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Exploring the Effect of Arm Swing on Countermovement Jump Performance Using Machine Learning and Ground Reaction Force Analysis

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INTRODUCTION:
Jump performance is a requirement for many physical activities. The ability to accurately classify different jumping styles can provide valuable insights into an athletes performance and aid in the development of training programs. This study aimed to investigate the impact of arm swing on the observed pattern of ground reaction forces during a countermovement jump (CMJ) and determine if it can be used to improve the classification accuracy of jumping styles. Our hypothesis was that the presence of arm swing would result in different ground reaction force patterns compared to a countermovement jump without arm swing.
METHODS:
Three hundred and thirty-two male adult high-level athletes from various sports performed a series of CMJ and CMJ with arm swing (CMJas) on a 1D force platform. A machine learning approach was adopted to analyze the force-time data recorded for each participant, using a random forest classifier [1]. The data were interpolated to 101 points and then transposed so that each force-time point represents a feature. SHapley Additive exPlanations (SHAP) analysis [2] was used to provide explanations about the models' predictions and insights about the most important features that best described each class force pattern. Also, to describe, interpret, and further explore the derived classification predictions, kinetic energy was calculated and statistically compared across the two jumps using the SPM1D paired t-test.
RESULTS:
The classification accuracy was 0.895 (CI 95%: 0.869 - 0.921). The SHAP-based variable importance ranked all the features (time points) according to their value for the model, to predict the class (CMJ or CMJas). The model showed that all features (time points) from 83 – 94% of the total jump duration were the most important in distinguishing between the CMJ and CMJas. Also, the model pointed out that vGRF is highly informative in separating the two jumps after 65% of the total jump duration. Further statistical analysis of the data revealed a significant difference in the produced kinetic energy with the CMJas prevailing from CMJ at ~90-100% ($t = 3.249$, $p < 0.05$) of jump duration.
CONCLUSION:
These findings confirmed that arm swing discriminates countermovement jumps, especially in the last part of the task. They also support the efficacy of the machine learning modeling approach for understanding the complexities of vGRF patterns in a laboratory setting. Overall, the work produced during the late phase of CMJ with arm swing produces a very distinct peak, which the classifier can capture and separate into two classes. Contrary to previous reports, no informative features were found before 65% of the jump duration, likely linked to the inconsistency due to the high variance of the force patterns during the unweighing and braking phases of both jumping techniques.

1. Breiman L. Mach Learn 2001
2. Lundberg et al. Adv Neural Inf Process Syst. 2017

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