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Short communication

Estimation of vertical ground reaction force during running using neural network model and uniaxial accelerometer

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ABSTRACT

Wearable technology has been viewed as one of the plausible alternatives to capture human motion in an unconstrained environment, especially during running. However, existing methods require kinematic and kinetic measurements of human body segments and can be complicated. This paper investigates the use of neural network model (NN) and accelerometer to estimate vertical ground reaction force (VGRF). An experimental study was conducted to collect sufficient samples for training, validation and testing. The estimated results were compared with VGRF measured using an instrumented treadmill. The estimates yielded an average root mean square error of less than 0.017 of the body weight (BW) and a cross-correlation coefficient greater than 0.99. The results also demonstrated that NN could estimate impact force and active force with average errors ranging between 0.10 and 0.18 of BW at different running speeds. Using NN and uniaxial accelerometer can (1) simplify the estimation of VGRF, (2) reduce the computational requirement and (3) reduce the necessity of multiple wearable sensors to obtain relevant parameters.

1. Introduction

Vertical ground reaction force (VGRF) is an important factor in analyzing human motion in sports, especially during running. It is more than twice of a person's body weight (BW) and much greater than the horizontal and lateral ground reaction forces. Excessive VGRF has been linked to the risk of running related injuries too (Messier et al., 2008). The standard measurement involves the use of calibrated force plate. Typically, one force plate is used to measure one step. Therefore, to monitor a series of continuous steps in a gait such as running, an instrumented treadmill embedded with two force plates is required. However, such treadmill is expensive and bulky.

Several wearable devices have been developed to estimate ground reaction force. Some of them use load cells (Veltink et al., 2005, Liu et al., 2010; Faber et al., 2010), while others use pressure sensors (Howell et al., 2013) and pressure insoles (Fong et al., 2008; Crea et al., 2014). Both methods have their strengths and weaknesses. A three-axis load cell can measure the three-dimensional force interaction between the foot and the ground (Liu et al., 2010). However, it is thick and heavy. On the other hand, pressure sensor has a slimmer profile, but it only measures force perpendicular to the sensing surface and it is prone to wear and tear. Hence, it is less durable and has a shorter lifespan.

Recent study by Karatsidis et al. (2017) reported the use of inertial sensor in estimating ground reaction forces and moments. This approach produced positive results. However, it requires the modelling and kinematic behaviors of human body segments. To do so, multiple sensors will need to be fitted on the body. This may constrain subject's motion during walking or running. It may take longer time to setup too.

With wider adoption of machine learning in various applications and wearable motion sensor in monitoring human activity, it is possible to estimate running ground reaction force from a wearable sensor using neural network model (NN). NN is an efficient computational model, which has been demonstrated to be useful in gait analysis (Oh et al., 2013). It is widely used to predict and distinguish walking gait (Schollhorn, 2004). It is also used to estimate VGRF based on measurements by foot pressure sensors (Billing et al., 2006; Jacobs and Ferris, 2015). However, to the best of our knowledge, none of existing study reported the use of NN and wearable motion sensor to estimate VGRF during running.

This study aims to estimate running VGRF using NN and uniaxial accelerometer. The proposed method involves the use of algorithm presented in Chew et al. (2017) to identify the foot initial

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contact (IC) and end contact (EC) using foot forward acceleration. This allows the acceleration to be segmented and normalized from IC to EC and be used as an input for NN. The accelerometer is placed on top of the running shoe – above the third metatarsal to minimize disruption to the subject's natural running gait. An instrumented treadmill is used to validate the accuracy of the proposed method.

2. Method

The inertial sensor (Opal, APDM Inc.) was placed on the right shoe and looped together using shoe string to minimize the measurement errors due to shock and vibration (Fig. 1). This sensor can measure acceleration, angular velocity and magnetic field with measuring range of ± 6 g m/s^2, ±2,000 deg/s, and ± 6 Gauss and has dimensions of 43.7 × 39.7 × 13.7 mm^3 with weight of less than 25 g (with battery). As only the forward acceleration (Acceleration along X-axis) is used in this study, it is referred as uniaxial accelerometer.

The participants were instructed to run on an instrumented treadmill equipped with two force plates (Mercury, H/P Cosmos Sports and Medical GmbH). Seven healthy male subjects (Age: 21.3 ± 0.5 years old; Height: 174.9 ± 6.6 cm; Weight: 63 ± 6.1 kg) participated this study. Subjects were briefed on the purpose and method of the experiment, before obtaining their consent. First, the participants were required to walk at a speed of 4 km/h for one minute. The treadmill speed was then increased to 8, 9 and 10 km/h for one minute each. Lastly, participants walked at 4 km/h for another minute before stopping. The recording of the inertial sensor and the treadmill was synchronized by an external trigger.

The acceleration was filtered using 2nd order Butterworth low-pass filter with cut-off frequency of 10 Hz. Several methods can be used to identify IC and EC during running (Alahakone et al., 2010). However, the algorithm presented in Chew et al. (2017) was selected because of its simplicity and compatibility. This algorithm uses the troughs in the foot forward acceleration when foot hits the ground and lifts off the ground as the indicators (Fig. 2). The deeper

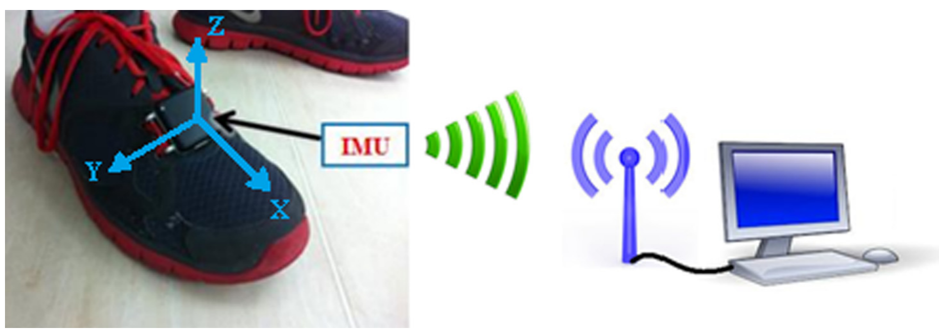

Fig. 1. Location of inertial sensor on shoe and its sensing axes.

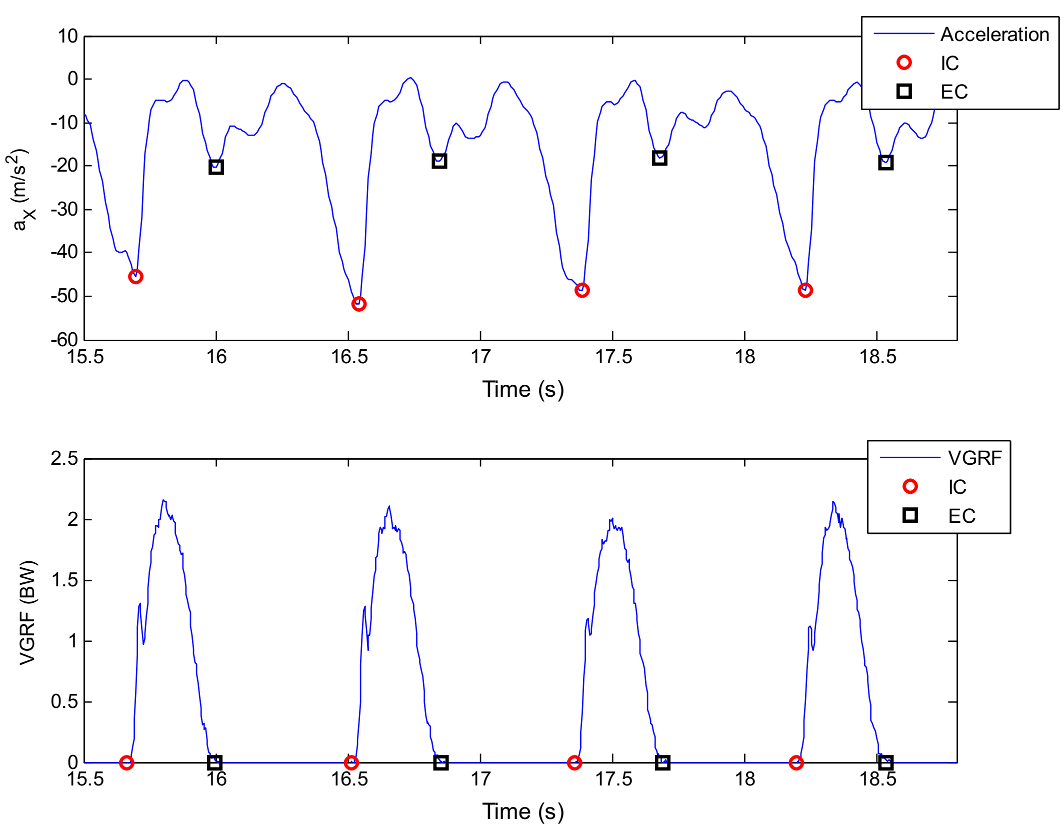

Fig. 2. Measured foot forward acceleration and the detected initial contact (IC) and end contact (EC) (Top figure) and measured vertical ground reaction force (VGRF) and the respective IC and EC (Bottom figure).

trough corresponds to IC and shallower trough corresponds to EC. Using these events, the acceleration is then segmented from IC to EC and scaled to 100 data points, which represents 100% stance phase. This process ensures the same amount of information is fed to the NN model.

Only the right foot VGRF was collected in this study. A threshold of 5 N was selected to identify IC and EC. Similar to the foot acceleration, VGRF were segmented and scaled to 100 data points. The magnitude of the VGRF were also normalized to subject's body weight (BW). Thirty stance phases were collected at each running speed. Thus, 630 stance phases were used here. The recorded average cadence, stride length, impact force (IF) and active force (AF) are presented in Table 1.

Neural network is commonly known as black box model because of its ability to learn from the data and to model a complex non-linear behavior of a system and the relationship between its input and output (Nelles, 2001). A two layers feed-forward NN was established (Fig. 3). The hidden layer consisted of 10 sigmoid neurons (*n1, n2,. . ., n10*) and the output layer has 100 linear neurons (*n1, n2,. . ., n100*). The NN input is the segmented foot acceleration: *x1, x2, . . ., x100*. The NN target and output are the measured and estimated VGRF: *y1, y2, . . . y100*. 280 randomly selected data (regardless of the running speed) were used for training and 120 data were used for validation and for testing. This network was trained using Levenberg-Marquardt backpropagation algorithm. The mean squared error was used as the performance function. MATLAB neural network toolbox was used as the platform to construct this network.

Several measures were computed to evaluate the accuracy of the proposed method. They were calculated for the remaining 230 data. The first measure is the Root Mean Square Error (*RMSE*). The second measure is the signal cross-correlation coefficient (*r*). This is used to quantify the waveform similarity between the estimated and measured VGRF. The remaining measures are the mean and standard deviation (SD) of the prediction error between IF and AF.

3. Results

The difference between the measured and estimated VGRFs is shown in Fig. 4. The estimated IF and AF occur at 18% and 48% of the stance phase and has magnitude of 1.18 BW and 2.19 BW

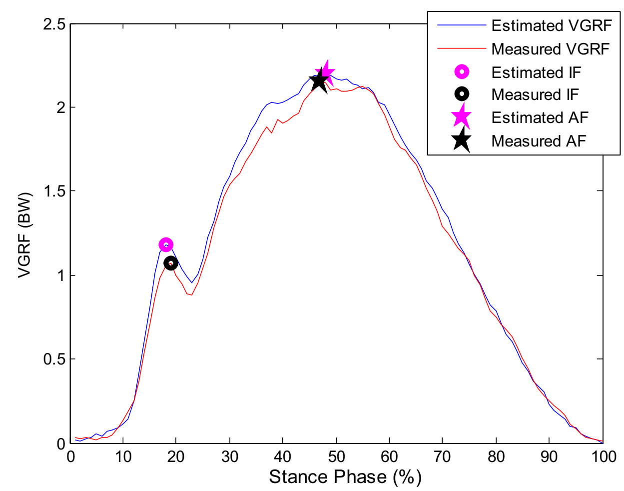

Fig. 4. The estimated and measured vertical ground reaction force (VGRF) and their respective impact force (IF) and active force (AF).

Table 1
The recorded average running gait parameters.

Speed (km/h)	Cadence (SD) (/min)	Stride length (SD) (m)	Impact force (SD) (BW)	Active force (SD) (BW)
8	148.35 (6.20)	173.89 (8.45)	1.28 (0.23)	2.11 (0.19)
9	151.01 (9.86)	188.31 (8.17)	1.35 (0.19)	2.22 (0.17)
10	157.11 (8.06)	204.48 (15.19)	1.49 (0.21)	2.25 (0.14)

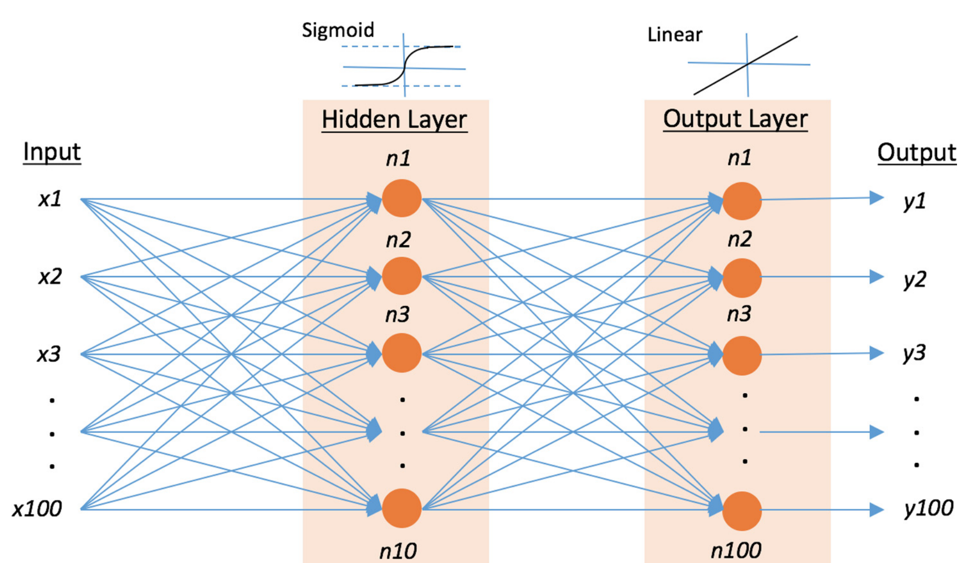

Fig. 3. Neural network model to estimate vertical ground reaction force during running. (*x1, x2, x3, . . . x100* are the inputs; n*1, n2, n3, . . ., n100* are the neurons; and *y1, y2, y3, . . ., y100* are the outputs).

Table 2
Differences between measured and estimated VGRF.

	8 km/h	9 km/h	10 km/h
Mean RMSE (SD) (BW)	0.017(0.010)	0.015(0.0072)	0.017(0.0091)
Average r	0.99	0.99	0.99
Mean Error IF (SD) (BW)	−0.12(0.235)	−0.10(0.21)	−0.18(0.25)
Mean Timing Error IF (SD) (% stance phase)	−0.59(3.389)	−0.78(2.984)	−1.3(3.1)
Mean Error AF (SD) (BW)	−0.099(0.180)	−0.10(0.155)	−0.12(0.16)
Mean Timing Error AF (SD) (% stance phase)	−0.54(5.74)	0.34(5.248)	−0.92(5.9)

respectively. These attributes were similar to the measured VGRF with differences of −1% of the stance phase and 0.11 BW for IF and 1% of the stance phase and 0.04 BW for AF. Negative timing error indicates that the measured IF or AF occurs earlier than the estimated force. The negative error in magnitude implies the measured IF or AF is greater than the estimate.

The quantitative results are presented in Table 2. The average errors of IF and AF were less than -0.18 BW and -0.12 BW respectively. These results indicated that NN underestimated IF and AF. Negative values were found in the timing errors too. The average *RMSE* between the estimated and measured VGRF ranged between 0.015 BW and 0.017 BW during running at 8, 9 and 10 km/h. The r values were close to 1, which implies that the waveform of estimated VGRF closely resembles the measured one.

4. Discussion

Running experiment and its relevant analysis are commonly performed using optical motion capture system and multiple force plates. Despite its accuracy, this method can only measure movements in a confined space and only capture limited number of gait cycles. Moreover, the runner has to accurately place his foot on the force plate to obtain valid measurements. Thus, it may not fully represent the natural running gait. Hence, many attempted to look for practical and economical alternatives (Gouwanda et al., 2016). Use of small and light wearable accelerometer can be one of the solutions. Unlike gyroscope and magnetometer, accelerometer is free of sensor drift and less prone to nearby magnetic field. It can monitor running gait in an open area too. Studies also demonstrated its viability in estimating spatial and temporal parameters of running gait (Yang et al, 2011; Bergamini et al., 2012; Chew et al., 2017). Uniaxial accelerometer offers several benefits. It decreases the overall manufacturing cost. It also reduces computational requirement of the controller and the load in storing and transmitting data wirelessly. This in turn reduces the size and weight of the sensor and minimizes the disruption to the runner's natural gait.

Several studies reported methods to estimate VGRF during walking or running (Oh et al., 2013; Fluit et al., 2014, Wille et al., 2014, Jung et al., 2016, Karatsidis et al., 2017). However, they can be complicated and require full kinematics behavior of human body segments. Use of NN and inertial sensor can overcome this issue. A well-trained NN can accurately estimate VGRF, as demonstrated here. This study also revealed that the IF and AF can be estimated with minimal errors regardless of the running speed. The *RMSE* and r further validated the viability of this approach – indicating the waveforms of the estimated and measured VGRFs were similar. However, an extensive data and prior knowledge is required to train NN. The more data it uses for the training, the better the NN will be in making a prediction.

There are several biomechanical differences between overground and treadmill running (Kluitenberg et al., 2012). One of them is due to the accommodation to the changed visual and auditory surroundings or fear (Savelberg et al., 1998). The others are caused by the effect of air resistance on running kinematics and the variations in belt speed (Pugh, 1970; van Ingen Schenau, 1980). The last factor is the running surface. Running surface can alter leg stiffness, which consequently changes the kinematics of the lower extremity (Ferris et al., 1999; Dixon et al., 2000). Nevertheless, instrumented treadmill is the only way to accurately and continuously measure the ground reaction force. Hence, it is used to examine the viability of NN and accelerometer in estimating VGRF.

Foot strike pattern can affect the VGRF (Almeida et al., 2015). Forefoot strike does not have apparent IF (Laughton et al., 2003). It also has lower vertical loading rate than rearfoot strike. This induces lower knee loading. However, as this study focuses on the feasibility of uniaxial accelerometer and NN, only rearfoot strike running was investigated. Also, up to 89% runners are rearfoot striker (Hall et al., 2013; Almeida et al., 2015). However, this should not diminish the possibility of NN in estimating VGRF of forefoot striker. NN can be trained to estimate forefoot striker's ground reaction forces if sufficient dataset and right training algorithm are used.

5. Conclusion

Use of wearable technologies to monitor human daily activity is on the rise. This includes the application of motion sensors to quantify the quality of human gait (walking and running). Similarly, machine learning technique such as neural network has been widely adopted in various fields to handle complex and non-linear problems. This is the first study that reports the application of NN and uniaxial accelerometer to estimate running VGRF. In future, 3D force profile will be estimated, potentially using acceleration, angular rate and magnetic field of the inertial sensor. An advanced model or training algorithm will be explored to handle these measurements and to make more accurate prediction.

6. Conflict of interest statement

We certify that there is no conflict of interest with any organization regarding the material discussed in the manuscript.

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