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The use of inertial measurement units to evaluate the impact load at landing in high level female gymnasts

E. Jolas[a], R. Le Crolan[a,b], Mathieu Ménard[c] and D. Haering[b]

[a]Ecole Normale Supérieure de Rennes, Bruz, France; [b]Université de Rennes, Inria, M2S, IRISA – EA 7470, F-35000 Rennes ; [c]Institut d'Ostéopathie de Rennes-Bretagne, Bruz, France

1. Introduction

Gymnastics landings lead to a significant number of injuries that particularly affect high-level adult female gymnasts in the lower extremity (e.g. O'Kane et al. 2011). While the link between mechanical impact load and injury is debated in the literature, some studies have shown through modelling that reducing ground reaction forces (GRF) could contribute to reducing the risk of both acute and chronic injury (Mills et al. 2010). On this basis, the impact load caused by different gymnastics skills has often been estimated in studies by means of peak resultant GRF. However, this impact load is not easily assessed by "traditional" tools in a training context (e.g., force plate). Sensors such as inertial measurement units (IMU) could then be used as they are more portable, affordable, and less invasive. However, current studies have not been able to show an agreement between the peak resultant accelerations from an IMU positioned on the second thoracic vertebra and those from the force plate in gymnastics (correlation of 0.427; Bradshaw et al. 2020). Yet, estimating these GRF could inform coaches about the external loads experienced by gymnasts, but also potentially internal loads, e.g. joint reaction forces, through inverse dynamics. While machine learning has already been used to predict GRF using IMU data (e.g. Oh et al. 2013), this has never been investigated in gymnastics before.

Therefore, the aim of this study was to develop models for estimating the peak resultant GRF measured by the force plate on jumps and back somersaults using the different parameters measured by IMU positioned on different body parts, to choose the one bringing the best agreement with peak resultant accelerations from the force plate.

2. Methods

2.1 Protocol

Four adult competitive female gymnasts performed four experimental conditions in a random order: a jump to the force plate, a jump from a height of 40 cm with and without a 30 cm landing mat, then, a backward somersault from a height of 40 cm on a 30cm landing mat. Ten successful trials per condition were recorded (i.e., respecting the competition landing technique). Two force plates (AMTI®, Watertown, U.S.A. 500Hz) measured the GRF. Eight Delsys® IMU (Trigno Avanti Sensor, Delsys®, ±12g, Boston, U.S.A ; 500Hz as Bradshaw et al., 2020) were placed on several anatomical points of the body, on the trunk, the upper and lower limb to measure accelerations, angular velocities, and orientations (figure 1).

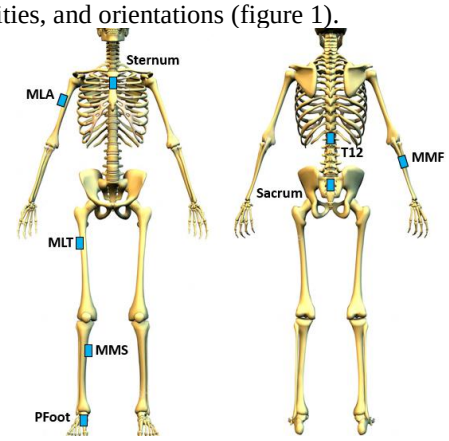


Figure 1: Placement of the eight IMU on the body

2.2 Data processing

Data processing and statistical analysis were performed using Spyder® software (Python Software Foundation, Fredericksburg, Beaverton, USA). The peak resultant GRF from the force plate expressed in body weight (BW) were taken for each trial in each condition. IMU data were filtered using a fourth-order Butterworth filter with a cut-off frequency of 85Hz (in agreement with the study by Campbell et al. 2020). IMU were synchronized using Dynamic Time Warping after resampling. The variables from the IMU available for use as model inputs were the peak on the x, y, z axes and peak resultant accelerations, angular velocities, and orientations.

2.3 Statistical analysis

Three IMU placements were selected for further analysis based on the good correlation of their variables with the target variable, indicating their importance, their impact in the models and thus in the prediction of the peak resultant GRF. As recommended by many data scientists (e.g. Géron, 2019), from these IMU, potential explanatory variables were standardized and reduced using Principal Component Analysis. Then, the data were randomly separated into two data sets, 80% of the data in the train-set, 20% in the test-set. Regression prediction models were trained with the train-set to predict the peak resultant GRF from the explanatory variables after selecting them.

These models were evaluated using Ten-Fold cross-validation (CV) to fix the hyperparameters of the algorithms used (e.g. Oh et al., 2013). Thus, seven regression models, selected in relation to the size of our dataset and based on previous studies (e.g. Géron, 2019) were compared for each of the IMU: linear

regression (LR), Ridge regression (Ridge), Lasso regression (Lasso), Decision tree (DT), Random Forest (RF), Support vector machine (SVM), K-nearest neighbors (KNN). Finally, meta-models were built using Stacking (i.e. Ensemble Learning), a meta-learning algorithm taking into account the predictions of previously built models in order to improve their performance. These different models were compared to each other on the test-set for each of the three IMU in order to identify the best performing model. For this, we used the adjusted R^2, the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the min-max normalized RMSE and MAE (in %) commonly used to evaluate models (e.g. Géron, 2019).

3. Results and discussion

The three IMU with the variables most correlated with the peak resultant GRF were positioned on middle lateral part of the thigh (MLT), proximal foot (between 2nd and 3rd tarsal; PFoot), middle medial part of the shank (MMS). The best performing models obtained for each of these IMU are shown in Table 1.

IMU placement	**PFoot**	**MLT**	**MMS**
Meta-learning algorithm (stacking)	Ridge	Ridge	RF
Constituting models	KNN, RF	KNN, LR	RF, SVM, Ridge
Adjusted R^2 Train-set	0.991	0.975	0.891
Adjusted R^2 Test-set	0.528	0.673	0.891
RMSE Test-set	1.13 BW 16.42 %	0.94 BW 13.68 %	0.55 BW 7.91 %
MAE Test-set	0.77 BW 11.12 %	0.67 BW 9.64 %	0.43 BW 6.25 %

Table 1: Evaluation of the best performing models in predicting the peak resultant GRF for each IMU

Thus, the position of the IMU on the body affects the prediction of GRF as hypothesized by Bradshaw et al. (2020). The best performing model on the test-set was obtained with MMS. Its performance reaches that of models created from kinematic data in the literature with %RMSE of 2.6±0.7%, 11.3±2.1% and 26.2±4.0%, correlations of 0.978 and 0.988, 0.736 (Oh et al. 2013), with %MAD of 4.6±0.7%, 4.0±0.8%, 10.5±3.3% and correlations of 0.97, 0.98, 0.80 (Leporace et al. 2018) for prediction of GRF on the anteroposterior, vertical and lateral axes during walking, using neural networks. However, the small number of data available for each variable in our study (n=142) does not allow us to state that the model built from MMS would obtain the same performance from a new dataset. In addition, after further analysis, the performance of this model differs according to the gymnastic skills, i.e. the experimental conditions performed.

4. Conclusions

The use of Machine Learning models could provide fairly accurate predictions of the peak resultant GRF when the IMU is positioned on the tibia for basic jumps in gymnastics. However, this constructed model, although quite accurate, shows variable performance depending on the gymnastic skills performed and needs to be improved by further testing, with more data and experimental conditions before it can be practically used by coaches. The use of IMU in gymnastics could eventually help them to manage the training load of gymnasts, reduce their risk of injury and consequently increase their performance.

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***Corresponding author. Email: elisa.jolas@ens-rennes.fr**