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Ground reaction force estimation using an insole-type pressure mat and joint kinematics
during walking

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Abstract

Kinetic analysis of walking requires joint kinematics and ground reaction force (GRF) measurement, which are typically obtained from a force plate. GRF is difficult to measure in certain cases such as slope walking, stair climbing, and track running. Nevertheless, estimating GRF continues to be of great interest for simulating human walking. The purpose of the study was to develop reaction force models placed on the sole of the foot to estimate full GRF when only joint kinematics are provided (Type-I), and to estimate ground contact shear forces when both joint kinematics and foot pressure are provided (Type-II and Type-II-val). The GRF estimation models were attached to a commercial full body skeletal model using the AnyBody Modeling System, which has an inverse dynamics-based optimization solver. The anterior-posterior shear force and medial-lateral shear force could be estimated with approximate accuracies of 6% BW and 2% BW in all three methods, respectively. Vertical force could be estimated in the Type-I model with an accuracy of 13.75% BW. The accuracy of the force estimation was highest during the mid-single-stance period with an average RMS for errors of 3.10% BW, 1.48% BW, and 7.48% BW for anterior-posterior force, medial-lateral force, and vertical force, respectively. The proposed GRF estimation models could predict full and partial GRF with high accuracy. The design of the contact elements of the proposed model should make it applicable to various activities where installation of a force measurement system is difficult, including track running and treadmill walking.

Introduction

Understanding the mechanisms of joint injuries and musculoskeletal diseases requires kinetics analysis of human motion. Walking is a fundamental and frequently-utilized motion, and thus can be used to understand the mechanical pathways of musculoskeletal problems of lower limb joints (Andriacchi et al., 2004, Koo et al., 2007). Kinetic analysis of walking typically requires the coordinates of body movements and ground reaction force (GRF). GRF can be translated as forces along the three orthogonal axes and a moment along the vertical

axis (Holden and Cavanagh, 1991) at the center of the pressure (COP) placed on the foot sole. The GRF is measured using a force plate; however, this can be difficult to measure such as during track running and treadmill walking.

GRF prediction is of great interest for simulating walking (Anderson et al., 2001). GRF can be estimated using equations for inverse dynamics of human motion (Zatsiorsky, 2002). Specifically, GRF is estimated starting from a free distal segment of a body and solving dynamics equations recursively up to the supporting segment on the other side. This method is applicable when only one external force is unknown, such as during the single stance phase of walking. Errors can accumulate during each recursive procedure and thus the estimated GRF can include a large error (Zatsiorsky, 2002). To overcome the accumulation of errors in estimating GRF, inverse dynamics and forward dynamics-based optimization methods have been developed (Xiang et al., 2010).

Koopman et al. (1995) introduced a method for GRF estimation using pure joint kinematics by combining inverse dynamics and optimization techniques. They included an empirical function to distribute body weight (BW) between feet during the double stance phase.

Accuracy of GRF estimation can increase when part of the GRF is provided, such as the pressure between the foot and ground. Insole-type pressure mats can record foot contact pressure distribution during walking. Likewise, state of the art insole-type pressure mat systems can also provide wireless recording, allowing for mobility and improved accuracy (Ahroni et al., 1998).

Vertical GRF and COP on the foot sole can be calculated from foot pressure data. Foot pressure data combined with joint kinematics during walking can be used to estimate the full

GRF during inverse dynamics analysis (Forner-Cordero et al., 2006) and forward dynamics analysis (Chumanov et al., 2010). In previous works, Forner-Cordero et al. (2006) used insole-type pressure mats and an inverse dynamics-based optimization method. Specifically, vertical GRF and COP obtained from pressure mats were corrected using coefficients obtained from calibration trials and as a function of gait phase, respectively. To estimate the forces in each foot during the double stance period, they added correction forces to each foot based on the relative COP locations in the left and right feet. Chumanov et al. (2010) introduced an alignment method between pressure mat coordinates and anatomical coordinates using 10 motion capture markers placed around the rim of a shoe sole. They used a 19-segment model generated with SIMM (MusculoGraphics, Santa Rosa, California, USA) and least squares forward dynamics for running trials that had no double stance phases; however, their method could not decompose the left and right limb ground shear forces without adding additional assumptions such as those used by Forner-Cordero et al.

Previous studies on forward dynamics-based optimization methods used viscoelastic elements between the foot and ground to estimate the forces in the element in the full body optimization process (Anderson and Pandy, 2001, Neptune et al., 2000). Anderson and Pandy (2001) added four contact elements whose ground vertical forces and shear forces varied depending on the height and displacement of the foot, respectively. Furthermore, Neptune et al. (2000) added 66 contact elements whose vertical and shear forces were represented by nonlinear functions of contact area and relative contact speed including shoe-specific parameters.

Details of the theoretical background of the inverse dynamics-based optimization and forward dynamics-based optimization are well described in the literature (Zatsiorsky, 2002,

Xiang et al., 2010, Rasmussen et al., 2001, Fregly et al., 2007, Delp et al., 1990). The purpose of the study was to develop GRF estimation models placed on the foot sole to estimate full GRF when only joint kinematics are provided, as well as to estimate ground contact shear forces when both joint kinematics and foot pressure were provided. The estimation accuracies of the models were tested using subjects' walking data. This study is similar to the work by Forner-Cordero (2006) who used an inverse dynamics-based optimization technique; however, we introduce a new type of contact element similar to those described in studies by Anderson et al. (2001) and Neptune et al. (2000). Our reaction elements consisted of smart force elements whose force directions were confined and activation was controlled depending on kinematic and kinetic environments. To test our methods for estimating GRF, we used an AnyBody commercial skeletal modeling system with inverse dynamics-based optimization solver (AnyBody Technology, Aalborg, Denmark).

Method:

Data acquisition

IRB approval and informed consents were obtained prior to testing. Seven healthy male subjects (age 23 ± 2 years, weight 67.0 ± 8.4 kg) performed a static trial and a walking trial at their normal walking speed (average 1.76 ± 0.26 m/s). Joint motion was recorded with a motion capture system at 100 Hz (12 cameras, MX T-40, Vicon, Oxford, UK). Insole type pressure mats at 100 Hz (F-scan, Tekscan, Boston, MA, USA) and two force plates at 1000 Hz (AMTI, Boston, MA, USA) were used together to measure the foot pressure for GRF estimation and to measure the full GRF for validation, respectively. The pressure mat had a

cell size of 0.26 cm^2 . The correlation between the pressure mat and force plate was verified previously (Ahroni et al. 1998, Mueller and Strube 1996).

Joint motion was captured using the Plug-in-Gait full-body marker set from Vicon systems (39 reflective markers). During the static trial, each subject stayed on top of the two force plates, with one foot on each force plate, wearing an insole type pressure mat inside each shoe. The forces and pressures measured during static trials were used to calibrate the absolute values from the pressure mat. The GRF measured from the force plate served as the primary standard and was compared with the estimated GRF.

Smart force element between the foot and ground

Our GRF estimation method was able to determine the unknown reaction forces between the ground and body using smart force elements whose force direction was confined and whose activation was dependent on other kinematic and kinetic conditions while solving the motion equations of human walking.

We developed two GRF estimation methods by using two different combinations of force components, namely, Type-I and Type-II. The Type-I model was appropriate in cases where only joint motion is available, while the Type-II model could be used when both joint motion and partial GRF (foot pressure here) data was available. The Type-I model comprised 52 smart force elements attached to and distributed uniformly on the foot sole, while the Type-II model had only one smart force element attached at the foot COP.

[Figure 1 HERE]

[Figure 2 HERE]

Each of the smart force elements in the Type-I model consisted of five linear reaction components as shown in Fig. 1(a). The linear reaction component in our test platform, the AnyBody Modeling System (Version 1.3), was able to pull (tension) in one direction. Two linear reaction components in the same direction but opposite sense were placed along each of the global x- and y-axes, which were parallel to the ground. One linear reaction component was placed such that it pushed the foot along the z-axis, which was vertical to the ground. Thus, the sense of the net force vector of each smart force element was confined to the cube shown in Fig. 1(a). The maximum force of the linear reaction component was 30 N, and the maximum vertical force and shear force that could be received by the 52 smart force elements were 1560 N and 2206 N, respectively. The maximum force of the linear reaction component was determined after testing values from 5 N to 50 N in a preliminary analysis. The estimated GRF converged when the maximum force reached 30 N, and almost no differences were observed up to 50 N (Fig. 3). Activation of the smart force element in the Type-I model was controlled by foot trajectory, and the trajectory of each smart force element attached to the foot was calculated from the provided joint kinematic data. The gait phase and foot ground contact period were automatically identified to locate a cylindrical region (diameter 9 mm, height 15 mm) on the ground for each smart force element as illustrated in Fig. 2(a). The cylindrical region defined the activation region of each smart force element and represented the location when the smart force element was in contact with the ground and able to receive force.

The Type-II model had only one smart force element whose composition was different from

that of the Type-I model. The smart force element in the Type-II model consisted of four reaction components as shown in Fig. 1(b). The Type-II model was appropriate for cases where the vertical force and its point of application were provided by external devices such as a pressure mat. Thus, in our experiments, the smart force element was placed at the COP provided by a foot pressure mat. Two linear reaction components in the same direction but opposite sense were set along each of the x- and y-axes. No reaction element was set in the z-axis, which was vertical to the ground. Thus, the sense of the net force vector of the smart force element was confined parallel to the ground and received only the ground shear force. The upper limit of the force of the linear reaction component was set to 100 N. Thus, the magnitude of the net shear force vector of the smart force element was limited to 141.4 N. The estimated GRF shear force converged when the upper limit was 100 N and did not change when the upper limit was increased up to 300 N (Fig. 3). Activation of the smart force element was controlled by the given vertical force, which was the total vertical force measured from the pressure mat as illustrated in Fig. 2(b). The Type-II model did not require pre-calculations to determine the activation period, which was different from the Type-I model.

Human skeletal model

The two GRF estimation models, Type-I and Type-II, were attached to a commercial AnyBody (AnyBody Managed Model Repository Version 1.3) full body skeletal model that had an inverse dynamics-based optimization solver. AnyBody uses its own scripting language to define its skeletal model, and the script file of the model was modified to include our smart force elements in each model. The AnyBody full body skeletal model has 19 body segments

and 38 rotational actuators (Damsgaard et al., 2006). The knee, elbow and subtalar joints had one rotational freedom, the elbow and wrist had two rotational freedoms, and other joints had three rotational freedoms.

The force received by each smart force element was determined for each frame together with the joint rotational moments using inverse dynamics-based optimization (Rasmussen et al., 2001). The optimization process is summarized in Appendix.

Pressure mat data processing and potential error

When using the Type-II model vertical GRF and COP on the foot should be calculated from foot pressure distribution. The vertical GRF is the sum of the forces born by each pressure sensor cell in the mat. The COP was determined using zero moment equations (Han et al, 1999) in the pressure mat coordinate system using MATLAB (Mathworks, Boston, MA, USA).

To apply the vertical GRF in the Type-II model, the coordinate of the COP was transformed to the anatomical coordinate system of the foot. With respect to the pressure mat data, the heel point, the anterior-most point close to the second toe, and the normal vector to the pressure mat plane were detected. In the foot anatomical model, the heel point, the second toe end point, and the normal vector of the plane made by the two points and the location of fifth metatarsal-phalangeal joint were selected. Although we placed three markers around the rim of the shoe sole and were very careful to match the points, there was the possibility of errors up to 10-15 mm when determining the foot COP.

We first ran GRF estimation simulation of the Type-II model with measured pressure mat

data, but we were also interested in understanding the performance of the Type-II model in estimating ground shear forces when an accurate vertical reaction force and COP were provided. Thus, we ran a separate simulation of the Type-II model with the vertical reaction force and COP derived from the force plate whose measurements were the primary standard in our study. The simulation results on these input data were referred to as Type-II-val.

Statistical performance analyses

Anterior-posterior (AP) shear force, medial-lateral (ML) shear force, and vertical force (only for Type-I model) were estimated during the stance phase of a gait cycle of the right leg using Type-I and Type-II models. The AP and ML shear forces were also estimated using the Type-II model with the input data from the force plate (Type-II-val).

The stance period of the gait cycle has an initial double stance period, followed by a single stance period and another double stance period. RMS errors of the estimations against the measurements from the force plate were calculated for each period.

The estimation accuracies for Type-I, Type-II, and Type-II-val were evaluated using one-way ANOVA followed by the Tukey post-hoc test. The estimation accuracies depending on single vs. double stance periods were also tested by one-way ANOVA followed by the Tukey post-hoc test.

The accuracy of the estimated COP using the force estimation results of the smart force elements in the Type-I model was quantified based on RMS distance errors against the COP from the force plate.

Results

The maximum force of the linear reaction components in the Type-I and Type-II models were determined in a preliminary test. The change and convergence of the estimated GRF was observed while increasing the maximum force from 5 N to 50 N, and from 50 N to 300 N for Type-I and Type II models, respectively, as illustrated in Fig. 3. For the Type-I model, the simulation results diverged when the maximum force was larger than 100 N, depending on subjects. Thus, all of the linear reaction components in each of the 52 smart force elements were set to have the same maximum force of 30 N, while those in the Type-II model were set to have maximum force of 100 N.

[Figure 3 HERE]

For the gait cycle of each subject, the AP shear force, ML shear force, vertical force and COP were estimated from the Type-I model, while separate determinations of the AP shear force and ML shear force were estimated from the Type-II and Type-II-val models. Representative GRF and COP estimation results for a subject are shown in Fig. 4. The estimated results were compared with the measured data from the force plate, which was our primary standard. As shown in Figs. 4(c) and 4(d), the vertical force measured from the foot pressure mat and the measured and transformed COP were plotted as values from the Type-II model, respectively.

From a qualitative standpoint, the vertical force and shear force estimations were more accurate during the single stance period than the double stance period. The path of the COP estimated using the Type-I model was located lateral to the true COP between mid-stance and

toe-off period. In addition, the measured and transformed COP from the foot pressure mat had a somewhat large error against the true COP from the force plate. The results suggested a trend for greater accuracy of knee adduction moment estimation in the Type-II-val model, when the COP was accurate, than was observed in the Type-I and Type-II models, when the COP was less accurate, as shown in Fig. 4(e).

[Figure 4 HERE]

We divided the stance phase of the gait cycle into initial-double-stance, mid-single-stance, and terminal-double-stance periods. The estimation errors of the forces against the measured forces were quantified separately for the three periods and shown as RMS errors in Fig. 5 and Table 1. The AP shear force and ML shear force were estimated with accuracies of approximately 6% BW and 2% BW in all three methods, respectively. Estimations from Type-I and Type-II-val were not significantly different. The inaccuracies in force measurement, COP measurement and transformation using the foot pressure mat caused significant differences in estimating AP shear force. The overall graph shape of the estimated vertical force looked close to the measured data (Fig. 4); however, the average RMS error was 13.75% BW, which was larger than other force estimation errors for the Type-I model.

[Table 1 HERE]

The accuracy of force estimation was highest during the mid-single-stance period with average RMS errors of 3.10% BW, 1.48% BW and 7.48% BW for AP force, ML force, and vertical force, respectively (Table 2). The accuracies during the initial-double-stance and

terminal-double-stance were statistically significantly different, but were not significant when compared with the accuracy during a mid-single-stance. The averages of RMS errors during the double stance were around 9% BW, 3% BW, and 14% BW for AP force, ML force, and vertical force, respectively, which were approximately twice as large as those during the single stance.

[Table 2 HERE]

The path of each COP was estimated in the Type-I model and measured and transformed in the Type-II model. The Euclidean distances on the ground against the COP measured with force plate were calculated for both models. The average (standard deviation) of the RMS errors of the Euclidean distances during the stance phase was 29.0 ± 6.7 mm and 34.5 ± 7.0 mm in the Type-I and Type-II models, respectively.

Discussion

Full and partial GRF could be estimated with accuracies ranging from 2 to 7% BW for shear forces and 13% BW for vertical force using the proposed models. The models were also tested using the AnyBody skeletal model, which utilizes an inverse dynamics-based optimization solver. The proposed models function as a virtual force plate between the foot and ground and had structures to support missing forces for motion equations of the inverse dynamics.

The structure of the smart force element in the Type-I model was designed to balance both

shear force and vertical force. The maximum force of an instance of the smart force element was constrained by the maximum force of each of the five linear reaction components, which was determined in a preliminary study after testing the convergence of the estimated GRF. The linear reaction components had the same maximum force of 30 N and the 52 smart force elements were placed evenly on the foot sole to make the model general and applicable to different gait types. A major limitation of this study is that only a normal gait and normal subjects were tested. For extreme gait styles, such as tip-toe walking, the positions of smart force elements should be changed to balance the concentrated body weight on specific areas. The maximum force should also be modified when testing obese subjects. Our simulation diverged in some subjects when the maximum force of the force element was larger than 100 N in the Type-I model. Thus, further investigation is required to understand the applicability of the suggested method in obese subjects.

The smart force element developed in this study was relatively simple compared with other contact elements developed in previous studies on foot contact models in forward dynamics simulation (Meglan, 1992, Gilchrist and Winter, 1996, Moreira et al., 2012). In an early study on forward dynamics simulation, a two-part foot model with viscoelastic contact elements was introduced (Meglan, 1992). More rigorous approaches have been introduced to physically model foot contact mechanics with spring/damper components (Gilchrist and Winter, 1996) and as a sphere-plane contact model (Moreira, 2012). GRF estimation result graphs have been presented previously, although they did not determine estimation accuracy (Gilchrist and Winter, 1996, Moreira et al., 2012).

The estimation accuracy for vertical force was 13.75% BW, which was rather large compared with the accuracies for AP force and ML force in the Type-I model. The vertical force

estimation graph over a gait cycle looked very close to the measured values compared with other forces (Fig. 4). The vertical force ranged from 0 to approximately 100% BW, while the ranges for AP force and ML force were approximately -25% BW to 25% BW and -10% BW to 10% BW, respectively. Thus, it seems that forces with larger fluctuations have a larger absolute error.

Providing measured COP paths and vertical GRF information did not substantially increase the accuracies in shear force estimates in the Type-II model but showed a trend of increased accuracy in knee adduction moment in Type-II-val. Previous studies suggested using an insole type pressure mat to provide the COP and net vertical GRF to predict shear forces (Forner-Cordero et al., 2006, Chumanov et al., 2010). The vertical GRF in the study of Chumanov et al. obtained from an insole type pressure mat had RMS differences ranging from 0 to 10% of the peak vertical GRF with estimation accuracies of 8% BW for AP force and 4% BW for ML force, which were close to the results obtained with the Type-II model. Based on the results obtained from the Type-II-val model, we found that the combined errors in the provided COP path and vertical GRF could deteriorate the accuracies by 2.7% BW and 0.6% BW for AP force and ML force, respectively. In an ideal situation when an accurate COP path and vertical GRF could be provided, the accuracies were 5% BW and 2% BW for AP force and ML force, which was similar to the accuracies in the Type-I model when the COP path and vertical GRF were not provided.

The prediction of force distribution during the double stance gait phase has been challenging due to the nature of redundant dynamic systems (Koopman et al., 1995, Forner-Cordero et al., 2006). In our models, we did not include any heuristic, physical or statistical functions to distribute forces between the left and right feet. During the single stance phase, the estimation

accuracy was as good as 3.1% BW, 1.5% BW, and 7.5% BW for AP force, ML force, and vertical force, respectively. As expected, the estimation errors doubled during the double stance phase while the error was not much different from the average error during the single stance phase. Forner-Cordero et al. (2006) achieved accuracies of 1-2% BW when estimating shear forces from partial GRF data from an insole type pressure mat; however, their method calculated the coefficients of a left-right force distribution function using data measured during calibration trials with force plates, which is unrealistic when using the suggested estimation methods in situations without a force plate.

We only used an inverse dynamics-based optimization solver in the present study. Thus, further studies should incorporate the Type-I and Type-II models into a skeletal model with muscles as actuators, or test the models using a forward dynamics-based optimization solver such as SIMM (Delp et al, 1990) or OpenSim (Delp et al., 2007).

In conclusion, two different GRF estimation models were developed using two different smart force elements. The two models were tested using a skeletal model with an inverse dynamics-based optimization solver. Full GRF could be estimated using the Type-I model when only joint kinematics data was provided. Partial GRF could be estimated using the Type-II model when the COP path and net vertical GRF were provided from a foot pressure mat. The estimation accuracies for shear forces in the two models were similar. Measurement errors in the COP paths and vertical GRF in the Type-II model deteriorated the estimation accuracies for shear forces. The accuracy of GRF estimation was twice as high during the single stance phase compared with the double stance phase.

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Conflict of interest statement

As far as the authors know there is no conflict of interest in this manuscript. This paper has been neither published nor submitted elsewhere for publication, in whole or in part, either in a serial, professional journal or as a part in a book that is formally published and made available to the public.

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Fig. 1 Smart force element in the Type-I model consisting of five reaction components. The net force vector is confined to a cube (a). Type-II model consisting of four reaction components. The net force is confined to a rectangle parallel to the ground (b).

Fig. 2 Schematics of the control of activation of smart force elements. Each of the 52 smart force elements is activated when they enter the matching cylindrical region in Type-I model (a). The smart force element in the Type-II model is activated when the vertical GRF is larger than a preset threshold (b).

Fig. 3 Maximum force of the linear reaction components determined by observing the convergence of the estimated GRF. The maximum force was tested from 5 N to 50 N for the Type-I model (a) and from 50 N to 300 N in the Type-II model (b)

Fig. 4 Representative estimation results for a single gait cycle of a subject. Results from the Type-I model show the estimated AP force (a), ML force (b), vertical force (c) and COP path (d). Results from the Type-II and Type-II-val models show estimated AP force and ML force. Knee adduction moment was estimated from all models (e).

Table 1 Estimation accuracies of Type-I, Type-II and Type-II-val quantified as the average (standard deviation) RMS errors.

Forces (% BW)	Type-I	Type-II	Type-II-val
Anterior-posterior force	5.82(5.82)	7.82(7.83)*	5.07(5.04)*
Medial-lateral force	1.87(1.85)	2.67(2.67)	2.06(2.03)
Vertical force	13.75(13.82)		
Knee adduction moment (% BW×Height)	1.37(1.36)	1.67(1.65)	1.13(1.10)

* $p < 0.05$ between Type-II and Type-II-val.

Table 2 Estimation accuracies for initial-double-stance, mid-single-stance and terminal-double-stance.

Forces (% BW)	Initial-double-stance	Mid-single-stance	Terminal-double-stance
Anterior-posterior force	7.95(6.10)* **	3.10(3.07)* ***	9.77(6.93)* ** ***
Medial-lateral force	3.74(3.55)* **	1.48(1.48)*	1.96(1.65)**
Vertical force (Type-I only)	13.75 (13.82)	7.47(6.70)***	15.68(13.73)***
Knee adduction moment (% BW×Height)	1.64(1.48)	1.25(1.25)	1.54(1.43)

* $p < 0.05$ between Type-I and Type-II.

** $p < 0.05$ between Type-I and Type-II-val.

*** $p < 0.05$ between Type-II and Type-II-val.

(a) Smart force element in Type-I model

(b) Smart force element in Type-II model

(a) Region-based activation in Type-I model

(b) Vertical force-based activation in Type-II model

(a) Anterior-posterior force

(b) Medial-lateral force

(c) Vertical force

(d) COP path

(e) Knee adduction moment