Estimating ground reaction forces in dynamic sports movements using instrumented insoles and deep learning

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Summary

The present study leverages deep learning to capture the relationship between an instrumented insole and force plate data and demonstrates the ability to estimate vertical ground reaction forces in seven sports movements based on the insole.

Introduction

Ground reaction forces (GRFs) are often measured in biomechanical laboratory settings to optimize athletic performance and estimate mechanical loads experienced with modeling packages [1]. Researchers have attempted to capture such information using instrumented insoles in combination with deep learning for walking and running to extend the measurements beyond the laboratory due to financial and technical restrictions of force plates [2,3]. While team-sport movements (e.g., changing speeds and directions) have demonstrated the association with high impact and repetitive external loads experienced by athletes [1], the capacity of deep learning with instrumented insoles is yet to be explored to estimate GRFs during dynamic movements featuring rapid force development and high magnitude. Hence this study aims to use instrumented insole data to estimate the vertical GRF for both cyclic (linear) and changing of direction (non-linear) movements in team sports.

Methods

14 healthy collegiate sport players performed 10 trials of walking, jogging, fast running, accelerating, decelerating, cutting (135 deg) and turning (180 deg with right foot pivoting) with their right foot landing on a force plate (1500Hz). A pair of commercial instrumented insoles (SportScientia Ltd., UK) with 9 Force Sensitive Resistors (FSRs) and an Inertial Measurement Unit (IMU) on each side (460Hz) were inserted under the original insoles. Insole data were upsampled to 1500Hz to synchronize with force plate data by cross correlating the insole's pitch velocity with an external IMU (attached to the lateral side of right shoe) that was hard synchronized with the force plate through a Vicon Nexus interface. Each trial was trimmed to stance only and time-normalized to 500 datapoints. A bi-directional long-short term memory (LSTM) model with attention mechanism was built to capture the temporal relationship between 9 FSR channels, 6 IMU channels, and bodyweight as inputs, and vertical GRF (vGRF) as output across all movements. All inputs from 10 participants were Min-Max scaled for training and a K-fold (K=5) cross validation with Mean Square Error as the loss function were implemented during model training. The estimated vGRF results were tested against those measured in the remaining 4 participants. Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2) were used to assess model performance.

Results and Discussion

The group mean pattern of vGRF curves were generally captured well for all movements. The greatest difference was found in jogging (0.3 BW) at the active peak. The model underestimated active peaks for jogging, running and accelerating, which possibly can be addressed by adding a penalty term in the current loss function to penalize poor predictions at peak values. This underestimating behavior was also observed in a similar study [2]. The similar RMSE but decreased R^2 in decelerating, cutting and pivoting can likely be explained by the greater variabilities between participants. This could also be attributed to the training and test datasets that were not generalized enough, which warrants the need for more training data. Furthermore, various data processing approaches (e.g., signal filtering, time normalization) can influence the model's performance and therefore will be scrutinized in further work.

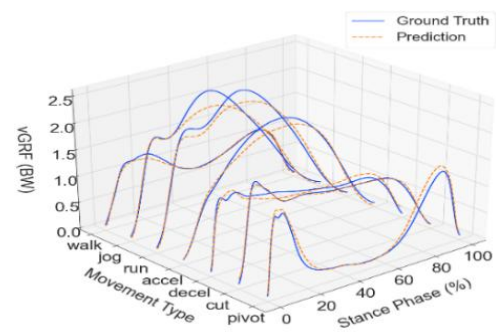

Figure 1: Averaged vGRF between ground truth and prediction.

Table 1: RMSE with standard deviation and R^2 for each movement.

	RMSE ± SD (BW)	R^2
Walking	0.08 ± 0.02	0.93
Jogging	0.18 ± 0.04	0.94
Running	0.17 ± 0.06	0.96
Accelerating	0.17 ± 0.07	0.94
Decelerating	0.19 ± 0.06	0.78
Cutting	0.20 ± 0.07	0.83
Pivoting	0.17 ± 0.04	0.89

Conclusions

The current LSTM model could accurately estimate vGRF across different movements, although further model regularization and individual evaluation is required.

References

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