COMPARISON OF DISCRETE POINT AND CONTINUOUS DATA ANALYSIS FOR IDENTIFYING PERFORMANCE DETERMINING FACTORS

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The aim of this study was to compare the effectiveness in identifying performance determining factors using discrete point analysis (DPA), functional principal component analysis (fPCA) and a novel technique, analysis of characterizing phases (ACP). Twenty five vertical ground reaction force (force) curves, recorded during a vertical countermovement jump, were analyzed. Due to bi-modal force curves, DPA inappropriately identified the rate of force development as a performance determining factor. In contrast, fPCA and ACP identified the phase around the peak before and after the rapid drop in force as a performance determining factor. While both continuous techniques showed greater benefit in analyzing the captured data than DPA, ACP seems to be more reliable because it does not rely on visual observation.

KEY WORDS: functional principal component analysis, analysis of characterizing phases.

INTRODUCTION: The identification of performance determining factors is a major goal for sports biomechanics. Performance determining factors provide useful information to athletes, coaches and sport scientists for developing and improving training programs in order to increase performance outcome. However, performance determining factors identified in vertical jump studies are often inconsistent, with some reporting peak vertical ground reaction force (force) as a performance determining factor (Dowling & Vamos, 1993; Cormie, McBride, & McCaulley, 2009), while others do not (Morrissey, Harman, Frykman, & Han, 1998; Newton, Kraemer, & Häkkinen, 1999; Petushek, Garceau, & Ebben, 2010). This might not be due to inter-participant variability alone. The vast majority of studies use a discrete point analysis (DPA) technique to identify performance determining factors. This approach holds three potential limitations: a) it uses just a few individual pre-selected data points to summarize a complex continuous signal and could therefore discard potentially important information, b) it cannot examine the time phase that performance determining factors are evident before and after the analyzed data point, and c) an inconsistency in selected variables exists between studies. One possible solution that addresses these issues is to examine continuous signals as a whole, which can be undertaken using a functional principal component analysis (fPCA) or a novel approach which we have termed analysis of characterizing phases (ACP). The aim of this study was to examine if the mentioned techniques differ in identifying performance determining factors in the vertical jumps from their force data.

METHODS: This study used 25 force curves captured during vertical jumps from 25 male athletes (age = 22.0 ± 4.0 years; mass = 77.8 ± 9.8 kg) who were free from any injury at time of data capturing and who were experienced in performing vertical jumps. The University Ethics Committee approved the study and all subjects were informed of any risk and signed an informed consent form before participation. Prior to the data collection, every subject completed a standard warm-up routine (Marshall, 2010). The subjects performed 15 maximum effort jumps without an arm swing, standing with each foot on a force platform and rested for 30 seconds between the trials. Two force plates (BP-600900, AMTI, MA, USA), each with a frequency of 250Hz, were used to record the produced force. Based on jump height, the best jump performance of each subject was identified and ranked across the participants. The top ten and lowest ten ranked performances were used to build a 'good' and a 'poor' performance group, while the five middle performances were discarded to maximise the differences between the groups of interest. All curves were normalized to body weight (BW) and only the propulsion phases were used for analysis.

For DPA, based on previous studies (Dowling & Vamos, 1993; Morrissey et al., 1998; Newton et al., 1999; Cormie et al., 2009; Petushek et al., 2010) the following prior selected data points were identified (Figure 1) and used for statistical analysis: a) initial force, b) mean force, c) peak force, d) time initial-to-peak force, e) percentage initial to peak force, f) time peak force to take off, g) initial-to-peak rate of force development (RoFD), and h) duration of the propulsion phase. RoFD was assessed as the rate of development from the initial force to the point at which the highest peak force occurred (Cormie et al., 2009).

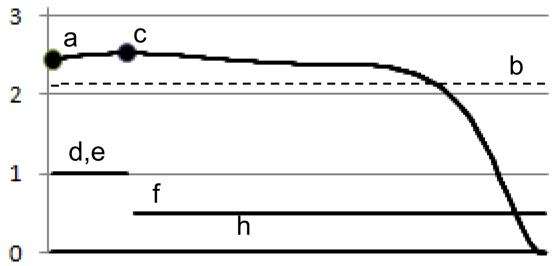

Figure 10: Identification of selected variables for the force

The continuous data analysis techniques used similar approaches to analyse data and are briefly explained together (for further information see: Ramsay, 2006; Harrison, Ryan, & Hayes, 2007). The transformation of the captured discrete data to functional data was the first step in both fPCA and ACP (Figure 2). While fPCA transforms only the force data, ACP transforms the force and the corresponding time data for analysis. The transformed force data was then used to compute a variance-covariance matrix (Step 2) which describes the variance in the data set. To examine the created matrix, both analysis techniques perform an Eigen analysis (Step 3a). Computed Eigen vectors, also called principal components, represent a specific pattern of variance stored in the data and the corresponding Eigen value represents its influence. The principal components and Eigen values were VARIMAX rotated. In contrast to fPCA, ACP analyzed the principal components (Step 3b) to identify and sort pattern-characterizing phases from high to low potential using the peak of each principal component. After the Eigen analysis was performed both techniques express the behaviour of each subject with a score (Step 4). fPCA used a principal component score, which reflects how a subject is affected by a principal component over the whole function, while ACP used a similarity score, which expresses the similarity of a subject to the best jump using the Euclidean distance within the phase with the highest pattern-characterizing potential between duplicated signals of the original data (i.e. it holds magnitude and temporal properties). To examine if differences between the 'good' and 'poor' jump groups exists, an independent t-test (Step 5a, $p<0.05$) was performed on the principal component and similarity scores. In contrast to fPCA, ACP returned to Step 4 (via Step 5b), if a statistical difference was evident, to recalculate the subject scores using the phase(s) with the next lower pattern-characterizing potential until no significant difference between the similarity

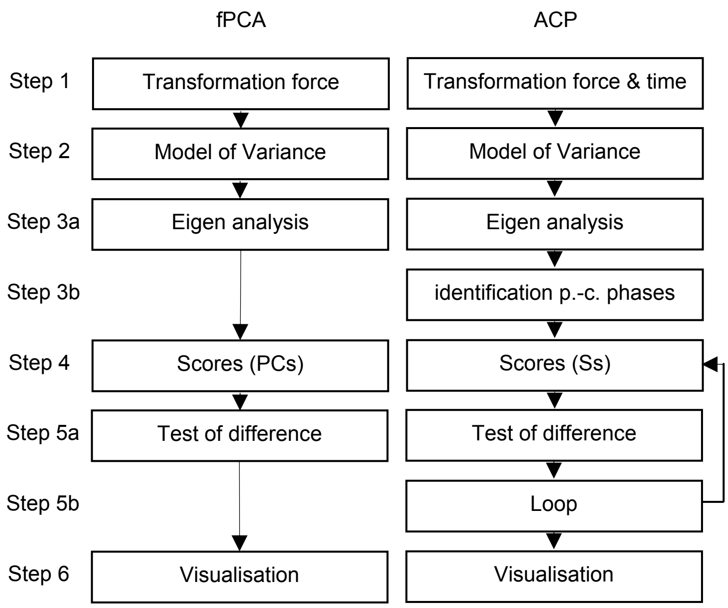

Figure 11: Illustration of steps used during an analysis using fPCA and ACP

scores exists (in steps of 5% of the peak). Lastly, both techniques visualise the results (Step 6) to aid interpretation. fPCA used a plot (Figure 3a) consisting of the functional overall mean curve and the a multiple of the computed principal component (as suggested in Ramsay, 2006), while ACP created a duplicate of the original data set to calculate and plot the mean curve for the 'good' and 'poor' performance groups, indicating on both mean curves where a significant difference between the two groups exist (Figure 3b).

RESULTS: Members of the 'good' performance group (31.4 ± 1.73 cm) jumped significantly higher ($p < 0.001$) on average (8.2 ± 1.93 cm) than the 'poor' (23.2 ± 2.12 cm) group. Using DPA, significant differences between the 'good' and 'poor' groups in pre-selected variables were found for: initial-to-peak RoFD (p=0.003). The continuous data analysis techniques used the first five principal components, which together describe 100 % of the variability in the data, with principal component 1,2,3,4 and 5 describing 22, 17, 28, 8 and 25 %, respectively. In fPCA and ACP, no differences in subject scores were found for the first to fourth principal component ($p > 0.05$), while the subject scores for the fifth principal component did differ ($p = 0.006$ in fPCA; $p = 0.045$ in ACP) between the 'good' and 'poor' performance groups (Figure 3).

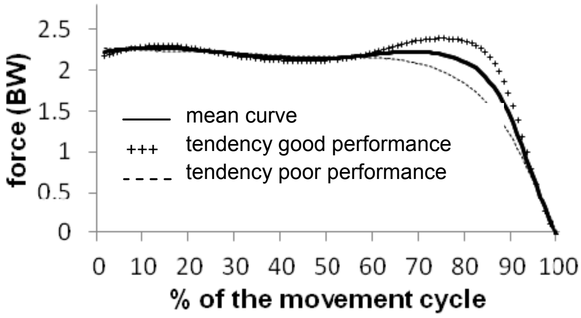

Figure 3a: Pattern of variation defined between the groups detected using fPCA by principal component 5.

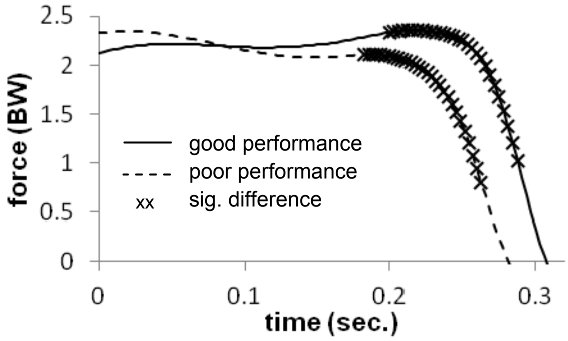

Figure 3b: Phase (65-93 %) of difference between the groups detected using ACP and principal component 5.

DISCUSSION: The examined data analysis techniques differed in identifying performance determining factors: DPA identified the initial-to-peak RoFD as a performance determining factor, fPCA identified the fifth principal component as a performance determining factor and, ACP identified the magnitude of the force in combination with the timing for the phase of 65-93% of the movement cycle as a performance determining factors. In fPCA, the visualisation of the fifth principal component (Figure 3a) indicates that the 'good' performance group tends to produce higher force values at the estimated area of 65-85 % in the movement cycle, while the peak force seems to continue for longer.

In relation to the initial-to-peak RoFD, separate examination of each curve and descriptive statistics indicated a large distribution in the position (timing) of the peak force, with many curves being bi-modal in nature. We believe implicitly that RoFD variables should describe the neuromuscular capacity to 'continue to increase force' and hence requires a continuous increase in force during the measurement. This criterion is not met in a bi-modal curve when peak force can occur at the second peak and when RoFD is calculated relative to initial or minimal force (as undertaken in this study and all of the research reviewed). Therefore, while initial-to-peak RoFD was found to be mathematically feasible it clearly compares different neuromuscular capacities, and hence is functionally irrelevant as it would not easily relate to either a specific exercise action or any subsequent instruction to change jump technique. Additional the bi-modal nature of the curves results in a non-significant 'peak force', in DPA. Subsequently, based on the findings of the continuous data analysis we divided the force curves into two phases (phase 1: 0-60%; phase 2: 60%-100%) and analyzed, using DPA, the peak force for each phase separately. A significantly higher peak force in the second phase ($p = 0.025$) was found in the 'good' performance group. In DPA, without the information of the continuous methods is the performance determining factor 'peak force' of the second phase covered by the bi-modal nature of the curves. This can explain contrasting findings in previous studies regarding RoDF (Morrissey et al., 1998; Newton et al., 1999; Cormie et al., 2009), peak force (Newton et al., 1999; Cormie et al., 2009; Petushek et al., 2010) or small correlations between peak force and jump height (Dowling & Vamos, 1993). In contrast to DPA, continuous data analysis is not influenced by variation in positions of key events (e.g. peak force). Additionaly, fPCA and ACP have no subjective influence on the data analysis and all phases that characterize a data set are examined regardless of what has been previously understood in the subject area. Therefore, the continuous techniques examined are more appropriate than DPA because they: a) compare only related phases of the curve and hence comparable neuromuscular capacities, b) analyse the whole data set rather than prior selected discete data points, and c) identify over which period data differ. These characteristics help in failing to identify important variables and consequently help to understand new or little researched fields more effectively than it is possible with DPA techniques.

The findings of the continuous data analysis techniques do not differ as both techniques identified higher forces produced over a longer period prior and after the rapid drop in force as a performance determining factor. However, finding of ACP are more reliable. In contrast to fPCA, ACP can facilitate a statistical analysis to determine significant different areas and the source (magnitude, timing or the combination of both) of the difference between the groups, while in fPCA no statistical information is provided about the source of the difference and the interpretation over which phase a difference exists relies on visual observation.

CONCLUSION: Only the continuous data analysis techniques identified the area around the peak prior and after the rapid drop in force as a performance determining factor. In particular, ACP seems to be more reliable than fPCA because it does not rely on visual observation and can facilitate a statistical analysis to determine the source (timing, magnitude and the combination of both) that causes the difference. The advantages of continuous data analyses methods highlight the potential of their use in analyzing biomechanical data related to other movements.

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