Prediction of running anteroposterior ground reaction forces from the vertical component through a deep learning approach: A preliminary study

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Summary

Studying ground reaction forces is essential for *in situ* running analysis; however, current reference disposals cannot be applied through ecological conditions. Recently, a size-adjustable instrumented track has been developed to measure vertical component of ground reaction forces out of the lab. This study aims to develop a neural network approach for predicting the anteroposterior component based on the measured vertical component as input. A public dataset of 9 500 running steps was used to train, validate and test the prediction model. Results showed that a convolutional neural network allows to predict the anteroposterior component with accuracy (relative Root Mean Square Error = 4.87 %). Thus, this model may be further applied to the size-adjustable instrumented track.

Introduction

Ground Reaction Forces (GRF) are crucial measurements for studying activities involving ground locomotion, particularly in running. Indeed, vertical GRF (vGRF) and anteroposterior GRF (AP-GRF) are frequently analyzed to monitor athletic performance [1]. While force plates are the most precise tools for measuring GRF, their high cost and limited recording area often restrict their use to laboratory settings. To overcome these limitations, researchers are currently developing innovative devices to measure GRF during ecological activities. For example, a size-adjustable instrumented track was recently developed to measure vGRF on 10 meters long [2]. Additionally, deep learning approaches have shown promising results in predicting GRF using accelerometer [3] or pressure insoles data as inputs [4]. However, accuracy of prediction could depend on variables as subject technique [4] or running velocity [5]. The objective of this study is to evaluate the performance of a Convolutional Neural Network (CNN) when predicting AP-GRF from vGRF while running at different velocities.

Methods

A public dataset consisting of nineteen participants (10 males, 9 females) running at five speeds (2.78, 3.0, 3.33, 4.0, and 5.0 $m \cdot s^{-1}$) on an instrumented treadmill (CAREN, Motek, The Netherlands) was used to train, validate, and test the prediction model [5]. The GRF data were preprocessed using a zero-lag, fourth-order Butterworth filter with a low-pass cutoff at 20 Hz. Steps were identified using a 20 N threshold, normalized by body weight. For each subject at each speed, 100 steps were selected, resulting in a total of 9,500 steps. These steps were randomly split into 70% for training, 15% for validation, and 15% for testing. The CNN prediction model was evaluated by computing root mean square error (RMSE), the RMSE relative to the signal amplitude (rRMSE) and the pearson correlation coefficients between measured and predicted data. Additionally, a complementary analysis examined the prediction accuracy of the model depending on running velocity.

Results and Discussion

All AP-GRF predictions exhibited significant correlations ($p<0.001$) with measured values, with a mean Pearson correlation coefficient of 0.99. The mean RMSE and rRMSE between the predicted and measured AP-GRF values was respectively of 21.71 ± 10.52 N and 4.87 ± 2.38 %. Running velocity (Figure 1) had no impact on the accuracy of the AP-GRF prediction. Therefore, AP-GRF prediction appeared robust under all conditions.

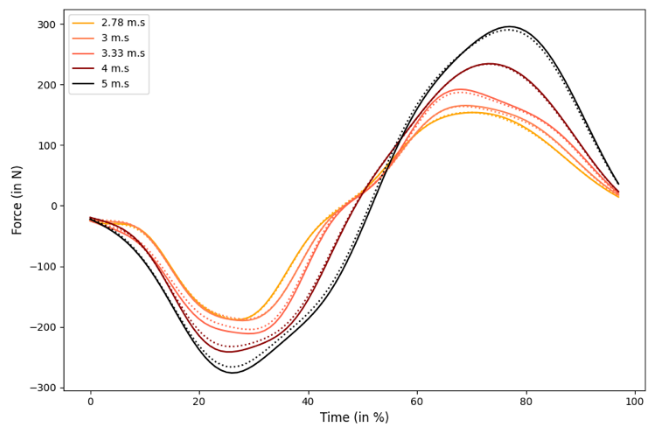

Figure 1 : Mean measured (solid line) and predicted AP-GRF (dashed line) depending on the running velocity.

Conclusions

Results from this study provide valuable insights for further research into predicting GRF components from measured data. Future studies should explore the transferability of this neural network-based approach when applied to measured data from ambulatory device, like a size-adjustable instrumented track [2].

References

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