Modelling and Prediction of Rugby Tackling Impact Force via Physics-Informed Machine Learning

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Summary

In this study we developed and validated the first physics-informed machine learning model that predicts collision force in Rugby Union tackles from kinematics data. A state-space Latent Force Model trained on staged tackle data demonstrated promising force estimates, with an average error of 314 N (9.5%). This is an encouraging starting point towards the adoption of physics-informed machine learning solutions in sport performance and injury prevention as it enables the objective measurement of external mechanical load experienced by players only from video footage.

Introduction

Accurate impact force prediction in Rugby Union is crucial for monitoring player load and informing injury prevention strategies. Data-driven approaches can be an alternative to mechanistic solutions, such as musculoskeletal modelling, for force prediction. However, data-driven methods can perform poorly with unseen data, and mechanistic solutions may fail to accurately represent a complex system even if all physical components are correctly described. In this study we aimed to develop and validate a *hybrid* approach that combines the *data-driven* and *mechanistic* views to learn the complex underlying physics of rugby tackles in the form of ODEs using machine learning.

Methods

Data from 10 participants performing 4 staged dynamic tackles against a moving punching bag (front and 45-degree tackles on both sides) were retrieved from [1]. Marker data scaled the Rugby Model [2] in OpenSim 4.4 for Inverse Kinematics. Pressure sensors mounted on the punching bag reconstructed impact force magnitude [3]. Three-dimensional coordinates for the head center of mass and shoulder, elbow, wrist, hip, knee and ankle joint centres alongside impact forces were used to train a custom state-space Latent Force Model [4]. The 40 variables were modelled as a system of second-order linear ODEs, driven by 25 unknown latent forces in the form of Gaussian Processes (GPs). The system was solved via linear Kalman smoothing. A leave-one-out approach was employed for testing, where trials from one participant were excluded from training to predict the impact forces. The latent force hyperparameters were learned independently per trial, while stiffness and damping parameters of each ODE and the correlation parameters between the ODEs and the latent forces were learned globally and shared across trials.

Results and Discussion

Mean RMSE over the entire force traces was 314.4 N ± 131.8 N (i.e. 9.5% ± 4.4%), while the mean RMSE for peak force was 485.5 N ± 334.9 N (i.e. 9.9% ± 6.1%). Figure 1 shows an example of a probabilistic solution produced at test time. As explained in [3], the original force magnitude reconstruction method from pressure data had a mean error of 320 N which may have added noise into the force traces and generated force values that are not dynamically consistent with the kinematics. This could explain the mean error of the physics-informed predictions.

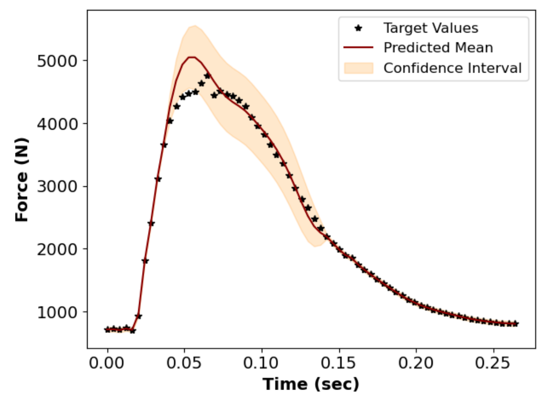

Figure 1: Representation of a solution produced at test time. The red line represents the mean of the GP, the shaded area shows confidence interval, and the black stars are the target values.

Future work will focus on training the model with dynamically consistent collision forces produced via tracking simulations.

Conclusions

We developed and validated the very first *hybrid* approach that integrates machine learning and ODEs and enables tackle force prediction only from kinematics. Our physics-informed model, unlike purely data-driven methods, allows extrapolation outside of the solution space learned through the training dataset. This is the first step to enable accurate and objective impact force estimation from video footage.

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References

[1] Seminati E. et al. (2017). *Sports Biomech*, **16**:1 58-75.
[2] Cazzola D. et al. (2017). *PLoS ONE*, **12**:1 e0169329
[3] Cazzola D. et al. (2014). *JSEng&Tech*, **228**:2 141-151
[4] Alvarez M. et al. (2013). *IEEE TPAMI*, **35**:11 2693-2705