SIMPLIFYING THE HIGH-PERFORMANCE BIOMECHANICAL ASSESSMENT OF HIGH JUMP TECHNIQUE

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A multitude of technical performance parameters are used to quantify high jump technique in the Australian high-performance environment, which can be time-consuming to measure and interpret. The purpose of this study was to investigate the efficacy of principal component analysis to simplify high-performance high jump biomechanical reports. Although 12 technical performance parameters were reduced into four principal components, the characteristics of the resultant components were non-intuitive. This study reveals that principal component analysis may not be suitable for simplifying the biomechanical reports provided to high-performance high jump coaches, and suggests that further investigations of alternative dimensionality reduction and feature importance techniques are required in addition to larger sample sizes.

KEYWORDS: biomechanics, key performance indicator, feature reduction

INTRODUCTION: High-performance coaches of elite and national level high jumpers are often provided with biomechanical reports of athlete technique that contain a multitude of technical performance parameters, such as foot contact time and knee angle at take-off contact (Nicholson, et al., 2018a; Panoutsakopoulos & Kollias, 2012). The measurement, interpretation, and distillation of the parameters into digestible reports is a complex and time-consuming process. Despite many studies describing the biomechanical parameters involved in high jumping (Adashevskiy, et al., 2013; Dapena, 2000; Nicholson et al., 2018a; Nicholson, et al., 2018b), attempts to facilitate their practical interpretation through dimensionality reduction or feature importance remains elusive (Rao, et al., 2013; Ritzdorf, 2009). Consequently, it is necessary to explore the use of dimensionality reduction techniques to simplify the biomechanical reports provided to high-performance high jump coaches and athletes.

Principal component analysis (PCA) aims to generate smaller groups of input variables, known as the principal components (PCs) while maintaining most of the variance in the input data. The PCs simplify the interpretation of the data by reducing the number of variables to interpret without discarding any of the original variables (Federolf, et al., 2014). One application of PCA reduced a total of 26 landmarks of alpine ski racing athletes, each represented by a three-dimensional coordinate system, into four principal components (Frederolf, et al., 2014). The variables with the greatest contribution (i.e., weighting or factor loading) to each PC were vertical trunk movement, changes in body inclination, distance between skis, and fore-aft movement. With these parameters, the techniques of the alpine ski racing athletes were described in a simpler manner, facilitating a more practical interpretation for coaches. Despite the success of PCA to simplify reports of athlete techniques and facilitate their practical interpretation, there exist minimal applications for high jump.

This study aimed to dimensionally reduce the number of technical performance parameters into PCs to simplify the biomechanical reports that are presented to coaches and athletes.

METHODS: This study was approved by the University's Human Ethics Committee (2020/ET000311). A total of 22 successful high jumps (i.e., cleared the bar) were used for the analysis. The sample consisted of two elite high jump athletes (one male and one female) with 13 and 9 jumps, respectively. Technical reports of these jumps were created by a qualified sports biomechanist and consisted of 12 technical performance parameters commonly assessed in the Australian high-performance environment (see Table 1 for a full list of parameters).

Table 1: Technical performance parameter definitions.

Technical Performance Parameter	Definition
Cadence	Average step frequency over the approach.
Knee angle at lowest point of take-off contact	The angle between the shank and thigh when the athlete's centre of mass is at the lowest point during the take-off step.
Knee angle at take-off contact	The angle between the shank and thigh at foot contact of the take-off step.
Knee angle difference	The difference in knee angles during the take-off step.
Lean angle difference	The difference in the lean angles during the take-off step.
Lean angle through hip at take-off contact	The angle between vertical and a vector that initiates at the ankle and terminates at the hip joint centre.
Lean angle through shoulder at take-off contact	The angle between vertical and a vector that initiates at the ankle and terminates at the shoulder joint centre.
Penultimate foot contact time	The time that the foot was in contact with the ground during the contact immediately before take-off.
Take-off distance to mat	The orthogonal distance to the high jump mat at take-off.
Take-off distance to stand	The perpendicular distance to the high jump stand on the side of approach at take-off.
Take-off foot contact time	The time that the foot is in contact with the ground during the take-off step.
Third last step foot contact time	The time that the foot is in contact with the ground during the third last step of the approach.

Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy were conducted to ensure that the data was suitable for dimensionality reduction (Stevens, 2012). The technical performance parameters were normalised to a mean of zero and standard deviation of one. An exploratory PCA was conducted to reduce the technical performance parameters into uncorrelated PCs. The explained variance of 10 PCs was derived to assess the minimum number of PCs required to explain a cumulative variance of greater than 80% in the data (Federolf et al., 2014). The factor loadings of the technical performance parameters were subsequently extracted to describe their contribution to each PC. All analyses were undertaken using custom Python 3.9 scripts (Van Rossum & Drake, 2009).

RESULTS: The KMO measure of sampling adequacy ($KMO = 0.68$) and Bartlett's test of sphericity ($p < 0.001$) suggested that the data was suitable for dimensionality reduction. The cumulative explained variance for 10 PCs indicated that four PCs were necessary to account for a total of 87.8% of the variance in the data. Consequently, four PCs were derived from the 12 technical performance parameters. The first principal component (PC1) had the greatest contributions from the lean angle through the hip at take-off contact (-0.34), penultimate foot contact time (0.34), take-off distance to mat (0.37), and take-off distance to the high jump stand (-0.39). The second principal component (PC2) had the greatest contributions from the knee angle at the lowest point of take-off contact (0.63) and take-off contact time (0.31). The third principal component (PC3) had the greatest contributions from cadence (0.65) and the lean angle difference (-0.46). Lastly, the fourth principal component (PC4) had the greatest contributions from the knee angle at take-off contact (0.44), the difference in knee angles (0.68) and the lean angle through the shoulder at take-off contact (0.36) (Table 2).

Table 2: Factor Loadings of the technical performance parameters to each principal component (PC). Parameters were assigned to the PC in which they had the most influence.

Technical Performance Parameter	PC 1	PC 2	PC 3	PC 4
Cadence			0.65	
Knee angle at lowest point of take-off contact		0.63		
Knee angle at take-off contact				0.44
Knee angle difference				0.68
Lean angle difference			-0.46	
Lean angle through hip at take-off contact	-0.34			
Lean angle through shoulder at take-off contact				0.36
Penultimate foot contact time	0.34			
Take-off distance to mat	0.37			
Take-off distance to stand	-0.39			
Take-off foot contact time		0.31		
Third last step foot contact time	-0.35			

DISCUSSION: High-performance coaches of elite high jumpers are often provided with biomechanical reports of athlete technique that contain various technical performance parameters. Digesting and implementing the information from these reports can be complex and time-consuming due to the number of parameters included, making it necessary to streamline the process by reducing the number of parameters reported. The purpose of this study was to explore the use of PCA as a means to dimensionally reduce the number of parameters that are reported to Australian high-performance high jump coaches.

Although the PCA reduced the number of parameters from 12 to four, the PCs are seemingly non-intuitive. For example, an intuitive PC might contain all three technical performance parameters related to knee angles because it provides coaches with a single variable that encapsulates the knee movement of the athlete's plant leg during take-off. However, the results indicate that the knee angle parameters contribute to different PCs. This is further demonstrated with the three parameters related to lean angles contributing to three different PCs. Additionally, the technical performance parameters that have the greatest contribution to PC1 mean that PC1 could be intuitively described as a *lead-in foot contact time and take-off location component*. However, such a description would overlook that the lean angle through the hip at take-off contact contributes to PC1, which could subsequently be ignored in practical applications by coaches. Consequently, the results of this analysis suggest that PCA is not suitable for dimensionally reducing the technical performance parameters in a manner that is practically useful to coaches and athletes at this point in time.

This finding is in contrast with a previous study, which found intuitive PCs for skiers (Federolf et al., 2014). This difference in findings is likely due to the difference in input parameters, with the current study utilising scalar technical performance parameters and the study conducted by Federolf and colleagues (2014) employing time-series data. Although time-series data may contain more information on athlete technique, these measures cannot be easily obtained in most training and competition environments, and, therefore, were not available for analysis in this study.

This study is limited in the small sample size used for analysis, where a larger number of high jump trials may reveal greater relationships between parameters and, therefore, different principal components. Additionally, the current study only included high jumps of two elite high jumpers, which likely introduces variability in the measured technical performance parameters due to differences in technique between individuals. Future research should include a greater number of high-jump trials and endeavour to perform athlete-specific dimensionality reduction to determine whether there are athlete-specific components. To achieve larger sample sizes, automation techniques need to be implemented to extract technical performance parameters from videos captured during training and competition.

This study also only considered technical performance parameters that are commonly collected by the Australian high-performance system, which is by no means exhaustive due to time and resource constraints. Future work should investigate whether dimensionality reduction can be used for all biomechanical components of high jumping technique and may also investigate feature importance assessments in relation to performance outcomes (e.g., peak height of the centre of mass) to determine a list of key performance indicators. In doing so, future analyses may be able to uncover trends associated with successful and unsuccessful performances.

CONCLUSION: This study explored a dimensionality reduction technique to simplify and aid the interpretation of biomechanical reports for coaches and athletes. Although PCA reduced 12 technical performance parameters to four principal components, the resultant components were not meaningfully interpretable. This result may be a result of the limited sample size used for analysis, which is problematic in many biomechanics and high-performance sports applications. Consequently, alternative dimensionality reduction techniques and methods of automation are required to better support high performance high jump coaches.

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