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Improving the ground reaction force prediction accuracy using one-axis plantar pressure: Expansion of input variable for neural network

Su-Bin Joo[a,1], Seung Eel Oh[a,b,1], Joung Hwan Mun[a,*]

[a] Department of Bio-Mechatronic Engineering, College of Biotechnology and Bioengineering, Sungkyunkwan University, 300 Chunchun, Jangan, Suwon, Gyeonggi 440-746, Republic of Korea
[b] Research Group of Smart Food Distribution System, Korea Food Research Institute, Seongnam, Gyeonggi 463-746, Republic of Korea

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ABSTRACT

In this study, we describe a method to predict 6-axis ground reaction forces based solely on plantar pressure (PP) data obtained from insole type measurement devices free of space limitations. Because only vertical force is calculable from PP data, a wavelet neural network derived from a non-linear mapping function was used to obtain 3-axis ground reaction force in medial-lateral (GRF_{ML}), anterior-posterior (GRF_{AP}) and vertical (GRF_V) and 3-axis ground reaction moment in sagittal (GRF_S), frontal (GRF_F) and transverse (GRF_T) data for the remaining axes and planes. As the prediction performance of nonlinear models depends strongly on input variables, in this study, three input variables – accumulated PP with respect to time, center of pressure (COP) pattern, and measurements of the opposite foot, which are calculable only with a PP device – were considered in order to improve prediction performance. To conduct this study, the golf swing motions of 80 subjects were characterized as unilateral movement and GRF patterns as functions of individual characteristics. The prediction model was verified with 5-fold cross-validation utilizing the measured values of two force plates. As a result, prediction model (correlation coefficient, r=0.73–0.97) utilized accumulated PP and PP data of the opposite foot and showed the highest prediction accuracy in left-foot GRF_V, GRM_F, GRM_T and right-foot GRF_{AP}, GRF_{ML}, GRM_F, GRM_T. Likewise, another prediction model (r=0.83–0.98) utilized accumulated PP and COP patterns as input and showed the best accuracy in left-foot GRF_{AP}, GRF_{ML}, GRM_S and right-foot GRF_V, GRM_S. New methods based on the findings of the present study are expected to help resolve problems such as spatial limitation and limited analyzable motions in existing GRF measurement processes.

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1. Introduction

Six-axis ground reaction force and moment (GRF_x, GRF_y, GRF_z, GRM_x, GRM_y and GRM_z) data is indispensable for inverse dynamics (Ren et al., 2008). Currently, 6-axis ground reaction forces(GRFs) data can only be measured using costly force plates (Choi et al., 2013), and thus cannot be used in outdoor settings or to study complex locations such as inclines. In addition, the intervals between force plates are fixed, causing further limitations for motion analysis (O'Connor et al., 2007). Portable insole-type plantar pressure (PP) measuring units have been presented as an alternative to force plates to address such problems (Fong et al., 2008); however, the PP data gained from such devices can only be used to compute the vertical direction GRF. Thus, it is necessary to estimate GRFs in the anterior-posterior (AP) and medial-lateral (ML) direction as well as sagittal, frontal, transverse plane ground reaction moments (GRMs).

To this end, several studies have aimed to measure GRF data of other axes and planes utilizing PP data. Cordero et al. (2004) utilized a linear equation for 3-axis GRF prediction based on PP and trajectory data obtained from an insole pressure system and motion capture system, respectively (correlation coefficient: vertical force=0.995–0.997; AP force=0.977–0.979; ML force=0.778–0.818). Likewise, Fong et al. (2008) utilized a linear regression model based on PP data to predict 3-axis GRFs in the vertical, AP, and ML direction with correlation coefficients of 0.989, 0.928, and 0.719, respectively. However, the two previous studies were limited in that they estimated only GRF information, excluding GRM, or required expensive equipment such as motion

* Correspondence to: Biomedical Engineering Laboratory, Department of Bio-mechatronic Engineering, College of Biotechnology and Bioengineering, Natural Sciences Campus, Sungkyunkwan University, 300 Chunchun, Jangan, Suwon, Gyeonggi, 440-746, Republic of Korea.
E-mail address: jmun@skku.edu (J.H. Mun).

[1] These authors made equal contributions to this work.

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capture systems to generate the prediction model. In the former case, the linear method used for prediction was a uniform prediction approach, which led to challenges in prediction accuracy regarding the ML axis with more dynamic gait fluctuation patterns.

To solve this problem of prediction accuracy, Rouhani et al. (2010) suggested a prediction strategy for GRFs using non-linear mapping functions and compared it with existing prediction models utilizing linear methods. According to their research, application of a nonlinear mapping function improves ML-axis GRF prediction accuracy slightly compared with a linear model (correlation coefficient: linear = 0.764; nonlinear = 0.780). Importantly, this method was able to predict for the first time the frictional. On the other hand, for the AP and vertical axes, the correlation coefficients of the GRF prediction accuracy were 0.957–0.967 and 0.906–0.908, respectively, which were similar to that of the linear model (correlation coefficients: vertical force = 0.967; AP force = 0.906).

To further improve the accuracy of the nonlinear-method predictions, Rouhani et al. (2010) suggested an additional input variable. Specifically, they assumed that the mapping performance would increase if the stance time percentage (STP) was taken into account in addition to the existing but limited input PP data. Importantly, the resulting nonlinear model employing STP exhibited a noticeably higher prediction performance than the model that did not include STP (correlation coefficient: vertical force = 0.952–0.970; AP force = 0.963–0.966; ML force = 0.788–0.793; frictional torque = 0.805–0.854). However, in terms of prediction accuracy, further improvement was desired as the model provided GRF prediction limited to 4 axes compared to the 6-axis GRF data obtained from force plates. And still, to replace force plate data solely with PP data from an insole pressure system, further research is necessary to develop a prediction method capable of estimating 6-axis GRF estimation at an enhanced level of accuracy.

Since the performance of nonlinear model prediction depends strongly on the input variables among configuration options such as structure, dataset characteristics, and so on (Oh et al., 2013), it can be assumed that if other input variables in addition to PP data and time information are utilized, data prediction accuracy may also improve. According to Lafond et al. (2004) and Han et al. (1999), GRFs occurring during movement are closely correlated with the center of pressure (COP) pattern, which can be simply calculated based on the pressure amplitude and distribution gained from the insole-type PP measuring device. Joo et al. (2014) reported that both legs are mutually affected by coordination while exercising, suggesting that PP data of the opposite foot may be useful as an input variable in nonlinear models for estimating GRFs. In this sense, it is expected that in forming a nonlinear method-based GRF prediction model solely with PP data without additional equipment, addition of the COP pattern and opposite-foot measured values along with PP data and time data may increase prediction accuracy.

The purpose of this study was to suggest a novel method to improve the performance of 6-axis GRF prediction during human body movement based on PP data and a non-linear mapping function by introducing several new input variables (time, COP pattern, measured value of the opposite foot) in addition to PP data. To this end, a wavelet neural network (WNN)-based 6-axis ground reaction force prediction model was developed from the individual characteristics of 80 subjects' golf swing movements with more diverse and fluctuating GRF pattern than gait motion. The golf swing motion was chosen for this study because the associated GRFs represent good examples of lateral movements that vary among individuals (Nesbit, 2005). These movements were applied to address the restrictions inherent to previous GRF prediction studies, which were only capable of analyzing standardized basic gait motion. The WNN utilized in this study is one of the most common non-linear mapping approaches currently in use, and combines the strong points of wavelet localization properties and those of a neural network. WNN was previously shown to exhibit the good performance in predicting non-linear movements of the human body among other non-linear prediction algorithms in the field of dynamics, including multi-layer perceptron-based artificial neural network (ANN) (Ardestani et al., 2014). In addition, the proposed method is free of the restrictions associated with force plates and motion capture systems, and is thus well suited for rapid on-field measurement in all settings, provided that subsequent future studies to generalize our method to other subject groups are successful.

2. Materials and methods

2.1. Subjects and procedures

Eighty golfers (age: 27.9 ± 7.3 years; height: 1.69 ± 0.14 m; weight: 65.8 ± 11.2 kg) comprising fourteen male and sixteen female pro-golfers and twenty-seven male and twenty-three females amateur golfers volunteered for our study at Sungkyunkwan University in Korea. The local ethics committee approved the study protocol, and informed consent was obtained from all subjects before beginning the study. The study participants inserted an insole-type device matching their foot size and fitted with 99 pressure sensors (Pedar Insole, Novel GmbH, Germany) in each of their own shoes (Rouhani et al., 2010) and performed a golf driver swing on two force plates (AMTI, Model:OR6-6-2000, USA). PP data from the plantar pressure-measuring device (insole sensor) was utilized for 6-axis GRFs prediction during movement. The 6-axis GRF data measured via the force plates was utilized to verify the insole sensor-predicted GRFs data. To detect the event and phase of the golf swing, two optical markers were attached on club heads and 6 infrared cameras and a motion analysis system (Vicon, UK) were utilized to obtain 3-dimensional trajectory information of the markers.

For experiments, preparatory swings were performed at least ten times to give the subjects an opportunity to adapt to the laboratory testing environment. The subjects then performed a total of five trial swings. The marker data was sampled at 120 Hz, the GRF data was sampled at 1080 Hz, and the PP data was sampled at 100 Hz. The marker data and the GRF data was synchronized based on VICON equipment, and the synchronized data was collected in real-time using a commercial motion analysis program (SB-Clinic software, SWING BANK Ltd., Korea). The PP data was synchronized with the GRF data within the commercial motion analysis program. This synchronization is possible because the total sum of PP and total sum of GRF are similar (Fong et al., 2008). Data obtained at different sampling rates were converted using a spline function to a final rate of 100 frames per golf swing. Data gathered from the insole sensor and the force plate used a 4th order Butterworth low pass filter at 7 Hz based on the FFT analysis results to remove noise (Winter, 2009).

2.2. Prediction model

2.2.1. Input variables selection

Non-linear prediction models produce varying prediction outcomes depending upon the input variables. Thus, it is important to optimize the selection of input variables (Oh et al., 2013). In this study, since multiple sets of information (6-axis GRFs) were predicted based only on the one-axis PP data obtained from insole sensors, the input variable pool was expanded by combining and re-producing measurement data to ensure prediction accuracy. In a previous study predicting GRF with PP data alone, the only input variable used for enhanced accuracy of nonlinear-method other than PP data was Stance Time Percent, which is a form of gait cycle frame data. Still, the prediction accuracy could be further improved if additional input variables were considered (Rouhani et al., 2010). Here, we aimed to develop a method in which no additional equipment other than PP data was necessary to generate the nonlinear method-based GRF prediction model. Therefore, not only the COP pattern data and the PP measurement value data of the opposite foot, but also the pressure value integrated to the time axis was used as an input variable.

For faster convergence of the prediction model and higher prediction accuracy, dimensions need to be reduced to the minimum number of input variables with sufficient representative and dependent (Youn et al., 2015). In this study, we combined Principal Component Analysis (PCA) and Mutual Information (MI) approaches. PCA is used to reduce dimensionality while keeping multi-dimensional data set loss at a minimum. However, principal components selected in this manner do not represent correlation with output variables, and instead only indicate representativeness. Therefore, despite high cumulative variance, some of the correlations with output variables may be relatively low. As a result, use of such principal components as input variables may undermine

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