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Accessible Ground Reaction Force Estimation Using Insole Force Sensors without Force Plates*

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***Abstract*— Ground reaction force (GRF) estimations using instrumented insoles relied on the use of costly force plates in previous works. This paper designed insoles with 15 force sensing resisters and presents an accessible estimation method of vertical GRF (vGRF) using the insole without any cost-prohibitive devices. To determine vGRF from the insole sensor forces, a subject-specific linear regression model was constructed using a least-squares method with a constraint and a bound. The regression matched the sensor forces during single-leg standing (SLS) to a subject's body weight with a linear constraint using data measured while walking. During SLS, standing static and shifting body weight were performed to enhance estimation accuracies. The accuracies of constructed models while walking were evaluated by comparison with the Nintendo Wii Balance Board (WBB) which can measure accurate vGRF compared with force plates. The results for an adult had 8–15 % root mean squared errors (RMSEs) with no significant deviations from previous methods which relied on force plates. From these results, the proposed method was validated as an accessible kinetic gait analysis system.**

I. INTRODUCTION

A kinetic gait analysis is to estimate joint moments from ground reaction forces (GRFs), their application point (COP: Center of Pressure) and kinematic parameters such as joint angles. It provides important information for clinical assessment and rehabilitation of patients with gait disorders by stroke, Parkinson's disease, or osteoarthritis [1]–[3].

Force plates are the gold standard sensor technology in kinetic analysis because of their high accuracy. However, they are often cost-prohibitive for general clinics. Moreover, their measurement range is limited by their fixed, in-ground installation. Thus, force plates do not readily support measurement during a long-range or continuous walking. Additionally, use of the plates may induce an unnatural gait and cause inaccuracies.

As an alternative to force plates, some companies have produced sensors that are embedded in the insole of a shoe and capable of measuring plantar pressure [e.g., Pedar (Novel, Munich, Germany) and F-Scan (Tekscan, South Boston, US)]. Although insole sensors measure only a unidirectional force as a vertical ground reaction force (vGRF), they provide reliable measurement for mobile gait analysis [4]. Nevertheless, the full cost of these commercial insole sensor systems remains prohibitive for use in clinical settings.

In contrast, previous works demonstrated instrumented insoles using a small number of sensors or local measurements on the sole. They estimated GRF from the sensor forces by machine learning approaches such as linear regressions [5]–[7] or nonlinear techniques [8]–[10]. In particular, Howell *et al.* [6] used a linear least squares regression for an instrumented insole consisting of 12 inexpensive force sensing resistors (FSRs) to estimate vGRF. Jacobs *et al.* [10] also developed a custom insole with pressure sensors and a tendon sensor consisting of a thin film load cell and trained artificial neural networks to predict three GRF components. The accuracies of their models had root mean squared error (RMSE) values—reflecting a difference between the measured data from force plates and the estimated line—of less than 10%.

These estimation models should be subject-specific to correspond to individual differences of sizes and shapes of feet. However, constructions of them still relied on the use of costly force plates. Thus, more accessible methods are necessary for the use in actual clinical settings and at home where cost-prohibitive devices are not available. In response, our group has proposed an accessible estimation method of vGRF without using force plates [11]. We have designed instrumented insoles with 12 FSRs and constructed linear regression models by matching sensor forces to a subject's body weight during single-leg standing (SLS). However, the accuracies were insufficient because of the number of sensors, their measurement range and linearity. In addition, model construction procedure had low versatility to differences of number of sensors and their position.

This paper designs an instrumented insole with 15 FSRs with better sensing properties and presents an accessible estimation method of vGRF using the insole sensors without force plates. To determine vGRF from the sensor forces, a subject-specific linear regression model was constructed by a least-squares method with a bound and a constraint. The regression matched the sensor forces while single-leg standing (SLS) to a subject's body weight with a linear constraint using data measured while walking. In the model constructions, static stand and two types of shifting body weight while SLS were performed. Estimation accuracies of vGRF while walking were evaluated by comparison with the Nintendo Wii Balance Board (WBB; Nintendo, Kyoto, Japan) which can measure high accurate vGRF compared with force plates, and lines estimated by the conventional method [6] which used

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Figure 1. Instrumented insole including 15 FSRs.

Figure 2. Designed insoles inserted into shoes and measurement devices.

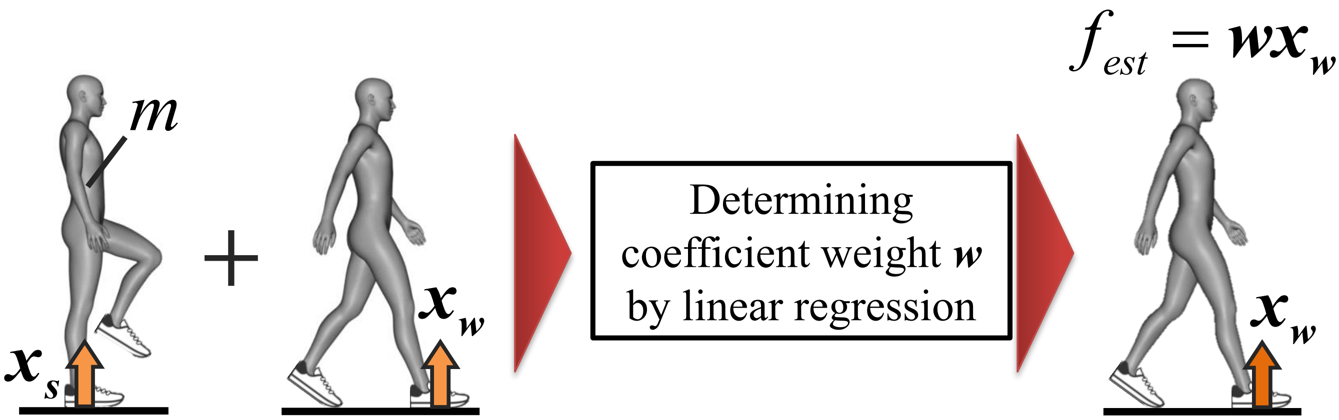


Figure 3. Overview of the vGRF estimation procedure.

costly force plates. From these evaluations, we validated the proposed method for accessible kinetic gait analysis.

I. METHODS

A. Hardware

An insole with 15 sensors was designed as shown in Fig. 1. The sensors were set on the OHP film shaped as an insole. A set of insoles for both feet was developed with all the sensors symmetrically arranged. The sensors were FSRs FlexiForce Standard Model A301 (Tekscan, South Boston, US) that have better force sensing properties such as linearity, hysteresis and drift than other thin-film force sensors. The active sensing area is a 9.53 mm (0.375 in.) diameter circle at the end of the sensor. The application of a force to the active sensing area of the sensor results in a change in the resistance of the sensing element in inverse proportion to the force applied. The sensors were calibrated using a Press Force Sensor 9313AA2 (Kistler, Winterthur, CH). The designed insoles were inserted into shoes (LD AROUND M, Mizuno, Tokyo, Japan) matched sizes as shown in Fig. 2. A circuit board containing a microcontroller, Op-amps, AD converters, a microSD card and a radio module was developed for both sides. A ribbon cable was used to connect each insole to its circuit board. The boards were placed on the backs of subjects' lower legs.

B. Study Procedure

An overview of the vGRF estimation procedure is shown in Fig. 3. First of all, a subject performed SLS and straight walking. The insole sensor forces measured from the motions were used to construct estimation models as an input of linear regression and a constraint. After calculations, the developed model estimated vGRF while walking.

In this study, a male subject (age: 23 years, body weight: 63.6 kg, height: 1.78 m, shoe size: 27.5 cm) was recruited. The subject provided informed consent prior to participation.

The subject wore shoes with the insoles inserted on both feet. The task executions were measured and recorded by the insoles and the two WBBs as shown in Fig. 4. Both the data from the insoles and the WBB were collected at 100 Hz. Both devices were synchronized by radio communications. The subject was asked to perform the following four tasks:

(1) *Static SLS*: The subject stood on right leg on the WBB and held the position for 10 s. This task was repeated five times.

(2) *Dynamic SLS_{AP}*: The subject stood on right leg on the WBB and then shifted his body weight in an

Figure 4. The Nintendo Wii Balance Board (WBB).

anteroposterior direction for 10 s. This task was repeated five times.

(3) *Dynamic SLS$_{APML}$*: The subject stood on right leg on the WBB and then shifted his body weight in anteroposterior and mediolateral directions for 10 s. This task was repeated five times.

(4) *Walking*: The subject walked straight across the WBBs at a self-selected pace with their sixth and seventh step contacting each of them. This task was repeated 15 times.

Now the SLS tasks were employed because vGRF during SLS substantially matched with a subject's body weight which was easy to measure by scales. The dynamic SLS takas were aimed to measure a motion which was more close to an actual walking.

C. Analysis

Recorded data from the insole sensors and the WBBs were analyzed using MATLAB (Mathworks, Inc., Natick, US). In the static and dynamic SLS, execution phases were determined as the duration from lifting to landing for the foot opposite the supporting side. The first and last 1-s intervals were then excluded as transient states. Variations of vGRF during the SLS tasks were evaluated by a root mean square values divided by a subject's body weight as the %RMS$_{SLS}$. In addition, COP generated from the insoles along the anteroposterior and mediolateral axes were calculated to evaluate shifting body weight during SLS. They were calculated using raw sensor forces as follows:

$$COP_X = \frac{\sum_{i=1}^{n} X_i F_i}{\sum_{i=1}^{n} F_i},\ COP_Y = \frac{\sum_{i=1}^{n} Y_i F_i}{\sum_{i=1}^{n} F_i} \qquad (1)$$

where F was a vector of sensor forces, X and Y were sensor coordinates in the insole.

To estimate vGRF from the insole sensor forces, a subject-specific linear regression model was constructed using a least-squares method with a bound and a linear constraint. The linear approach was employed because it was more suitable for a line fitting with limited training data than nonlinear approach such as neural networks if data from force plates were not available. The MATLAB Optimization Toolbox was used to calculate the regression weighting insole sensor forces during SLS to match a subject's body weight. The regression form was applied as follows:

$$\min_{\boldsymbol{x}} \frac{1}{2}\sum_{j=1}^{N}\left(\sum_{i=1}^{n} w_i x_{sij} - m\right)^2 \ \text{s.t.} \begin{cases} \sum_{i=1}^{n} w_i x_{wi} \le 1.4m \\ b_l \le w_i \end{cases} \qquad (2)$$

where n was a number of input sensors, w was a coefficient weight vector for sensor forces, x_s was a input data matrix of insole sensor forces during SLS, m was the subject's body weight and N was the sampling data size. In the linear inequality constraint, x_w was a data matrix of sensor forces from stance phases following the fourth step of natural walking in the task (4), and $1.4w$ was 140% of a subject's body weight reflecting a typical vGRF peak during stance phases of walking [13]. This value was newly reconsidered in this study because the value defined in our previous study [11] could not correspond to change of vGRF peak which depends on walking velocity. The lower bound of a weight vector, b_l, was set to 0 because a negative weight was unnatural in force calculation.

Using the regression, estimation models were constructed for an each trial of all the SLS tasks. Accuracies of these fittings were evaluated by %RMSE$_{\text{fit}}$ which was root mean squared error (RMSE) during SLS divided by a subject's body weight and calculated as follows:

$$\%\text{RMSE}_{\text{fit}} = \frac{\sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(m_j - m_{fitj}\right)^2}}{m} \times 100 \qquad (3)$$

where m_{fit} was a fitting result from the sensor forces to a subject's body weight.

Estimation accuracies of each model were evaluated by comparison with the WBBs. %RMSE$_{\text{est}}$ which provides an estimation error of vGRF during stance phases contacting the WBBs in the straight walking task (4) was calculated as follows:

$$\%\text{RMSE}_{\text{est}} = \frac{\sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(F_{wj} - F_{estj}\right)^2}}{m} \times 100 \qquad (4)$$

where F_p was the vGRF measured by the WBBs and F_{est} was estimated from insole sensor forces by constructed models.

To validate the proposed method, comparative models were built by the conventional approach [6]. The method fitted sensor forces during walking to data measured by the WBBs using a linear least squares regression without constraints. The conventional models were constructed using data from different combinations of nine trials in the task (4). Then they were evaluated by comparison with the WBBs in the other one trial as %RMSE$_{\text{est}}$.

TABLE I. COP DISPLACEMENTS DURING SLS TASKS

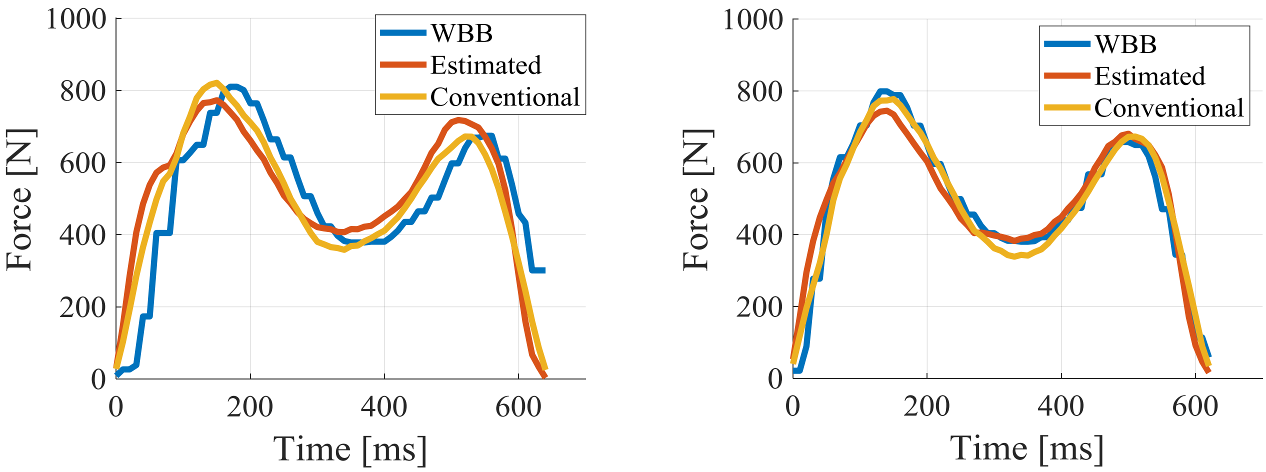
	Static SLS		Dynamic SLS_{AP}		Dynamic SLS_{APML}	
Sub.	X (AP) [mm]	Y (ML) [mm]	X (AP) [mm]	Y (ML) [mm]	X (AP) [mm]	Y (ML) [mm]
A	32.0 (±11.0)	13.4 (±2.6)	181.5 (±2.7)	23.1 (±1.2)	178.4 (±3.9)	35.3 (±1.4)

TABLE II. $\%RMS_{SLS}$ AND $\%RMSE_{FIT}$ DURING SLS TASKS

	%RMS			$\%RMSE_{fit}$		
Sub.	Static SLS	Dynamic SLS_{AP}	Dynamic SLS_{APML}	Static SLS	Dynamic SLS_{AP}	Dynamic SLS_{APML}
A	0.5 (±0.1)	2.8 (±0.1)	2.3 (±0.2)	1.5 (±0.2)	13.0 (±1.8)	19.5 (±1.9)

TABLE III. $\%RMSE_{EST}$ IN STRAIGHT WALKING

Sub.	Static SLS	Dynamic SLS_{AP}	Dynamic SLS_{APML}	Conventional
A	11.3 (±2.9)	15.1 (±4.9)	13.6 (±5.2)	9.9 (±3.0)



(a) A trial with lowest estimation accuracy of the proposed model.

(b) A trial with highest estimation accuracy the proposed model.

Figure 5. vGRF measured by th WBBs and estimated by proposed and conventional models using insole sensor forces.

I. RESULT

The results of COP displacement along the anteroposterior (AP) and mediolateral (ML) axes generated from the insoles during the SLS tasks are summarized in Table I. $\%RMS_{SLS}$ which is a variation of vGRF during the SLS tasks for the subject and overall were summarized in Table II. $\%RMSE_{fit}$ which indicates a fitting accuracy of the regression calculated by the proposed and conventional methods are summarized in Table III. The results of $\%RMSE_{est}$ which indicates a vGRF estimation accuracy of the models while walking are summarized in Table IV. The mean (±standard deviation) values of proposed and conventional models are given for the subject. The vGRF measured by the WBBs and estimated by the conventional and the proposed model constructed from static SLS during while walking are plotted in Fig. 5

II. DISCUSSION

The results showed that the proposed method was available for accessible kinetic gait analysis using an instrumented insole with a small number of force sensors.

As illustrated in Table I, the displacements of COP generated from the insole were larger in dynamic SLS than static SLS because of voluntary shifting body weight. In addition, the results of $\%RMSE_{fit}$ were 1–2% and 11–21% of models from static and dynamic SLS respectively as shown in Table II. These results were natural because vGRF during the dynamic SLS changed wider than static tasks by a vertical acceleration of the center of gravity according to the shifting body weight.

Table III shows that the models constructed from static SLS had higher estimation accuracies than dynamic SLS and they had 8–15% of $\%RMSE_{est}$ which were the highest accuracies in the proposed models with no significant deviations from conventional methods as can be seen from Fig. 5. In addition, accuracies of the proposed method were improved from our previous report [11]. On the other hand, $\%RMSE_{est}$ of the models from dynamic SLS were still 8–20% and SLS_{APML} had higher accuracies than SLS_{AP}. These results corresponded with our previous report [11] and suggested that input sensors data including pressure distribution patterns close to actual walking can enhance the estimation accuracy.

III. Conclusion

We have proposed an accessible vGRF estimation method using an instrumented insole with 15 force sensors. To estimate vGRF from the insole sensor forces, a subject-specific linear regression model was constructed using a least-squares method with a bound and a linear constraint. The regression used only the subject's body weight and insole sensor data measured from SLS and straight walking.

The models from static SLS had the highest accuracies which were 8–15% RMSE with no significant deviations from conventional methods relied on costly force plates. Besides, %RMSE of the models from dynamic SLS were 8–20% and the results indicated input sensors data including pressure distribution patterns close to actual walking can enhance the estimation accuracy.

From these results, we found that the method was effective for the use in actual clinical settings and at home where cost-prohibitive systems such as costly force plates or commercially insoles were not available.

Future work will increase number of subjects and compare vGRF estimation accuracy of the models with force plates which have higher accuracy and temporal resolution than the WBBs. Similarly, COP generated from the insoles should be validated because that the COP is essential information to estimate joint moments in kinetic gait analysis. Besides, the proposed method should be validated to correspond to differences of shoe size. In addition, we will examine more accurate estimation approaches base on other machine learning techniques such as a neural networks.

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