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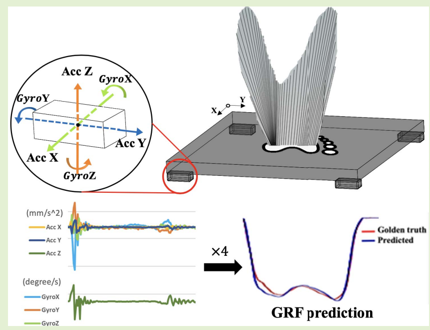
IMU Sensors Beneath Walking Surface for Ground Reaction Force Prediction in Gait

Chao-Che Wu, Yu-Tang Wen, and Yun-Ju Lee, *Member, IEEE*

***Abstract*—*Objective*: Utilization of inertial measurement units (IMU) data for ground reaction force (GRF) prediction has been widely studied and documented when these sensors attach to the body segments. However, it was inconvenient and required people's cooperation. A novel approach of the current study was setting IMU sensors mounted underneath the walking surface to measure footstep induced structural vibration. We aimed to conduct the force plate to validate the prediction accuracy of this approach. *Methods*: Fifteen hundred steps were recorded from five individuals. Twenty-four measured features from four IMU sensors were treated as inputs to the long short-term memory model for multidimensional GRF predictions. The GRF data from the force plate were considered as the ground truth for comparisons. The accuracy performance was determined by the normalized root mean square error (NRMSE) method. *Results*: The averaged NRMSE was 6.05%, 3.93%, and 4.37% for Fx, Fy, and Fz, respectively. *Conclusion*: The accuracy was comparable with IMU sensors attached to the body, particularly in the vertical direction. The current study demonstrated the feasibility of this approach and successfully predicted ground reaction force with high accuracy. *Significance*: The validation of IMU sensors mounted underneath the walking surface for GRF prediction provides an alternative method for biometrics in gait.**



***Index Terms*—Inertial measurement unit, ground reaction force, long short-term memory, gait.**

I. Introduction

THE unique gait characteristics have been recognized and used for human identification as behavioral biometrics [1], [2]. Gait biometrics has become a popular research topic for it overcomes the traditional method problem that uses static measures [3], [4] for personal identification. In gait biometrics, gait pattern recognition could be human motion and captured by camera, wearable devices for motion detection or ground reaction force (GRF) prediction, walking surface with pressure sensors for GRF and center of pressure calculation, and etc. [5]. These could be classified into visual-based and nonvisual-based approaches. Among all different nonvisual-based measurements, individual GFR has shown great promise in the accuracy of gait biometrics [6]–[9].

Inertial measurement units (IMU) typically contains an accelerometer for linear acceleration, a gyroscope for angular velocity, and a magnetometer for magnetic orientation. These IMU sensors have been attached to different body segments as a wearable device and used to predict GRF in gait [10]–[13], such as attached to C7 with Scaled Acceleration' method for the GRF vertical component [12]. An accelerometer was attached to the shank and using multilayer perceptron networks models to predict GRF [11]. All these studies were in the situation of IMU sensors attaching to the body and the accuracy of predication reached 95%. Among these researches, gait recognition reveals the importance of GRF, which is an essential feature for personal identification. However, it is somehow inconvenient and required people to cooperate wearing these devices.

Alternatively, accelerometers were mounted underneath the walking surface and used to measure footstep generated vibrations [14], [15], which has been applied for gender classification [16] Meanwhile, the performance of gait recognition has been great improved with the progress of deep learning. Processing in deep learning models, the data of accelerometer and the gyroscope from smartphones used for gait recognition showed over 93% accuracy in person identification [17]. Therefore, the current study aims to propose a new approach of GRF predication by mounting IMU sensors underneath the walking surface to detect vibration induced by footstep and process in the deep learning models. We anticipated that the high accuracy of GRF prediction for each individual would confirm the application of this approach and contribute to biometrics with further employing gait recognition.

Manuscript received March 2, 2020; revised April 9, 2020; accepted April 13, 2020. Date of publication April 16, 2020; date of current version July 17, 2020. This work was supported by the Ministry of Science and Technology (MOST), Taiwan, through the Young Scholar Fellowship Program, under Grant MOST-108-2636-E-007-002. The associate editor coordinating the review of this article and approving it for publication was Prof. Octavian Postolache. *(Corresponding author: Yun-Ju Lee.)*

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Digital Object Identifier 10.1109/JSEN.2020.2988296

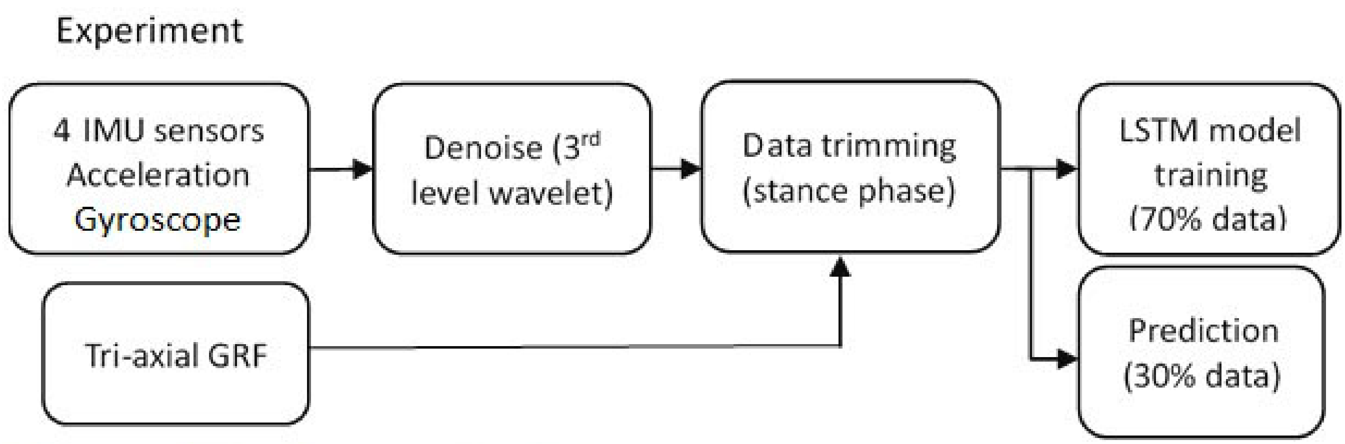

Fig. 1. Study overall design.

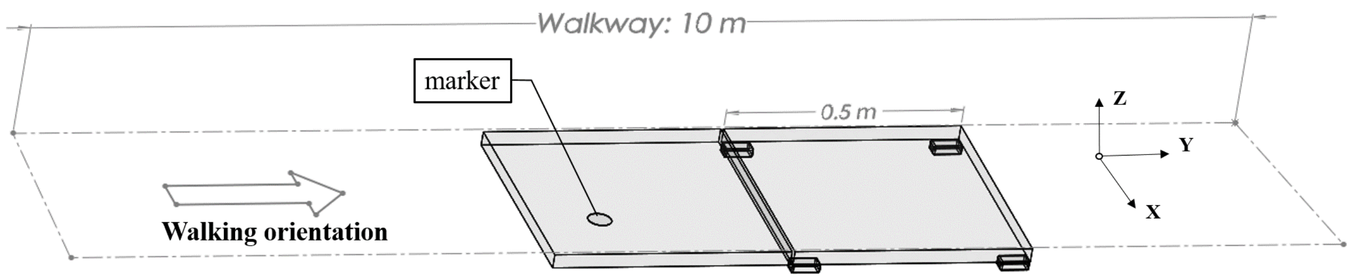

Fig. 2. Experimental setting. A marker is set on the first force plate as a target for participants' right feet to step on it. A, B, C, and D points are the locations of four IMU sensors.

II. Methods

The overall study design is shown in Figure 1.

The experimental settings are illustrated in Figure 2. Two force plates (Advanced Mechanical Technology Inc., USA) were set in the walkway. Four IMU sensors (Delsys Inc, USA) were mounted to four corners of the second force plate for measuring acceleration and gyroscope. Five healthy individuals (3 males, 2 females, age: 24 $\pm$ 2 years, weight: 64 $\pm$ 11 kg and height: 1.68 $\pm$ 0.02 m) were instructed to start walking at least five steps before right foot stepping on the marker. Participants walked with their comfortable walking speed over force plates with one step on each force plate for 300 walking trials. The sampling rate of IMU sensors and force plates were 148 Hz and 1037 Hz and synchronized by the Vicon Nexus system (Vicon Motion System, 2018).

The IMU sensors recorded two vibrations induced by heel strike and toe off, respectively. The acceleration and gyroscope data were de-noised utilizing third-level discrete wavelet transform. Subsequently, all signals were given a zero initial value to remove the offset of the raw data. The force plate data were re-sampled at 148 Hz in Labview software (National Instrument, 2018) to match with the IMU data. The heel contact point of the IMU data was determined by the first non-zero value point of vertical GRF and the following 120 samples were extracted as the stance phase period. III illustrates the accelerometer data and gyroscope data of four IMU sensors from one participant and the stance phase period could include complete vibration signals from heel contact to toe off.

For GRF prediction, the sequence to sequence Long Short-Term Memory (LSTM) model was conducted using Tensorflow environment with Python3.6 (Python Software Foundation, USA). The accelerometer data and gyroscope data from four IMU sensors were all included as the 24 features of the LSTM model. Three components of GRF data (Fx: medial/lateral, Fy: anterior/posterior, and Fz: vertical) were predicted separately. LSTM model is composed of three hidden layers and another batch normalization layer. Three hidden layers of 150/250/100 neurons were used in predicting Fx and Fy and the epoch was set to 40. The curve of Fz were more consistent among the steps and a simpler model of 100/200/100 was found having better predicting results. However, the value of Fz was higher that epoch was set to 110 to get a convergent result. Loss function and optimizer of mean square error and RMSprop were used. The seventy percent of 300 steps for each participant was randomly chosen as training data; the rest 30% were as testing data., The normalized root mean square error (NRMSE) shown in Eq. (1) were calculated to analyze the accuracy of the GRF predication.

$$\text{NRMSE}\ (\%) = \frac{\sqrt{\left(\sum_0^{t_{end}}\left[\left(GRF_{measured}(t) - GRF_{predicted}(t)\right)^2\right]\right)/N}}{\max GRF_{measured}t - \min GRF_{measured}t} \times 100 \tag{1}$$

In Eq. (1), N is the sample size being extracted starting from 0 to t_{end}, which is 120 in the current dataset. The larger NRMSE

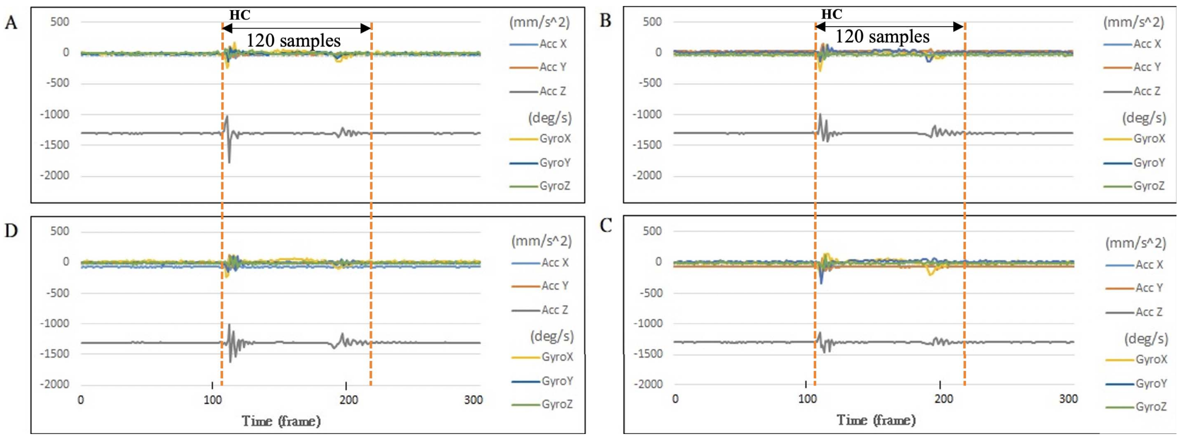

Fig. 3. Accelerometer data and gyroscope data of four IMU sensors from one participant. A, B, C, and D subplots are corresponding to the placement of four sensors shown in the experimental setting (Fig 2). HC represents the heel contact point and two vertical dash lines indicate the vibration period.

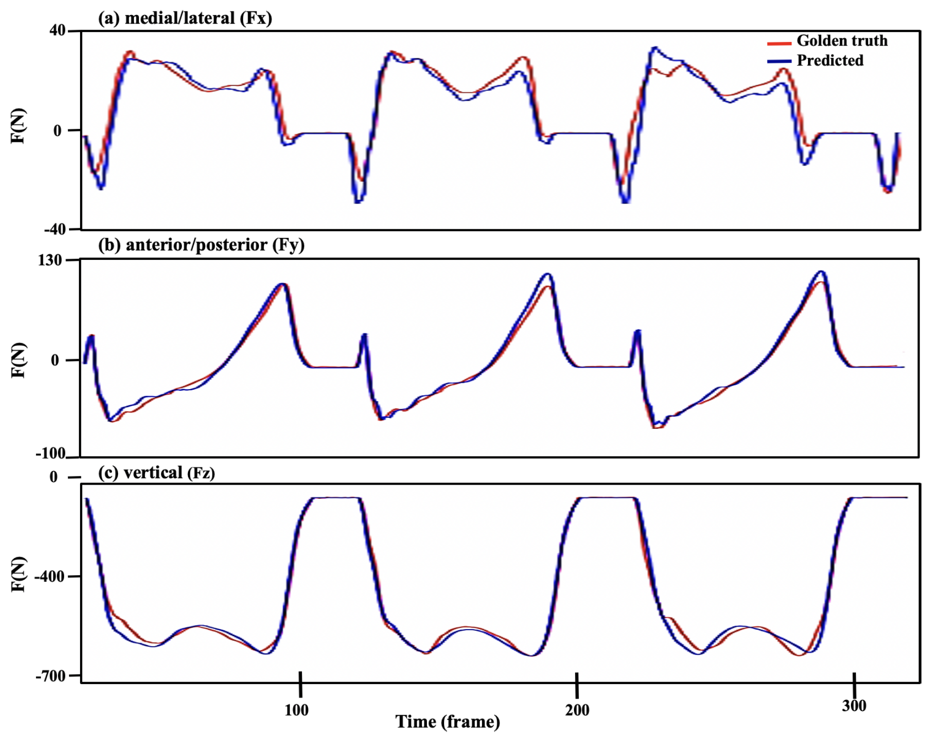

Fig. 4. The golden truth (red lines) and predicted (blue lines) ground reaction force of three steps in the (a) medial/lateral, (b) anterior/posterior, and (c) vertical directions.

value indicates the larger deviation between the golden truth and predicted GRF.

III. Results

Three respective steps of predicted and measured GRF from the same participant (Fig 3) are shown in Figure 4. Red lines are golden truth values from force plates and blue lines are predicted results from IMU data for three components of GRF. In Figure 4, test-set mean golden truth GRF is shown as thick red lines and blue lines depicts mean of predicted GRF. In Figure 5, the corresponding red and blue shaded areas are the range of Max/Min value for the golden truth and predicted GRF, respectively. The purple area indicated the overlap range between the golden truth and predicted GRF (Fig 5). For this typical example, NRMSE was 4.66% in the medial-lateral direction, 3.24% in the anterior-posterior direction, and 3.36% in the vertical direction.

For the accuracy of the prediction, NRMSE of three directions in five participants were listed in Table I. In medial/lateral direction, NRMSE in the range of 4.6–7.6% with mean and standard deviation of 6.0% and 1.1%. In anterior/posterior direction, NRMSE were in the range of 3.2-5.0% with mean and standard deviation of 3.9% and 0.5%. In vertical direction, NRMSE were in the range of 3.3-5.6% with mean and standard deviation of 4.3% and 0.8%.

IV. Discussion

Either using IMU data or perceptron network models was not new for GRF prediction [10]–[13]. However, all these IMU sensors were acted as a wearable device and required to

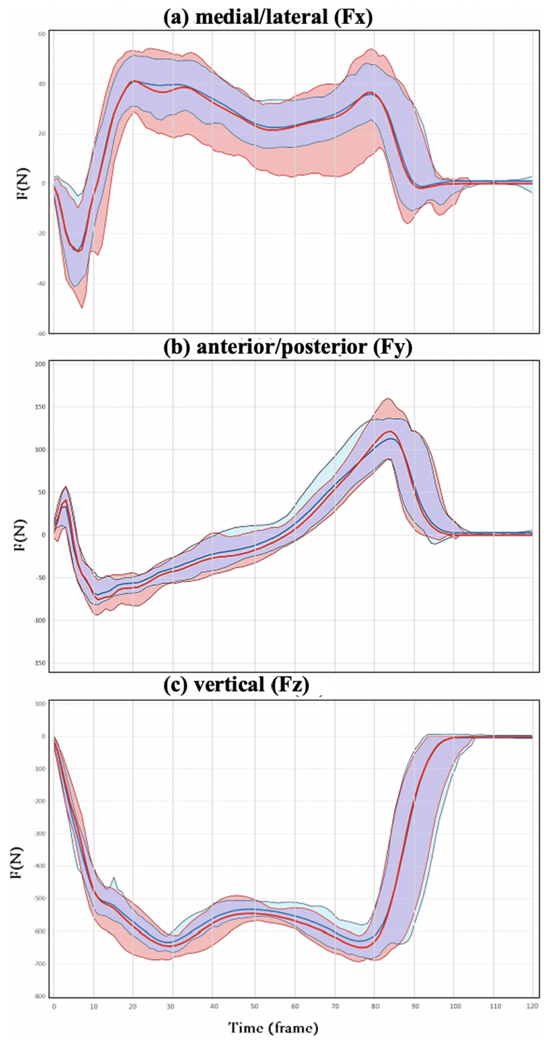

Fig. 5. Golden truth mean GRF (red thick lines) and the range of Max/Min value (red shaded area); predicted mean GRF (blue thick lines) and the range of Max/Min value (blue shaded area) in the (a) medial/lateral, (b) anterior/posterior, and (c) vertical directions.

attach to the body. The current study is a novelty approach to mount IMU sensors underneath the walking surface for GRF prediction with the LSTM model. LSTM is one of the recurrent neural networks and particularly designed for sequential data. For time series prediction, LSTM has shown promising outcomes in all different filed [19]. Hence, the sequential dataset like GRF during walking is perfectly applicable to conduct the prediction with the LSTM model.

For the LSTM model in the current study, the inputs were data of tri-axial acceleration and angular velocity for each IMU sensor as 24 features from four IMU sensors. It has been reported that using both accelerometer and gyroscope data could complementarily improve the performance of deep learning based gait recognition, including the LSTM model [17]. After data trimming, the hyperparameters of the LSTM model were tuned from scratch. Subsequently, batch normalization layer was found to be of great importance among different model structures, which performed best in the model with four hidden layers. Finally, NRMSE was used to evaluate the difference between the golden truth and predicted

TABLE I
NORMALIZED ROOT MEAN SQUARE ERROR OF MULTIDIMENSIONAL GRF PREDICTION FOR EACH PARTICIPANT, OVERALL MEAN, AND STANDARD DEVIATION

NRMSE (%)	Fx	Fy	Fz
Participant 1	4.66	3.24	3.36
Participant 2	6.65	5.01	3.32
Participant 3	4.92	3.67	5.61
Participant 4	7.65	3.84	4.76
Participant 5	6.38	3.95	4.78
Mean	6.05	3.93	4.37
[18]	(1.11)	(0.58)	(0.89)

GRF, which showed less than 5% in the anterior/posterior and vertical directions.

For evaluation of the difference, NRMSE of predicted GRF and golden truth value were calculated as an indication of accuracy performance [12]. The slightly higher error rate in the medial/lateral direction was observed for all participants. Taking the representative participant in Fig 5(a) as an example, the range of Max/Min value from the golden truth (red shaded area) was even larger than the blue shaded area of predicted GRF. The purple area was the overlap range between the golden truth and predicted GRF. The larger red shaded area indicates the wider range of the golden truth GRF, which has been reported that during walking, the medial/lateral GRF could result in substantial variation compared to the other two directions [20]. However, the prediction range from the LSTM model was relatively robust to the mean predicted value as well as the mean golden truth value. It suggests that the LSTM model was not only a correct approach in time series GRF prediction but also succeed extracting features from the accelerometer data and gyroscope data [17]; even the IMU sensors were mounted underneath the walking surface. On the other hand, mean NRMSE and the standard deviation were 4.3% and 0.8% in the vertical direction, which was comparable with IMU attached to C7 (4.4% SD 1.1%) [12]. Overall, NRMSE was considered in the acceptable range for the multidimensional GRF prediction. Based on our best knowledge, the current study was the first one to conduct this experimental setting to predict multidimensional GRF by deep learning. In addition, the characteristic M shape of the typical vertical GRF has been well associated with gait recognition features [21]. Hence, this approach provided high accuracy GRF prediction, which could further apply for personal identification [9].

V. CONCLUSIONS

The current study demonstrated the promising GRF prediction by the data of IMU sensors from the walking surface with LSTM models. Although only one step during one walking trial was selected, the feasibility of predicting GRF by mounting IMU sensors underneath the walking surface was proved. Further investigation is needed on continuous walking steps in different walking conditions as well as larger datasets.

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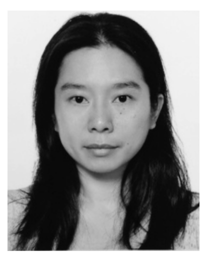

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