Classification of Treadmill Running Fatigue With Machine Learning

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Insight

SFI RESEARCH CENTRE FOR DATA ANALYTICS



INTRODUCTION

- Running has increased in popularity resulting in more injuries especially amongst amateur runners [1]
- Fatigue reduction of maximal force/power production
 - results in biomechanical form changes to compensate [2]
 - strain on the tendons, joints, and ligaments of the lower body and back
 - detection of fatigue can reduce injuries

fatigue detection

- velocity, force, and EMG analysis in biomechanics lab expensive and intrusive
 - using IMU is cheaper and can be used in the field
- **support vector machines** and **random forest** classification typically used [2,3]

OBJECTIVES

- 1 feature extraction and selection on treadmill data using automatic ML algorithms
- 2 exploration of multiple difference machine learning models for fatigue classification of treadmill data

3 cross-training between treadmill and track fatigue classification models

FEATURE SELECTION

H20 selected features

MLJAR selected features

Acc_WR_Z_mean Acc_WR_Y_mode Acc_WR_Y_max

Algorithm	Neural Network	Random Forest	Xgboost	Catboost
f1 score	0.3852	0.606604	0.581303	0.612859

Fig 2. MLJAR supervised output suggests that the CatBoost algorithm will perform best for fatigue classification and neural networks will perform significantly worse

ALGORITHM EXPLORATION







DISCUSSION & CONCLUSION

- H20 and autoML allow for optimized feature reduction for track and treadmill data independently
 - for treadmill data length, gyro_y_dwc_m, and acc_wr_x_dwc_m are the only admissible features for classification
- Random forest model predicts fatigue most accurately
- cross-training improves results



Acc_WR_Z_range Acc_WR_X_energy Gyro_X_25% Acc_WR_X_dwc_m Acc_WR_Z_dwc_m Gyro_X_dwc_m Gyro_Y_dwc_m Mag_Y_dwc_v

Fig 1. Selected features outputted by automatic ML python algorithms. H20 infogram displays total information (a measure of how much the variable drives the response) plotted against net information (a measure of how unique the variable is) for treadmill data

future work

- account for class imbalances/collect more balanced data
- expand cross-training to all models
- explore more data preprocessing

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