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Authors: Chris Richter[1,2], Noel E. O'Connor[2], Brendan Marshall[1] and Kieran Moran[1]

Affiliations: [1] Applied Sports Performance Research, School of Health and Human Performance, Dublin City University, Dublin, Ireland. [2] CLARITY: Centre for Sensor Web Technologies, Dublin, Ireland.

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ANALYSIS OF CHARACTERIZING PHASES ON WAVEFORMS – AN APPLICATION TO VERTICAL JUMPS

Chris Richter[1,2], Noel E. O'Connor[2], Brendan Marshall[1] and Kieran Moran[1]

[1] Applied Sports Performance Research, School of Health and Human Performance, Dublin City University, Dublin, Ireland

[2] CLARITY: Centre for Sensor Web Technologies

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Correspondence Address: Chris Richter, CLARITY: Centre for Sensor Web Technologies,
Room L1.29 Computer Science Building,
Dublin City University,
Dublin 9, Ireland

email: chris.richter2@mail.dcu.ie
Tel: 00353 1 700 6830

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Abstract:

The aim of this study is to propose a novel data analysis approach, ‘Analysis of Characterizing Phases’ (ACP), that detects and examines phases of variance within a sample of curves utilizing the time, magnitude and magnitude-time domain; and to compare the findings of ACP to discrete point analysis in identifying performance related factors in vertical jumps. Twenty five vertical jumps were analyzed. Discrete point analysis identified the initial-to-maximum rate of force development ($p = .006$) and the time from initial-to-maximum force ($p = .047$) as performance related factors. However, due to inter-subject variability in the shape of the force curves (i.e non-, uni- and bi-modal nature), these variables were judged to be functionally erroneous. In contrast, ACP identified the ability to: apply forces for longer ($p < .038$), generate higher forces ($p < .027$) and produce a greater rate of force development ($p < .003$) as performance related factors. Analysis of Characterizing Phases showed advantages over discrete point analysis in identifying performance related factors because it: (i) analyses only related phases, (ii) analyses the whole data set, (iii) can identify performance related factors that occur solely as a phase, (iv) identifies the specific phase over which differences occur, and (v) analyses the time, magnitude and combined magnitude-time domains.

Keywords: analysis of characterizing phases, countermovement jump, motion analysis, performance related factor

Word Count: 2201

Introduction

Identification of performance related factors is a major goal in sports biomechanics as they provide useful information for optimizing training interventions. Traditionally discrete point analysis techniques are used to identify performance related factors, which hold a number of limitations: (i) only a few individual pre-selected data points are used to summarize a complex continuous signal, thereby discarding the vast majority of the signal and potentially important information, (ii) key events selected for analysis vary across studies, and (iii) performance related factors can occur over phases that are not necessarily captured in a single data point. In consequence, biomechanists have sought new ways to analyse data as a continuous signal,[1-3] such as functional data analysis which: examines a sample of curves described by functions rather than discrete data points, does not require linear time normalization which can alter the data,[4] and uncovers the underlying structure while maintaining all of the signal information.[4-10] However, there are two possible limitations to functional data analysis as currently employed in biomechanics.[4-10] Firstly, it does not inherently identify key-phases,[a] it tends to be applied to the whole function assuming that key-phases have an overwhelming effect on the generated output score. In consequence, it has the potential to mask performance related factors. Secondly, it cannot examine the combined magnitude-time domain,[b] which can hold important information. To date, no data analysis technique addresses the aforementioned limitations. The aim of this study is to propose a novel data analysis approach; 'Analysis of Characterizing Phases' (ACP), and to compare its findings to discrete point analysis when identifying performance

[a] To analyze key-phases it is necessary to pre-select or visually identify them prior to analysis, which can result in the identification of false key-phases.

[b] The magnitude-time domain merges the information from a waveform's shape and timing. This combination enables the identification of performance related factors that are dependent on both amplitude and time (i.e. impulse-momentum relationship in countermovement jumps).

related factors within the vertical ground reaction force (force) during the propulsive phase of the countermovement jump.

Methods

Twenty five male athletes (age = 22.0 ± 4.0 years; mass = 77.8 ± 9.8 kg), experienced in performing the countermovement jump and free from lower limb injury participated in this study. The University Ethics Committee approved the study. All participants were informed of any risk and signed an informed consent form before participation.

Prior to data collection every participant performed a standard warm-up routine consisting of low intensity jogging, stretching and a self-selected number of sub-maximal and maximal countermovement jumps. Each participant performed 15 maximum effort countermovement jumps without an arm swing, standing with each foot on a separate force platform. Participants rested for 30 seconds between trials. Two force plates (BP-600900, AMTI, USA) recorded the force (1000Hz). Based on jump height, the best jump performance of each subject was identified and used for analysis. Jump height was calculated by the centre of mass vertical velocity at take-off ($V_{take-off}$), with take-off determined when force fell below 5 N (Equation 1 and 2).

$$V_{take\ off} = \left(\int_{start\ propulsion\ phase}^{take-off} (force - BW)\ dt\right) / \ body\ mass \qquad \text{Equation 1}$$

$$Jump\ height = (V_{take-off})^2/(2 \times g) \qquad \text{Equation 2}$$

Only the force-time curve during the propulsion phase was analysed. The start of the propulsion phase was identified from the power-time curve of the body's centre of mass.

For the discrete point analysis, the following 'key' points were examined: initial force, mean force, maximum force, initial-to-maximum rate of force development, time from initial-to-maximum force, percentage initial-to-maximum force, time from maximum force to take-off and propulsion phase duration.[11-16] Initial-to-maximum rate of force development was calculated (Equation 3) from the initial force to the point *i* at which the maximum force occurred.[11] All results are reported as mean ± standard deviation.

$$RFD(i) = \frac{force(i) - force(1)}{\Delta time} \quad \text{Equation 3}$$

Force and continuous rate of force development curves were analyzed using ACP (Figure 1). Continuous rate of force development was determined by differentiating the functional force data.

Normalization: The captured samples differed in length/duration and had to be normalized before applying ACP. A basis b-spline system was used for normalization to avoid linear time normalization. General properties of basis b-spline system are outlined elsewhere.[5,18,19]

Identification of Characterizing Phases: To identify characterizing phases the force variance-covariance matrix was calculated and analyzed using an Eigen analysis.[c] This seeks to find a simplified description of the variance-covariance matrix by solving the Eigen function generating Eigen vectors, called principal components, and Eigen values. Principal components can be seen as a series of loadings, where high positive or high negative values demonstrate high distribution, indicating a specific 'pattern of variance'. Every principal component has a corresponding Eigen value that represents the influence it has on the data set. The sum of all Eigen values fully describes the system created by the variance-covariance matrix where each Eigen value indicates the effect size of the corresponding principal component. Principal components were considered until they described 99% of the data's variance.[20] To increase the interpretability of the retained principal components a VARIMAX

[c] A variance-covariance matrix should only be used if the used data does not differ in unit or origin.[17]

rotation was performed.[5,9,10] The rotated principal components are used to identify pattern-characterizing phases, called key-phases. The position and sign of the principal component's absolute maximum were used to establish the key-phase start and end point. The last value differing in sign before and after the absolute maximum defined the start and end of the key-phase, respectively (Figure 2a). Each key-phase is separated into segments, based on thresholds (e.g. 100%, 95% and 90% of the principal component peak). These segments vary in their pattern-characterizing potential from high to low. The highest pattern-characterizing potential is defined by the data between thresholds 1 and 2 (Figure 2b). The second highest pattern-characterizing potential is defined by the segments between thresholds 2 and 3 prior and after the segment with the highest pattern-characterizing potential, and so on.

Examining pattern-characterizing phases: Similarity scores were calculated for each participant within identified key-phases. These scores measure the relationship between curves with respect to time, magnitude and the combined magnitude-time domain, and were used for statistical analysis. Similarity scores were generated by calculating the Euclidean distance between two curves (Equation 4), which is the root sum of all squared distances defined by the curves of a participant q and the best jump p at every point i within the selected segment.

$$Similarity\ score = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \qquad \text{Equation 4}$$

A low similarity score indicates high similarity between the signals, and vice versa. Where a significant difference between the similarity scores is evident, the similarity scores were recalculated within the segments of the next lowest pattern-characterizing potential phase.[d] This process is terminated when a non-significant stage, the start point, or the end

[d] In the example given (Figure 2), the score for the second iteration is calculated using the data ranging from 80.1-81.8 % and 87.7-88.5 % of the movement cycle (individually), without the data within the highest pattern-characterizing potential (81.8-87.7 %).

point of the key-phase is reached. This approach explores the total phase over which a difference exists and avoids a possible overwhelming effect of a highly significant key phase erroneously causing a non-significant phase to appear significant.

The present study used a correlation analysis ($p = .05$) to examine the relationship between discrete points (discrete point analysis) or similarity scores (ACP) and jump height. Factors that significantly correlated with jump height (performance outcome) were defined as performance related factors and classified into weak ($r^2 < .09$), moderate ($.09 < r^2 < .49$) and strong ($r^2 > .49$).[21]

Results

The discrete point analysis technique did not identify any relationship between jump height and either high forces or the duration of force application (Table 1). Factors that did correlate with jump height were initial-to-maximum rate of force development and time from initial-to-maximum force (Table 1).

Analysis of Characterizing Phases found key-phases in both force and rate of force development which correlated with jump height (Table 2, Figure 3 and 4). Similarity scores for the time domain correlated with jump height ($p = .041$, $r^2 = .16$) for all key-phases, indicating that higher jumps were achieved by a longer force application. Similarity scores in force correlated with jump height for key-phases spanned by principal component 4 and 5 in the magnitude and magnitude-time domains. These scores indicated that higher jumps were achieved by generating higher forces over a phase of 64-96 % of the cycle. Similarity scores for rate of force development correlated with performance for key-phases spanned by principal component 2, 3 and 7 in the magnitude domain, and 2, 3, 6 and 7 in the combined magnitude-time domain. The rate of force development similarity scores indicated that higher jumps were achieved by a greater magnitude in rate of force development over a phase of 18-80 % and 88-99 %.

Discussion

The analysis techniques identified different performance related factors. Maximum force was not a performance related factor using discrete point analysis, but was a strong factor with ACP. Visual examination of each force curve indicated a significant variation in their shape, with curves being either non-, uni- or bi-modal in nature, and in the case of bi-modal curves the maximum force could occur at either peak. This may explain the contrasting findings between the analysis techniques. To examine this possibility each force curve was divided into two phases (phase1: 0-60 %; phase2: 60-100 %) and the magnitude and timing of the maximum force in each phase was re-examined for correlation to jump height.[e] The timing and magnitude of the maximum force in the second phase were subsequently identified as moderate performance related factors ($p = .003$, $r^2 = .315$ and $p = .039$, $r^2 = .172$, respectively). Due to the pre-selection of 'key' events and the inability to take into account their position, discrete point analysis can fail to identify performance related factors. This may explain previous contrasting findings, all of which used discrete point analysis, with some reporting maximum force as a performance related factor while others did not.[11-16] Discrete point analysis identified the time from initial-to-maximum force and the initial-to-maximum rate of force development as moderate performance related factors. While these variables are mathematically feasible, they are functionally erroneous. Firstly, the time from initial-to-maximum force is highly distributed due to the multi-modal nature of the force curves. A separate analysis of early and late peaking athletes found no relationship with jump height for either group ($p > .106$). Secondly, rate of force development should

[e] These phases were based on the findings of ACP

describe the neuromuscular capacity to '*continue* to increase/decline force'. This criterion is not met in the bi-modal force curves where maximum force can occur at the second peak and when discrete rate of force development is calculated relative to the start of the propulsion phase.[11-14] For similar reasons, initial-to-maximum rate of force development can be calculated using the maximum force in the first or second phase. In consequence, the variables 'time from initial-to-maximum force' and 'initial-to-maximum rate of force development' would not easily relate to either a specific exercise or an instruction to change jump technique. This may partly explain the contrasting results in previous studies, all of which utilised discrete point analysis, where some studies reported initial-to-maximum rate of force development as a performance related factor while others did not. [11,13,14]

Analysis of Characterising Phases showed that high forces correlate with jump height within the phase of 64-96 % in the magnitude domain and the combined magnitude-time domain. In addition, ACP found continuous rate of force development to correlate moderately to strongly with jump height in the magnitude domain (32-79 % and 90-98 %) and the combined magnitude-time domain (18-80 % and 88-99 %). This provides important information for improving performance and indicates the advantage of ACP over discrete point analysis. However, we believe that the higher decline in continuous rate of force development (88-99 %) is due to the higher force and their extended period of application towards the end of the propulsion phase. Consequently, the higher decline in continuous rate of force development is functionally erroneous because no one would attempt to deliberately reduce force as fast as possible prior to take off; rather the higher and more prolonged forces must simply decline to zero quicker prior to take-off.

In conclusion, ACP seems to be more effective at identifying performance related factors in the force curves of countermovement jumps than discrete point analysis because it: (i) analyses only related phases of curves and hence examines comparable neuromuscular capacities, (ii) analyses the whole data set rather than prior selected features, (iii) can examine performance related factors that occur solely as a phase, (iv) identifies the specific phase over which differences occur and, (v) analyzes the time, magnitude and magnitude-time domain. As such, ACP was able to identify the exact movement phase over which a training program should aim to alter technique or neuromuscular capacities to generate a greater impulse. In terms of jump height, the ability to: a) apply forces for longer, b) generate higher forces over an extended period towards take-off (64-95 % of the propulsion phase) and c) generate higher rate of force development (18-80 % of the propulsion phase) appear to be performance related factors.

References

1. Chau T. A review of analytical techniques for gait data. part 1: Fuzzy, statistical and fractal methods. Gait Posture. 2001;13(1):49-66.

2. Chau T. A review of analytical techniques for gait data. part 2: Neural network and wavelet methods. Gait Posture. 2001;13(2):102-120.

3. Ramsay JO, Silverman BW. Applied functional data analysis: Methods and case studies. 1st ed. New York, NY: Springer Verlag; 2002.

4. Donà G, Preatoni E, Cobelli C, Rodano R, Harrison AJ. Application of functional principal component analysis in race walking: An emerging methodology. Sports Biomechanics. 2009;8(4):284-301.

5. Ramsay JO. Functional data analysis. 2nd ed. New York, NY: Springer Verlag; 2006.

6. Donoghue OA, Harrison AJ, Coffey N, Hayes K. Functional data analysis of running kinematics in chronic achilles tendon injury. Medicine & Science in Sports & Exercise. 2008;40(7):1323-1335.

7. Newell J, McMillan K, Grant S, McCabe G. Using functional data analysis to summarise and interpret lactate curves. Comput Biol Med. 2006;36(3):262-275.

8. Godwin A, Takahara G, Agnew M, Stevenson J. Functional data analysis as a means of evaluating kinematic and kinetic waveforms. Theoretical Issues in Ergonomics Science. 2010;11(6):489-503.

9. Harrison A, Ryan W, Hayes K. Functional data analysis of joint coordination in the development of vertical jump performance. Sports Biomechanics. 2007;6(2):199-214.

10. Ryan W, Harrison A, Hayes K. Functional data analysis of knee joint kinematics in the vertical jump. Sports Biomechanics. 2006;5(1):121-138.

11. Cormie P, McBride JM, McCaulley GO. Power-time, force-time, and velocity-time curve analysis of the countermovement jump: Impact of training. The Journal of Strength & Conditioning Research. 2009;23(1):177-186.

12. Dowling JJ, Vamos L. Identification of kinetic and temporal factors related to vertical jump performance. Journal of Applied Biomechanics. 1993;9(4):95-110.

13. Morrissey MC, Harman EA, Frykman PN, Han KH. Early phase differential effects of slow and fast barbell squat training. Am J Sports Med. 1998;26(2):221-230.

14. Newton RU, Kraemer WJ, Häkkinen K. Effects of ballistic training on preseason preparation of elite volleyball players. Medicine & Science in Sports & Exercise. 1999;31(2):323-330.

15. Petushek E, Garceau L, Ebben W. Force, velocity, and power adaptations in response to a periodized plyometric training program. International Symposium of Biomechanics in Sports. 2010;28(1):262-265.

16. Sheppard JM, Cronin JB, Gabbett TJ, McGuigan MR, Etxebarria N, Newton RU. Relative importance of strength, power, and anthropometric measures to jump performance of elite volleyball players. The Journal of Strength & Conditioning Research. 2008;22(3):758-765.

17. Jolliffe IT. Principal component analysis. 2nd ed. New York, NY: Springer Verlag; 2002.

18. Daffertshofer A, Lamoth CJC, Meijer OG, Beek PJ. PCA in studying coordination and variability: A tutorial. 2004:19(4):415-428.

19. Eilers PHC, Marx BD. Flexible smoothing with B-splines and penalties. Statistical science. 1996;11(2):89-121.

20. Richter C, McGuinness K, Gualano L, O'Connor NE, Moran K. Identification of an optimal principal components analysis threshold to describe jump height accurately using vertical ground reaction forces. Symposium International Society of Biomechanics, Natal. 2013, In Press.

21. Cohen J. Statistical power analysis for the behavioral sciences. 2nd ed. Hillsdale, NJ: Lawrence Erlbaum; 1988.

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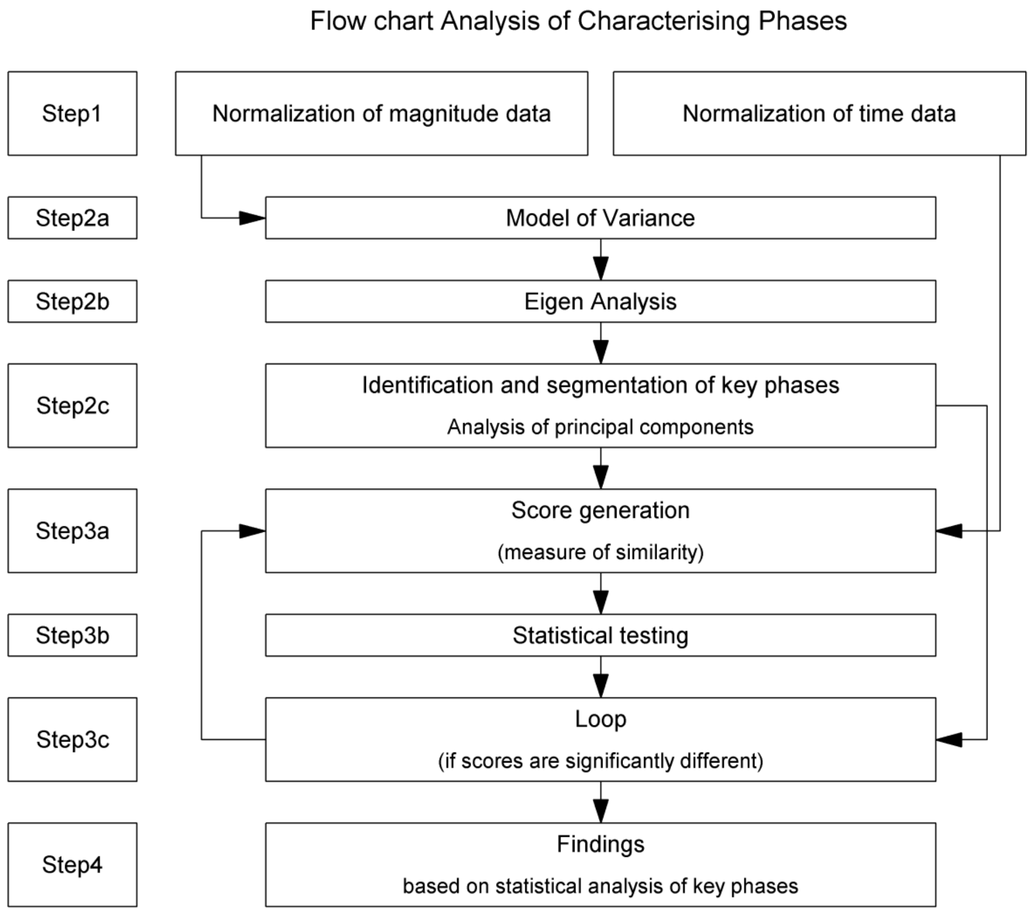

Figure 1: Shows a flow chart describing the process of ACP

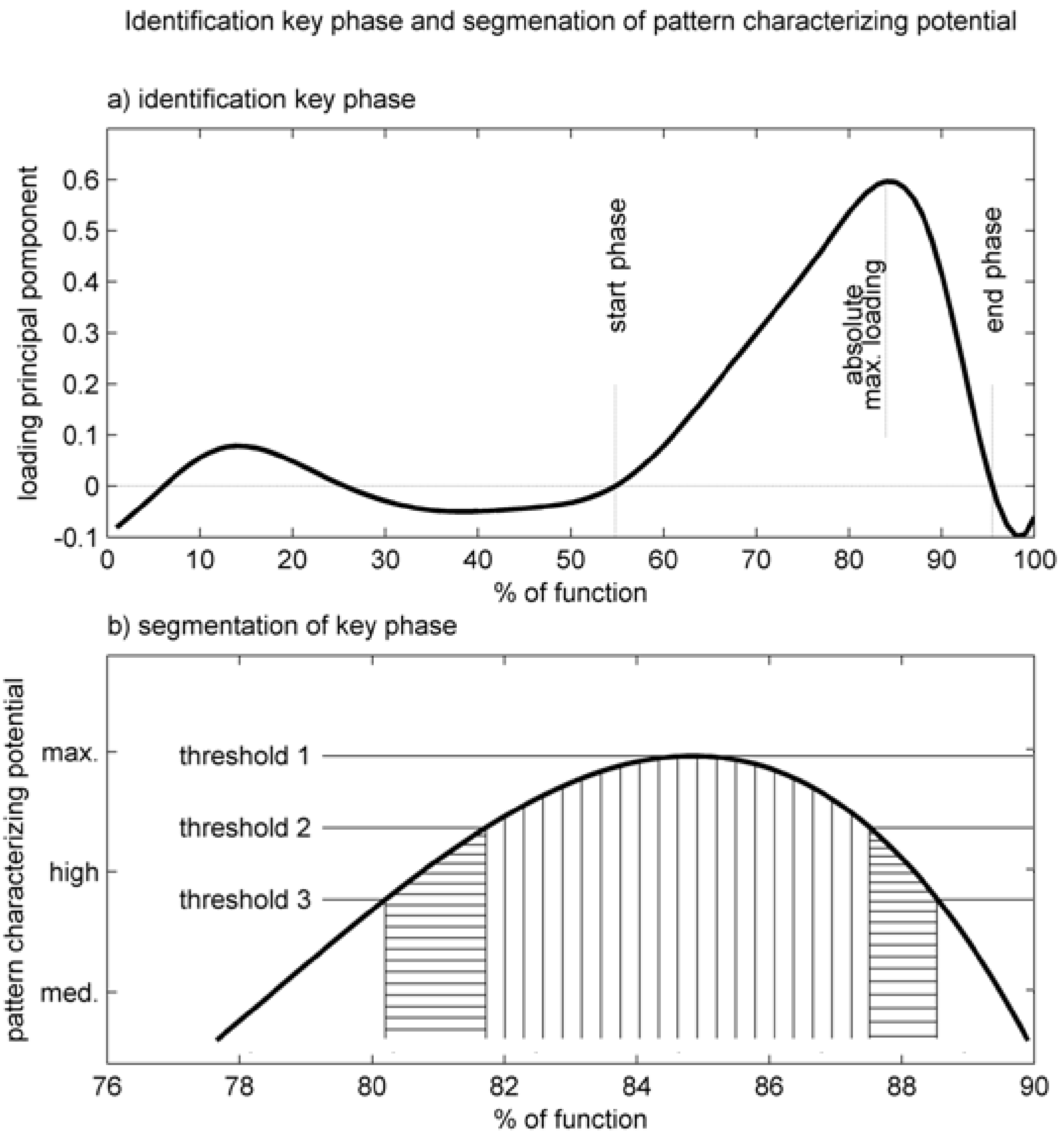

Figure 2: Visualisation of **a**) the detection of the start and the end point of a key-phase over the whole function and, **b**) the separation of a key phase into segments with different pattern-characterizing potential

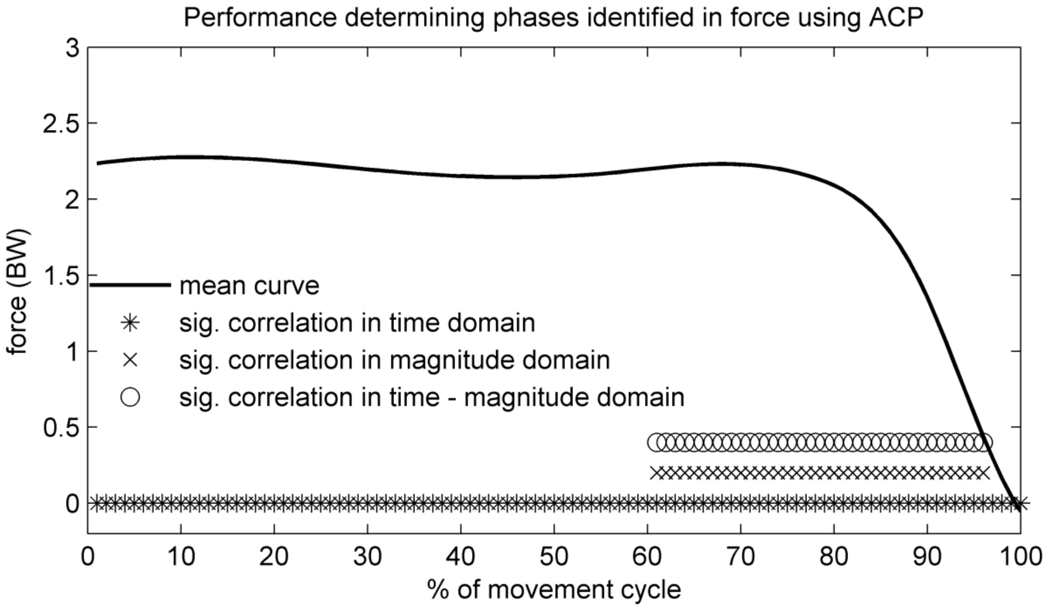

Figure 3: Summarizing findings of ACP indicating that a greater impulse is generated in 'better' jumpers by applying forces for longer, higher forces over the movement cycle of 64-96 % and, higher forces in the combined magnitude-time domain over the movement cycle of 64-96 %

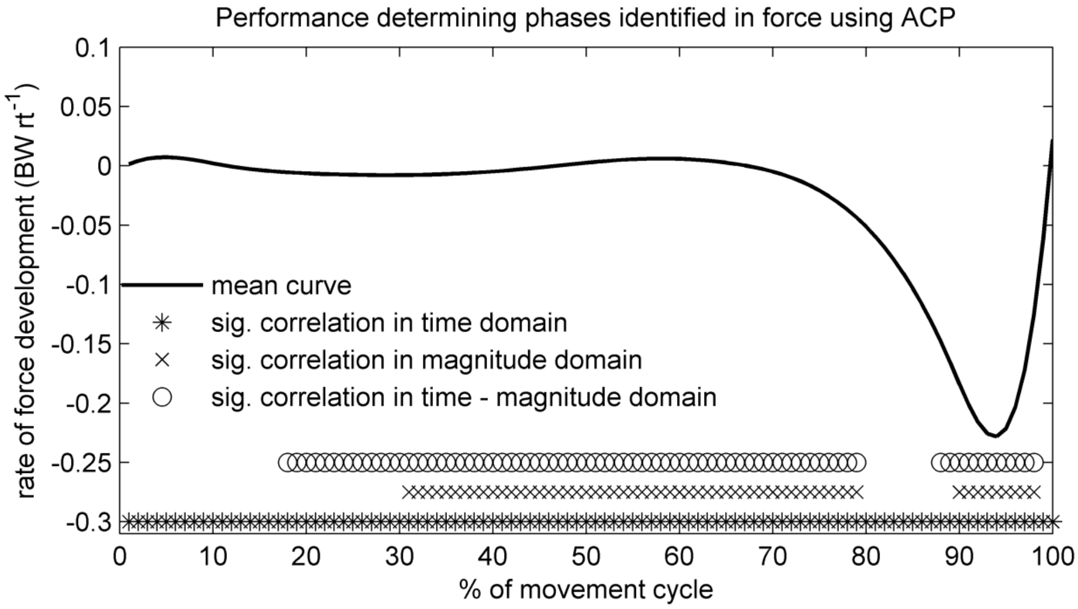

Figure 4: Summarizing findings of ACP indicating that a greater impulse is generated in 'better' jumpers by a longer forces application, higher rate of force development over the movement cycle of 32-78 % and, higher rate of force development in the combined magnitude-time domain over the movement cycle of 18-80 %

Table 1: Descriptive statistics of the selected data points in the discrete point analysis

Variable	p-value	r-value (r^2)
initial force (BW)	p = .155	r = -.293 (.09)
mean force (BW)	p = .125	r = .315 (.10)
maximum force (BW)	p = .506	r = .139 (.02)
time initial-to-maximum force (s) *	p = .047	r = .401 (.16)
percentage initial-to-maximum force (%)	p = .060	r = .381 (.14)
time peak-to-take-off (s)	p = .187	r = -.273 (.07)
discrete rate of force development (BW s^{-1})*	P = .006	r = .537 (.29)
duration propulsion-phase (s)	p = .051	r = .395 (.16)

*significant correlation to jump height

Table 2: Descriptive statistics of computed similarity scores in force and continuous rate of force development in ACP

		Similarity scores of force				
		variability (%)	range pattern | key phase (%)	correlated phase (%)	p-value	r-value (r^2)
PC 1	combined	22	6-61 | 26-37	no	p = .960	r = .010 (<.01)
PC 2	combined	17	30-86 | 55-62	no	p = .105	r = .330 (.11)
PC 3	combined	28	1-32 | 1-4	no	p = .470	r = .142 (.02)
PC 4	combined*	8	81-100 | 93-95	81-96	p < .001	r = .722 (.52)
	magnitude*			91-96	p < .001	r = .737 (.54)
PC 5	combined*	25	55-96 | 82-86	64-95	p < .001	r = .711 (.51)
	magnitude*	-		64-94	p < .001	r = .686 (.47)

		Similarity scores of continuous rate of force development				
		variability (%)	range pattern | key phase (%)	correlated phase (%)	p-value	r-value (r^2)
PC 1	combined	40%	23-100 | 83-87	no	p = .299	r = .127 (.05)
PC 2	combined*	27%	80-100 | 94-95	88-99	p < .001	r = .670 (.45)
	magnitude*			90-98	p = .007	r = .525 (.28)
PC 3	combined*	18%	69-85 | 69-85	69-80	p = .038	r = .417 (.17)
	magnitude*			69-79	p = .038	r = .418 (.17)
PC 4	combined	3%	3-28 | 7-9	no	p = .088	r = .348 (.12)
PC 5	combined	6%	93-100 | 93-100	no	p = .090	r = .429 (.18)
PC 6	combined*	3%	1-55 | 19-27	18-55	p = .008	r = .516 (.27)
PC 7	combined*	3%	31-88 |59-67	31-79	p = .020	r = .459 (.21)
	magnitude*			32-78	p = .008	r = .520 (.27)

* significant correlation to jump height