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Factors influencing in-game player activity in rugby league: a new approach

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INTRODUCTION:
Player activity and load profiling are important in training and management decisions to optimise performance in rugby league. Player movement is a complex phenomenon, involving both spatial (place on field) and temporal (time in match) dimensions. Current approaches to activity profiling typically rely on univariate measures derived from distance-based variables collated from GPS data to classify profiles and player movement with user-defined numeric thresholds, where the metrics used are often aggregated to one observation per match. These approaches have yielded useful insights into player activity profiles in rugby league and other sports. However, two important research areas are less amenable to analysis with this approach: (i) Investigating the influence of in-game events on player movement (e.g., do activity states change following a try?), and (ii) Combining different dimensions of player activity (e.g., speed, directionality, and acceleration) when constructing activity profiles.
The aim of this study was to introduce Hidden Markov Models (HMMs) - a flexible, data-driven, and statistically robust approach capable of modelling the complexity of player movement. We applied HMMs to both rugby league training and match GPS data to address these two research questions and thus provide valuable tactical and player management decision support.
METHODS:
We fitted several HMMs to 1000 rugby league player training GPS files across five training modalities and 215 match GPS files across 35 matches of one team from the 2018 and 2019 English super league competitions. Activity states were constructed jointly from player speed, direction and PlayerLoad data. We investigated the effect of both elapsed time and score difference on the probability of being in or transitioning between different states of activity in a match context. We also compared the activity and load profiles between training modalities and between training and matches.
RESULTS:
The HMMs successfully combined multiple movement variables to detect different activity states for both training and match data, and to reveal the probability of being in these states as a function of the two time-varying covariates. Players were more likely to engage in directed, high speed movement as well as very undirected, slow movement at the beginning of a match and when behind on the scoreboard. There are some key differences in activity profiles within training modalities and between training and matches, notably a high-activity training state rarely accessed by players during matches.
CONCLUSION:
HMMs are capable of modelling the complexity of player movement in rugby league and can be used to investigate the influence of in-game, time-varying factors on player movement as well as several other research questions of interest. HMMs therefore offer a statistically robust method to profile player activity data that can provide decision support for optimal performance in rugby league as well as several other sports.

Topic: Statistics and Analyses

Presentation Oral