HYSTERESIS COMPENSATION FOR GROUND CONTACT FORCE MEASUREMENT WITH SHOE-EMBEDDED AIR PRESSURE SENSORS

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ABSTRACT
This paper reviews the design of smart shoes, a wearable device that measures ground contact forces (GCFs) for gait analysis. Smart shoes utilize four coils of silicone tubes adhered directly underneath the shoe insole at key points of interest. Air pressure sensors connect to each tube coil to measure pressure changes caused by compression. This paper presents static and dynamic calibration performed on each sensing coil to establish a model of internal pressure and the GCF. Based on the model, a phase lead filter is designed to account for the hysteresis effect and visco-elastic properties of the silicone tube in order to provide accurate GCF measurements. To design this filter, the air bladder is modeled using a standard linear solid (SLS) model. The prediction error minimization (PEM) algorithm is then implemented to identify the continuous-time transfer function of this SLS model, which is then transformed to discrete time domain to implement in a digital processor. Mechanical characterization and testing on a healthy subject are performed to validate the model and its capability to compensate for hysteresis in GCF measurement.

I. INTRODUCTION
In recent years, sensor embedded shoes attained great popularity as mobile sensing devices to detect human ground contact forces (GCFs) [1, 2]. They provide necessary information to detect gait phases for applications such as rehabilitation and gait analysis [3]. Various force sensors have been studied to measure GCFs. Razian and Pepper developed a tri-axial pressure sensor based on piezoelectric copolymer film [4]. Kothari et al. proposed a capacitive sensor to measure the pressure between the foot and ground [5]. Force sensitive resistors (FSRs) are most commonly used sensors to measure GCFs [6, 7]. However, they exhibit considerable hysteresis, sensitivity to shear force and changes in response characteristics with prolonged use [8]. These characteristics, along with their nonlinearity and low durability, make FSRs unsuitable for practical use in GCF measurement. Huang et al. used a ninth order polynomial to compensate for non-linearity of FSRs [9]. In other paper, Hall et al. used a fourth order polynomial function of voltage to calibrate the FSRs [10]. As an alternative to FSRs, Kong et al. measured pressure in air bladders installed on a shoe insole for more reliable and stable GCF measurement [2]. Much like FSRs, hysteresis is the most common problem faced in many pressure sensors [6,10]. This presents major issues in GCF measurement due to the rapid fluctuation in GCFs during a step.

In this paper, the design of smart shoes is reviewed. These shoes are developed for applications including rehabilitation and other clinical monitoring where GCF measurement provides useful insight. Also, this method of GCF measurement using smart shoes does not require expensive equipment such as force plates and can operate outside lab settings. A sensing unit similar to that introduced by Kong et al. is used [2]. Silicone tubing is coiled and adhered underneath a shoe insole then connected to an air pressure sensor. GCFs are calculated by measuring changes...
in pressure created during compression, caused in walking by a foot. In order to achieve accurate GCF measurement, the sensing unit is calibrated with the help of an Instron 5944 series material testing machine [11]. To properly calibrate the unit, tube coils are subjected to both static and dynamic loading.

The novelties of this paper include the application of prediction error minimization (PEM) system identification method to estimate the parameters of sensor system, and the design of phase lead filter based on the estimated parameters. The following topics are discussed in this paper:

1) The design of an GCF measurement system based on air pressure based force sensing.
2) The setup to perform static and dynamic calibration tests on the air bladders using an Instron machine.
3) The design of an algorithm to identify the dynamic model of the whole sensing unit and the construction of a filter to reduce hysteresis in the air bladder and pressure sensors.

The remainder of this paper is organized as follows: section II demonstrates the design of the sensing unit in smart shoes. Section III describes the methodology for static and calibration tests performed on the sensing unit and discusses the calibration results. In section IV, the modelling of air bladder using SLS model is described. Section V details the PEM approach followed in the paper. Section VI discusses the implementation of the phase lead filter. Section VII gives the experimental results from a healthy subject. Conclusion and the future work are presented in section VIII.

II. DESIGN OF SENSING UNIT IN SMART SHOES

In an effort to obtain accurate results, a new sensing unit is made prior to smart shoe testing. This sensing unit is constituted by coiled silicone tubes and an air pressure sensor. Taking survey of existing solutions, FSRs are commonly used for GCF measurement. However, FSRs perform poorly due to their non-linearity, lacking durability and capability to measure distributed loads common in most any gait. An alternative solution utilizing air pressure sensors proposed by Kong et al. offers better readings, increased durability and stable measurement of distributed loads [2].

Four tubes are coiled and adhered to the bottom side of a shoe insole under the toes, inner and outer metatarsals (Meta1 and Meta4), and heel as shown in Figure 1(a). The coils function as air bladders and connect to air pressure sensors. When loaded different, during a step for instance, the tube coils are compressed, generating pressure which, in turn, is measured by the air pressure sensors. In this system, GCF is calculated from the pressure in the tube coils. Certain assumptions are made, including the lack of radial deformation and dynamic effects within the air bladder. Based on these assumptions, pressure change is proportional to force applied i.e., $P(t) = \frac{F(t)}{A(t)}$.

Silicone tube and unidirectional gauge pressure sensors are used to construct the sensing unit. Silicone tube is selected for use due to its minimal creep [2] and desirable stiffness, rigidity and toughness. Unidirectional gauge pressure sensors from First Sensors HDI series are used. Pressure sensors with 200 mbar measurement range are connected to tubes coiled under the heels and metatarsals. Toes sustain less load than the heels and metatarsals. Therefore, 100 mbar pressure sensors are connected to the tubes coiled underneath the toes for higher resolution.

The sensor box provides housing for the four air pressure sensors on each shoe as shown in Figure 1(b). The air pressure sensors connect to a microcontroller which reads their output voltage through analog port connect to computer with bluetooth. The computer then, processes and analyzes data. The sampling rate of the smart shoes can go up to 200 Hz with the bluetooth module. It is important to calibrate the sensing unit prior to actual usage in order to achieve accurate GCF measurements. To perform static and dynamic calibration tests on the sensing unit, an Instron 5944 mechanical testing machine capable of applying compressive and tensive loads is selected.

III. CALIBRATION TEST SETUP
A. Testing apparatus and configuration

Calibration testing apparatus is comprised of the sensing unit itself, an Instron 5944 mechanical testing machine [11] and a
National Instruments myRIO. As shown in Figure 2, the sensing unit lays on an anvil, the Instron machine applies compressive load to the tube coils, and the myRIO measures analog signals from the air pressure sensors. Test instructions are sent to the Instron machine by Bluehill 3 software running on a computer. The myRIO receives analog signals from the Instron and air pressure sensors, and sends the information to the computer via LabVIEW. To accurately calculate GCFs from pressure readings in practice, the relationship between pressure readings and load on each sensing node must be established and the dynamic characteristics of each sensor must be determined. To achieve this, individual calibration tests are performed with static and dynamic loading. Figure 3 displays one example of data received during a static calibration test.

In static testing, the Instron machine applied a compressive load to individual tube coils, maintained that load for five seconds, then removed load. The test performed this process for loads from 50N to 800N in 50N intervals. Static tests were conducted for all 8 sensing nodes. In static testing, load is applied in two phases. The first phase begins unloaded, then load is applied at 50N/s and halted 5N below the desired load. In the second phase, the final 5N are applied over five seconds. With load applied, the load cell is halted and kept stationary for another five seconds. Finally, the load cell is retracted, reducing load at 50N/s until complete unloaded. The system then rests for five seconds before repeating the entire cycle for a new load. The static calibration procedure is described in Figure 4(a).

In dynamic testing, the Instron machine applied compressive load at the various rates. In loading phase, load was applied at a specified rate in N/s until 800 N of load is reached. Thereafter, in the unloading phase, load is reduced at same rate until the system is unloaded again. This cycle is repeated for loading rates of 50, 100, 200, 400, 600 and 800N/s. The steps followed for dynamic calibration is shown in Figure 4(b).
FIGURE 5. DYNAMIC TEST (RATE OF LOADING 50-800 N/S): VOLTAGE OUTPUT FROM a) INSTRON AND b) AIR PRESSURE SENSOR. c) LOW SPEED (100N/S) (d) HIGH SPEED (800N/S)

B. Discussion on calibration test results

At the first stage of the process, calibrated weights were statically placed over tube coils in order to obtain the relationship between applied force and the pressure change i.e., output voltage of the pressure sensor. The loading range of weights and increment between each reading are selected to be within the limits of the sensor. Thus, by using test setup, loads are increased from 0 to 800N with the waveform shown in Figure 3. Most importantly, Figure 3 illustrates the similar waveform between applied load and recorded pressure in static load conditions. Minor hysteresis is observed during load changes as apparent in the bowed lines during bulk loading and unloading in Figure 3(b).

For the dynamic test, triangular waveform of loading and unloading is generated by Instron machine at variable loading rates from 50N/s to 800N/s as shown in the Figure 5(a). Hysteresis is observed during loading and unloading. The sensor follows upper side of the curve during loading and lower side of the curve during unloading as shown in Figures 5(c) and 5(d). Hysteresis effect increases with higher rate of loading.

IV. APPROACH FOR DESIGNING HYSTERESIS COMPENSATOR

A. Dynamic model for air bladder

In order to accurately capture the dynamic characteristics of the air bladder system, a standard linear solid (SLS) model is employed, which is used for modelling visco-elastic materials such as silicone tubing [2]. This model consists of one damper and two Hookean springs, one connected in parallel and the other in series with the damper. The air bladder and equivalent standard linear model are shown in Figure 6. It is assumed that there are no inertia and air leakage in the air bladder. Therefore, mass $M$ is assumed to be zero. The force balance equation for air bladder system is:

$$ (P - P_{atm} - f)A - k_1(x - x_0) + \frac{k_2cs(x-x_0)}{2} = 0. \quad (1) $$

Here $P$ and $P_{atm}$ are the absolute and atmospheric pressure in the tube, $A$ is the effective area of the air bladder which is assumed to be constant. $x - x_0$ is the deformation in the tube. Here $s$ in (1) refers to a derivative operator in the Laplace domain. Gauge pressure $P_G$ is the difference between $P$ and $P_{atm}$. The governing transfer function between the force applied $f$ over large area and gauge pressure $P_G$ is derived in [2]:

$$ f = P_G + [k_1 + \frac{k_2cs}{k_2 + cs^2}] \frac{x_0^2}{nRT} P_G \equiv \frac{b_1 + b_2 s}{a_1 + a_2 s} P_G, \quad (2) $$

where

$$ a_1 = k_2, a_2 = c, \quad (3) $$
\begin{align}
b_1 &= k_2 [1 + k_1 \frac{x_0^2}{nRT}], \\
b_2 &= c [1 + (k_1 + k_2) \frac{x_0^2}{nRT}].
\end{align}

Physical properties of the silicone tube are as follows: \( n = 4.2075 \times 10^{-9} \text{[mol]}, R = 8.3145 \text{[m}^3\text{pak}^{-1}\text{mol}^{-1}], \) \( T = 300k \) and \( x_0 \) is the inside diameter of the undeformed silicone tube which is 2 mm in our case. Here, \( P_0 \) is available from the air pressure sensor. However, it is difficult to get load measurement directly from \( P_0 \); as it is not easy to calculate effective area of cross section for distributed loads. Thus, it becomes important to identify the relationship between applied force and pressure change in order to estimate GCF from the pressure sensor readings. As a result, we will identify the coefficients \( a_1, a_2, b_1 \) and \( b_2 \) in (2) in a data driven approach.

V. PREDICTION ERROR MINIMIZATION (PEM) ALGORITHM

To identify the coefficients of the first order transfer function, a PEM approach is applied. The main objective of this algorithm is to minimize the weighted norm of the prediction error which is the difference between measured and predicted output. This algorithm basically performs two steps to estimate the coefficients: 1) initialize parameters, and 2) update parameters.

A. Initialization of coefficients for transfer function

To initialize numerator and denominator of the first order transfer function, Simplified Refined Instrumental Variable method for Continuous time systems (SRIVC) algorithm is employed [12]. SRIVC is one of the successful stochastic identification method where the noise \( w(t) \) is assumed to be discrete-time, and of white noise process \( w(t) \sim N(0, \sigma_w^2) \). True system contains input \( u(t) \) and output \( x(t) \), which are the load measurement data collected from air pressure sensors and Instron. The main aim of the SRIVC is to create an auxiliary model equivalent to the true system which can approximate transfer function of the true system \( \frac{B(s, \theta^*)}{A(s, \theta^*)} \) as shown in Figure 7.

True system model

The input \( u(t) \) and output \( x(t) \) sampled data are available in the time domain from air pressure sensors and Instron respectively. The operator polynomial representation of the true system for input \( u(t) \) and output \( x(t) \) is

\begin{align}
A(s, \theta^*)x(t) &= B(s, \theta^*)u(t), \\
y(t) &= x(t) + w(t).
\end{align}

The measured output \( y(t) \) is the measured output contaminated with white noise \( w(t) \). The operator polynomial is in the Laplace domain and true parameter \( \theta^* \) can be defined by

\begin{align}
A(s, \theta^*) &= s^n + a_1^* s^{n-1} + \ldots + a_n^*, \\
B(s, \theta^*) &= b_0^* s^m + b_1^* s^{m-1} + \ldots + b_m^*,
\end{align}

\( \theta^* = [a_1^* \ldots a_n^* b_0^* \ldots b_m^*]^T \).

From (2), our system should consist of one zero and pole. Therefore, \( n=m=1 \) which gives

\begin{align}
A(s, \theta^*) &= s + a_1^*, \\
B(s, \theta^*) &= b_0^* s + b_1^*,
\end{align}

\( \theta^* = [a_1^* b_0^* b_1^*]^T \).

Transfer function \( T \) for the true system representing dynamic model with input \( u(t) \) and output \( x(t) \) is

\[ T = \frac{x(t)}{u(t)} = \frac{b_0^* s + b_1^*}{s + a_1^*}. \]

By comparing (13) and (2)

\begin{align}
a_1^* &= \frac{a_1}{a_2}, \\
b_0^* &= \frac{b_2}{a_2}, \quad \text{and} \quad b_1^* = \frac{b_1}{a_2}.
\end{align}

Let us assume that the value of \( a_2 = 1 \) which means the value of \( c \) becomes equal to 1 from (3). Further, this assumption is valid since the coefficients \( k_1, k_2 \) and \( c \) are coupled, the value of \( c = 1 \) results in one set of values for \( k_1 \) and \( k_2 \). The increment or decrement in \( c \) changes \( k_1 \) and \( k_2 \) values accordingly. For our case, \( c \) is assumed to be one. Thus, the problem of estimating three coefficients automatically reduces to two i.e., to estimate \( k_1 \) and \( k_2 \) only. Therefore, coefficients \( a_1^*, b_0^* \) and \( b_1^* \) need to be estimated in order to identify the continuous-time transfer function for the true system i.e., the dynamic model of air bladder and the sensor.
Auxiliary model

To estimate system parameter vector \( \theta^* \) from sampled input and output, SRIVC method creates an auxiliary model as shown in Figure 7. This is an approximation of the true system which takes the input \( u(t) \) and estimates the output \( \hat{x}(t) \) with no noise. The auxiliary model approximating the true system equations (10), (11) and (12) is:

\[
y(t) = \frac{D(s, \theta)}{C(s, \theta)} u(t) + e(t), \tag{15}
\]

\[
e(t) = y(t) - \Phi^T(t) \theta, \tag{16}
\]

\[
\Phi(t) = \left[ -\frac{dy(t)}{dt} \frac{du(t)}{dt} u(t) \right]^T, \tag{17}
\]

\[
\theta = [a_1^* b_0^* b_1^*]^T. \tag{18}
\]

Here, \( a_1^* \), \( b_0^* \) and \( b_1^* \) are the estimates for \( a_1^* \), \( b_0^* \) and \( b_1^* \) in (14). The single input, single output (SISO) model in the continuous time domain is algebraically equivalent to the discrete time SISO model explained in [13]. The equation containing error function \( e(t) \) in (16) can be written as

\[
e(t) = \frac{1}{C(s, \theta)} [C(s, \theta) y(t) - D(s, \theta) u(t)], \tag{19}
\]

\[
Z(s) = \frac{1}{C(s, \theta)}. \tag{20}
\]

where \( Z(s) \) is given by pre-filter. In SRIVC method, the state variable filter (SVF) proposed by young (1964) is used as a prefilter. The minimal order SVF has the form [14]:

\[
Z_{svf}(s) = \left( \frac{\beta}{s + \beta} \right)^n, \tag{21}
\]

where \( n \) is the system order and filter time constant \( \lambda \) is apriori and usually \( \lambda = \beta \). Now, taking \( Z(s) \) in (20) inside the square bracket (19), error function \( e(t) \) becomes

\[
e(t) = C(s, \theta) y_f(t) - D(s, \theta) u_f(t), \tag{22}
\]

\[
y_f(t) = C(s, \theta)^{-1} u_f(t) = \frac{u(t)}{C(s, \theta)}. \tag{23}
\]

The derivative of \( y_f(t) \) and \( u_f(t) \) is given by:

\[
y_f^{(i)}(t) = f_i(t) * y(t) \quad i = 0, 1, \tag{24}
\]

\[
u_f^{(i)}(t) = f_i(t) * u(t) \quad i = 0, 1. \tag{25}
\]

Here \( y_f^{(i)}(t) \) and \( u_f^{(i)}(t) \) are the \( i \)-th derivative of \( y_f(t) \) and \( u_f(t) \), respectively. \( i \) is 0 and 1 in our case. * is the convolution operator and filters take the form,

\[
f_i(t) = L^{-1} \left( \frac{s^i}{C(s, \theta)} \right), \tag{26}
\]

where \( L^{-1} \) is the inverse Laplace transform. Therefore, the auxiliary model at the \( n \)-th sampling instant \( t = t_n \) can be written as

\[
e(t_n) = y_f(t_n) - \Phi^T(t_n) \theta, \tag{27}
\]

\[
\phi_f(t_n) = [-\frac{dy_f(t_n)}{dt}, -\frac{du_f(t_n)}{dt}, u_f(t_n)]^T. \tag{28}
\]

To obtain an initial estimate of \( \theta \) for a data sample of length \( N \), the following equations are used:

\[
V_N = \frac{1}{N} \sum_{i=1}^{N} \phi_f(t_i) y_f(t_i), \tag{29}
\]

\[
\theta = V_N^{-\frac{1}{2}} \sum_{i=1}^{N} \phi_f(t_i) y_f(t_i). \tag{30}
\]

The prefilter in SRIVC method provides \( C(s, \theta) \) from the user defined \( \lambda \). From equations (29) and (30), initial value of \( \theta \) can be estimated.

B. Updating coefficients of transfer function

Nonlinear least square search method is employed to iteratively adjust the unknowns in true system (6), as well as estimate of the instrument variable at each iteration of the algorithm, until that converges. Instrument variable at each iteration is given by

\[
\hat{x}(t) = \frac{D(s, \theta)}{C(s, \theta)} u(t). \tag{31}
\]

Here, \( \theta \) is the estimated vector obtained at the previous iteration. Estimating coefficients of \( \theta \), \( a_1^* \), \( b_1^* \) and \( b_0^* \) in (19) can identify the values \( k_1, k_2 \) and \( c \) given in (2). However, we considered \( c \) is always equal to 1.

To update the initialized parameters for the transfer function, a set of non-linear least squares search methods Gauss Newton [15], Levenberg Marquardt [16,17] and trust region reflective Newton [18] from the system identification toolbox MATLAB R2015b were adopted. Trust region based search methods are chosen in our approach because they have better convergence properties than regular line search method [19]. The main objective of these search methods is to reduce the error \( e(t) \) given in (16) by minimizing weighted prediction error norm.
C. Algorithm summary

a) Input: \( x(t) \) and \( u(t) \)
where \( x(t) \) and \( u(t) \) are the load measurement data available from Instron and air pressure sensor in time domain sampled at 100 Hz.

b) Prediction error minimization:
1. Define a value for filter time constant \( \lambda \) and maximum tolerance value \( \mu \).
2. Apply SRIVC method to find the initial estimate of \( \theta \), which is the estimate of the continuous system parameter vector \( \theta^0 \) from sampled input-output data using (29) and (30).
3. Update the value of \( \theta \) on the basis of cost function using nonlinear least square search method. The cost function is a positive function of prediction error \( e(t) \) given in (16). For a model with \( n \) number of outputs, the cost function has the following general form:

\[
Cost(\theta) = \frac{1}{N} \sum_{t=1}^{N} e^T(\theta) We(t, \theta),
\]

where \( N \) is the number of data samples, \( e(t,\theta) \) is an n-by-1 error vector at a given time \( t \), parameterized by the parameter vector \( \theta \). \( W \) is the weighting matrix and it is a constant independent of \( \theta \).
4. Repeat step 3 until the maximum relative percentage of the estimated parameter \( \theta \) in successive iterations is less than the tolerance value \( \mu \) defined in the first step.

c) Continuous to discrete time domain transform: continuous time transfer function obtained from PEM method is discretized using bi-linear transformation for the real-time implementation.
d) output: \( r(t) \) is the filtered signal obtained by filtering incoming air pressure signals \( u(t) \).

VI. IMPLEMENTATION OF PHASE LEAD FILTER

Two types of air pressure sensors with range 100 mbar and 200 mbar were used in smart shoes. The sensor with 100 mbar range was used for toe sensing point and other with 200 mbar range were used for all other sensing points. The dynamic calibration tests were performed on sensors at left toe, left heel, right toe and right heel. The load measurement data were available simultaneously from the air pressure sensor and Instron at the sampling rate of 100 Hz. This collected time sampled data from the air pressure sensor and Instron were used as input and output in our proposed algorithm to identify the transfer function.

Trust region reflective Newton (TN) search method showed better performance compared to Gauss Newton (GN) and Levenberg Marquardt (LM) search methods in terms of fit percentage.

For instance, on the left toe data, TN method exhibited 90.23 % fit percentage while LM and GN showed 83.62 % and 78.76 % respectively. Therefore, trust region reflective Newton method search method was employed to identify the transfer function.

The identified values for \( k_1, k_2 \) and \( c \) in (4) are displayed in Table 1 along with their transfer function equations for four sensing points separately. There are certain points that can be inferred from Table 1:

1. If \( k_1 = k_2 = 0 \) or nearly equal to zero, this explains that the materials exhibit weak visco-elastic effect and no signal processing is required. From Table 1, it is clear that the coefficients \( k_1 \) and \( k_2 \) of any sensing units are not zero or even close to zero. It means that the material exhibits considerable visco-elastic effect. Therefore, it becomes necessary to carry out signal processing on the raw data.
2. If \( k_1 \gg 0 \), it means the material is stiff and the gain of the transfer function in (2) is very large such that noise will be amplified. From Table 1, it is clear that the value of \( k_1 \)'s are in the range from 1.341 to 2.025. This implies that material exhibits considerable stiffness and noise gets amplified over time.
3. If the magnitude of the pole is greater than zero i.e., \( \left| \frac{a_1}{a_2} \right| > \left| \frac{b_1}{b_2} \right| \), the transfer function amplifies the high frequency range of the measured signal. The magnitude of the poles are greater than zeros which implies filter designed on the basis of this transfer function will show magnifying characteristics in the high frequency range with the phase lead.

The filter exhibits magnifying characteristics in the high frequency range with the phase lead. The performance of the hysteresis compensator designed for left shoe sensing unit can be seen in Figure 8. Filtered signal shows improved linearity in measurements with reduced hysteresis compared to raw signal. A variance level of 2.23N in root mean square is observed in the filtered signal which is nearly 0.3 percent of total load applied i.e., 800N. The root mean square error (RMSE) metrics are used to compare between the filtered and raw signal.
FIGURE 8. LEFT TOE SENSING UNIT COMPENSATOR PERFORMANCE

Root mean square error (RMSE) metrics: a) RMSE between load measurement from Instron \( x(t) \) and raw data measurement \( u(t) \) from air pressure sensors. b) RMSE between load measurement data from Instron \( x(t) \) and filtered signal \( r(t) \) after applying hysteresis compensator. c) Improvement percentage \( P\% \) can be defined as 
\[
\frac{\text{RMSE}(u) - \text{RMSE}(r)}{\text{RMSE}(u)} \times 100.
\]

where

\[
\text{RMSE}(u) = \sqrt{\frac{\sum_{i=1}^{N} (x_i - u_i)^2}{N}}, \quad (33)
\]

\[
\text{RMSE}(r) = \sqrt{\frac{\sum_{i=1}^{N} (x_i - f_i)^2}{N}}, \quad (34)
\]

where \( N \) is the total number of data samples.

Table 2 displays the calculated metrics for four sensing units individually. Instron generated triangular waveform of loading range 0 to 800N with loading rates 100, 200, 400, 600 and 800N/s. This table compares filtered and raw data in terms of RMSE metrics. Improvement percentage \( P\% \) reveals the improvement seen in the filtered signal after designed filter is applied. It is clear from the range of \( P\% \) that filtered signal shows less RMSE value compared to raw signal. These filters provide better performance at lower rates of loading than at higher speeds. For instance, considering left toe sensing unit, the \( P\% \) is 75.36\% at 100 N/s and reduces to 68.27\% at 800 N/s. Even though \( P\% \) decreased with an increase in loading rates, filter exhibited sufficient compensation in hysteresis for varying loads as shown in Figure 8(b). Filtered signal shows better linearity with less hysteresis at both low and high speed.

VII. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed phase lead filter on the GCF measurements, Data were collected from various trails of walking and standing activities performed by a healthy subject. The healthy subject is male, weight 53 kg, and is 5 feet 10 inch tall.

1) For the standing trail, subject initially did toe movement i.e., he stood on tiptoe. Then, he went back to the normal standing position and remained still for the whole trail. This activity was performed for a period of 60 seconds. Figure 9 shows the raw and filtered GCF estimate from sensing units during standing trail. Total GCF exerted by the subject is calculated for both raw and filtered data. Total GCF estimate i.e., sum of the GCF estimate of all the eight sensing units from raw data is 618N, where from filtered data, it is 535.2N. Therefore, subject weighting 53kg can normally exert 519.4N on the ground. Thus, the filtered signal provides more accurate estimate.

2) For the walking trail, subject performed continuous walking on treadmill for 2 minutes at a speed of 6 mph. Figures 10 and 11 show the performance of the hysteresis compensator for the walking trail. The raw data collected during this trail
are processed using the designed filter and compared with raw data for the left shoe and right shoes. The plot is drawn between GCF estimate from all sensing units and time interval from 20 to 26 seconds. From Figures 10 and 11, it is observed that in each walking step, the subject initially touched the ground with the heel followed by Meta4, Meta1 and finally toe. It can also be inferred from Figures 10 and 11 that the subject applied more force on the right side than left, and more specifically, right heel compared to left. Although, raw and filtered signal show similar GCF pattern during walking, differences can be observed in terms of the amplitude. For instance, from Figure 11, it can be seen that the filtered signal provides a lower estimate of heel GCF than the raw data.

VIII. CONCLUSION AND FUTURE WORK

In this paper, a design for smart shoes was reviewed. Each shoe contained four sensing units to measure GCFs at the heel, Meta1, Meta4 and toe positions. Static and dynamic calibration tests were performed on each sensing unit using Instron material testing machine. A digital filter was proposed which could compensate for the hysteresis effect in sensing unit and provide accurate GCFs estimates. The approach followed in designing this filter consisted of two parts: 1) dynamic modeling of the air bladder using standard linear solid (SLS) model, and 2) The PEM approach to identify transfer function of the compensate model. The filtered signal and raw data were compared with the data from Instron. In addition, standing and walking practical experiments were conducted on a healthy subject to verify the performance of the proposed filter.

REFERENCES


