Wearable motion sensors and artificial neural network for the estimation of vertical ground reaction forces in running

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Abstract— **Biomechanical load assessments are becoming increasingly important in the sporting community; however, there are still numerous difficulties in monitoring them in a field environment outside of specialized biomechanical monitoring laboratories. Inertial Measurements Units (IMUs) have been showing promising results in the modeling of biomechanical variables. This study explores the application of an artificial neural network (ANN) in the estimation of runners' vertical ground reaction forces (GRFs) based on the accelerometry collected from two wearable motion sensors developed in-house and attached on the shanks. Data collected from fourteen runners running at three different speeds (8, 10, 12 km/h) were used to train and validate the ANN. Predictions were compared against gold-standard measurements from a pair of pressure in-soles. Root mean square error (RMSE) was used to evaluate the performance of the models. Further investigations, e.g., the use of principal components analysis (PCA) and the impact on the estimation of several GRF-related variables, were carried out to provide useful insights regarding the portability of the model to low-power resource-constrained devices. Findings indicate that ANNs in conjunction with accelerometry may be used to compute vertical ground reaction forces (RMSE: 0.148 BW) and related loading metrics in running accurately.**

Keywords* — *Ground Reaction Forces; Wearable; Accelerometers; IMU; Running

I. Introduction

Researchers' interest toward ground reaction forces (GRFs) has been growing steadily [1], due to their association with overuse-related running injuries from the repeated impact loading of the foot [2]. Even though their direct measurement in running is feasible via instrumented treadmills and force platforms [3] or optoelectronic systems [4], this is only possible under controlled conditions in specialized lab settings. Wearable technology, therefore, represents an excellent alternative for the estimation of GRFs in real-world conditions.

Pressure-based insoles have been proposed as a solution for open-field scenarios; however, despite the numerous studies available [5], the commercial products on the market [for instance, 6-7] still show several issues in terms of cost and performance degradation over time.

Inertial measurement units (IMUs), due to their low-cost and small-size, have been used to record kinematics in any environment for prolonged time periods [8]. Numerous methodological approaches have been investigated for the estimation of GRFs via IMUs, such as biomechanical models [9], artificial neural networks (ANNs) [10], or mass-spring-damper systems [11]. A recent comparison study has highlighted that accelerometry in conjunction with ANNs may return the most accurate approximations [12] due to the network's ability to model complex non-linear patterns.

Three-layered, feed-forward, ANNs with backpropagation have been typically adopted for this goal [10, 13]. However, the impact of different architectures -i.e. number of neurons in the hidden layer or principal component analysis (PCA) - and the network's estimation accuracy on GRF-related variables [14] (e.g., impact peak, active peak, loading rate, and impulse) has not been investigated yet. Ultimately, models should generalise accurately from unseen inputs while being portable for low-power resource-constrained devices (i.e. foot pods).

The objective of this research is to extend the work carried out in the estimation of running GRFs via optoelectronics [13], to IMUs worn on the shanks. Analyses were carried out on running trials captured with gold-standard pressure in-soles and wearables developed in-house. Hardware development details are also provided. Investigations on the most effective ANN architecture provided useful insights for portability to low-power devices and extension to open-field scenarios.

II. Methods

A. Hardware Platform

The developed hardware platform (Figure 1) measures 50 × 90 × 10 mm and is equipped with a high-performance low-power 32-bit microcontroller, a 9 DOF inertial sensor, a Bluetooth low-energy transmitter, and a removable micro SD card for data storage. The sampling rate is at 238 Hz.

B. Loadsol Pressure In-soles

The Loadsol system [15] measures vertical GRFs on the plantar surface of the foot in static and dynamic movements. Utilizing three flexible flat sensors (on front, mid, and rear foot) the system measures the force between the foot and the shoe (Figure 2), regardless of which part of the foot is in contact with the insole. The vertical component of the GRFs is computed from the overall pressure distribution. The system has been recently validated in a number of scenarios [16, 17]. Technical specifications involve a force range from 20 to

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2500N, sampling rate at 100 Hz, and Bluetooth communication for data transfer to a tablet.

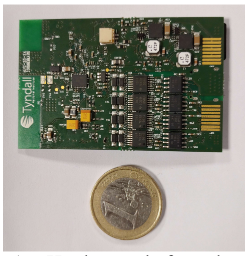

Figure 1. Hardware platform developed

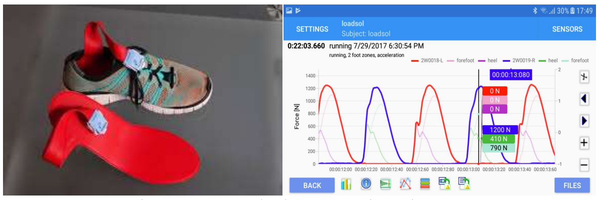

Figure 2. Loadsol pressure in-soles [15]

C. Participants and Data Collection

In order to evaluate the GRF estimation algorithms, fourteen healthy volunteers were recruited from Tyndall National Institute, community groups and social clubs (14 subjects; 10 males; mass 70±8 kg; age 29±3.4 years). Participants were excluded if they reported any previous musculoskeletal disorder. Recruits were between 20 to 40 years of age and able to comfortably run on a treadmill. Participants were asked to attend a single session and run on a treadmill at different speeds (8, 10, and 12 km/h) for approximately 30s per recording. Each participant was fitted with two IMUs attached on the lateral side of the shanks with elastic bands and with a pair of shoes (same model) with the pressure in-soles. Kinematics and kinetics were stored on the IMUs and the tablet used to interact with the pressure in-soles, respectively. For each recording, accelerations for each shank were logged, along with the vertical GRFs for each leg. Data from IMUs and pressure in-soles (Figure 3) were synchronized manually in post-processing using a recognizable event (a vertical jump generating a spike in both foot pressure and acceleration signals) as a reference for alignment.

Accelerometry data was filtered with a low-pass, second order, zero-phase shift Butterworth filter with cut-off frequencies of 15 Hz. Angular velocity was used for the automatic segmentation of the recorded trials by detecting the toe-offs and heel-strikes. A threshold of 20 N in the vertical component of the GRFs was also employed for the identification of the same events. Vertical linear accelerations and GRFs were both scaled to 100 data points from heel-strike to toe-off and GRFs were additionally normalised to body weight (BW). Overall, 42 running trials of 30s and 60-70 stance phases each were used for the analysis.

The study received approval by the Clinical Research Ethics Committee at the University College Cork.

D. Artificial Neural Network

A feed-forward ANN was developed in Python 3 (Python Software Foundation, Delaware, US) using the Tensorflow source-platform. The model was fed with the vertical linear local component of the acceleration signal of each stance and was trained to estimate the vertical GRF component. The ANN consisted of an input layer of 100 neurons, a hidden layer whose neurons adopt *tanh* as the activation function and dropout as a regularization method, and an output layer with 100 linear neurons generating predictions scaled to 100 data points. Root mean square error (RMSE) was used as loss function to compare predicted and measured values. Backpropagation and Adam optimizer were used for training.

The dataset was randomly split into training, validation and test sets (8, 3 and 3 subjects, respectively). A grid search on the training set attained optimal values for the following hyper-parameters: number of training epochs (1000 or 2000), batch size (128 or 256), and dropout rate (0.2 or 0.5). For each combination of hyper-parameters' values, a leave-one-subject-out cross-validation (LOSO-CV) was carried out. The combination of hyper-parameters that returned estimates with the lower mean RMSEs was considered as the optimum. To demonstrate that the networks were able to generalize their predictions with the selected set of hyper-parameters' values, the generated models were evaluated using the validation set.

Consecutively, training and validation sets were merged into a single new training set (11 subjects), a LOSO-CV re-trained the ANN model, and the validation errors were calculated. RMSEs evaluated the predictions of the final test set (3 subjects) and errors were grouped based on running speed. The analysis was repeated for three different number of neurons in the hidden layer (3, 5, 10), and when using PCA, for several principal components (3, 5, 8, 10, 15, 20, 25, 50).

E. Ground Reaction Forces Metrics

Four vertical GRF metrics, easily extrapolated from the vertical GRF waveform and commonly reported in the literature, were also investigated. They include the vertical GRF active and impact peaks, the VALR (vertical average loading rate), and the vertical GRF impulse. Further details on these can be found in [14]. When the vertical impact peaks were not visible, they were timed at 13% of the stance [18].

III. Results and Discussion

Table I summarizes the performance of the model using only ANNs. The architecture adopted in [13] was used as a reference and a different number of hidden layer neurons was tested. Due to the dropout regularization, the different models present similarities at all speeds. RMSEs were comparable to those reported in [13], e.g., mean test error (all speeds, 10 neurons) was 0.148 BW vs 0.134 BW in [13]. Figure 4 (top) shows the predicted and measured body-weight normalized vertical GRFs averaged for all the stances of the test set at separate running condition (8, 10, 12 km/h). It is evident that predictions were highly precise for all running speeds.

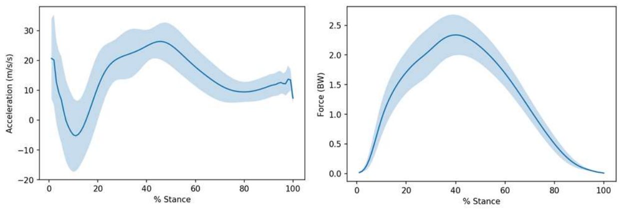

Figure 3. Accelerations and vertical GRFs envelopes (training data)

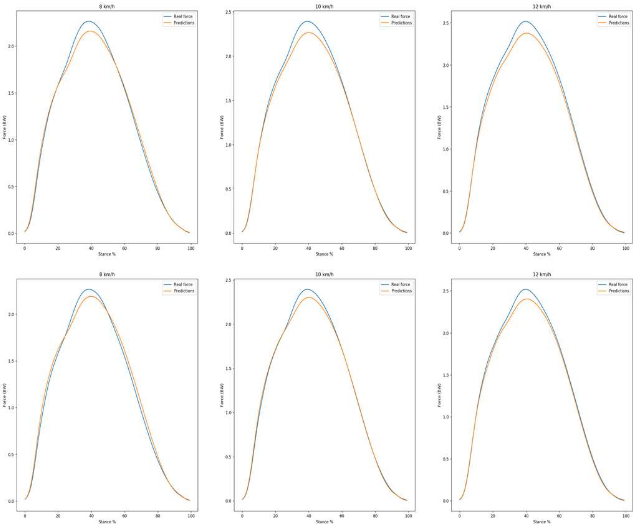

Figure 4. Predicted GRFs (orange) vs Actual GRFs (blue): (top) ANN model (10 neurons), (bottom) ANN + PCA model

TABLE I. ANN PERFORMANCE

# Neurons Hidden Layer	*Training Error [a]*	*Test Error [a] (8 km/h)*	*Test Error [a] (10 km/h)*	*Test Error [a] (12 km/h)*	*Test Error [a] (all speeds)*
3	0.25 (0.06)	0.136 (0.01)	0.13 (0.02)	0.166 (0.04)	0.146 (0.03)
5	0.255 (0.06)	0.127 (0.02)	0.143 (0.025)	0.17 (0.04)	0.149 (0.03)
10	0.248 (0.06)	0.13 (0.026)	0.136 (0.017)	0.17 (0.03)	0.148 (0.024)

a. Training/Test errors expressed in RMSE BW mean (standard deviation)

Figure 4 (bottom) shows the results of the best ANN + PCA model (10 hidden layer neurons and 10 principal components). Figure 5 shows an example of the performance of the models evaluated in the grid search for different principal components. The grid search returned an average training error on the initial 8 subjects from 0.239 to 0.265, with the best option being the 10 principal components, while the impact of the hidden layer size was limited (Table II).

Evidently, results with and without PCA were largely similar (Tables I and II). However, slightly better performance was obtained with PCA at low-moderate speeds, with a performance decrease at 12 km/h. Nevertheless, the ANN + PCA model relies on only 1210, 655, and 433 weights (with 10, 5, 3 hidden neurons, respectively), against the 2110 weights of the ANN-only model (i.e. a reduction of 57%, 31%, and 20.5%, respectively, with limited loss of performance), facilitating the implementation on low-power.

TABLE II. ANN + PCA BEST MODEL PERFORMANCE

# Neurons Hidden Layer	*# Principal Components*	*Training Error [a]*	*Test Error [a] (8 km/h)*	*Test Error [a] (10 km/h)*	*Test Error [a] (12 km/h)*	*Test Error [a] (all speeds)*
10	10	0.249 (0.068)	0.125 (0.018)	0.132 (0.013)	0.172 (0.03)	0.146 (0.02)
5	10	0.248 (0.07)	0.127 (0.015)	0.125 (0.017)	0.17 (0.044)	0.143 (0.027)
3	10	0.252 (0.068)	0.129 (0.024)	0.13 (0.015)	0.175 (0.04)	0.148 (0.027)

a. Training/Test errors expressed in RMSE BW mean (standard deviation)

TABLE III. GROUND REACTION FORCES METRICS

Metrics	*ANN Model (all speeds)*	*ANN + PCA Model (all speeds)*	*Actual Result (all speeds)*
Impact Peak (BW)	1.17 (0.17)	1.21 (0.14)	1.17 (0.13)
Active Peak (BW)	2.28 (0.09)	2.31 (0.10)	2.41 (0.15)
VALR (BW/s)	10.77 (1.74)	11.15 (1.5)	10.59 (1.31)
Impulse [a] (BW*s)	124.47 (5.42)	126.6 (4.24)	127.9 (7.95)

a. Time-normalised signal was used for integration

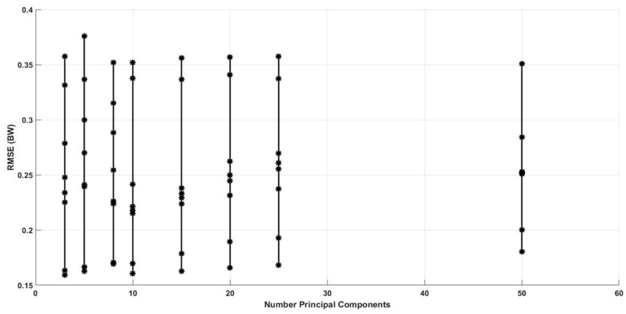

Figure 5. Example of models performance during grid search. RMSE training error (for each subject) plotted vs the number of principal components (neurons in the hidden layer set to 10)

Finally, Table III shows the impact of the developed models on the estimation of GRF-related metrics. The ANN-only model tends to be more accurate on the impact GRF peak with low errors also on the VALR; however, errors were higher on active peak and impulse values. The largest error among the metrics was 5.4% (active peak). The ANN+PCA shows, instead, higher accuracy on the active rather than the impact peaks (largest error: 5.3% for VALR).

The present study explored the application of ANN models in the estimation of runners' vertical GRFs based on the accelerometry collected from two wearable IMUs built in-house and attached on the shanks of the runner. Findings indicate that our models may be used to accurately estimate vertical GRF waveforms and loading metrics in running. The successful combination of the developed ANNs with a wearable system may allow the estimation of GRFs to be extended to open-field applications. However, this study presents some limitations: the number of recruits was limited and with no musculoskeletal injuries; hence, it is impossible to indicate if the system could generalize well to injured subjects. Moreover, even though the Loadsol pressure in-soles have been shown to have performances similar to gold-standard force platforms [16, 17], their reduced sampling rate (100 Hz) may be a limiting factor in the estimation of high-speed activities.

IV. CONCLUSION

This study reports on the potential application of ANN and PCA models with accelerometry for the accurate estimation of vertical GRFs in running. The predictions were accompanied with notably low errors, especially at lower speeds. Moreover, the results show the feasibility for the portability of the models to low-power resource-constrained devices with limited impact on the overall performance. With the use of IMUs being on the rise, the presented combination of ANN and wearables may potentially lead to the widespread measurement of biomechanical loads in open-field.

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