NEURAL NETWORK METHOD TO PREDICTING STANCE-PHASE GROUND REACTION FORCE IN DISTANCE RUNNERS

Alec C. Miller, Marwan Aljohani, Hoon Kim, and Kristof Kipp

Department of Physical Therapy, Marquette University, Milwaukee, WI, USA

The purpose of this study was to use machine learning (artificial neural network – ANN) to predict vertical ground reaction force (vGRF) from tibial accelerations in runners with various foot strike patterns and running speeds. Thirty-eight healthy runners ran at a pace at which they spent most of their training time (LSD), 15% faster than LSD (LSD15), and 30% faster than LSD (LSD30). vGRF and IMU-based accelerations from the tibia were collected during the last 30 seconds at each speed and were used to calculate the resultant tibial acceleration (RTA). Stance-phase vGRF and RTA from 34 subjects from all speeds were used to train the ANN. Trials from two males and two females were used to test the ANN. The prediction error of the ANN was 102.4 N (1.6 N/kg or 0.16 BW) across the entire stance phase of running. The ability to predict GRF with an ANN and only RTA as input appears to be practical and feasible.

KEYWORDS: distance running, machine learning, biomechanics, wearable technology

INTRODUCTION: Running is a popular mode of exercise in the United States. Unfortunately, up to 79% of runners experience some type of running related injury every year (van Gent et al., 2007). Ground reaction forces (GRF) and rate of loading (ROL) are measures that have been linked to running related injuries (Hreljac, 2004). These measures require force plates or pressure-instrumented treadmills to collect GRF and calculate ROL. This equipment can be expensive and often inaccessible for most clinicians.

The GRF experienced by the body is a sum of the products of all segmental accelerations and their respective masses. Recent research suggests that data from up to six segments may be needed to accurately predict GRF during running with linear regression models (Verheul et al., 2018). There is also evidence that a two-mass model can be used to sufficiently predict GRF during sprinting (Clark et al., 2017). However, these models use video data as input, which may require expensive motion capture systems and additional data processing. Wearable technology, like inertial measurement units (IMU), can collect segmental accelerations and may present an affordable alternative to calculate GRF (Wundersitz et al., 2013).

Recently artificial neural networks (ANN) have been used to predict peak GRF during running from biomechanical data, which included IMU-based accelerations (Niemela et al., 2017). In addition, other authors used ANN to predict stance-phase GRF during running from either single or multiple IMU (Jie-Han et al., 2018 & Wouda et al., 2018). These results suggest that ANN can predict GRF with only a single-segment of tibial acceleration. It would be of interest, however, to determine if the prediction accuracy of ANN extends to different populations of runners (e.g., based on foot-strike pattern) and across different speeds. The purpose of this study was to train an ANN to predict vertical (vGRF) from tibial accelerations in male and female runners with different foot strike patterns and at different running speeds.

METHODS: The current study was approved by the IRB at Marquette University. Participants were informed of the study's purpose and signed an informed consent document before participation. Thirty-eight healthy runners (18 males and 20 females; age 23 ± 3 years; height 171 ± 9 cm; weight 64 ± 9 kg; reported average weekly mileage 52 ± 25 km/week) were recruited. All participants ran at least 16 kilometers per week, had no history of lower extremity surgery, and were free of musculoskeletal injury over the previous 6 months.

An IMU (Delsys Inc., MA, USA) was securely attached to the medio-distal tibia of the participant's dominant leg and were asked to run on a pressure-instrumented treadmill (Noraxon Inc., AZ, USA) at the speed where they spend most of their training time (i.e., their long-slow distance pace – LSD). Participants were allowed a five-minute warm-up at their approximate LSD speed. Participants then ran at three different speeds: LSD, 15% faster than LSD (LSD15), and 30% faster than LSD (LSD30). Participants ran at each speed for approximately 2 minutes. vGRF and tibial accelerations were collected during the last thirty seconds of each speed. Data were acquired and synchronized through a Vicon motion capture system (Oxford, UK).
Filter cutoff frequencies for vGRF and tibial accelerations were determined with residual analysis (Winter, 2009). Data were filtered with a dual-pass, fourth order low-pass Butterworth filter at cutoff frequencies of 13 Hz and 16 Hz, respectively. Triaxial accelerations of the distal tibia were used to calculate the resultant tibial acceleration (RTA – Equation 1).

$$RTA = \sqrt{X^2 + Y^2 + Z^2} \text{ (Equation 1)}$$

The stance phase during running was defined as the interval between heel strike and toe-off, which were defined off a 10 N vGRF threshold. RTA and vGRF from the stance-phase of ten strides were time-normalized and averaged.
A four-layer feed-forward ANN with sigmoid transfer functions between the input-hidden layer and hidden-hidden layer, and a linear transfer function between the hidden-output layer was developed with the Neural Network Toolbox in MATLAB (Mathworks Inc., MA, USA). Levenberg-Marquardt backpropagation was used to adjust the network's weights and biases. The training goal was set to the smallest worthwhile change squared ($SWC^2 = (0.2 * SD_{vGRF})^2$) and half of SWC^2 (558.8 and 279.4, respectively). The minimum performance gradient was set to SWC/100 (0.237). Initial mu was set at 0.001, with a decrease factor of 0.1, increase factor of 10, and maximum value of 1^{10}. Training was allowed for 1000 epochs and no time limit. Maximum validation fail was set to 20 epochs. The number of neurons in the hidden layers were systematically changed from five to 20 in increments of five. A total of 12 network configurations were thus developed and tested.
Average stance-phase vGRF and RTA from 34 subjects (16 males and 18 females; height 171 ± 8.6 cm; weight 64.1 ± 9.2 kg; 24 rearfoot strike runners; LSD speed 2.97 ± 0.49 m/s) at all three speeds were used to train the ANN. Trials from two males and two females, who exhibited different foot-strike patterns, were used to test the ANN. Each ANN configuration was trained ten times to account for the random initiation of the network weights and biases. The ANN was then tested on the trials from the four runners who were withheld for testing (table 1). The performance of the network was assessed by the root mean squared error (RMSE) between test subjects' predicted and actual vGRF for each of the 120 neural networks. Data from the ANN that yielded the lowest RMSE during testing was reported and used for further analysis. The correlation coefficient between the actual and predicted vGRF was calculated, differences between test subjects' actual and predicted peak vGRF from each speed were assessed with a related samples t-test, and percent differences between subjects' actual and predicted peak vGRF were calculated and reported.

Table 1: Test Subject Demographics

Subject	Sex	Height (cm)	Weight (kg)	Dominant Leg	Footstrike Pattern	LSD Speed (m/s)	LSD15 Speed (m/s)	LSD30 Speed (m/s)
1	Female	159	52.16	R	Rearfoot	2.73	3.13	3.53
2	Female	160	52.62	R	Midfoot	2.37	2.73	3.08
3	Male	173	55.79	R	Rearfoot	3.22	3.71	4.2
4	Male	173	69.4	R	Forefoot	3.04	3.49	3.93

RESULTS: LSD, LSD15, and LSD30 speeds were 2.95 ± 0.48, 3.39 ± 0.56, 3.84 ± 0.62 m/s, respectively. The ANN with ten hidden nodes in both hidden layers and a training goal of half of

SWC² produced the smallest test RMSE (training RMSE: 77.8 N; validation RMSE: 127.7 N; testing RMSE: 102.4 N). Strong linear correlations between actual and predicted vGRF were found for training (*r*: 0.974; $p < 0.01$) and testing (*r*: 0.967; $p < 0.01$) (figure 1) subjects. No significant differences ($t = -0.23$; $df = 11$; $p = 0.82$; $d = -0.07$) were found between test subjects' actual and predicted peak vGRF, and the average difference between actual and predicted peak vGRF were 0.25 ± 0.19 BW (13.9 ± 11.7 percent error).

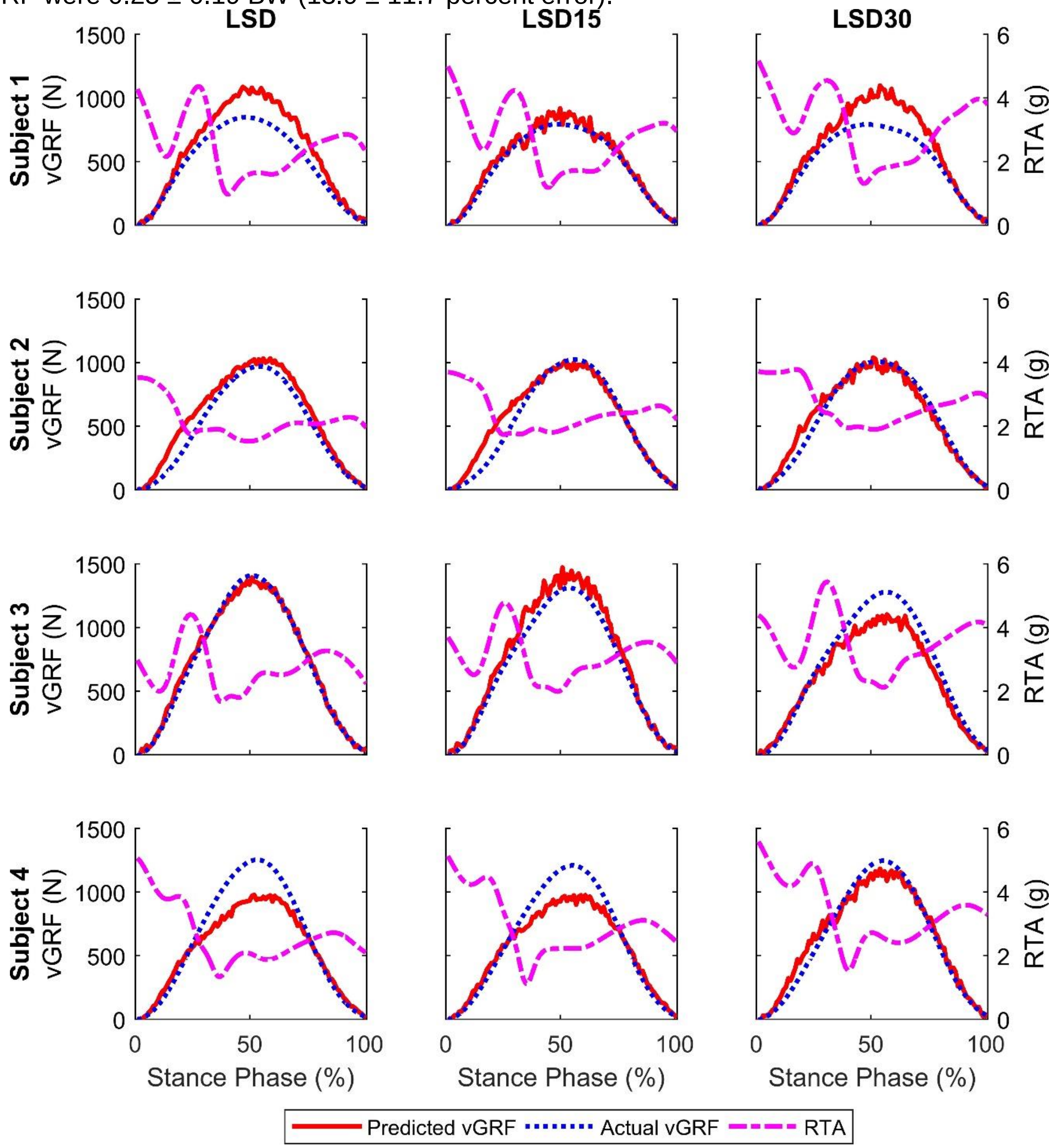

Figure 1: Predicted vGRF (red), actual vGRF (blue), and RTA (magenta) of test subjects 1 (top row), 2 (second row), 3 (third row), and 4 (last row) during LSD (first column), LSD15 (second column), and LSD30 (last column).

DISCUSSION: The purpose of this study was to train an ANN to predict vertical (vGRF) from tibial accelerations in male and female runners with different foot strike patterns and at different running speeds. The goal of this study was to create an ANN that could generalize to different types of runners (e.g., different foot strike patterns). The prediction error of the ANN was 102.4 N (1.6 N/kg or 0.16 BW) across the entire stance phase of running. The magnitude of this error is small, as compared to other studies of slow- and moderate-speed running where errors of 1-3 N/kg were reported based on predictions from full-body segment accelerations (Verheul et al., 2018). In addition, the average difference between actual and predicted peak vGRF (0.25 ± 0.19 BW) is slightly larger compared to other predictions of peak vGRF from ANN that used only discrete variables as inputs (Niemela et al., 2017), which suggests that the current ANN performed on par with other GRF prediction models reported in the literature.

The way in which subjects are grouped may have large influence on the performance of a neural network. A study by Jie-Han and colleagues used a two-layer feed-forward neural network to predict vGRF from uniaxial foot accelerations with high accuracy (Mean RMSE: 0.015 BW; average *r*: 0.99) (Jie-Han et al., 2018). However, Jie-Han et al. (2018) randomly chose validation and testing data, where there were 90 vGRF time-series per subject, which means that their network was both trained and tested on GRF profiles from the same subjects. A network with an exclusive testing data set may decrease the prediction performance, but may also be more practical for predicting vGRF of new subjects in a clinic or lab.

Using a population with large variability as a source for the training data set may also limit the prediction accuracy of the neural network. A study by Wouda et al. (2018) used IMUs from the sacrum and both tibias to predict vGRF of both legs with the use of an ANN. When the network was tested on a representative subject, accuracy of the network (Left and Right leg RMSE: 0.26 and 0.32 BW; *r*: 0.978 and 0.950) decreased when compared to a subject-specific neural network (Left and Right leg RMSE: 0.10 and 0.09 BW; *r*: 0.997 and 0.997). While a generalizable network may be more convenient for quick vGRF estimation, a network trained on data only from the subject being tested will provide greater accuracy.

CONCLUSION: The ability to predict GRF with an ANN and only RTA in a population with large variability appears to be practical and feasible. The use of only one IMU allows quick and easy predictions of vGRF in large-group training settings. However, a model with large generalizability may also increase prediction errors, which may not be ideal for clinical assessments, such as return-to-sport testing. Future studies may want to determine if subject-specific models improve the accuracy of vGRF prediction and validate these models in over-ground running.

REFERENCES

Clark, K.P., Ryan, L.J., & Weyand, P.G. (2017). A general relationship links gait mechanics and running ground reaction forces. *Journal of Experimental* Biology, 220, 247-258.

Hreljac, A. (2004). Impact and overuse injuries in runners. *Medicine and Science in Sports and Exercise, 36,* 845-849.

Jie-Han, N.K., Gouwanda, D., & Zheng, C.Y. (2018). Estimation of Vertical Ground Reaction Force during Running using Neural Network Model and Uniaxial Accelerometer. *Journal of Biomechanics, 76,* 269-273.

Niemelä, M., Kulmala, J.P., Kauppi, J. P., Kosonen, J., & Äyrämö, S. (2017). Prediction of active peak force using a multilayer perceptron. *Sports Engineering, 20*, 213-219.

Van Gent, R.N., Siem, D., van Middelkoop, M., Van Os, A.G., Bierma-Zeinstra, S.M.A., & Koes, B.W. (2007). Incidence and determinants of lower extremity running injuries in long distance runners: a systematic review. *British Journal of Sports Medicine, 41*, 469-480.

Verheul, J., Gregson, W., Lisboa, P., Vanrenterghem, J., & Robinson, M.A. (2018). Whole-body biomechanical load in running-based sports: The validity of estimating ground reaction forces from segmental accelerations. *Journal of Science and Medicine in Sport,* epub ahead of print.

Winter, D.A. (2009). Biomechanics and motor control of human movement. John Wiley & Sons.

Wouda, F.J., Giuberti, M., Bellusci, G., Maartens, E., Reenalda, J., Van Beijnum, B.J.F., & Veltink, P.H. (2018). Estimation of Vertical Ground Reaction Forces and Sagittal Knee Kinematics During Running Using Three Inertial Sensors. *Frontiers in Physiology, 9*, 218.

Wundersitz, D.W., Netto, K.J., Aisbett, B., & Gastin, P.B. (2013). Validity of an upper-body-mounted accelerometer to measure peak vertical and resultant force during running and change-of-direction tasks. *Sports Biomechanics, 12*, 403-412.