# ESTIMATION OF GROUND REACTION FORCES DURING RUNNING USING INERTIAL MEASUREMENT UNITS AND ARTIFICIAL NEURAL NETWORKS

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The purpose of this study was to develop a system to estimate ground reaction forces during running using inertial measurement units and artificial neural networks. Kinematics of the pelvis and feet and ground reaction forces were measured using an inertial measurement system developed by Casio and Kistler force plates from seventy-nine runners (57 males and 22 females). Two long short-term memory based neural networks were used to estimate the instants of foot-strike and toe-off, and anteroposterior and vertical ground reaction forces from the triaxial accelerations and angular velocities measured by inertial measurement units fixed to the pelvis and foot of support leg. Although there are some limitations due to the small sample size, the results of this study showed the potential of estimating the ground reaction forces during running using a small number of inertial measurement units and artificial neural networks.

**KEYWORDS:** long short-term memory, Kalman filter, artificial intelligence.

**INTRODUCTION:** Analysis of running motion has traditionally been limited to laboratory-based measurements, because it requires data from a motion capture system and/or force plates. Previous studies of running motion have focused on a part of long distance oveground running (Enomoto et al., 2008) or treadmill running (Kram et al., 1998). However, information on the ground reaction forces and their changes during long distance overground running could be useful not only for improving running performance but also for preventing running injuries.

In recent years, inertial measurement units (IMUs) have been used in several biomechanical studies (Camomilla et al., 2018; Wouda et al., 2018). Enomoto et al. (2017) presented an accurate and precise IMU measurement system developed by Casio to estimate running speeds and step variables like step lengths and frequencies. The IMUs can be easily attached to body segments and measure motion data with less restriction for several hours. However, there are several limitations on the use of IMU raw data because of signal noise and limited information about segment position and orientation in space. The IMU's orientation in space can be calculated by transforming IMU data into the global coordinate system. The use of a Kalman filter enables identification of IMU orientation in space (Hirose & Kondo, 2014).

While IMUs can measure kinematic data, it is difficult to estimate ground reaction forces and joint kinetics from kinematic data. Some studies have used an artificial neural network (ANN) to predict unmeasured kinematic and kinetic data. Wouda et al. (2018) reported that joint kinematics and vertical ground reaction force during running could be estimated from IMU data by use of ANNs. The purpose of this study was to develop a system to estimate ground reaction forces during running using IMUs and ANNs.

**METHODS:** Seventy-nine runners (57 males and 22 females, age = 36.6 ± 13.7 yrs, mass = 58.1 ± 8.1 kg, height = 1.67 ± 0.05 m) participated in this study approved by the Research Ethics Committee of the Graduate School of Comprehensive Human Science, University of Tsukuba. Written informed consent was obtained before the experiment.

The subjects performed running trials over a 20 m runway at the four different speeds (2.4 ± 0.3 m/s, 3.0 ± 0.3 m/s, 3.6 ± 0.3 m/s, 4.2 ± 0.3 m/s), and the number of trials of each subject was ranged from four to nine to cover all the four running speeds. Ground reaction forces and

running motions were captured by four force plates (9281B×2, 9287C×2, Kistler Instrument AG, Switzerland, 1000Hz) and a 16-camera Vicon MX system (Vicon, Oxford, UK, 250Hz) with 35 reflective markers fixed on the bony landmarks according to the Plug-in-Gait marker placement. In addition, time-synchronized triaxial accelerations (output range was ±16 g) and angular velocities (output range was ±2000 dps) of the pelvis and feet were measured using three IMUs, 'Casio sensing units', fixed to the sacrum and the dorsum of the feet (200 Hz). For the measured accelerations and angular velocities of the pelvis, the data were transformed from local coordinate system to the global coordinate system using a Kalman filter (Hirose & Kondo, 2014). The state and observation equations used in this study were as follows:

$$\boldsymbol{x}_{t+1} = \boldsymbol{A}_t \boldsymbol{x}_t + \boldsymbol{B}_t \boldsymbol{u}_t + \boldsymbol{w}_t,$$

$$\begin{bmatrix} \psi_{t+1} \\ \theta_{t+1} \\ \phi_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \psi_t \\ \theta_t \\ \phi_t \end{bmatrix} + \begin{bmatrix} dt & 0 & 0 \\ 0 & dt & 0 \\ 0 & 0 & dt \end{bmatrix} \begin{bmatrix} \dot{\psi} \\ \dot{\theta} \\ \dot{\phi} \end{bmatrix} + \boldsymbol{w}_t, \qquad (1)$$

$$\boldsymbol{y}_t = \boldsymbol{C}_t \boldsymbol{x}_t + \boldsymbol{v}_t,$$

$$\begin{bmatrix} \theta_t \\ \varphi_t \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} tan^{-1}(\frac{-a_x}{\sqrt{a_y{}^2+a_z{}^2}}) \\ tan^{-1}(\frac{a_x}{a_z}) \end{bmatrix} + \boldsymbol{v}_t, \qquad (2)$$

where ψ, θ, φ are Euler angles, *dt* is time interval (0.005 s), *w* and *v* are process noise and observation noise, and $a_x$, $a_y$, $a_z$ are calculated as follow:

$$\begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} = \begin{bmatrix} gsin\theta_t \\ -gcos\theta_t sin\varphi_t \\ -gcos\theta_t cos\varphi_t \end{bmatrix}, \qquad (3)$$

where *g* is gravitational acceleration. Kalman filter processing consisted of the following equations and state variables are estimated by repeated calculations:

$$\widehat{\boldsymbol{x}}_{t+1} = \boldsymbol{A}_t \boldsymbol{x}_t + \boldsymbol{B}_t \boldsymbol{u}_t, \qquad (4)$$

$$\widehat{\boldsymbol{P}}_{t+1} = \boldsymbol{A}_t \boldsymbol{P}_t \boldsymbol{A}_t + \boldsymbol{Q}_t, \qquad (5)$$

$$\boldsymbol{K}_t = \widehat{\boldsymbol{P}}_t \boldsymbol{C}^T{}_t (\boldsymbol{C}_t \widehat{\boldsymbol{P}}_t \boldsymbol{C}^T{}_t + \boldsymbol{R}_t)^{-1}, \qquad (6)$$

$$\boldsymbol{x}_t = \widehat{\boldsymbol{x}}_t + \boldsymbol{K}_t (\boldsymbol{y}_t - \boldsymbol{C}_t \widehat{\boldsymbol{x}}_t), \qquad (7)$$

$$\boldsymbol{P}_{t+1} = (\boldsymbol{I} - \boldsymbol{K}_{t+1} \boldsymbol{C}_t) \widehat{\boldsymbol{P}}_{t+1}, \qquad (8)$$

where *P* is an error covariance matrix, *K* is a Kalman gain, *Q* and *R* are covariance matrices of *w* and *v*.

The process to estimate anteroposterior and vertical ground reaction forces from IMU data was conducted in two stages, using two long short term memory (LSTM) based networks (Fig. 1). In the first stage, the inputs to the network (LSTM1) were the measured triaxial accelerations and triaxial angular velocities of the pelvis and foot of the support leg by IMUs. LSTM1 was trained to estimate the instants of foot-strike and toe-off determined by the measured vertical ground reaction force. In the second stage, the inputs to the network (LSTM2) were triaxial accelerations and triaxial angular velocities of the pelvis and foot of the support leg which were trimmed from the foot-strike to toe-off estimated by LSTM1. LSTM2 was trained to estimate the
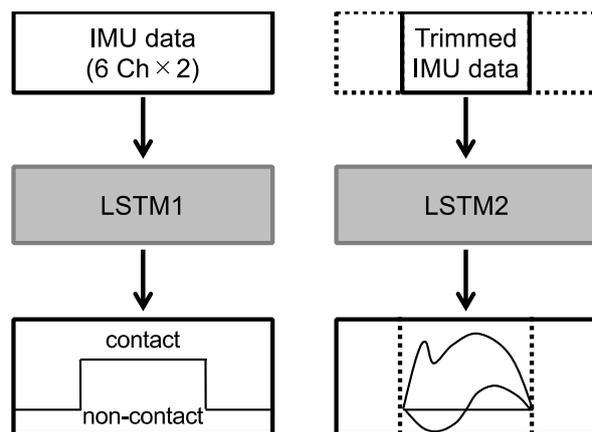


Fig. 1  Conceptual diagram of artificial neural network used in this study.

anteroposterior and vertical ground reaction forces normalized by the subjects' body mass. LSMT1 and LSMT2 each consisted of a LSTM layer with 512 hidden units and a hyperbolic tangent activation and a fully connected layer. For LSTM1, a softmax layer was used to predict output classes, i,e, contact or non-contact phases. The data of three subjects (2 males and 1

female) were randomly selected for the test data (19 trials), and the data of all other subjects were used as the training data (458 trials).

To compare the measured and estimated instants of foot-strike and toe-off and anteroposterior and vertical ground reaction forces, root mean squared errors (RMSEs) were calculated. The correlation coefficient ρ between measured and estimated ground reaction forces was calculated as the average of z transformed Pearson's correlation coefficients of all test data (Corey et al., 1998).

**RESULTS:** Differences in the instant of foot-strike and toe-off determined by the vertical ground reaction force and estimated by LSTM1 ranged from -15 ms (-3 frames at 200Hz) to +10 ms (+2 frames) (Fig. 2). Root mean squared errors (RMSEs) of estimated foot-strike and toe-off instants were 7.3 ms (1.5 frames) and 4.9 ms (1.0 frames), respectively.

Fig. 3 shows mean and standard deviation of the anteroposterior and vertical ground reaction forces measured by the force plates and estimated by LSTM2 for three subjects' test data
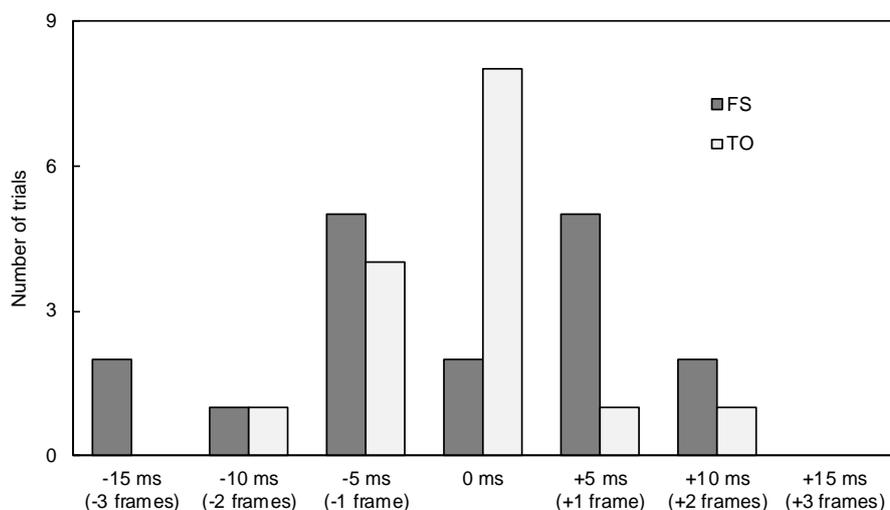


Fig. 2     Frequency distribution of differences in the measured and estimated instants of foot-strike (FS) and toe-off (TO) (N=19).
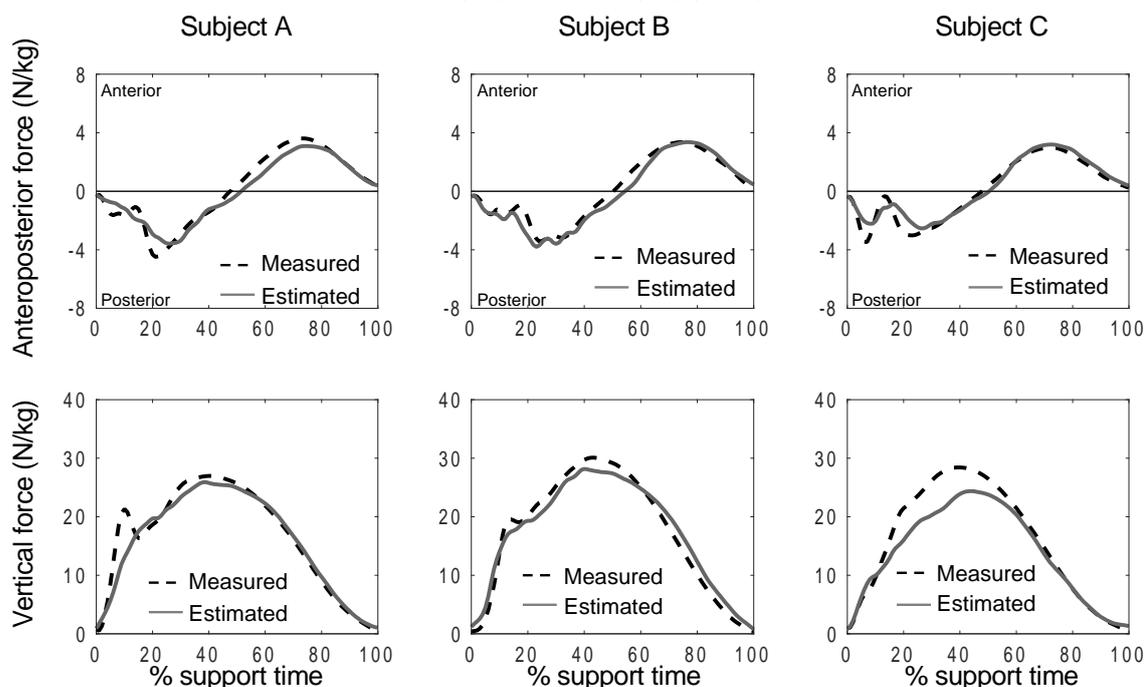


Fig. 3     Mean and standard deviation of anteroposterior and vertical ground forces measured by force plates and estimated by the neural network for test data (three subjects).

(N=19). Mean RMSE of 19 trials were 0.9 ± 0.4 N/kg for the anteroposterior force, 3.3 ± 1.7 N/kg for the vertical force. The correlation coefficients between measured and estimated ground reaction forced for all test data were $\rho = 0.93$ for the anteroposterior forces, and $\rho = 0.96$ for the vertical forces.

**DISCUSSION:** The results of the present study showed that the instant of toe-off was better estimated than that of foot strike. It may be assumed that estimation of foot-strike from IMU data could be easier than that of toe-off, because of the high frequency impact force experienced at foot-strike. However, in this study there was variation in the pattern of impact force loading, with some subjects exhibiting impact force immediately after foot-strike (eg. Subject A, Fig. 3), and other subjects showing no impact force (Subject C). It was noted that the subjects in this study showed different foot-strike patterns. These differences could increase RMSE of the foot-strike event detection compared to toe-off.

The correlation coefficient $\rho$ indicates that the measured and estimated ground reaction forces were strongly correlated for both anteroposterior and vertical forces. Wouda et al. (2018) estimated vertical ground reaction forces during treadmill running using approximately 4000 data set and reported that correlation coefficients between measured and estimated vertical ground reaction forces were ranged from 0.90 to 0.99. Although the number of data set of this study was much smaller than Wouda et al. (2018), the anteroposterior and vertical ground reaction forces were accurately estimated. The use of Kalman filter and LSTM based neural networks could play an important role in the accurate estimation with the small training data set. The results of this study suggest the potential of estimating ground reaction forces during running using IMUs and ANNs.

**CONCLUSION:** This study developed a system to estimate anteroposterior and vertical ground reaction forces using IMUs at the pelvis and foot and LSTM based neural networks. Although there are some limitations due to the small sample size, the results of this study suggest that anteroposterior and vertical ground reaction forces as well as the instant of foot-strike and toe-off during running can be accurately estimated from triaxial accelerations and angular velocities measured by IMUs using LSTM neural networks.

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