Prediction of ground reaction forces in level and incline/decline walking from a multistage analysis of plantar pressure data

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ABSTRACT

Knowing the ground reaction forces (GRFs) during walking has various biomechanical applications in injury prevention, gait analysis, as well as prosthetic and footwear design. The current study presents a method for predicting the GRFs in level and incline/decline walking that may be used in various outdoor biomechanics studies geared towards the above applications. The method was developed to predict the complete set of GRFs at walking inclinations of 0°, ±5°, ±10°, ±15°, and ±20°. Plantar pressure insoles were used to obtain inclination-specific, linear regression models based on three periods of gait stance phase, and the model-determined GRFs were compared with those measured from a forceplate. The three periods were determined based on the observed shifting of load-bearing insole sensors from heel to forefoot during walking, i.e., heel-strike, midstance, and toe-off. Six subjects wearing minimalist shoes fitted with plantar pressure insoles containing 99 pressure sensors performed ten walking trials at each of the aforementioned inclinations on an adjustable ramp with an embedded forceplate. Data from contact of the instrumented shoes with the forceplate were used to create linear regressions to transform insole pressure data into a complete set of GRFs. The root mean square error (RMSE) over peak recorded values were on average 10%, 3%, 21% for level walking and 11%, 4%, 23% for ramp walking in the respective anteroposterior, vertical, and mediolateral directions. The multistage linear regression model developed in the current study may be an acceptable option for estimating GRFs during walking in various environments without the restraint of a forceplate.

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1. Introduction

To date, a vast majority of studies involving walking on various surface conditions are restricted to utilize a forceplate to obtain ground reaction forces (GRFs) (Lay et al., 2006; McIntosh et al., 2006; Wannop et al., 2014). Previous attempts to obtain GRF data without the restriction of a forceplate have developed devices that use inertial sensors and attach to shoes, such as thin strain gauge transducers (Davis et al., 1998), piezoelectric copolymer films (Razian and Pepper, 2003), or force transducers (Liedtke et al., 2007). These devices, however, are largely customized, relatively difficult to use, and not validated for ramp walking. A study by Forner Cordero et al. (2004), however, obtained GRFs during level walking by using plantar pressure insoles combined with kine-matic data from a motion capture system. The use of a motion capture system in an outdoor environment for extensive studies is not feasible as the calibration may be difficult, and the target volume would still be limited to that which is visible to the motion capture cameras. In contrast, a study by Fong et al. (2008) used plantar pressure data combined with linear regression models calibrated from a forceplate to predict GRFs during level walking. While the level of accuracy in the study of Fong et al. (2008) was generally low when compared with the earlier study by Forner Cordero et al. (2004), the methods used by Fong et al. (2008) did not require the use of a motion analysis system and therefore could be used in outdoor environments. The relatively lower accuracy in Fong et al. (2008) may be due to the methods that include a single-stage analysis of plantar pressure data in the development of linear regression models, while multiple distinct stages are involved in the stance phase of gait, e.g. heel-strike, midstance, and toe-off (Perry and Burnfield, 2010).

Multistage regression has been largely used in various scientific disciplines, such as clinical pharmacology (Morris et al., 2010) and

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studies on health statistics (McClellan et al., 1994; Permutt and Hebel, 1989). In clinical statistics, while the formation of a multi-stage regression model varies depending on its application, the basic idea is to make better predictions in clinical studies (Cleophas and Cleophas, 2014). It is remarkable, however, that while numerous regression models have been used in biomechanics data analyses (Iglesias-Soler et al., 2018), multistage regression is rarely used in gait biomechanics, given the multistage patterns of many gait conditions (Perry and Burnfield, 2010). The purpose of the current study was to develop a multistage method to analyze plantar pressure data for the prediction of a complete set of GRFs in level and incline/decline walking. It was hypothesized that splitting plantar pressure data into three periods based on the stance phase of walking gait, i.e. heel-strike (HS), midstance (MS), and toe-off (TO), with separate linear regression models would (1) increase the accuracy of prediction compared to the single-stage regression method by Fong et al. (2008), and (2) develop a more versatile method that would allow for the prediction of GRFs during incline/decline walking, therefore providing a research avenue to study lower extremity biomechanics in diverse, outdoor environments.

2. Methods

2.1. Subjects

Six male subjects ranging in age 21 to 36 years and mean height and weight of 171.5 ± 3.5 cm and 70.5 ± 4.7 kg, respectively, participated in the study. Prior to testing, written informed consent was received from each subject, and approval for the study was obtained from the local Institutional Review Board. Subjects were interviewed to ensure they were healthy, without any known pathology or major lower body injuries within the past ten years.

2.2. Instrumented ramp

A 4.88 m long, 0–20° adjustable ramp was built and used for the level and incline/decline walking trials. An AMTI forceplate (Advanced Mechanical Technology Inc., Watertown, MA, USA) was embedded in the center of the ramp walkway that was flush with the walking surface. To minimize vibrations and flex of the walkway, as well as to ensure valid force measurements from the forceplate, four 2.44 m steel beams and two 1.22 m by 1.22 m steel plates supported the ramp's 2.44 m midsection. Additionally, two side brackets were bolted to the side of the ramp at its center (forceplate location). A textured paint was applied to the ramp surface and forceplate to increase friction and create a nonslip condition required at these augmented inclinations. For safety purposes a level platform was attached to the top of the ramp, and railings were added to the platform and sides of the walkway (Fig. 1). Subjects were instructed to use the railings if they needed to. The subjects, however, did not use the railings during these reported tests.

2.3. Data collection

Each subject performed ten walking trials at each ramp inclination, i.e. 0° (level walking), ±5° (plus represents incline walking and minus represents decline walking), ±10°, ±15°, and ±20°. During the walking trials, subjects wore Merrell Trail Glove minimalist shoes (Wolverine World Wide, Inc., Rockford, MI, USA) which were fitted with wireless pressure insoles (Novel Pedar model w, Munich, Germany). Each insole contained 99 sensors that measured plantar pressures at a sample rate of 100 Hz. The forceplate data were recorded at a sample rate of 1000 Hz. Before each set of trials the subjects were asked to practice walking at their normal cadence along the walkway so that starting points could be deter-

mined in order for their right foot to consistently strike the forceplate.

2.4. Data analyses and model formulation

For each subject at each ramp inclination, between-trials repeatability analyses were performed to generate coefficients of correlation (R values) with respect to both the plantar pressure data and the forceplate data. After the walking trials, the forceplate data were resampled at 100 Hz to match the plantar pressure data. Trial data were then manually trimmed by removing unuseful steps to include only the data from the right foot's contact with the forceplate. The range of contact data was determined to start with the first nonzero pressure reading and end with the last nonzero pressure reading of the right foot's stance phase. Forceplate data (with a threshold of 10 N) were also manually trimmed to match its corresponding plantar pressure nonzero value segment. Since each subject performed ten walking trials for each ramp inclination, nine were used to generate a regression model for the given ramp inclination, while one trial chosen at random was set aside to later assess the accuracy of the generated model by comparing predicted values using plantar pressure data against forceplate GRF data (Weaver et al., 2016).

The vertical orientation of the insoles' capacitance sensors allowed direct output of the vertical component of the GRF by the plantar pressure insole system. To further divide the data of each footstrike, plantar pressure plots of the vertical GRF were referenced to determine the midstance frame (Fig. 2). Midstance frame was chosen as the minimum value between the two characteristic maxima of the vertical GRF curve. This minimum point of the vertical GRF curve has been documented to occur consistently in walking and is a reduction in downward force as the body 'flies' over the leg in midstance (Levine et al., 2012; Perry and Burnfield, 2010). The start, end, and midstance frame of each trial were chosen based solely on data from the plantar pressure system to allow the later process of predicting the GRFs to be done by the system independently.

Trial data were first split in half at the midstance frame. An Excel macro was used to generate coefficients of determination (R^2 values) between each individual insole sensor's pressure readings and the forceplate measurements. Three insole sensors from each half of the footstrike (before and after midstance frame) that exhibited the highest 3 linear correlations (determined with R^2 values) were chosen to create pressure masks, with a total number of selected sensors being 6 in each regression model, which was considered to be adequate (Fong et al., 2008). Slope and intercept constants were then created between these pressure masks and the forceplate measurements of the GRFs. This process of creating a linear regression using pressure mask values as inputs was done for the anteroposterior and mediolateral components of the GRF. For the vertical component, the vertical forces calculated from the plantar pressure system consistently exhibited the highest R^2 values compared to insole sensors, and therefore the plantar pressure system calculation of vertical forces was used instead of a pressure mask to create the linear regression and serve as its input when predicting the vertical GRF. The slope, intercept and R^2 values used were an average from the nine trials at each ramp inclination.

The linear regressions generated from the first half of the footstrike were used to predict the GRFs from the first nonzero pressure reading until two frames before the midstance frame, forming the first segment of the model, i.e. heel-strike. The linear regression generated from the second half of the footstrike were used to predict from the fourth frame past the midstance frame until the last nonzero pressure reading, forming the third segment of the prediction model, i.e. toe-off. The second segment of the model, i.e. midstance, used a weighted combination of both regres-
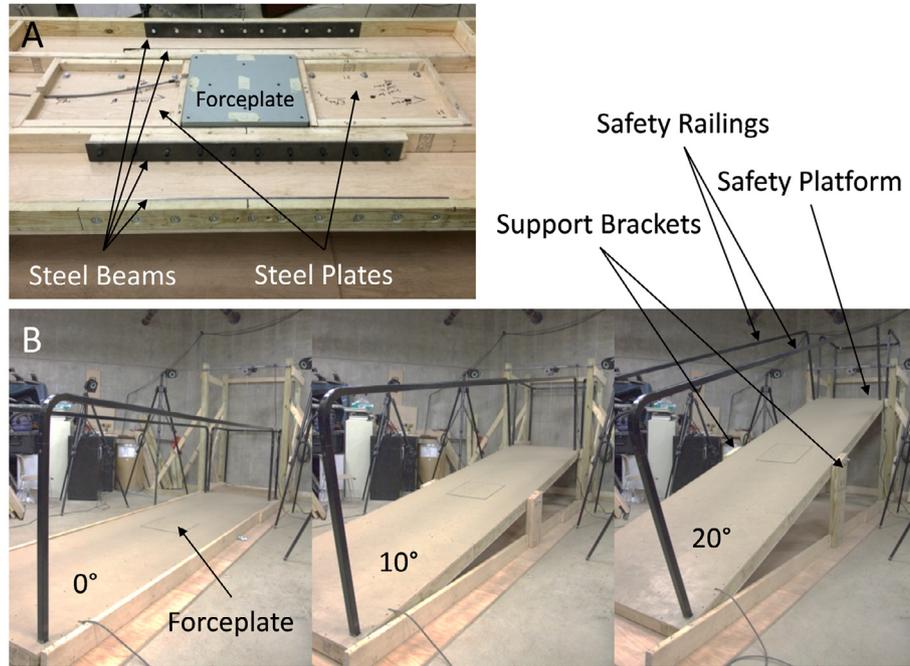
Fig. 1. (A) Midsection of the ramp showing the internal steel support structure and the location of the forceplate; (B) The instrumented ramp with support brackets, safety railings and platform in 3 different inclination conditions.
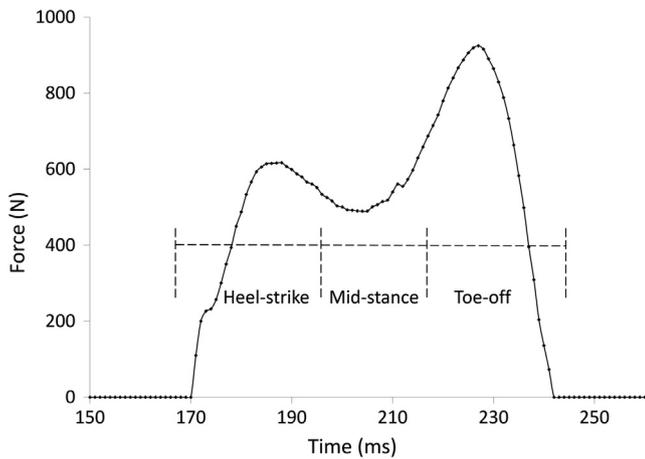

Fig. 2. A representative vertical force curve from the plantar pressure system for 10° incline walking trial with three schematic periods of gait stance phase elicited.

sion models and was inserted into the model to account for the change in load bearing sensors as a gradual shift. Eq. (1) is a general format of the model, where $M(P)^{\theta}_{x,y,z}$, is the model output which is a function of the plantar pressure insole measurements, P. The model was dependent on the ramp inclination, θ, and the component of GRF being predicted denoted by x, y, z for the mediolateral, anteroposterior, and vertical directions, respectively.

$$M(P)^{\theta}_{x,y,z} = \begin{cases} f(P) = m_1 * \left(\bar{P}_{c,d,e}\right) + b_1, & P_{HS} \leq P \leq P_{MS-3} \\ \begin{bmatrix} .9 \\ .7 \\ .6 \\ .4 \\ .3 \\ .1 \end{bmatrix} * f(P) + \begin{bmatrix} .1 \\ .3 \\ .4 \\ .6 \\ .7 \\ .9 \end{bmatrix} * g(P), & P_{MS-2} \leq P \leq P_{MS+3} \quad (1) \\ g(P) = m_2 * \left(\bar{P}_{f,g,h}\right) + b_2, & P_{MS+4} \leq P \leq P_{TO} \end{cases}$$

$f(P)$ is the linear regression used for the HS phase of the model with slope and intercept constants, m_1 and b_1. $\bar{P}_{c,d,e}$ arbitrarily represents the pressure mask input made from three sensors: c, d, and e. Similar to $f(P)$, $g(P)$ is the linear regression used for the TO phase. $P_{HS} \leq P < P_{MS-3}$ denoted the range of plantar pressure values used for the HS phase which was from the first non-zero pressure value, P_{HS}, until two frames before MS frame, P_{MS-3}. Likewise, the MS phase used pressure values from the second frame before MS frame, P_{MS-2}, until the third frame past the MS frame, P_{MS+3}. Lastly, the TO phase used pressure values from the fourth frame past MS frame, P_{MS+4}, until the last nonzero pressure value, P_{TO}.

For each of the six subjects on each ramp inclination the GRFs were predicted for one trial and the root mean square errors (RMSEs) were computed in Excel between the data measured with the forceplate and those estimated from the regression models. RMSEs were then averaged for each ramp inclination and used as the indicator of accuracy (Fong et al., 2008; Forner Cordero et al., 2004).

3. Results

The ten trials for a given subject at a given ramp inclination were highly repeatable, with a general coefficient of correlation $R \geq 0.90$ for the forceplate data and an $R \geq 0.85$ for the plantar pressure data. There were increases in RMSE as the ramp inclination increased for the vertical and anteroposterior directions (Table 1).

The three regressions for each component of the GRF from Subject 1's 10° incline trials were presented as an example in Fig. 3. This set of regression equations was representative of the multi-stage model for any given subject and ramp inclination. Locations of the three highest correlated sensors used for model inputs of Subject 1 on each ramp inclination were shown as an example in Fig. 4. It can be seen that of the 99 insole sensors for a specific subject, the three most highly correlated sensors were not the same between ramp inclinations. Similarly, for a specific ramp inclina-

Table 1
Average RMSEs, presented in force N and percentage of the corresponding peak values, of 6 subjects' walking trials for each ramp inclination. Comparison of accuracy with the studies of Fong et al. (2008) and Forner Cordero et al. (2004) was shown for level (0°) walking only.

		GRF Prediction RMSE in Force N (% of Peak Value)		
		Vertical	Medial/Lateral	Anterior/Posterior
0° (level)	Current study	26.95 (3%)	10.05 (21%)	20.12 (10%)
	Fong et al. (2008)	45.79 (5%)	11.71 (28%)	27.41 (12%)
	Forner Cordero et al. (2004)	27.84–30.13	7.30–7.51	7.53–9.15
5°	Incline	35.28 (4%)	9.94 (28%)	19.59 (9%)
	Decline	35.23 (4%)	14.01 (24%)	30.87 (15%)
10°	Incline	40.69 (5%)	9.40 (24%)	26.15 (10%)
	Decline	31.64 (3%)	14.56 (26%)	38.59 (14%)
15°	Incline	37.29 (4%)	8.92 (21%)	29.08 (9%)
	Decline	33.46 (4%)	12.47 (19%)	42.30 (13%)
20°	Incline	42.22 (5%)	10.71 (23%)	39.25 (11%)
	Decline	38.09 (4%)	12.52 (20%)	40.35 (10%)

$$M(P)_x^{+10°} = \begin{cases} f(P) = 0.52 * (\bar{P}_{23,24,25}) - 1.74 \\ \begin{bmatrix} .9 \\ .7 \\ .6 \\ .4 \\ .3 \\ .1 \end{bmatrix} * f(p) + \begin{bmatrix} .1 \\ .3 \\ .4 \\ .6 \\ .7 \\ .9 \end{bmatrix} * g(p) \\ g(P) = 0.30 * (\bar{P}_{57,64,74}) + 0.65 \end{cases}$$

$$M(P)_y^{+10°} = \begin{cases} f(P) = -1.25 * (\bar{P}_{30,60,67}) - 26.22 \\ \begin{bmatrix} .9 \\ .7 \\ .6 \\ .4 \\ .3 \\ .1 \end{bmatrix} * f(p) + \begin{bmatrix} .1 \\ .3 \\ .4 \\ .6 \\ .7 \\ .9 \end{bmatrix} * g(p) \\ g(P) = -1.53 * (\bar{P}_{71,79,86}) - 40.1 \end{cases}$$

$$M(P)_z^{+10°} = \begin{cases} f(P) = 1.09 * (P_z) - 9.44 & P_{HS} \le P \le P_{MS-3} \\ \begin{bmatrix} .9 \\ .7 \\ .6 \\ .4 \\ .3 \\ .1 \end{bmatrix} * f(p) + \begin{bmatrix} .1 \\ .3 \\ .4 \\ .6 \\ .7 \\ .9 \end{bmatrix} * g(p) & P_{MS-2} \le P \le P_{MS+3} \\ g(P) = 1.14 * (P_z) - 167.9 & P_{MS+4} \le P \le P_{TO} \end{cases}$$

Fig. 3. Exemplary regression models for Subject 1, 10° incline GRF predictions. x, y, and z represent components of GRFs in mediolateral, anteroposterior, and vertical directions, respectively.
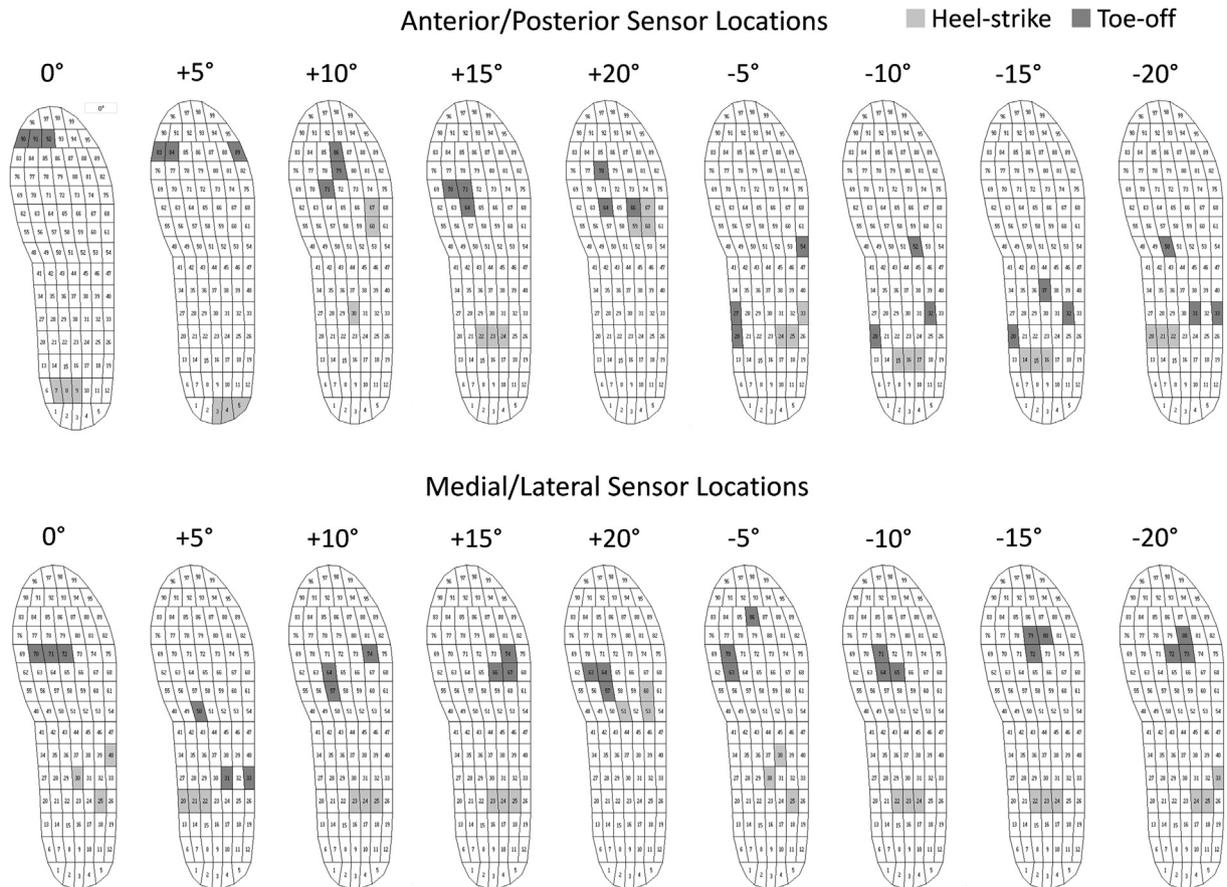

Fig. 4. Locations of sensors with the highest linear correlations between pressure outputs and forceplate data based on 9 walking trials of Subject 1.
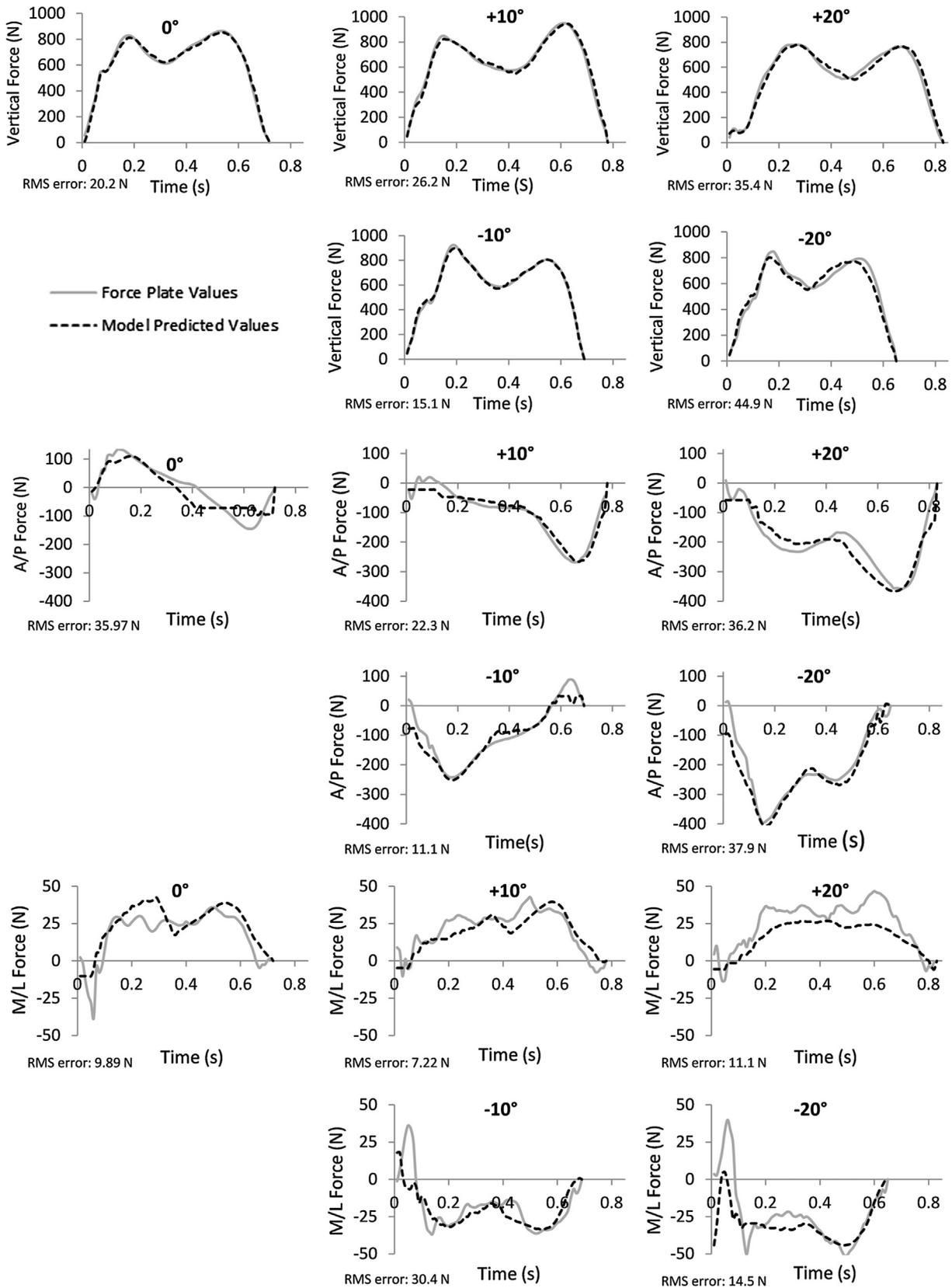
Fig. 5. Forceplate values and model predicted values of GRFs for Subject 1 at ramp inclinations 0°, ±10°, and ±20°.

tion, the most highly correlated sensors were not the same between subjects either. Lastly, Fig. 5 showed GRF prediction plots overlaid with the forceplate measured forces from the first subject for each of the ramp inclinations.

4. Discussion

Compared with studies from the literature the relatively low RMSEs shown in the current study support the hypothesis that a

multistage regression model can be used to more accurately predict GRFs for level and incline/decline walking. The current study showed that a regression model based on three periods of a gait stance phase improved prediction accuracies when compared with the one-stage regression model used in Fong et al. (2008) by 18.84, 1.66, and 7.29N or 41%, 14%, and 27% in the respective vertical, mediolateral, and anteroposterior directions. The RMSEs of the multistage regression model, when compared with the study of Forner Cordero et al. (2004), which also used the similar insoles to generate GRFs curves, improved slightly in the vertical direction but not in the mediolateral or anteroposterior directions. Forner Cordero et al. (2004), however, utilized a motion capture system to collect gait dynamics which assisted in the GRF calculations. The increases in RMSEs for the vertical and anteroposterior directions as ramp inclination increased may be due to the trend for increases in maximum values of the vertical and anteroposterior GRF components as the ramp inclination increased, which was observed in the current study as well as in a previous study (Lay et al., 2006).

It should be noted that the multistage regression models are ramp inclination and subject specific. Indicators of the model's specificity are the differences in location of the most highly correlated sensors between ramp inclinations and between subjects. The variation in location of the most highly correlated sensors across ramp inclinations was most likely due to differences in gait, such as the ankle, knee and hip angles (Lay et al., 2006). The difference in location of the most highly correlated sensors between subjects was likely due to differences in gait biomechanics between subjects. A limitation of the current study was that it involved only a specific minimalistic shoe design. A goal of future laboratory studies would be to determine if the current methodology is also footwear specific, before outdoor biomechanical studies are planned. Future studies should also aim to assess the impact of surface texture on the accuracy of the model predicted GRFs. In addition, preliminary studies were conducted in this laboratory to test various choices of (1) number of the highly correlated sensors, (2) number of frames involved in formulating the regression model for the midstance period, and (3) differently weighted equation for the midstance period in Eq. (1). The current set of these parameters was shown to generally provide decent results in terms of lower RMSEs and a smooth transition from heel-strike to toe-off, and was therefore utilized in the study for the purpose of standardization. Another limitation of the study was that only one forceplate was included for the development and validation of regression models. While the between-trials repeatability analyses showed highly repeatable plantar pressure data and forceplate data, future research may evaluate GRFs in several steps using multiple forceplates. Finally, while speed of gait could play an important role in the correlation between plantar pressure and GRFs, the current study only evaluated one walking speed. Future studies may develop regression models as a function of various speeds, such as for walking, jogging, and running.

In summary, the multistage model developed in the current study was shown to be a viable tool for estimating the GRFs during laboratory walking on level and incline/decline ramp surfaces due to its small RMS errors and its simplicity requiring plantar pressure insoles and calibration trials. A limitation of its future use in

random outdoor settings may be the need to conduct pre-trial laboratory calibration studies to establish the specific linear regression parameters for each subject, each surface inclination, and potentially each shoe design and surface texture. This multistage model may then allow for future studies dealing with injury prevention, gait analysis, as well as prosthetic or footwear design in relatively diverse outdoor environments where surfaces may be simulated by various levels of inclination.

Conflict of interest statement

The authors have no conflicts of interest to disclose.

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References

Cleophas, E.P., Cleophas, T.J., 2014. Multistage regression, a novel method for making better predictions from your efficacy data. Am. J. Ther. 21, e175–e180.

Davis, B.L., Perry, J.E., Neth, D.C., Waters, K.C., 1998. A device for simultaneous measurement of pressure and shear force distribution on the plantar surface of the foot. J. Appl. Biomech. 14, 93–104.

Fong, D.T., Chan, Y.Y., Hong, Y., Yung, P.S., Fung, K.Y., Chan, K.M., 2008. Estimating the complete ground reaction forces with pressure insoles in walking. J. Biomech. 41, 2597–2601.

Forner Cordero, A., Koopman, H.J., van der Helm, F.C., 2004. Use of pressure insoles to calculate the complete ground reaction forces. J. Biomech. 37, 1427–1432.

Iglesias-Soler, E., Fariñas, J., Mayo, X., Santos, L., Jaric, S., 2018. Comparison of different regression models to fit the force-velocity relationship of a knee extension exercise. Sports Biomech., 1–16

Lay, A.N., Hass, C.J., Gregor, R.J., 2006. The effects of sloped surfaces on locomotion: a kinematic and kinetic analysis. J. Biomech. 39, 1621–1628.

Levine, D., Richards, J., Whittle, M., 2012. Whittle's Gait Analysis. Livingstone/Elsevier, Churchill.

Liedtke, C., Fokkenrood, S.A., Menger, J.T., van der Kooij, H., Veltink, P.H., 2007. Evaluation of instrumented shoes for ambulatory assessment of ground reaction forces. Gait Posture 26, 39–47.

McClellan, M., McNeil, B.J., Newhouse, J.P., 1994. Does more intensive treatment of acute myocardial infarction in the elderly reduce mortality? Anal. Using Instr. Variables: JAMA 272, 859–866.

McIntosh, A.S., Beatty, K.T., Dwan, L.N., Vickers, D.R., 2006. Gait dynamics on an inclined walkway. J. Biomech. 39, 2491–2502.

Morris, M.S., Domino, E.F., Domino, S.E., 2010. Opioid modulation of oxytocin release. J. Clin. Pharmacol. 50, 1112–1117.

Permutt, T., Hebel, J.R., 1989. Simultaneous-equation estimation in a clinical trial of the effect of smoking on birth weight. Biometrics 45, 619–622.

Perry, J., Burnfield, J.M., 2010. Gait Analysis. Normal and Pathological Function. Slack Incorporated.

Razian, M.A., Pepper, M.G., 2003. Design, development, and characteristics of an in-shoe triaxial pressure measurement transducer utilizing a single element of piezoelectric copolymer film. IEEE Trans. Neural. Syst. Rehabil. Eng. 11, 288–293.

Wannop, J.W., Worobets, J.T., Ruiz, R., Stefanyshyn, D.J., 2014. Footwear traction and three-dimensional kinematics of level, downhill, uphill and cross-slope walking. Gait Posture 40, 118–122.

Weaver, B.T., Fitzsimons, K., Braman, J., Haut, R., 2016. The role of shoe design on the prediction of free torque at the shoe-surface interface using pressure insole technology. Sports Biomech. 15, 370–384.