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Prediction of lumbar fatigue during gymnastics landings using statistical modelling and *Machine Learning*

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1. Introduction

Gymnastics, and more specifically landing, is associated with a high rate of injuries, particularly to the back. This is due to the fact that landing involves strong ground reaction forces as well as important body rotations, hence as a result of repetitive landing, these movement patterns can lead to significant muscle fatigue, which increases the risk of injury (Campbell et al., 2019). Fatigue influences kinematics during repetitive movements such as drop jumps or crate lifting by decreasing hip and knee flexion angles and increasing trunk instability through a greater shift in centre of mass (Kazemi et al., 2021). Under laboratory conditions, muscle fatigue is usually measured by EMG (Thrope et al., 2017). However, incorporating EMG measurement into everyday training is difficult, it requires a fair amount of money, proper setup time and data processing. Thus, considering that fatigue affects kinematics, motion capture seems to be another possible way to measure athlete's fatigue. Coupling this tool with *Machine Learning* models would also reduce analysis time. This would further reduce the workload of the athlete.

The main objective of this study is to predict the fatigue in the lumbar region during landing repetitions only using the kinematic data of the athlete. A second objective of our research is to identify the best machine learning model for our data and the variables that would most predict fatigue during gymnastics landing. In agreement with the literature, we think that fatigue will lead to a decrease in the knee and hip flexion angles and in the displacement of centre of mass.

2. Methods

2.1 Protocol

Four females competitive gymnasts without history of back injury or pain, performed 30 gymnastics landings before a fatigue protocol and 30 others gymnastics landings after. The landings were made from a 70 centimetres platform to a 30 centimetres

mat placed over an AMTI® force platform (ATMI, Watertown, United States, 1000 Hz). In addition, motion capture was recorded during the landings using 21 infrared cameras Qualisys Oqus 700+® (Qualisys, Göteborg, Sweden, 500 Hz) and the Marker set of Muller et al. (2019) composed by 39 markers on the whole body. The fatigue protocol consisted of a maximum of repetitions of the deadlift until exhaustion at 50% of the 1RM (maximal load). The 1RM was previously established using a five repetitions test. Before and after the fatigue protocol, maximal strength assessment was performed using an isokinetic ergometer CON-TREX® (Médimex, Lyon, France) to verify if the subject was exhausted. The ergometer was set to perform trunk flexion at an angular velocity of 20 degrees per second.

2.2 Data processing

We performed 60 jumps per subject, so all in all 240 trials. Due to excessive movement and unexpected stress on the foot markers, significant data loss occurred and not all trials could be analyzed. Thus, we retained a total of 152 trials, i.e. 19 trials per subject and per condition (i.e. fatigue or no fatigue). The kinematical parameters of the landing were extracted using the CusToM toolbox (Muller et al., 2019) in Matlab® and Python®: the maximum height of the centre of mass, the maximal and average angles and angular velocities of the hip, knee and ankle joints. We also recorded the peak force and impulse using the force platform. All these kinematic parameters were then used in our *Machine Learning* model.

2.3 Statistical analysis

The objective is to use supervised classification models to classify our data into two classes: fatigue and not fatigue.

We divided our data set into a training data set containing 80% of our data and a test data set containing 20% of the data. Both groups contained half fatigued and half non-fatigued data to keep the balance of simple training. Then, we used the “features_importance” and the “permutation_importance” functions from Scikit-Learn on Python. Both of these functions result in a classification for order of importance after all available variables have been entered. All the variables described in the subsection “Data processing” were introduced as inputs to these functions (i.e. a total of 25 variables). Then, we selected the three best model-specific variables with the highest predictive power as inputs for each model, improving the performance of our current model. For the SVM, the *Random Forest* and the KNN the three variables selected as input were: the maximal height

of centre of mass, the peak vertical force and the maximal angular velocity of the hip in the transverse axis. For the linear models (LR, NB), the three variables selected as input were: the average angular velocity of the ankle angle and the impulse in antero-posterior and vertical axis. We tested five supervised classification *Machine Learning* models: *Random Forest* (RF), *Support Vector Machine* (SVM), *K-Nearest Neighbours* (KNN), *Logistic Regression* (LR) and *Naïves Bayes* classification (NB). Then, we performed a cross-validation of the training dataset with a K-fold (K=10). This consists of dividing the data set into a number of folds, in our case 10. The first fold is used to test the model and the others to train the model. Then the operation is repeated so that each fold is used once to test the model.

To evaluate the model, we used the accuracy score a ratio of correctly predicted observation to the total observations.

3. Results and discussion

The model with the highest prediction rate is the Random Forest. Based on kinematic data, it predicts 83% of fatigue on the cross-validation train dataset and 84% on the test dataset (Table 1). To our knowledge, no study in gymnastics has predicted fatigue from kinematic data however, in walking, fatigue could be predicted to 84.6% with IMU and an SVM (Guaitolini et al., 2020).

	RF	SVM	KNN	NB	LR
Accuracy train-dataset	0.83	0.62	0.76	0.5	0.53
Accuracy test-dataset	0.84	0.53	0.69	0.67	0.66

Table 1 Accuracy of different *Machine Learning* models on the cross-validation train dataset and on the test dataset

The three variables most predictive of fatigue are: the maximal height of centre of mass, the peak vertical force and the maximal angular velocity of the hip in the transverse axis. Thus, a decrease in gymnastics performance through a decrease in the acrobatics height of the jump would be a predictive element of the athlete's fatigue (Schärer et al., 2019).

4. Conclusions

In conclusion, the kinematic variables predicted 84% of fatigue. More subjects and data are needed to strengthen the prediction model. The changes in height of the centre of mass, the peak vertical force at the landing and the maximum angular velocity of the

hip in the transverse axis are the three most predictive variable to differentiate fatigue from non-fatigue.

Further, this study could be continued by using other tools such as inertial units or increasing the complexity of the model by adding several elite level subjects. However, under similar conditions, with e.g. different jump heights and/or different acrobatic figures. This would allow a generalised statement, perhaps also in terms of an ecological environment.

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