Estimation of Resultant Knee Joint Moments in Elite Rugby Players During Cutting Maneuvers Using Wearable Sensors

Zixiang Gao, Robin Trama, David McNish, Darren J. Stefanyshyn, John W. Wannop
Human Performance Laboratory, Faculty of Kinesiology, University of Calgary, Calgary, Canada
Email: zixiang.gao@ucalgary.ca

Summary

Wearable pressure insole sensors demonstrated the ability to accurately estimate knee resultant joint moments (JM) during high-risk movements performed by elite rugby players using machine learning (ML) techniques.

Introduction

Rugby is a popular sport worldwide, with the majority of injuries occurring on the lower extremity. Within these lower extremity injuries, knee joint injuries, particularly anterior cruciate ligament (ACL) injuries, are highly prevalent [1]. Elevated knee joint moments have been linked to a heightened risk of musculoskeletal injuries. However, obtaining JM outside of a laboratory setting remains challenging.

Previous studies have employed in-shoe pressure systems (IPS) with ML techniques to estimate ankle JM during cyclic movements, achieving promising conclusion [2]. Whether this approach can accurately predict knee JM during complicated high-risk movements in rugby remains to be determined.

Methods

31 elite rugby players from North America (8 Male, 23 Female) were recruited for this study to perform a 90° V-cut movement on an infilled artificial turf surface (FieldTurf) embedded with a force plate (Kistler). IPS data (Xsensor, *n=235*) were collected synchronously with lower extremity kinematics (Vicon) and kinetics across 135 trials in total. The kinematic and kinetic data was used to calculate the knee resultant JM (Visual3D).

The genetic algorithm-deep forest regression (GA-DFR) method was employed to optimize the plantar pressure sensor layout, with hyperparameter tuning conducted to identify the optimal parameters. The process has been detailed in previous research [2], with modifications made to better suit the characteristics of the current dataset and movement (Fig 1(a)). Additionally, SHAP (Shapley Additive Explanations) was employed to interpret the “black box” models. 5 classical data driven models: Long short-term memory (LSTM), Linear regression (LR), Deep neural network (DNN), Convolutional neural network (CNN) and DFR were used to predict knee resultant JM.

Results and Discussion

The optimized IPS layout (*n=16*) was primarily concentrated in the forefoot region (Fig 1(b)). Additionally, as shown in Fig 1(c), Data from the initial contact and push-off phase contributed the most to the machine learning model than mid-stance, indicating that these phases have the greatest direct impact on knee resultant JM.

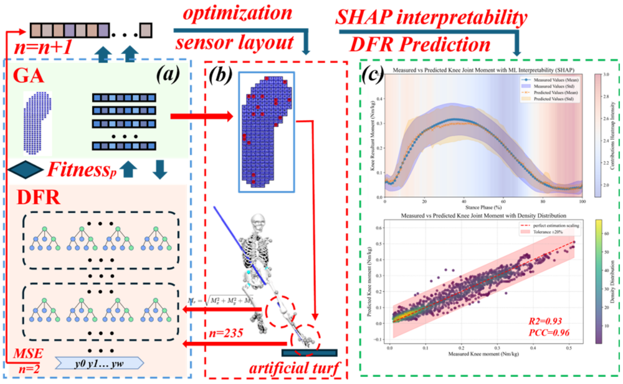

Figure 1: (a) GA-DFR optimization process. (b) Data collection, calculation and optima sensor layout. (c) Measured vs Predicted knee joint resultant moment with SHAP.

Table 1: Performance of knee resultant moment estimation using five data-driven models, evaluated with R^2, Pearson Correlation Coefficient (PCC), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE).

Model	R^2	*PCC*	*MAE*	*RMSE*
LSTM	0.8236	0.9112	0.0384	0.0512
LR	0.7718	0.8834	0.0469	0.0582
DNN	0.8913	0.9486	0.0313	0.0402
CNN	0.8574	0.9352	0.0334	0.0460
DFR	0.9262	0.9624	0.0028	0.0331

As shown in Table 1, a comparison of the performance across 5 various ML models revealed that the DFR model achieved the best performance (*R2=0.93, PCC=0.96*), this finding highlights the potential of deploying such models in wearable systems for real-time biomechanical feedback during training and competition out of laboratory [3].

Conclusions

The GA-DFR model developed in this study can accurately predict knee resultant JM in rugby elite players during high-risk movements. These findings can provide a valuable foundation for designing training programs and developing systems for monitoring knee joint load in rugby players during practice and game activities.

Acknowledgments

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References

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