PERFORMANCE RELATED FACTORS IN COUNTERMOVEMENT JUMPS: IDENTIFIED USING A CONTINUOUS SUBGROUP ANALYSIS APPROACH

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The aim of this study was to examine the benefit of utilizing a subgroup analysis design over a single group analysis design, and determine if performance related factors differ across individuals in countermovement jumping. Joint kinematics and kinetics were used to cluster 122 individuals into four groups, based on their movement strategy. The ability to describe jump height across a single group and subgroup analysis design was assessed to measure the performance of both analysis designs, and performance related factors were identified across the generated clusters. Findings highlight a greater ability of the subgroup analysis design to describe jump height, indicating a benefit of utilizing a subgroup analysis. This is supported by the performance related factors identified, which differed across individuals.

KEY WORDS: single group analysis, subgroup analysis, continuous waveform analysis, performance related factors, countermovement jump

INTRODUCTION: Performance related features found across countermovement jump studies are often inconsistent, which makes it difficult to conclude how neuromuscular capacities or the movement technique have to be altered to enhance the performance outcome (jump height). One possible source for inconsistencies is the commonly used single group analysis design (Stergiou & Scott, 2005; Nicholas Stergiou, 2004), which can result in the masking of performance related factors because individuals use different movement strategies that may differ in their performance related factors (Vanezis & Lees, 2005). A possible solution to avoid such masking effects is the use of a subgroup analysis design; where similar movement patterns are clustered into separate groups. The benefit of a subgroup analysis has been demonstrated in gait studies (e.g. Toro, Nester, & Farren, 2007; von Tscharner, Enders, & Maurer, 2013) but has not been examined when identifying performance related factors in the countermovement jump. The aim of this study was to examine (a) the benefit of a subgroup analysis, and (b) if countermovement jump performance related factors differ across individuals.

METHODS: This study recruited 122 athletes, who were free from any injury and experienced in performing a CMJ. The University Ethics Committee approved the study; all subjects were informed of any risks and signed an informed consent form before participation. Prior to data collection, every subject completed a standard warm-up routine. The subjects performed 15 maximum effort countermovement jumps without arm swing, standing with each foot on a force platform, and rested for 30 seconds between the trials. A motion analysis system (Vicon 512 M, Oxford Metrics Ltd, England) and two force plates (BP-600900, AMTI, MA, USA) recorded the position of twelve spherical reflective markers (250 Hz) and the vertical ground reaction force (1000 Hz), respectfully. Jump height was calculated by the centre of mass velocity at takeoff. Based on jump height, the best jump performance of each subject was chosen for data analysis. All curves were normalized to body mass and only the propulsion phases were used for analysis because the performance outcome (jump height) is fully determined by the propulsion phase (impulse-momentum relationship). Kinematic and kinetic variables for each joint were computed for the left and right body side and were averaged before data analysis. Joint kinetics were calculated using inverse dynamics (Winter, 2009). To classify the data, subject scores (similarity scores) were computed over key phases using Analysis of Characterising Phases (Richter et al., 2013a). Key phases were identified using VARIMAX rotated functional principal components, which retained more than 99 % of the variance within the data's magnitude domain (Richter et al., 2013b). Subject scores were normalized and fed into a hierarchical clustering approach, which generated four clusters. The normalization of similarity scores was performed by transforming them into their correlation matrix. It should be noted that the utilized clustering process was identified as the optimal clustering solution prior to applying the clustering. Subsequently, Analysis of Characterising Phases was applied utilizing both a single and a subgroup analysis design to generate similarity scores, which were used in a correlation analysis to identify performance related factors. A feature (similarity score) was considered to be a performance related factor if it correlated significantly with jump height (performance outcome). Performance related factors were classified into weak ($r^2 < 0.09$), moderate ($0.09 < r^2 < 0.49$) and strong ($r^2 > .49$; Cohen, 1988). To examine the benefits of the subgroup over a single group analysis, the ability to describe jump height (r^2-value of a regression analysis) was compared utilizing the whole data set (single group) and the generated clusters (subgroup analysis). To examine if performance related factors differ across movement strategies, the performance related factors found across the generated clusters (subgroup analysis) were compared. All statistical analyses were performed using MatLab (R2012a, MathWorks Inc., USA).

RESULTS: The average ability to describe jump height across the subgroups was 92 % (the weighted mean was 88 %) and 85 % when using a single group analysis. Cluster 1 contained six subjects and the performed regression analysis explained 100 % of the variances in jump height ($r^2 = 1.00$). The small sample size in cluster 1 limits the statistical power of the cluster and increases the probability of committing a type II error (Cohen, 1988). Hence, it was discarded for further statistical analysis. Cluster 2 contained 40 subjects and the performed regression analysis explained 96 % of the variances in jump height. Cluster 3 contained 25 subjects and the regression analysis explained 90 % of the variances in jump height. Cluster 4 contained 51 subjects and the regression analysis explained 80 % of the variances in jump height. Jump height was significantly greater in cluster 2 compared to cluster 4 and close to being significantly greater than cluster 3 (Table 1). Performance related factors identified within each cluster and the single group analysis are listed in table 1 and illustrated in figure 1.

Table 1: Summary of performance related factors identified within the propulsion phase across the generated clusters and the single group design

	variable	Cluster 2	Cluster 3	Cluster 4	Single group
Jump height (Confidence Int.)		0.41 m* (0.39-0.43)	0.37 m (0.34-0.40)	0.37 m* (0.35-0.39)	0.38 m (0.37-0.40)
ankle	angle	---	63-100 %	---	62-100 %
	angular velocity	57-100 %	---	83-100 %	89-100 %
	moment	24-82 %	13-100 %	1-99 %	7-100 %
	power	27-96 %	89-100 %	66-100 %	70-100 %
knee	angle	---	88-100 %	88-100 %	47-100 %
	angular velocity	78-100 %	95-100 %	71-100 %	86-100 %
	moment	95-100 %	98-100 %	1-85 %	1-93 %
	power	95-100 %	98-100 %	12-86 & 95-100%	25-92 & 96-100 %
hip	angle	1-100 %	---	39-100 %	1-100 %
	angular velocity	30-100 %	97-100 %	79-100 %	29-100 %
	moment	1-100 %	98-100 %	10-88 %	1-100 %
	power	12-100 %	98-100 %	27-88 %	8-100 %

* significant difference (cluster 2 > cluster 4; p = 0.05)

DISCUSSION: Comparing the ability to describe jump height between the single and subgroup analysis design indicates greater capacity of the subgroup analysis to describe jump height (+6 %). This supports the use of a subgroup analysis over a single group level analysis and is in agreement with previous gait studies (Toro et al., 2007; von Tscharner et al., 2013). Further, the subgroup analysis design was able to capture specific characteristics of a movement strategy, which resulted in a more appropriate solution to identify performances related factors.

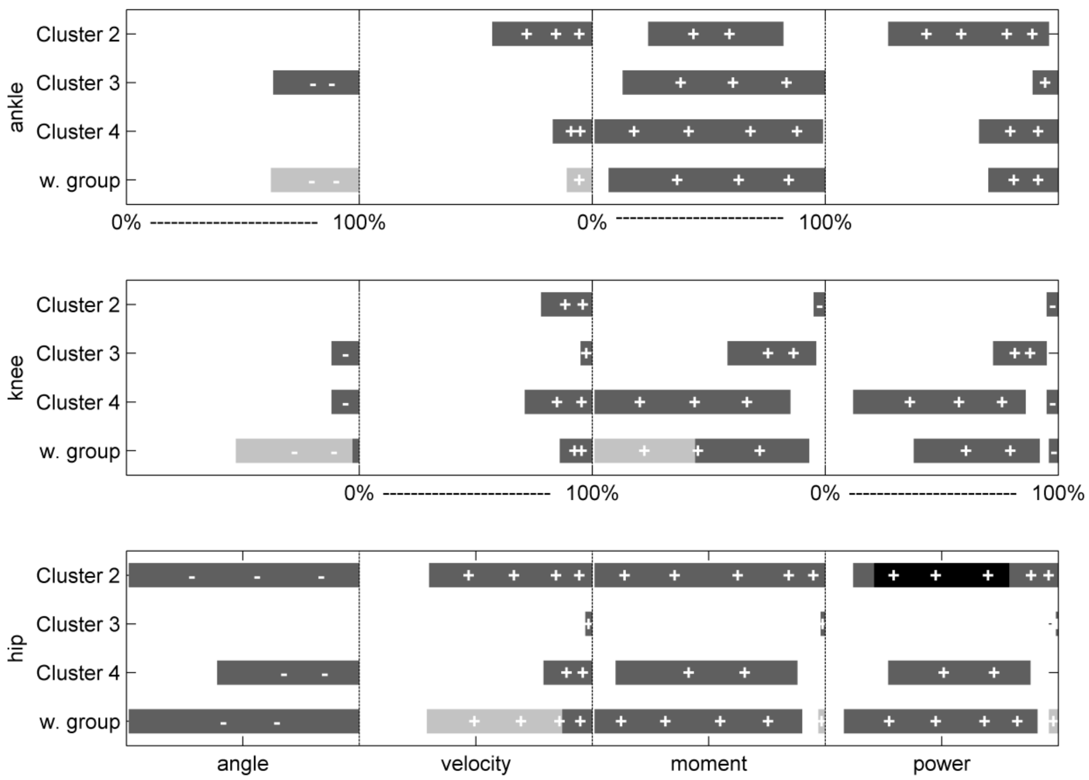

Figure 1: Performance related factors identified within the propulsion phase across the generated clusters and the single group design. Light grey areas are weakly correlated, grey areas are moderately correlated and black areas are strongly correlated. The symbols '+' and '-' indicate a positive and negative correlation, respectively.

Comparing performance related factors across the generated clusters highlights some similarity but also differences across the clusters (Figure 1). The differences in performance related factors support the assumption that different movement strategies (clusters) have different performance related factors. As such, each cluster is likely to respond uniquely to different training interventions. For example, performance related factors in cluster 2 indicate that having a smaller hip angle and increasing the magnitude of hip kinetics over the entire movement cycle results in a higher jump height, while people belonging to cluster 3 only benefit from enhancing hip kinetics in the very last part of the movement cycle (97-100%) and not from smaller hip angles. People within cluster 3 would benefit more from executing the countermovement jump using smaller ankle joint angles and increasing the magnitude of knee kinetics at the end of the propulsion phase. People within cluster 4 should aim to increase the magnitude of ankle kinetics throughout the movement, knee kinetics at the start, and the ability to maintain magnitudes of knee and hip kinetics in the middle phase. This highlights again the benefit of using a subgroup analysis when identifying performance related factors. A single group analysis does not account for different movement strategies, indicating that a training intervention may not be of benefit to some individuals. For example, the single group analysis suggests increasing knee moments throughout the whole propulsion phase to enhance jump height; however, this is only the case for cluster 4 but not for clusters 2 and 3. Another limitation of the single group analysis is that a movement strategy of a cluster can artificially alter the strength of a performance related factor. This is indicated by the strength of the performance related factors identified in ankle angle, knee moment and hip angular velocity. While the single group analysis design was able to identify group specific factors, it underestimated the magnitude of the correlation for specific clusters.

The findings clearly show that different individuals have different performance related factors. However, the generated clusters also differed in their jump height (cluster 2 was significantly greater than cluster 4 and was close to being significantly greater than cluster 3). This might indicate a better movement strategy *per se* by those in cluster 2. However, this requires further experimentation.

CONCLUSION: The subgroup analysis design was able to provide a greater ability to describe jump height and gave a much deeper insight into what factors relate to jump height. Hence, contrasting findings between previous studies that examined vertical jumping at a single group level of analysis can, at least in part, be explained by the limitations associated with a single group design. Performance related factors differ across individuals, indicating that different training interventions should be used by different individuals or subgroups.

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