = \frac{V(s) F_x(s)}{U(s) V(s)}$$

where $V(s), U(s), F_x(s)$ were the frequency-domain representations of the velocity, input motor control and AP force signals, respectively. Specifically,

$$\frac{F_x(s)}{V(s)} = m \cdot s \tag{17}$$

$$\frac{V(s)}{U(s)} = \frac{G}{\omega_n^2 + \frac{G}{\omega_n} s + 1} \tag{18}$$

where $\omega_n, \zeta$ are, respectively, the natural frequency and damping ratio between $u(t)$ and $v(t)$, the motor input signal and the belt velocity. The classic second-order transfer function, $\frac{V(s)}{U(s)}$, was determined by sending a step signal of 0.5V to the right belt and recording the position of a 22kg load for two (2) seconds. Then, the position data was differentiated in Matlab and plotted against time in order to inspect the step response characteristics. The parameters in the denominator of $\frac{V(s)}{U(s)}$ were estimated from the step response and then tuned such that $\omega_n = 35$rad/s, and $\zeta = 0.8$. The gain $G$ was provided by the treadmill manufacturer and was $G = 0.59$ m/Vs.

An error criterion function was used for the least squares optimization that minimized the error on both the magnitude and phase of the FRF in order to avoid introducing bias into the optimized parametric model. The absolute and relative errors on the mass estimate, relative to the expected mass, were calculated to assess the accuracy of the identification.

### 3 RESULTS

#### 3.1 Static Calibration

The matrix $C_{\text{stat}}$ resulted in cross-talk values for $F_x, M_x, M_y$ with similar entries at the index positions that corresponded to the original $C_{\text{man}}$ matrix entries. The matrix entries that corresponded to $F_x, F_y, M_z$ were zero because neither AP nor ML reference forces were applied during calibration with $C_{\text{stat}}$. This shows that calculating $C_{\text{stat}}$ in those directions was an underdetermined problem. Therefore, all outcome $F_x, F_y, M_z$ calculations with $C_{\text{stat}}$ were calculated as zero. The GRF estimates in all directions and the CoP are shown in Table 1, where the $C_{\text{stat}}$-calculated forces in $F_x, F_y, M_z$ are omitted. Not only was the GRF estimate improved, but the CoP estimate was also improved. This shows that the cross-talk values contributed to improved GRF and CoP estimates. Because no non-zero matrix values were present for the horizontal forces or $M_z$, $C_{\text{stat}}$ is appropriate for use on static datasets, where no AP or ML forces are applied. The $C_{\text{man}}$ RMSE’s show that the right belt signals had a higher error than the left belt signals before re-calibration. The re-calibration with $C_{\text{stat}}$ improved the error such that the magnitudes were similar for both the left and right belt, thereby eliminating this static nonlinearity.

When $C_{\text{stat}}$ was used to estimate the GRF and CoP on dynamic data, the RMSE’s again improved in the AP direction and the moments, in comparison to the estimates from $C_{\text{man}}$, as shown in Table 2. The $F_z$ error was higher than the $C_{\text{man}}$-calculated $F_z$ error, which shows that the cross-talk values in $C_{\text{stat}}$ mitigated the vertical force calculation, further demonstrating that $C_{\text{stat}}$ is suitable for purely vertical forces. The CoP error increased relative to the static dataset because the CoP calculation depends on $F_z$.

Under experimental conditions, the measured $F_z$ force in time was a sinusoid, whose error approached

<table>
<thead>
<tr>
<th>Belt</th>
<th>Signal</th>
<th>$C_{\text{stat}}$-Calculated</th>
<th>$C_{\text{man}}$-Calculated</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>$F_x$</td>
<td>-</td>
<td>1.13 ± 0.17</td>
</tr>
<tr>
<td></td>
<td>$F_y$</td>
<td></td>
<td>0.67 ± 0.02</td>
</tr>
<tr>
<td></td>
<td>$M_x$</td>
<td>0.67 ± 0.13</td>
<td>1.02 ± 0.05</td>
</tr>
<tr>
<td></td>
<td>$M_y$</td>
<td>0.31 ± 0.05</td>
<td>2.02 ± 1.37</td>
</tr>
<tr>
<td></td>
<td>$M_z$</td>
<td>0.29 ± 0.06</td>
<td>1.28 ± 0.12</td>
</tr>
<tr>
<td></td>
<td>CoP</td>
<td>2.10 ± 0.95</td>
<td>14.23 ± 9.39</td>
</tr>
<tr>
<td>R</td>
<td>$F_x$</td>
<td>-</td>
<td>5.72 ± 4.31</td>
</tr>
<tr>
<td></td>
<td>$F_y$</td>
<td></td>
<td>3.50 ± 2.19</td>
</tr>
<tr>
<td></td>
<td>$M_x$</td>
<td>0.65 ± 0.15</td>
<td>1.65 ± 0.35</td>
</tr>
<tr>
<td></td>
<td>$M_y$</td>
<td>0.31 ± 0.03</td>
<td>1.20 ± 0.41</td>
</tr>
<tr>
<td></td>
<td>$M_z$</td>
<td>0.44 ± 0.03</td>
<td>2.10 ± 0.96</td>
</tr>
<tr>
<td></td>
<td>CoP</td>
<td>2.60 ± 1.01</td>
<td>11.37 ± 8.69</td>
</tr>
</tbody>
</table>
zero when the load was near the center of the treadmill and increased when the load moved toward the edges of the treadmill surface. These fluctuations meant that spatial nonlinearities were present even after re-calibration. This shows that the cross-talk terms for calculating $F_z$ in $C_{stat}$ were not effective in reducing the spatial nonlinearities under dynamic conditions. This is a result of having used only static loads in the calibration process.

### 3.2 Dynamic Calibration

The matrix $C_{dyn}$ contained cross-talk values with similar entries at the index positions that corresponded to the original $C_{man}$ matrix entries. The matrix entries that corresponded to $F_y$ were equal to zero because no ML reference forces were applied during calibration with $C_{dyn}$ and are therefore omitted from the current analysis. The RMSE’s of the GRF and CoP for static data were improved with $C_{dyn}$ when compared to the values for $C_{man}$ in Table 1. The $C_{dyn}$ errors are shown in Table 3. In comparison to $C_{man}$, $C_{dyn}$ improved the force estimates in all directions and in the CoP. In comparison to $C_{stat}$, the RMSE was higher in $F_z$ because its matrix entries in $C_{dyn}$ depended more on contributions from the AP and ML force transducers to calculate $F_z$ than those in $C_{stat}$ did. Static data do not contain AP or ML components, so the $C_{dyn}$ matrix could not utilize these values in calculating $F_z$. Therefore, $C_{dyn}$ is not as suitable a calibration matrix for use with purely static data as $C_{stat}$ is.

Under experimental conditions, $C_{dyn}$ improved the GRF and CoP errors, relative to $C_{man}$, as shown in Table 4. In comparison to the validation on the static data, $C_{dyn}$ performed similarly on the dynamic data, but the $F_z$ error was lower. This was because there was AP and ML force interaction on the $F_z$ calculation, which allowed the calculation to follow and correct the fluctuating vertical force in time. In addition, there was more resolution in $F_z$ during the $C_{dyn}$-calibration process than in the $C_{stat}$ calibration process, such that more vertical load levels were included in the least-squares problem. This resulted in a better $C_{dyn}$ approximation than in the static calibration case.

Both re-calibration matrices $C_{stat}$ and $C_{dyn}$ reduced the spatial nonlinearity of the CoP error, for static and dynamic datasets, which arises when the CoP error depends on the point of force application. Only the CoP-error results for $C_{dyn}$ are presented here as they are visually comparable to those of $C_{stat}$. Using $C_{dyn}$, the CoP error was reduced to $<1$ cm in the static validation test set, over all regions of the treadmill, as shown in Figure 3. The figure represents the surfaces of both the left and right belts of the treadmill, in three-dimensional space. The $C_{man}$-calculated CoP errors are indicated in blue, and the $C_{dyn}$-calculated errors are indicated in red. The $C_{man}$-calculated CoP’s were higher at the +AP portions of each belt, which is expected for the extremities of the force plates.

When $C_{dyn}$ was used to correct the CoP error on
3 and 4 show that $C_{\text{dyn}}$ was able to correct the CoP error under both static and experimental conditions. The CoP reduction further shows that the method of simulating the CoP movement during the dynamic calibration procedure was effective in accommodating loads that have a constantly moving CoP.

Comparable spatial nonlinearities are present during static and dynamic loading, which were both minimized by using either $C_{\text{stat}}$ or $C_{\text{dyn}}$. This shows that normalizing $F_z$ with the moments $M_x, M_y$ as in the case of the CoP calculations, minimizes the effect of the spatial nonlinearity of $F_z$ in the CoP calculation. However, as was previously mentioned, $C_{\text{stat}}$ predicted a higher $F_z$ error on dynamic data than on static data. In addition, the overall CoP error during experimental conditions was higher with $C_{\text{stat}}$ than with $C_{\text{dyn}}$. This, coupled with the fact that $C_{\text{stat}}$ cannot predict AP forces, shows that $C_{\text{stat}}$ is not useful for dynamic datasets and, by extension, for use under experimental conditions. Even though $C_{\text{dyn}}$ was not as accurate as $C_{\text{stat}}$ or $C_{\text{man}}$ for static data, it achieved the best error results for dynamic data. Overall, $C_{\text{dyn}}$ calculated the most accurate GRF and CoP among the three calibration matrices for experimental conditions and was therefore chosen as the matrix to calculate the GRF for SIPE.

### 3.3 Systems Identification

Between 0.2Hz and 10Hz, the model $H(s)$ from 16 was fitted onto the spectral estimate of the frequency-response function (FRF), of the $C_{\text{dyn}}$-calibrated $F_x$ signal and the input signal, $u(t)$, as shown in Figure 5. The coherence of $F_x(t)$ to the input signal, $u(t)$ shows that at frequencies up to 0.2Hz, the SNR is low.
in the $F_x$ signal, which is why the coherence is low at those frequencies for the relationship between $F_x$ and the input signal. Between 0.2Hz and 10Hz, the relationship is almost perfectly linear, which implies that a linear dynamic model can be applied to this relationship.

The mass that was estimated with the second-order parametric model was 21.55kg, which gives an absolute error of 0.45kg and relative error of 2%. This shows that $C_{dyn}$ was able to estimate the mass of the load even with a mean $F_x$ RMSE $> 1$N and while neglecting ML forces.

4 DISCUSSION

The current results do not show whether there is a difference between using dynamic re-calibration during static or experimental operation in order to reduce the GRF and CoP errors. Therefore, it cannot be concluded that dynamic calibration during experimental conditions is necessary for an instrumented treadmill. However, it can be concluded that dynamic calibration, in general, is more time-efficient than the static calibration that was performed in this study. Dynamic re-calibration minimizes the time needed to obtain enough observations to avoid over-fitting in the least-squares problem. The dynamic re-calibration process obtains more data points in a smaller amount of time than what a static calibration would need in order to obtain the same number of data points. A future study should compare the effect of both kinds of dynamic re-calibration methods on the GRF and CoP accuracy.

The current study determined that a static, linear correction matrix was appropriate for the dynamic re-calibration under experimental conditions. No correction was made with a static nonlinear matrix because the proposed calibration method presupposes no a priori knowledge of the GRF or CoP error. In comparison to other reported instrumented treadmill errors in the literature, Collins [10], Kram [11] and Dierick [13], whose reports have focused on CoP errors, the current dynamic calibration method reduced the CoP RMSE error to less than those reported for data taken during static operation of the treadmill. Kram and Collins reported CoP errors during the dynamic operation of the treadmill, which were higher than the present results.

The current study could not establish a relationship of the GRF and CoP error to the dynamics of the moving load or parts of the treadmill. Limitations to the current study made it difficult to thoroughly study the effect of the moving load dynamics on the GRF and CoP error. First, the acceleration of the load in the AP direction during re-calibration was not high enough to establish a high signal-to-noise ratio. Therefore, the $F_x$ RMSE was not a clear representation of the deterministic error but rather of the signal noise, and no relationship could be determined to the velocity or acceleration. Second, the same loading speed was used for both calibration and validation, so it is not known whether the current correction matrix can be applied to slower- or faster-moving datasets. Third, only one load level was used during dynamic calibration. Future studies should include various speeds and load levels in calibration and validation datasets in order to determine how well a static correction matrix can account for a more diverse, experimental dataset.

The dynamics of the treadmill may be better analyzed from a finite-element approach [14]. Finite element methods have been employed to study how velocity and acceleration wavefronts travel through the belts in conveyor belt systems, taking into account the friction in the system. During transient conditions, such as starting and stopping, it has been shown that transverse vibrations in the belt are caused by resonance in the belts’ idlers.

Despite not having used more loading speeds in the calibration, the correction matrix was able to give a good parameter estimate during SIPE. The correction matrix was created using dynamic loading at 0.1Hz, which was lower than the identification frequencies. In addition, movement in the ML direction was neglected, which was justified because ML forces were not considered in the parametric model during SIPE. Nevertheless, the current calibration method showed that higher error tolerances provided a parameter estimation with a 2% relative error. The GRF errors under dynamic conditions on the left belt, where SIPE was conducted, met the requirements for accurate inverse dynamic analyses, except in $F_x$, but a future study should determine whether the parameter estimate could be improved if the $F_x$ RMSE could be further reduced by using higher AP accelerations and loading during the re-calibration process.

Future research should focus on optimizing the $F_x$ GRF error to levels required for accurate inverse dynamic analyses. A more accurate GRF and CoP would widen the application of the instrumented treadmill to sound inverse dynamic analyses of gait biomechanics. Furthermore, a method to incorporate ML reference forces into the re-calibration procedure should be devised under experimental conditions if future gait analysis and SIPE experiments will use models that account for movement in the ML direction.

5 CONCLUSION

REFERENCES


