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Spring-loaded inverted pendulum modeling improves neural network estimation of ground reaction forces

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ABSTRACT

Inertial-measurement-unit (IMU)-based wearable gait-monitoring systems provide kinematic information but kinetic information, such as ground reaction force (GRF) are often needed to assess gait symmetry and joint loading. Recent studies have reported methods for predicting GRFs from IMU measurement data by using artificial neural networks (ANNs). To obtain reliable predictions, the ANN requires a large number of measurement inputs at the cost of wearable convenience. Recognizing that the dynamic relationship between the center of mass (CoM) and GRF can be well represented by using spring mechanics, in this study we propose two GRF prediction methods based on the implementation of walking dynamics in a neural network. Method 1 takes inputs to the network that were CoM kinematics data and Method 2 employs forces approximated from CoM kinematics by applying spring mechanics. The gait data of seven young healthy subjects were collected at various walking speeds. Leave-one-subject-out cross-validation was performed with normalized root mean square error and *r* as quantitative measures of prediction performance. The vertical and anteroposterior (AP) GRFs obtained using both methods agreed well with the experimental data, but Method 2 yielded improved predictions of AP GRF compared to Method 1 ($p = 0.005$). These results imply that knowledge of the dynamic characteristics of walking, combined with a neural network, could enhance the efficiency and accuracy of GRF prediction and help resolve the tradeoff between information richness and wearable convenience of wearable technologies.

1. Introduction

The need for gait monitoring by using a wearable inertial measurement unit (IMU) is growing rapidly. Most IMU-based wearables provide information about the speed of the user and the distance traveled. However, not only kinematic data, but kinetic data is also useful to monitor injury risk and gait performance more detail. Specially, recent studies have demonstrated that ground reaction forces (GRFs) could serve as important indices of gait symmetry, joint loading, and rehabilitation progress for post-stroke patients (Allen et al., 2014; Bowden et al., 2006; Roelker et al., 2018). Technical barriers to the development of wearable GRF monitoring systems include the relatively large sizes and weights of the force transducers, limited availability of sensors that can measure three-dimensional (3D) forces, and short lifespans of the sensors owing to repeated contact impact.

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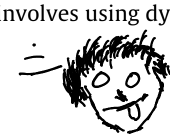
To realize GRF monitoring by using wearables, researchers have attempted to predict GRFs from motion data by using various methods, for example, the full body model (Jung et al., 2016; Karatsidis et al., 2017). Recently, artificial neural networks (ANNs), which are nonlinear regression tools, have been widely used for predicting GRFs with good prediction performance (Johnson et al., 2018; Leporace et al., 2018; Lim et al., 2020; Oh et al., 2013). Among the kinematic data of multiple body segments, 14 highly GRF-correlated variables were used as inputs to a network capable of reliable GRF prediction (Oh et al., 2013). This implies that wearable motion monitoring systems are affected by the tradeoff between information richness and wearable convenience. Recently, kinematic data collected from IMU measurements of each of the leg shanks were used to reliably predict GRFs by using an ANN (Leporace et al., 2018). Although the trials of the test subjects were included in the training dataset, accurate GRF predictions using the data of a couple of IMU measurements highlighted the possibility of reliable kinetic monitoring by using kinematic information.

Another approach used to predict kinetics from kinematic data involves using dynamic gait characteristics, which can be modeled



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using spring mechanics. The dynamic relationship between GRFs and the center of mass (CoM) can be well represented using spring mechanics (Geyer et al., 2006; Jung and Park, 2014; Kim and Park, 2011; Lee et al., 2014; Lim and Park, 2019; Whittington and Thelen, 2009). A variety of spring-loaded inverted pendulum (SLIP) models have successfully been used to emulate experimental GRF data obtained from various subject groups under various walking conditions (Jung and Park, 2014; Kim and Park, 2011; Lee et al., 2014). Based on the mechanical relationship between CoM trajectory and GRF, unmeasured joint kinematics and GRFs were predicted by conducting partial GRF measurements (Ryu and Park, 2018). Owing to the simplicity of the model, however, the spring mechanics did not capture every aspect of gait dynamics like impact transient near heel strike, which led to quantitative errors in the SLIP-model-based predictions of GRFs and joint kinematics (Lim and Park, 2018; Ryu and Park, 2018).

Based on SLIP characteristics, it was demonstrated in a recent study that the relationship between CoM kinematics and lower-extremity kinematics and kinetics, including GRFs, could be simplified to a first-order function of CoM kinematics (Lim et al., 2020). Based on these relationships, in this study, lower limb kinematics and kinetics were predicted using a simple feedforward network and the CoM kinematics data acquired using a sacrum-mounted IMU. However, even when other pieces of kinematic information in addition to displacement, such as velocity and acceleration, were used as input data, the prediction performance did not improve considerably.

Therefore, we proposed 'SLIP hybrid' GRF prediction method to improve prediction accuracy based on the dynamic resemblance between SLIP model and human walking. To verify the effect of SLIP hybrid method, we compared prediction accuracy to prediction method using kinematic information. In this study, the method using CoM kinematics is called 'Method 1′', and the SLIP hybrid method is called 'Method 2′'. Method 1 uses various kinematic information calculated from the CoM trajectory as input data to the ANN, similarly to a previous study (Lim et al., 2020). Method 2 involves converting CoM displacement data to force by using the SLIP model. We validated both proposed methods by comparing predicted GRF to experimentally measured GRF.

2. Methods

2.1. Method 1—CoM kinematics

The first method employs CoM kinematics (CoM displacements, velocities, accelerations, and time) as input data for the neural network, as outlined in a previous study (Lim et al., 2020) (Fig. 1A). The velocity and acceleration of the CoM are calculated using the five-point stencil method (Sauer, 2018). The CoM displacement is reset to zero at each heel strike (HS), that is, at the starting point of the stance phase. All input data are normalized using the 0–1 normalization method (Lim et al., 2020).

Therefore, in Method 1, the input data at time t_i are a 7×1 vector consisting of seven components ($\left[x(t_i), y(t_i), v_x(t_i), v_y(t_i), a_x(t_i), a_y(t_i), t_i\right]^{\mathrm{T}}$).

2.2. Method 2—SLIP transform

The second method employs GRF values approximated using the SLIP characteristics between the CoM and the GRFs as inputs to the neural network (Fig. 1B). The two steps in the conversion process are obtaining the model parameters and calculating the GRFs (Fig. 2). Four model parameters are obtained: the ground contact point O, leg length l, leg angle θ, and spring constant k. The ground contact point is determined using the kinematic constraint of the leg length at the moments of heel strike (HS) and toe-off (TO) in the stance phase (Fig. 2B), as follows (Eq. (1)):

$$(x_{\mathrm{HS}} - O)^2 + y_{\mathrm{HS}}^2 = (x_{\mathrm{TO}} - O)^2 + y_{\mathrm{TO}}^2 = l_0^2 \tag{1}$$

where x and y are the AP and vertical positions of the CoM, and the subscripts HS and TO denote heel strike and toe-off, respectively. l_0 denotes the length of the resting leg. With the specified ground contact point and the CoM position measurement (x, y), the leg length and leg angle during the stance phase can obtained as follows:

$$\begin{cases} l(t) = \sqrt{(x(t) - O)^2 + y(t)^2} \\ \theta(t) = \tan^{-1}\left(\frac{x(t)-O}{y(t)}\right) \end{cases} \tag{2}$$

From the measured data, in which the average GRF of a single support phase is equal to approximately 95% of a subject's body weight, the spring stiffness k is obtained using the following relationship: $k\Delta l_{avg} = 0.95\, mg$, where m and g are mass and gravitational constant, respectively; and Δl_{avg} is the average change in leg length during the single support phase. The final step in the conversion process involves calculating the GRFs by multiplying the leg length with the spring constant k, such that $F_x = k\Delta l \sin\theta$ and $F_y = k\Delta l \cos\theta$ (Fig. 2C). Given that stiffness is a function of walking speed (Kim and Park, 2011; Ryu and Park, 2018), walking speed was used as an input as well. Therefore, the input data consisted of the following three components: calculated Fx, calculated Fy, and walking speed. Thus, in Method 2, the input data at time t_i consist of a 3×1 vector ($\left[F_x(t_i), F_y(t_i), V_{gait}\right]^{\mathrm{T}}$).

2.3. ANN structure and training network

The ANN used in this study has the three-layered feedforward structure (input layer–hidden layer–output layer), and it employs point-by-point estimation. In Method 1, the input layer consisted of seven nodes as follows: two displacements, two velocities, two accelerations, and time. In Method 2, the input layer consisted of three nodes. The hidden layer used in both methods consisted of 20 nodes, followed by a sigmoidal activation function, and the output layer consisted of two output nodes, one along each GRF. In the training network, the loss function of the network was set as the mean square error (MSE) of the predicted GRFs relative to the measured data. We used the Adam optimizer for the backpropagation process (Kingma and Ba, 2014) and set the learning rate to 0.05. The maximum epoch was set to 1000. Neural network programming was performed using Pytorch 4.0.1 (Paszke et al., 2017).

2.4. Data collection

To validate the proposed GRF prediction method, we collected approximate CoM position data by using a sacrum marker as an approximation of CoM position (Grad et al., 2004). Seven young (25.0 ± 2.9 years) and healthy male subjects with average heights and weights of 168.8 ± 7.5 cm and 72.1 ± 7.7 kgf, respectively, participated in multiple 1-min treadmill walking trials at walking speeds of 1.0–2.3 m/s after signing informed consent forms approved by the internal review board of KAIST. The test speeds were determined based on the preferred gait speed of each subject, midpoint between the preferred and maximum speeds, and a speed slower than the preferred speed by an amount equal to approximately 20% of the difference between the preferred and maximum speeds (Lim et al., 2020). At each test speed, each participant performed three one-minute trials in a random order, and we collected these data for analysis. The sacrum position was obtained as the midpoint between the left posterior superior iliac spine (PSIS) and the right PSIS markers, as measured using a motion capture system (Motion Analysis Hawk®), and the GRFs were

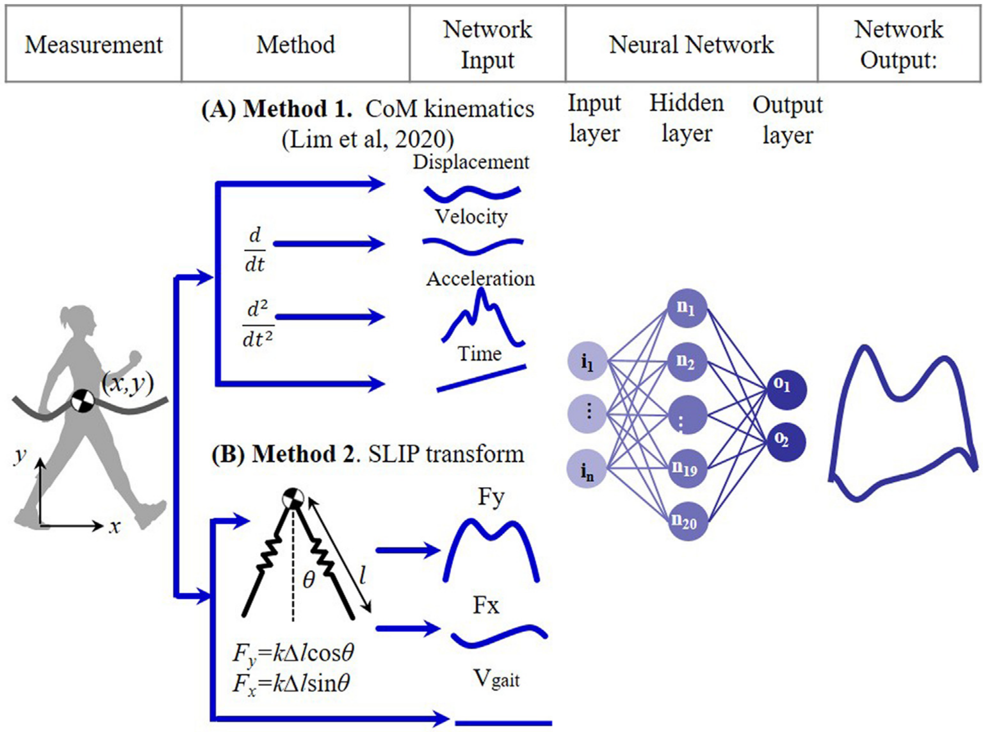

Fig. 1. Schematics of the GRF prediction methods using an ANN from a single CoM measurement. Two different network input types, CoM kinematics and calculated GRF, were used to predict GRF in (A) Method 1 and (B) Method 2. Method 1 has seven input nodes for position, velocity, acceleration, and time data of the CoM in the sagittal plane, whereas Method 2 has three input nodes for the vertical and AP components of the calculated force based on spring mechanics and measured gait speed. The predicted GRFs are obtained from the output node.

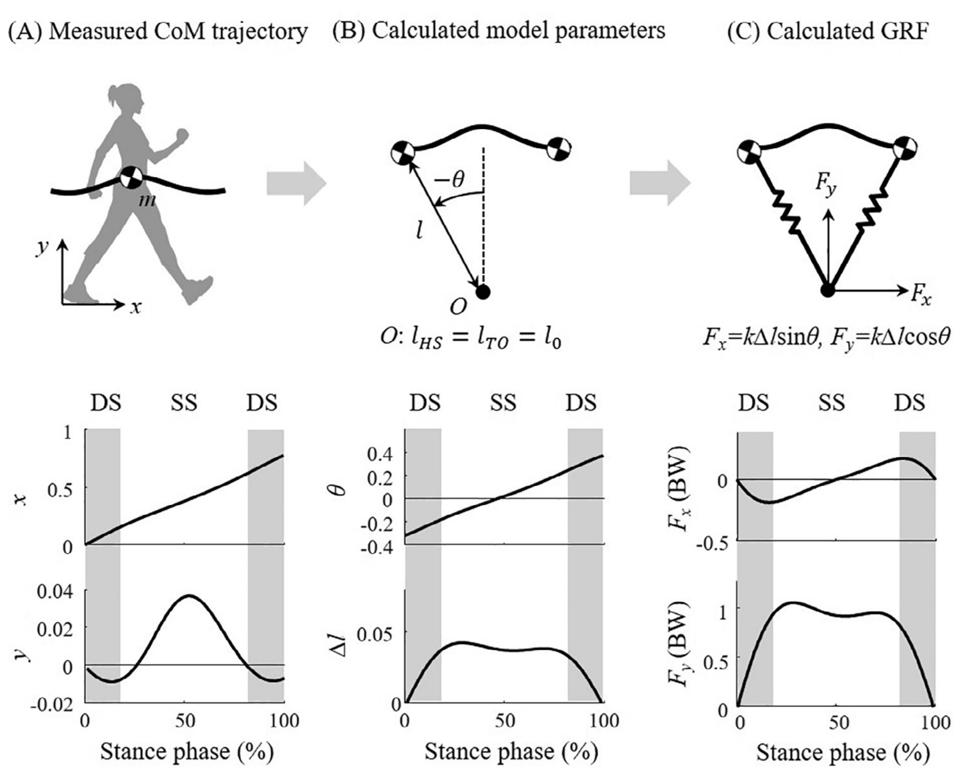

Fig. 2. The procedure to estimate GRF using a compliant walking model. From (A) the measured CoM trajectory during the stance phase, (B) the calculated corresponding leg motion relative to the ground contact point, *O*, makes the spring lengths at the beginning and end of the stance phase equal to each other. (C) The corresponding ground reaction force is obtained using the resistive spring force with the spring stiffness approximated from the user's body weight and spring deflection during the single support phase. The gray shaded area presents the double support phase.

measured using an instrumented treadmill with force plates (Bertec, FP 6012®). Motion and force data were collected at the sampling frequencies of 100 Hz and 200 Hz, respectively. Both sets of data were filtered using a fifth-order low-pass Butterworth filter with a cutoff frequency of 10 Hz. Ten consecutive steps in the middle of each trial were extracted and separated by stance phase for network training. The gait events (heel strike (HS) and toe-off (TO)) were calculated using the force data. We compensated for anteroposterior displacement by adding treadmill speed × time. To match the sampling size of the training dataset, the stance phase data were resampled to 200 points. The total stance phases we'd collected were 630 steps (7 subjects × 3 speeds × 30 stance phases). The entire post-processing was conducted using MATLAB R2018a (MathWorks, Inc., Natick, MA, USA).

2.5. Statistical methods for validating proposed methods

To validate the proposed prediction methods, we used leave-one-subject-out (LOSO) cross-validation. 540 steps of six subjects were used for training model, and 90 steps of the other subject were used for one validating (testing). Therefore, every 630 steps were used for validation. As quantitative measures of the prediction performance, normalized root mean square error (NRMSE) values normalized against the range of each direction of the GRF and the Pearson correlation coefficient (r) were used. For comparing two proposed methods, we calculated p-value using one-tailed, two-sample, paired t-test and effect size (Cohen's d) to test hypothesis that the prediction error (NRMSE) of Method 2 is lower than that of Method 1 (Cohen, 1988).

3. Results

Both Method 1 and Method 2 predicted vertical and anteroposterior (AP) GRFs (Fig. 3A), in the range of about 3~10% NRMSE (Fig. 3B). Specifically, for Method 1, the average and standard deviation of the NRMSE and r values of the predicted vertical and AP GRFs were 6.93 ± 4.02% and 6.48 ± 2.93%, and 0.98 ± 0.01 and 0.98 ± 0.01, respectively. For Method 2, the average and standard deviation of the NRMSE and r values of the predicted vertical and AP GRFs improved to 6.30 ± 1.31% and 5.28 ± 0.99%, and 0.98 ± 0.01 and 0.98 ± 0.01, respectively (Table 1). The NRMSE of the AP GRFs predicted using Method 2 was approximately 1% smaller than the NRMSE of the AP GRFs predicted using Method 1 ($p = 0.005$, the Cohen's d = 0.55) (Fig. 3B). Although there was no significant difference in the NRMSE values of the vertical GRF predicted using Methods 1 and 2, the deviation of error seemed to be larger with Method 1 than that with Method 2. As the walking speed increased, the prediction performance of both GRF prediction methods worsened, but the decrease in performance was greater for Method 1 than that for Method 2 (Table 1).

4. Discussion

In this study, we proposed SLIP hybrid GRF prediction method converting CoM kinematics data into force by using the SLIP model (Method 2), and compared prediction performance to the method that using CoM kinematics (Method 1). The accuracy of vertical GRF prediction was similar in both methods. However, the SLIP hybrid method could predict AP GRF more accurately.

Because SLIP mechanics can well describe walking characteristics, various SLIP models have been used to predict GRFs under various gait conditions (Geyer et al., 2006; Jung and Park, 2014; Kim and Park, 2011; Lim and Park, 2018; Lim and Park, 2019), including a recent SLIP model that attempted to predict GRFs based on the spring-like mechanical characteristics of the CoM and GRFs (Ryu and Park, 2018). Although spring mechanics can serve as a very simple mechanical platform for relating the CoM with GRFs, the quantitative representability of spring mechanics is somewhat limited owing to its simplicity (Ryu and Park, 2018). Interestingly, many studies that have estimated GRFs from various kinematic data have included the kinematic data of a body part that is close to the CoM, such as the sacrum and L5. (Guo et al., 2017; Johnson et al., 2018; Lim et al., 2020; Wouda et al., 2018). Even though the proposed Method 1 is similar with (Lim et al., 2020), it yielded a different prediction result. This difference could be ascribed to weight initialization of the feedforward neural network (Chan et al., 2000). In addition, we've tried to predict GRF using various combination of CoM kinematics as input data to expand Method 1, and NRMSEs in each method did not show statistically significant difference (Fig. 4, Table 2). This result is similar to previous study that also had used various combination of CoM kinematics from sacrum-mounted IMU (Lim et al., 2020).

In contrast to Method 1, the prediction performance of Method 2 was superior, especially its prediction of the AP GRF, even though the number of input variables was smaller than that used for Method 1. Comparing to other combinations of CoM kinematics, prediction NRMSE of Method 2 was significantly lower ($p < 0.05$, Cohen's d = 0.55~0.80) (Fig. 4, Table 2). Because of the double support phase, it is difficult to predict GRFs, even from accurate CoM kinematics data. Therefore, many studies have estimated GRFs by using various techniques, for instance, smooth transient assumption (STA), foot–ground contact model (FCM), and neural networks (Lugrís et al., 2011; Oh et al., 2013; Ren et al., 2008). By contrast, Method 2 directly converted CoM displacement data into force through simple calculations. It has been reported that the performance of machine learning can arguably be improved by employing suitable input data or input domain (Fernando and Shamseldin, 2009; Oh et al., 2013; Zurada et al., 1994). This is consistent with the research results indicating that it is possible to improve machine learning performance by reducing the objective function domain (Yu et al., 2007).

Not only preferred walking speed, we also predicted GRFs for various walking speeds (Table 1). As the walking speed increased, the prediction error of the vertical GRF increased. Studies in the literature that have estimated GRFs at various speeds by using the SLIP model have reported elevated GRF prediction errors at higher walking speeds (Lim et al., 2020; Ryu and Park, 2018). This finding could be interpreted as a limitation of the spring dynamics of walking, which does not simulate fast walking. In other words, the relationship between CoM kinematics and GRF becomes weaker as the walking speed increases, and another input component may probably be needed.

Compared to previous attempts to predict GRFs by using ANNs (Johnson et al., 2018; Leporace et al., 2018; Oh et al., 2013), the proposed method was found to be more efficient without sacrificing prediction accuracy. Specifically, the number of measurement inputs was significantly reduced from 11 (Oh et al., 2013) or two (Leporace et al., 2018) to one CoM measurement in the present study. However, the prediction performance was slightly better with additional measurement input trials (Table 3). In previous studies, except (Lim et al., 2020), the inclusion of test subjects' data in the network training dataset might be the reason for the high accuracy of GRF prediction. We separated the training dataset of nine trials of seven subjects from the test dataset of the other subjects and still achieved good agreement between the predicted GRFs and the corresponding experimental data (Table 3).

Although the proposed methods yielded good predictions of the GRFs, this study had few limitations, for instance, a limited number of subjects, limited output, and a few technical issues pertaining to wearable device application. First, this study validated the proposed methods by using the data of seven subjects. Although

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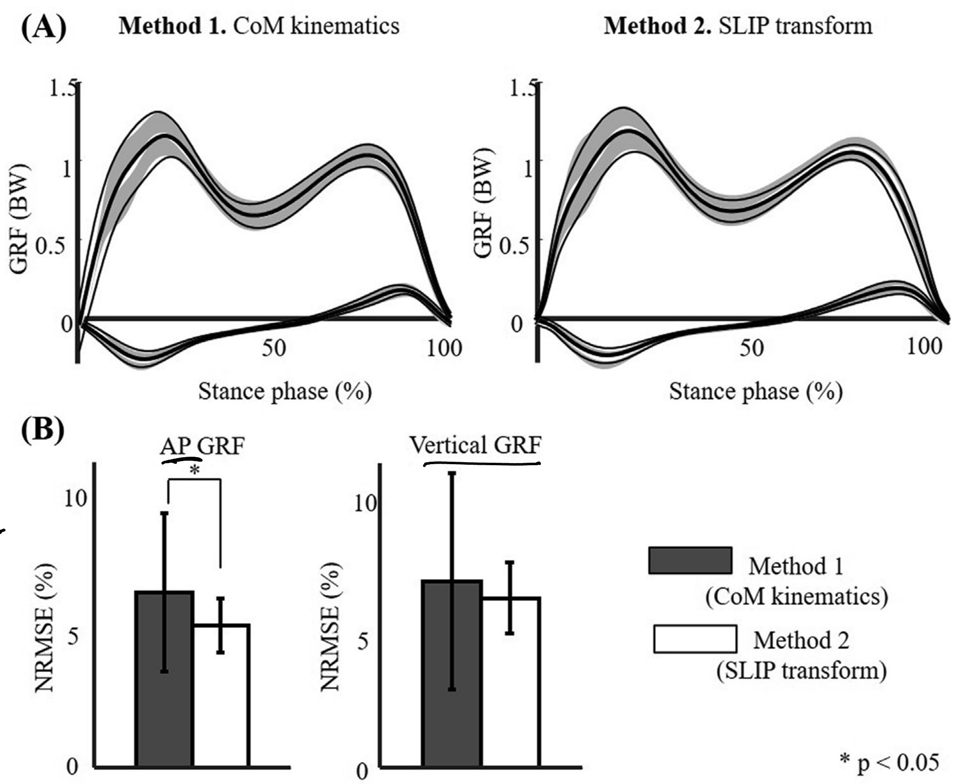

Fig. 3. The prediction result of proposed both methods. (A) Predicted GRF using Method 1(left) and Method 2(right). (B) NRMSE of prediction AP GRF (left) and Vertical GRF (right). The darker shaded area presents Method 1 (CoM kinematics) and the brighter area presents Method 2 (SLIP transform). The star sign (*) represents significant difference between two methods where p-value is less than 0.05. The p-value was calculated by two-sample *t*-test.

Table 1
NRMSEs and Pearson correlation coefficient (r) of the proposed GRF prediction methods by gait speed.

	Method 1. CoM kinematics (Lim et al)				Method 2. SLIP transform			
	Vertical GRF		Anteroposterior GRF		Vertical GRF		Anteroposterior GRF	
Walking Speed	NRMSE (%)	r	NRMSE (%)	r	NRMSE (%)	r	NRMSE (%)	r
Slow	5.96 ± 1.60	0.97 ± 0.02	6.53 ± 2.53	0.97 ± 0.02	5.82 ± 0.58	0.98 ± 0.01	5.40 ± 1.31	0.98 ± 0.01
Self-selected	6.08 ± 1.56	0.98 ± 0.01	5.98 ± 1.51	0.98 ± 0.01	5.86 ± 0.63	0.98 ± 0.01	5.23 ± 0.91	0.98 ± 0.01
Fast	8.77 ± 6.56	0.98 ± 0.01	6.96 ± 4.40	0.98 ± 0.01	7.22 ± 1.88	0.98 ± 0.01	5.20 ± 0.83	0.98 ± 0.01
Total	6.93 ± 4.02	0.98 ± 0.01	6.48 ± 2.93	0.98 ± 0.01	6.30 ± 1.31	0.98 ± 0.01	5.28 ± 0.99	0.98 ± 0.01

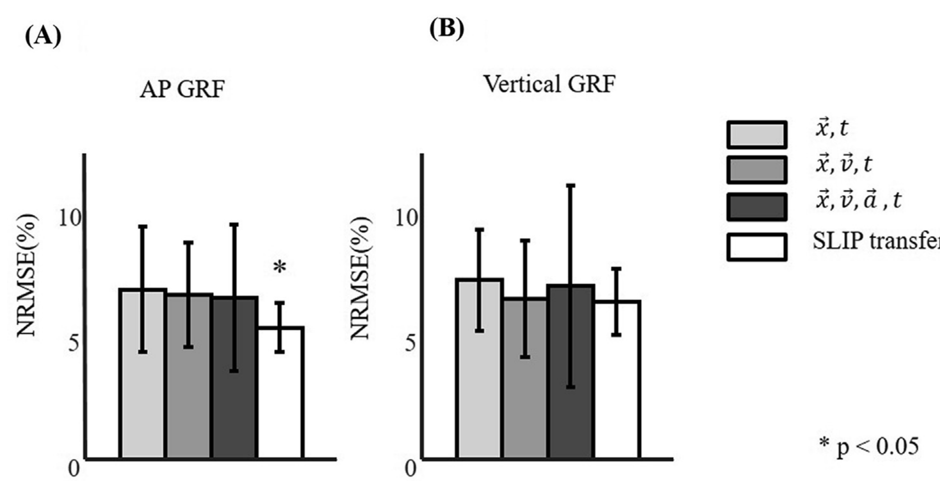

Fig. 4. The prediction NRMSE of (A) anteroposterior (AP) GRF, (B) vertical GRF using various combination of CoM kinematic as inputs (gray) and SLIP transfer (white). $\vec{x}$denotes displacement, $\vec{v}$ denotes velocity,$\vec{a}$ denotes acceleration, and $t$denotes time. The star sign (*) represents significant difference between two methods where p-value is less than 0.05. The p-value was calculated by two-sample *t*-test.

Table 2
The prediction NRMSEs of various combination.

Method	CoM kinematics (Method 1)			SLIP transform (Method 2)
Input data	x, y, t	x, y, v_x, v_y, t	$x, y, v_x, v_y, a_x, a_y, t$	F_x, F_y, V_{gait}
Vertical GRF	7.18 ± 2.02	6.45 ± 2.33	6.93 ± 4.02	6.30 ± 1.31
AP GRF	6.81 ± 2.51	6.60 ± 2.01	6.48 ± 2.93	5.28 ± 0.99

Table 3
NRSEs and Pearson correlation coefficients (r) of the previous and proposed methods for GRF prediction.

	S.E. Oh et al. (2013)		G. Leporace et al. (2018)		H. Lim et al. (2020)		The proposed methods			
							Method 1. CoM kinematics		Method 2. SLIP transform	
# of subjects	48		17		7		7			
Movement	Overground walking		Overground walking		Treadmill walking		Treadmill walking			
# of measurement	11 (Optical marker)		2 (located at each shanks)		1 (sacrum mounted IMU)		1 (Optical marker)			
Input data (# of input nodes)	14 kinematic information (14)		3D displacement, velocity, acceleration, jerk, stance phase, time (14)		2D displacement, velocity, acceleration, time (7)		2D displacement, velocity, acceleration, time (7)		2D calculated GRF, walking speed (3)	
Prediction method	GRNN		FFNN		FFNN		FFNN		FFNN	
Prediction result	rRMSE (%)	r	MAD (%)	r	NRMSE (%)	r	NRMSE (%)	r	NRMSE (%)	r
Vertical GRF	5.8 ±1.0	0.98	4.6 ±0.7	0.97	6.26 ±1.24	0.96 ±0.03	6.93 ±4.02	0.98 ±0.01	6.30 ±1.31	0.98 ±0.01
AP GRF	7.3 ±0.8	0.97	4.0 ±0.8	0.98	6.16 ±1.76	0.98 ±0.01	6.48 ±2.93	0.98 ±0.01	5.28 ±0.99	0.98 ±0.01
ML GRF	19.8 ±2.2	0.92	10.5 ±3.3	0.80	–	–	–	–		

previous studies did not use LOSO cross validation, they did use the data of 14–48 subjects. Because the intra-subject GRF variability is rather high (Rouhani et al., 2010), it is necessary to validate the methods by using the data of a greater number of subjects for confirming network generalization of the proposed methods. Second, compared to previous studies that estimated 3D GRFs (Johnson et al., 2018; Leporace et al., 2018; Oh et al., 2013), this study only estimated two-dimensional GRFs in the sagittal plane. Several studies have demonstrated the possibility of using the 3D SLIP model, but various controls are needed to simulate humans by using the 3D SLIP model (Budday et al., 2012). If a simple transform similar to the one used in this study can be applied to the 3D model, Method 2 can expectedly be extended to predict GRFs in 3D. The third limitation is application to real wearable devices. Although the network performance improved when using Method 2, several technical issues were encountered when applying the proposed method to wearable devices, especially IMUs. (Lim et al., 2020) discussed several issues related to the estimation of unmeasured information by using a sacrum-mounted IMU. They discussed the integration of raw acceleration data from the IMU, estimation of gait speed, detection of gait events from sacrum acceleration, and sensitivity in relation to IMU location. These issues should be considered when applying the proposed method to an actual IMU, as in (Lim et al., 2020). Specifically, Method 2 proposed in this study uses CoM displacement and gait speed information. Therefore, it is expected that the integration problem and the accuracy of gait speed estimation will greatly affect the estimation results compared to the methods proposed in previous studies or Method 1. However, many studies have been conducted recently for estimating walking speed with an error of 0.01–0.06 m/s or less than 10% by using simple regression, walking models, or machine learning (Li et al., 2010; Lim et al., 2020; Song et al., 2007) and walking trajectory with an error of 6–12 cm (Lim et al., 2020). Because the error in vertical displacement was approximately 20% in this work, further studies on prediction sensitivity should be conducted for implementation of the method in IMUs.

In conclusion, we were able to predict GRFs accurately using an ANN and a single CoM measurement and improve the performance of the ANN by changing the input data domain with a simple SLIP model. The results implied that biomechanical knowledge could be combined with emerging technologies, for example, machine learning techniques. We hope that this idea can be extended to applications other than walking, such as in fields in which diverse types of unmeasured biomechanical information are estimated using various machine learning techniques.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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